Introduction.

The concepts of technological change, technological progress, and the technological division of labor are widely used in economics and some other strands of social science. Adam Smith's (1937) view of the division of labor is, for example, one grounded in a technological division of labor, rather than a division of labor based on ecclesiastical, administrative, or military grounds. Due to the combinatorial nature of technological change, which we will discuss in the next section, it is possible to make inter-societal comparisons of technology, and to judge one technology as more or less advanced than another. Unfortunately, the leading cross-cultural database, the Standard Cross-Cultural Sample (SCCS) (Murdock and White 1969), does not have a good theoretically grounded ordinal measure of technology. The best available measure is a three-technology ranking found in SCCS v153, which ranks metalwork as higher than loom weaving which is higher than pottery; the most advanced societies have all three technologies and the least advanced have none.

In this paper we present a more detailed measure of technological level, ranking societies from more advanced to less, where we base that ranking on a theoretical view of technological change first presented by the sociologist S.C. Gilfillan, and then by the Institutional economist Clarence Ayres and the urban theorist Jane Jacobs.

Technology as a cumulative process.

Technology develops as the elements of preexisting technology are combined into new forms (Gilfillan 1935:6; Ayres 1944:112). The tent, for example, combines the technology of leatherwork or weaving with the technology of wood, stone, or bone frame construction. An element of technology like the tent is “essentially a complex of most diverse elements” (Gilfillan 1935:6)—a society can only possess the tent if it has the technology to access the required raw materials (skin, fiber, wood), if it possesses the technology to manufacture the tools (needles, knives) needed to process the raw material, and if it has the technology (travois, cart, sled; domesticated canids, camelids, equids) to carry the tent from place to place. Thus, not only does the element of technology emerge as the combination of preexisting elements, but the use of that technology requires yet other preexisting elements.

Technology is cumulative in this sense, that each new element of technology is enabled by those that already exist. The more elements of technology that exist, the greater the possibilities for new combinations, so that new technology can emerge at an accelerating rate. While social evolution has no necessary direction, the cumulative nature of technology and its potential to accelerate make technological change “progressive” (Ayres 1944:111,119), such that technological “change is continuous and cumulative and always in the same direction, that of more numerous and more complex technological devices” (Ayres 1944:123).

Nevertheless, a variety of factors affect the rate at which combinations are actually made, so that technology will develop at different rates in different social environments. Clarence Ayres (1944:131) suggests that *sedentism* greatly facilitates technological progress, since the ability to reside in one spot allows the “accumulation of technical materials”, which then become available for further combinations. The development of agriculture therefore constitutes a new technology especially favorable to technological change—since it not only provides new elements for further combinations, but also makes it easier to create those combinations. Ayres (1944:152) sees printing as another element of technology that facilitates technological change; one could argue that *writing and record-keeping* generally work in this way. Ayres (1944:117-118) also points out that new elements of technology are often created by outsiders who can look at existing tools with innocence, and that it is in regions where different cultures come into contact that an existing tool is most likely to be appraised with new eyes. *Cross-cultural contact* is thus favorable to new and innovative combinations; a striking example of this is the development of the early modern European ship as a vessel combining features of Mediterranean and North Sea ships (Ayres 1944:143). Ayres views technology as a dynamic force that is stifled by what he terms “ceremonial” patterns—beliefs, norms, and behavior that establish and maintain status (Ayres 1944: Chapter 8). *Urbanization* is therefore favorable to technological change, since cities are collections of strangers with relatively weak attachment to shared traditions (Ayres 1944:146).

Jane Jacobs conceives of economic development as the process of an economy “adding new work to old” (Jacobs 1969:47), where this process occurs through combinations of “divisions of labor”. Cities contain elaborated divisions of labor and are therefore the locations where most new work is created (Jacobs 1969:48). *Trade* between cities exposes a city to new products, spurring imitation (Jacobs 1969: Chapter 5); a process David Hume (1985) called the “demonstration effect of trade”.[1] For example, Tokyo imported bicycles in the late 19th century, and there soon appeared small repair shops. Spare parts were expensive to import, so repair shops began to manufacture bicycle parts—each shop specializing in one part and buying other parts as needed. Eventually a few shops began to buy large numbers of parts in order to assemble them into completed bicycles. The introduction of bicycle manufacturing thus took the form of small incremental additions to the division of labor within the Tokyo economy (Jacobs 1969:61-62). Like Ayres, Jacobs sees outsiders as the usual source of new work. For example, the modern brassiere was developed by a dressmaker’s shop, not an undergarment firm. Where restrictions such as zoning or guild regulations keep work within stable categories, little new work is created (Jacobs 1969:60).

