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Inequality across prefectures in Japan: An S factor analysis

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Abstract

Two datasets of Japanese socioeconomic data for Japanese prefectures (N=47) were obtained and merged. After quality control, there were 44 variables for use in a factor analysis. Indicator sampling reliability analysis revealed poor reliability (54% of the correlations were |r| > .50). Inspection of the factor loadings revealed no clear S factor with many indicators loading in opposite than expected directions.

A cognitive ability measure was constructed from three scholastic ability measures (all loadings > .90). On first analysis, cognitive ability was not strongly related to 'S' factor scores, r = -.19 [CI95: -.45 to .19; N=47]. Jensen's method did not support the interpretation that the relationship is between latent 'S' and cognitive ability (r = -.15; N=44). Cognitive ability was nevertheless related to some socioeconomic indicators in expected ways.

A reviewer suggested controlling for population size or population density. When this was done, a relatively clear S factor emerged. Using the best control method (log population density), indicator sampling reliability was high (93% |r|>.50). The scores were strongly related to cognitive ability r = .67 [CI95: .48 to .80]. Jensen's method supported the interpretation that cognitive ability was related to the S factor (r = .78) and not just to the non-general factor variance.

Key words: general socioeconomic factor, S factor, Japan, prefectures, inequality, intelligence, IQ, cognitive ability, cognitive sociology

1. Introduction

Desirable socioeconomic outcomes for persons, and larger units such as countries, tend to correlate positively with other desirable socioeconomic outcomes and negatively with undesirable ones, which in turn tend to correlate positively with each other. When this is the case one can extract a general factor

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such that generally the positive outcomes have positive loadings and the negative outcomes negative loadings. The factor has been called the *general socioeconomic factor* (S factor) and is similar to the g factor of mental ability (Jensen, 1998; Kirkegaard, 2014b). The S factor has been replicated across numerous datasets at different levels of analysis (Kirkegaard, 2014a, 2014b, 2015a, 2015e; Kirkegaard & Fuerst, 2014; Kirkegaard & Tranberg, 2015).

Desirable (/undesirable) socioeconomic outcomes at the aggregate-level have often been found to correlate positively (/negatively) with estimates of cognitive ability for the same regions, e.g. (Carl, 2015; Kura, 2013; Lynn, 1979, 1980; Lynn & Cheng, 2013). Because the S factor is an aggregate of such outcomes, it is not surprising that S scores have been found to have strong positive correlations with cognitive ability as well, e.g. (Kirkegaard, 2015b, 2015c, 2015f).

One prior study has examined socioeconomic outcomes at the aggregate-level in Japan (Kura, 2013). However, an S factor was not extracted from the socioeconomic outcomes so it is unclear if the general pattern of results hold in Japan as it did in the other countries.

Japan is a densely populated country[2] and has a number of administrative divisions. At the highest level there are prefectures which number 47. Below this are a variety of other administrative divisions such as municipals (about 1700). The hierarchical structure is not simple ("Administrative divisions of Japan," 2015); lower level divisions sometimes contain different types of subdivisions. Aside from administrative divisions, there are also 8 geographic regions, which are similar to those for the United States (Northeast, Midwest, West, and South) ("List of regions of Japan," 2015). Figure 1 shows a map of Japan.

2 Among the top 100 most populous countries, Japan ranks 12th with a population density of about 336 per km^2. For comparison, South Korea has one of 503 (ranked 3rd), the United Kingdom one of 262 (ranked 15th), and France one of 118 (ranked 32nd) ("List of sovereign states and dependent territories by population density," 2015).

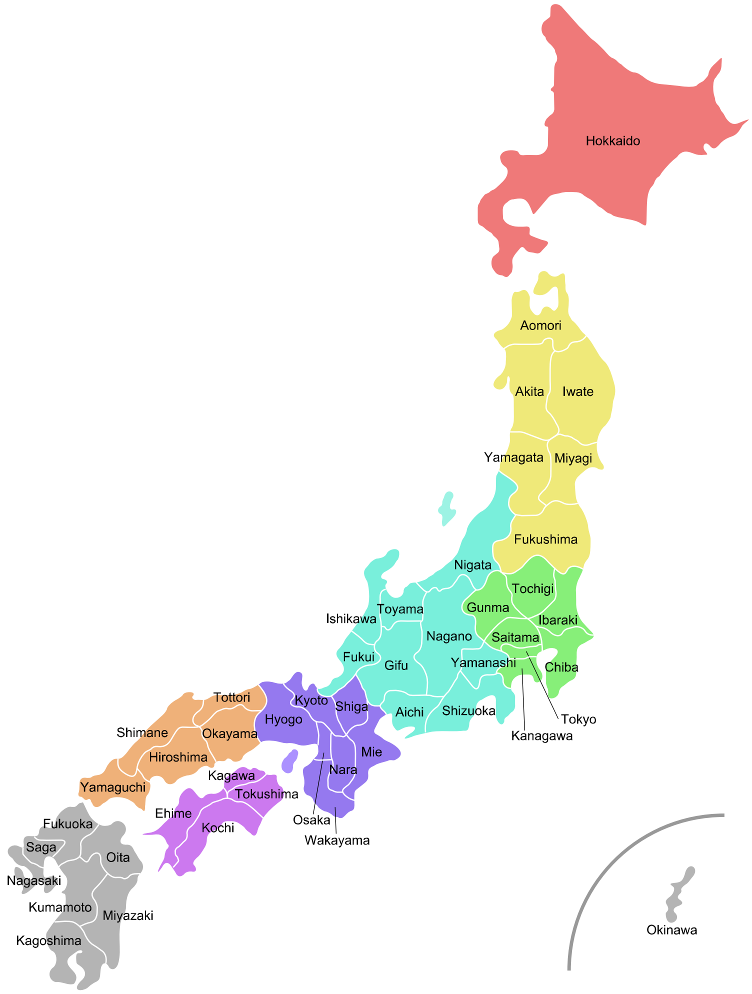

Figure 1: Map of Japanese regions (colors) and prefectures (white borders). From Wikipedia ("Administrative divisions of Japan," 2015).

2. Data

2.1. Data from Kenya Kura

The previous paper on