S.C. Gilfillan (1935:47), much like Jacobs, finds urbanization and a highly articulated division of labor conducive to technological change. He emphasizes that the integration of the specialized parts is especially critical, giving *transportation technology* a special importance in facilitating technological change. The Roman failure to achieve accelerating technological progress he attributes to their inferior transportation technology—no horseshoe, a harness that could strangle a horse, a hard-to-steer cart, and unseaworthy merchant ships (Gilfillan 1935:51). New technology displaces the old, and where enterprises have durable physical capital (such as solid, well-built structures) there is an incentive to preserve that capital and to resist innovations. Likewise, when new technology would make obsolete the human capital of workers or the social capital of principals and managers, that technology is resisted (Gilfillan 1935:56-57). Thus, a *growing population* is especially favorable to the introduction of new technology, since that technology can enter as an addition to the current stock of capital, rather than as a replacement (Gilfillan 1935:58-59).

The development of new technology thus requires pre-existing elements of technology and the hands and minds of persons who will combine that technology in new ways. The greater the

[1] See Hume’s essays "Of Commerce" (1752) and "Of the Jealousy of Trade" (1758).

number of pre-existing elements and the greater the number of combining persons, the greater the rate at which technology will develop.

Data and method

Variables v2126 through v2175 in the Standard Cross-Cultural Sample (SCCS) are dummy variables indicating the presence of tasks such as water-fetching or weaving in each of the 186 SCCS societies. Since technology is cumulative, a society with advanced tasks will contain the less-advanced tasks that are prerequisites for the advanced tasks—e.g., a society with "net-making" (v2158) will also have the ability to make "rope or cordage" (v2160). We base our measure of technological level on these dummy variables, employing the 186 x 47 data matrix **D**, each row of which is a society, each column a task, and each cell either a one (indicating the presence of that task in that society) or a zero (indicating the absence of the task in that society).[2]

Our measure of the technological level of a society is the weighted sum of the number of tasks present in that society:

$$\tau = \mathbf{D}\, w \tag{1}$$

Where τ is a 186 x 1 vector giving the ordinal technological level of a society, **D** is our 186 x 47 binary data matrix with ones indicated the presence of the column task in the row society, and w is a 47 x1 vector of weights where more advanced tasks correspond to higher weights.

We derive the weights w by reasoning that more advanced tasks are enabled by the presence of less-advanced tasks. We thus find how tasks are associated with each other in the 186 societies of the SCCS, employing the 186 x 47 data matrix **D**:

$$\mathbf{B}=\mathbf{D}'\mathbf{D} \tag{2}$$

B is a 47 x 47 matrix giving the number of times each row task is found together with each column task across the 186 societies. The diagonal gives the total number of times each task occurs. Dividing each row in **B** by its diagonal element gives the matrix **V**, where each cell gives the probability that the column task is present, conditional on the row task being present.

$$v_{ij} = b_{ij}/b_{ii} = Prob(task\ j\ is\ present \mid task\ i\ is\ present) \tag{3}$$

If technology j is a precursor to a technology i, then j should be present whenever i is present, and v_{ij} should be close to one. On the other hand, if i is a precursor to j, then i should exist in many societies without j, and v_{ij} would be a number considerably lower than one. Thus we interpret v_{ij} as the probability that j is a precursor technology to i.

We subtract the transpose of **V** from **V** to get matrix **N** = **V**-**V**′. Each cell n_{ij} gives the *net difference*[3] between the probability that task j is a precursor to task i and the probability that task i is a precursor to task j. A positive number indicates that task j is the precursor to i; a negative number indicates that i is the precursor to j.

[2] Three of the 50 variables are redundant and therefore dropped: v2148 (Cooking) and v2152 (Water Fetching) are present in all societies, and v2137 (Planting) is identical to v2139 (Harvesting).
[3] The term *net difference* is borrowed from Lieberson (1976), who uses the term to describe a similar subtraction of probabilities.

$$n_{ij} = b_{ij}/b_{ii} - b_{ji}/b_{jj} \tag{4}$$
$$= \text{Prob}(\text{task } j \text{ is present} \mid \text{task } i \text{ is present}) - \text{Prob}(\text{task } i \text{ is present} \mid \text{task } j \text{ is present})$$

Since a task with more precursors will be a more advanced technology, we sum across the net to get a measure of the technological level of task *i*:

$$w_i = \Sigma_j \, n_{ij} \tag{5}$$

The technological level τ should be calculated in a multiple imputation context, since all of the SCCS variables contain missing data. Below is a snippet of `R` code that calculates τ for a dataframe `smi` containing multiple imputed datasets indexed by the variable `smi$.imp`. All 47 technology dummies must be present in `smi`, and the following code executed after imputation.

```
tchx<-paste("v",c(2126:2175),sep="")
tchx<-setdiff(tchx,c("v2137","v2148","v2152"))
is.na(smi$tech)<-TRUE
for (i in 1:max(smi$.imp)){
  zh<-which(smi$.imp==i)
  ddd<-as.matrix(smi[zh,tchx])
  bb<-(t(ddd)%*%ddd)
  bb<-bb/diag(bb) #Prob(column task present|row task present)
  rs<-round(rowSums(bb-t(bb)),4)
  smi[zh,"tech"]<-
as.numeric(scale(ddd%*%as.matrix((rs)))*1.5+10)
}
```

Discussion of estimated values.

Table 1gives some descriptive statistics for the 47 SCCS task dummies, as well as the weights for each of the 47 tasks. The weights *w* are the means from 30 imputed datasets; the maximum and minimum values across the 30 imputed datasets are also shown. Table 2 presents the average technological level τ for each of the 186 SCCS societies across the 30 imputed datasets.

The weights *w* in Table 1 seem reasonable. Loom weaving is higher than spinning which is higher than cordage; dairy is higher than milking which is higher than large domestic animals; leather is higher than skins, and so on. At first glance, it may seem anomalous that smelting is higher than metal, but since metal sources are localized, and metal is a weight-losing product, much cheaper to process close to the source, it is clear that many societies would obtain metal through trade, and only a few would obtain it through their own smelting.

The SCCS societies differ in their focal dates, so that societies coded from more recent ethnographies are likely to have access to more advanced technology. Figure 1 shows a map of the technological level τ scores: small, yellowish points are societies with the lowest levels and large, reddish points are the highest levels. The light blue borders are convex hulls showing regions of high positive spatial autocorrelation (in these regions, a society's technological level is likely to be similar to its neighbors). The highest ranking societies have both dairy and metalwork, and include most African pastoralists. Societies in the Americas and Melanesia lack large domesticated animals, and tend to have low values.

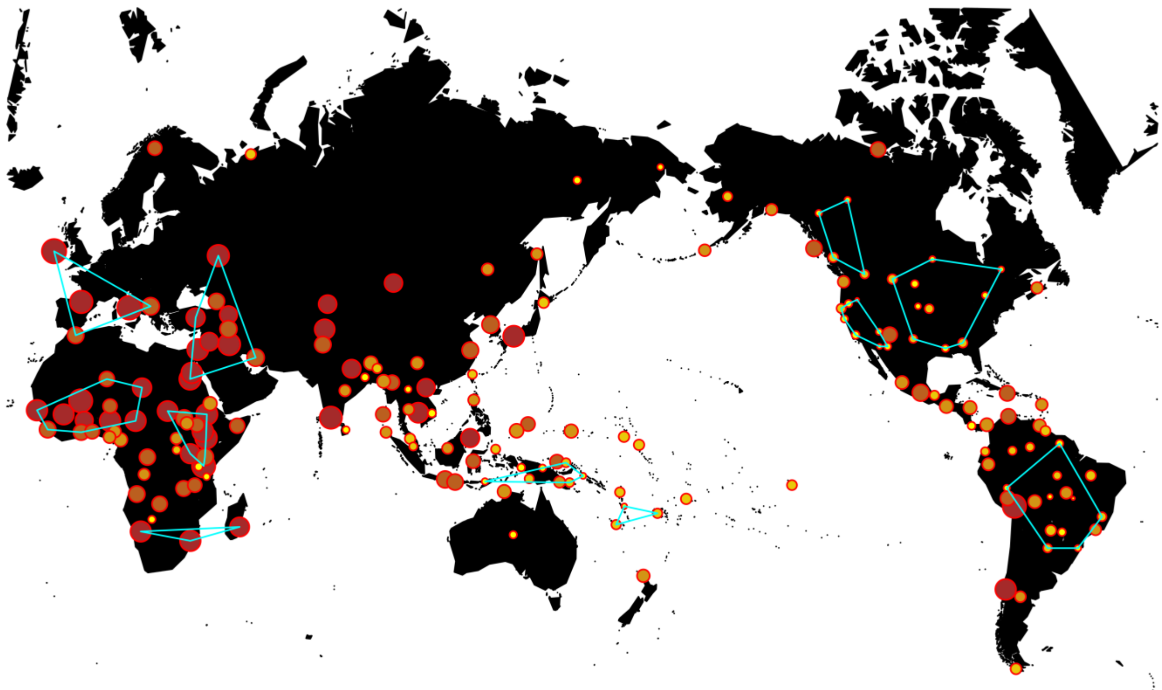
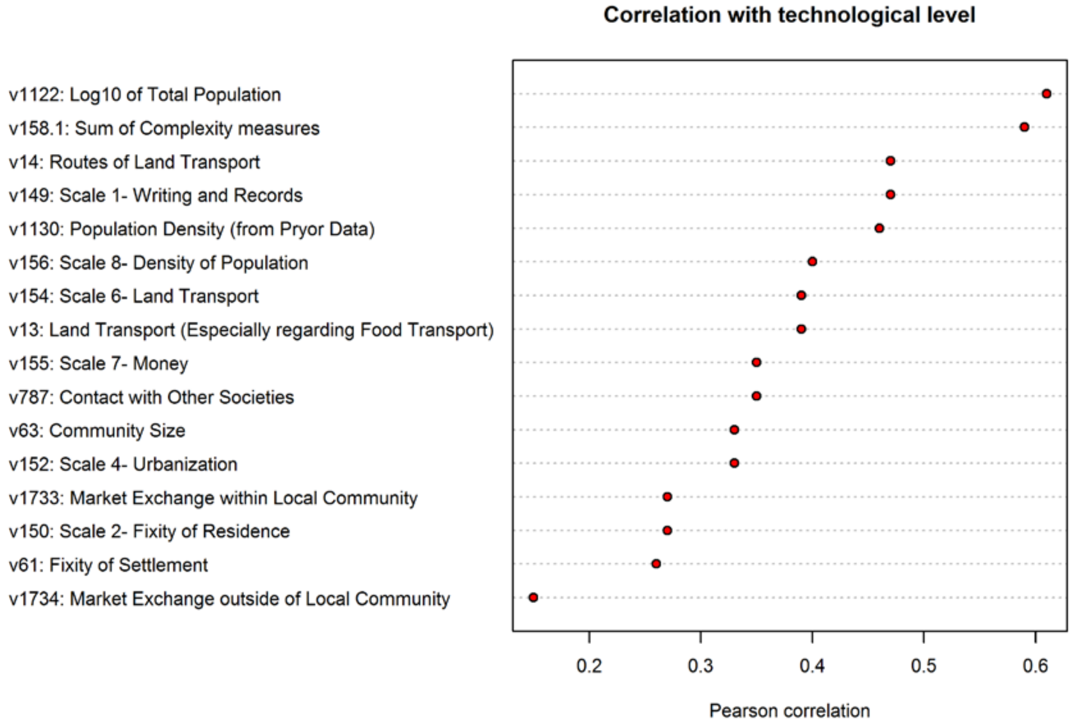


Figure 1: Technological level (not spatially smoothed). Larger red points represent higher values, smaller yellow points low values. The cyan lines demarcate convex hulls around regions of significant local autocorrelation.

In our brief discussion of the views of Gilfillan, Ayres, and Jacobs, we mentioned that technological level was hypothesized to be higher in societies that are sedentary, possess writing and record-keeping, engage in significant cross-cultural contact and trade, are urbanized, have advanced transportation technology, and have a growing population. Figure 2 (top) shows the Pearson correlation coefficients between technological level τ and measures of these hypothesized covariates. All correlations are highly significant and of the expected sign. Perhaps the only surprise is that sedentism is one of the weakest of these covariates: pastoral peoples with dairy and metal technology rank high with our measure of technological level.

Our measure of technological level correlates highly (r=.59) with the SCCS measure of overall societal complexity (SCCS v158.1), which is formed as the sum of ten different ordinal measures: Writing and Records; Fixity of Residence; Agriculture; Urbanization; Technological Specialization; Land Transport; Money; Density of Population; Political Integration; and Social Stratification. Societal complexity includes much more than simply the level of technology, and one can see from the bottom chart in Figure 2 that some less complex societies have high levels of technology (such as the Masai) and some complex societies rank relatively low on level of technology (such as the Siamese). Thus, our measure of technological level should be useful for those who seek a metric for the technological division of labor, not confounded with the elements of division of labor based on hierarchy and stratification.



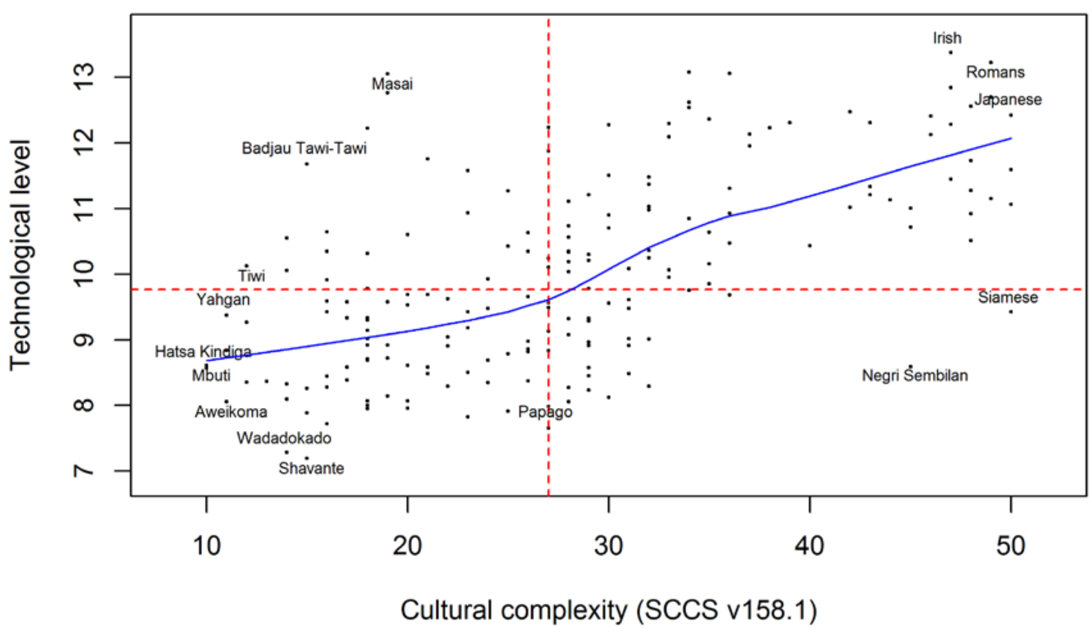


Figure 2: Correlation coefficients for measures hypothesized to covary with τ (top). Technological level correlates highly with cultural complexity, but is nevertheless different (bottom). Dotted red lines mark median values; the solid blue line is the lowess smoother (Cleveland 1979).

Tables

Table 1: Weights *w* for the 47 identifiable technologies.

SCCS	description	N	mean	sd	$\hat{b}_{ii}$	w	w_{max}	w_{min}
v2164	Manufacturing: Wood	182	0.995	0.074	185	-12.166	-12.026	-12.312
v2175	Miscellaneous: Housebuilding	185	0.995	0.074	185	-12.164	-12.024	-12.313
v2150	Extractive Industries: Fuel Gathering	179	0.994	0.075	185	-12.153	-12.016	-12.301
v2143	Food Preparation: Vegetal: Food Preparation	178	0.989	0.106	184	-11.882	-11.599	-12.068
v2169	Miscellaneous: Fire	185	0.984	0.127	183	-11.718	-11.580	-11.867
v2160	Manufacturing: Rope or Cordage	170	0.982	0.132	183	-11.647	-11.370	-11.868
v2173	Miscellaneous: Burden Carrying	155	0.981	0.138	181	-11.226	-10.604	-11.611
v2168	Manufacturing: Musical Instruments	170	0.953	0.212	178	-10.430	-10.020	-10.639
v2144	Food Preparation: Butchering	167	0.952	0.214	177	-10.265	-9.649	-10.706
v2126	Food Collection: Vegetal	179	0.944	0.230	175	-9.634	-9.175	-9.947
v2140	Food Production: Small Domestic Animals	180	0.928	0.260	173	-9.232	-8.693	-9.505
v2171	Miscellaneous: Bodily Mutilation	164	0.921	0.271	170	-8.215	-7.513	-9.016
v2151	Extractive Industries: Lumbering	169	0.917	0.276	169	-7.918	-7.226	-8.771
v2130	Food Collection: Fowling	157	0.898	0.303	165	-7.004	-5.193	-7.855
v2159	Manufacturing: Basketmaking	170	0.876	0.330	163	-6.851	-6.390	-7.374
v2127	Food Collection: Insects, and/or Small Land Fauna	133	0.865	0.343	160	-5.588	-4.443	-6.489
v2132	Food Collection: Trapping	171	0.883	0.322	159	-5.490	-4.853	-6.756
v2165	Manufacturing: Bone	140	0.900	0.301	158	-5.158	-4.211	-6.499
v2131	Food Collection: Fishing	182	0.841	0.367	156	-4.916	-4.441	-5.087
v2157	Manufacturing: Matmaking	163	0.822	0.384	153	-4.473	-3.564	-5.143
v2145	Food Preparation: Preservation	161	0.807	0.396	153	-4.381	-3.787	-4.819
v2133	Food Collection: Large Land Fauna	180	0.800	0.401	147	-2.386	-1.864	-3.085
v2146	Food Preparation: Drinks	170	0.782	0.414	144	-2.207	-1.741	-2.906
v2135	Food Production: Land Clearance	184	0.761	0.428	142	-1.732	-1.612	-1.909
v2139	Food Production: Harvesting	185	0.762	0.427	142	-1.732	-1.612	-1.909
v2162	Manufacturing: Clothing	163	0.779	0.416	139	-0.837	0.167	-1.665
v2138	Food Production: Crop Tending	182	0.736	0.442	138	-0.691	-0.566	-0.868
v2136	Food Production: Soil Preparation	184	0.734	0.443	137	-0.430	-0.314	-0.614
v2153	Intermediate Processing: Skins	173	0.723	0.449	135	0.234	1.059	-0.360
v2166	Manufacturing: Stone	143	0.727	0.447	135	0.741	2.188	-0.530
v2158	Manufacturing: Netmaking	155	0.710	0.455	130	1.982	3.325	0.572
v2161	Manufacturing: Leather	163	0.650	0.478	123	3.393	4.397	2.600
v2163	Manufacturing: Pottery	172	0.645	0.480	121	3.767	4.426	2.968
v2154	Intermediate Processing: Spinning	156	0.641	0.481	118	4.665	6.422	3.696
v2129	Food Collection: Honey	106	0.642	0.482	117	5.112	6.488	3.877
v2172	Miscellaneous: Bonesetting/Surgery	98	0.622	0.487	114	5.650	7.780	3.373
v2141	Food Production: Large Domestic Animals	184	0.587	0.494	109	6.692	6.832	6.492
v2170	Miscellaneous: Laundering	127	0.591	0.494	108	7.048	9.594	5.170
v2174	Miscellaneous: Boatbuilding	175	0.549	0.499	102	8.966	9.595	8.304
v2155	Intermediate Processing: Loom Weaving	170	0.524	0.501	97	10.331	11.541	9.611
v2128	Food Collection: Shellfish/Small Aquatic Fauna	162	0.475	0.501	89	12.363	13.440	11.603
v2167	Manufacturing: Metal	179	0.480	0.501	87	12.754	13.062	12.330
v2142	Food Production: Milking	185	0.314	0.465	58	20.581	20.762	20.401
v2134	Food Collection: Large Aquatic Fauna	177	0.282	0.451	53	20.679	21.097	20.380
v2149	Extractive Industries: Mining/Quarrying	147	0.279	0.450	57	21.450	23.135	19.183
v2147	Food Preparation: Dairy	178	0.270	0.445	54	21.707	22.035	21.507
v2156	Intermediate Processing: Smelting	162	0.228	0.421	48	24.412	25.262	23.386

Notes: *N*, *mean*, and *sd* are from the original SCCS data. Last four columns are results from multiple imputed datasets (m=30); $\hat{b}_{ii}$ = the average number of times task was present across the 30 imputed datasets (average diagonal of matrix **B**); w = measure of technological level (row sums of matrix **P**); and the maximum and minimum values of w across the 30 imputed datasets.

Table 2: Ranks of SCCS societies in technological level τ.

SCCSid	society	missing	τ	τ_{max}	τ_{min}
179	Shavante	4	7.194	7.705	6.930
137	Wadadokado	2	7.282	7.490	7.122
151	Papago	7	7.657	7.897	7.561
174	Nambicura	1	7.720	7.941	7.543
101	Bunlap	47	7.828	8.464	7.336
125	Montagnais	5	7.886	8.079	7.625
142	Pawnee	2	7.910	8.089	7.636
121	Chukchee	0	7.949	8.025	7.843
127	Northern Saulteaux	6	7.960	8.195	7.778
99	Siuai	3	7.982	8.162	7.771
128	Slave	6	8.003	8.698	7.822
180	Aweikoma	7	8.054	8.374	7.805
144	Huron	5	8.054	8.399	7.615
170	Amahuaca	4	8.068	8.238	7.935
150	Havasupai	0	8.071	8.165	8.003
129	Kaska	1	8.092	8.279	7.935
89	Alorese	11	8.120	8.446	7.800
72	Lamet	2	8.139	8.271	7.872
10	Luguru	7	8.236	8.560	7.895
148	Chiricahua	4	8.259	8.662	8.045
95	Kwoma	2	8.274	8.548	8.146
80	Vedda	1	8.277	8.521	8.101
146	Natchez	5	8.290	8.763	7.898
135	Eastern Pomo	1	8.292	8.361	8.208
138	Klamath	0	8.325	8.446	8.261
141	Hidatsa	7	8.348	8.749	7.914
2	Kung	0	8.351	8.484	8.279
91	Aranda	1	8.365	8.472	8.262
165	Saramacca	6	8.373	8.669	8.213
120	Yukaghir	6	8.388	8.780	8.169
181	Cayua	4	8.441	8.616	8.205
94	Kapauku	0	8.449	8.573	8.362
62	Santal	6	8.484	8.870	8.123
136	Lake Yokuts	7	8.486	8.742	8.328
157	Bribri	10	8.506	9.039	8.176
9	Hatsa Kindiga	1	8.572	8.678	8.484
74	Rhade	6	8.578	8.931	8.228
147	Comanche	2	8.581	8.900	8.406
166	Mundurucu	4	8.584	8.924	8.277
82	Negri Sembilan	7	8.586	9.014	8.071
13	Mbuti	0	8.611	8.734	8.499
167	Cubeo	11	8.612	9.069	8.228
168	Cayapa	4	8.687	8.910	8.431
163	Yanomamo	1	8.690	8.958	8.497
139	Kutenai	4	8.704	8.902	8.243
183	Abipon	5	8.719	9.105	8.409
143	Omaha	5	8.788	8.908	8.555
98	Trobriands	2	8.817	9.107	8.619
113	Atayal	13	8.835	10.342	8.378
178	Botocudo	5	8.836	9.131	8.613
97	Lesu	3	8.859	9.076	8.749
93	Kimam	1	8.904	9.002	8.815
88	Tobelorese	7	8.911	9.363	8.395
145	Creek	13	8.913	9.324	8.334

SCCSid	society	missing	τ	τ_{max}	τ_{min}
122	Ingalik	2	8.918	9.092	8.788
134	Yurok	3	8.918	9.341	8.642
154	Popoluca	5	8.962	9.227	8.760
103	Ajie	4	8.979	9.167	8.817
102	Mbau Fijians	6	9.014	9.480	8.595
69	Garo	7	9.016	9.411	8.769
140	Gros Ventre	2	9.017	9.248	8.890
132	Bellacoola	7	9.046	9.289	8.848
100	Tikopia	1	9.078	9.336	8.901
105	Marquesans	4	9.130	9.218	9.067
164	Barama Carib	6	9.144	9.584	8.699
176	Ramcocamecra	4	9.179	9.679	8.764
77	Semang	2	9.268	9.513	9.045
107	Makin	8	9.289	9.815	8.441
53	Yurak	8	9.302	10.145	8.376
106	Upolu	2	9.323	9.455	9.168
108	Marshallese	3	9.324	9.452	9.178
182	Lengua	4	9.330	9.558	9.025
118	Ainu	3	9.334	9.537	9.137
186	Yahgan	0	9.373	9.482	9.297
185	Tehuelche	4	9.422	9.580	9.199
85	Iban	3	9.425	10.107	8.974
76	Siamese	9	9.425	9.793	9.272
112	Ifugao	7	9.475	10.381	8.834
177	Tupinamba	2	9.480	9.572	9.385
78	Nicobarese	8	9.491	9.852	9.185
92	Orokaiva	1	9.529	9.697	9.383
6	Suku	7	9.559	10.240	8.861
60	Maria Gond	0	9.564	9.707	9.457
119	Gilyak	3	9.578	10.239	9.355
126	Micmac	4	9.580	9.714	9.455
130	Eyak	6	9.587	10.377	9.366
28	Azande	0	9.610	9.737	9.510
133	Twana	0	9.621	9.691	9.541
161	Callinago	1	9.659	9.906	9.419
115	Manchu	13	9.685	10.649	9.234
123	Aleut	4	9.686	9.937	9.318
175	Trumai	5	9.692	10.118	9.194
17	Ibo	9	9.756	10.564	9.256
16	Tiv	2	9.783	10.081	9.392
169	Jivaro	1	9.784	9.983	9.611
67	Lolo	7	9.855	10.844	8.954
162	Warrau	4	9.913	10.315	9.585
104	Maori	4	9.926	10.140	9.720
31	Shilluk	5	9.950	10.356	9.751
152	Huichol	3	10.040	10.586	9.550
173	Siriono	0	10.059	10.175	9.967
158	Cuna	8	10.066	10.816	9.367
70	Lakher	3	10.084	11.135	9.152
156	Miskito	1	10.106	10.270	9.967
90	Tiwi	1	10.125	10.235	10.030
155	Quiche	9	10.154	10.625	9.861
109	Trukese	0	10.191	10.292	10.103
15	Banen	4	10.208	10.431	9.994
38	Bogo	13	10.245	11.396	9.388

SCCSid	society	missing	τ	τ_{max}	τ_{min}
68	Lepcha	5	10.249	10.656	9.999
111	Palauans	5	10.304	10.606	9.937
52	Lapps	15	10.318	10.830	9.474
8	Nyakyusa	6	10.333	10.628	9.592
96	Manus	2	10.348	10.676	10.187
87	Toradja	2	10.349	10.621	10.149
25	Wodaabe Fulani	4	10.350	10.511	10.132
110	Yapese	1	10.362	10.476	10.184
32	Mao	2	10.426	10.570	10.164
18	Fon	4	10.432	10.717	10.321
171	Inca	1	10.475	10.681	10.280
71	Burmese	5	10.515	10.987	9.950
79	Andamese	1	10.548	10.691	10.327
36	Somali	7	10.565	11.346	9.749
159	Goajiro	2	10.604	10.717	10.519
41	Tuareg Ahaggar	5	10.630	10.951	10.253
149	Zuni	2	10.635	10.970	10.509
124	Copper Eskimo	3	10.646	10.768	10.346
4	Lozi	5	10.701	11.210	10.371
160	Haitians	9	10.715	11.694	9.537
7	Bemba	0	10.737	10.831	10.634
19	Ashanti	9	10.846	11.195	10.597
14	Nkundo	7	10.899	11.659	10.201
84	Balinese	10	10.922	11.337	10.346
55	Abkhaz	11	10.928	11.241	10.431
131	Haida	0	10.931	11.046	10.849
5	Mbundu	5	10.980	11.377	10.613
59	Punjabi	3	11.004	11.197	10.756
42	Riffians	6	11.020	11.581	10.526
20	Mende	8	11.031	11.370	10.264
114	Chekiang	21	11.066	12.027	9.798
30	Otoro	5	11.112	11.566	10.304
153	Aztec	3	11.131	11.286	10.928
83	Javanese	8	11.154	11.466	10.415
57	Kurd	8	11.208	11.571	10.996
11	Kikuyu	1	11.212	11.459	11.085
58	Basseri	13	11.268	11.982	10.454
116	Koreans	4	11.274	11.622	11.123
48	Gheg	13	11.308	12.337	10.432
56	Armenians	20	11.332	12.473	10.309
23	Tallensi	4	11.368	11.519	11.098
73	Annamese	6	11.448	12.012	11.165
66	Khalka	9	11.481	11.679	11.168
65	Kazak	7	11.505	12.677	10.721
46	Rwala	1	11.578	11.674	11.493
63	Uttar Pradesh	0	11.590	11.710	11.518
86	Badjau Tawi-Tawi	6	11.679	11.896	11.430
47	Turks	8	11.733	12.159	11.488
40	Teda	2	11.757	12.000	11.595
81	Tanala	3	11.876	12.026	11.516
12	Ganda	4	11.951	12.236	11.832
64	Burusho	6	12.093	12.338	11.863
75	Cambodians	11	12.125	12.720	11.597
29	Fur	1	12.135	12.219	12.065
1	Nama	3	12.226	12.965	11.873

SCCSid	society	missing	τ	τ_{max}	τ_{min}
22	Bambara	2	12.228	12.334	12.143
27	Masa	10	12.235	12.747	11.238
3	Thonga	3	12.275	12.546	11.808
43	Egyptians	8	12.284	13.073	11.724
184	Mapuche	4	12.294	12.899	11.998
21	Wolof	12	12.307	13.035	11.316
26	Zazzagawa Hausa	10	12.309	12.727	11.632
33	Kafa	1	12.363	12.584	12.224
44	Hebrews	2	12.409	12.525	12.170
117	Japanese	13	12.419	13.287	11.672
37	Amhara	4	12.477	12.663	12.169
39	Barabra	9	12.537	13.080	11.600
54	Russians	11	12.560	13.460	11.737
35	Konso	3	12.622	12.769	12.367
45	Babylonians	7	12.696	13.889	11.805
61	Toda	1	12.762	12.914	12.630
50	Basques	4	12.842	12.949	12.655
34	Masai	0	13.054	13.185	12.883
24	Songhai	9	13.061	13.456	12.209
172	Aymara	1	13.082	13.204	12.854
49	Romans	5	13.228	13.463	12.978
51	Irish	5	13.378	13.664	12.999

Notes: The number of variables with missing values for each society is given; there are 47 variables in all. Technological level τ is the mean from 30 imputed datasets, using equation 1. The scores are standardized, with a mean of 10 and a standard deviation of 1.5. The maximum and minimum scores across the 30 imputed datasets are also given.

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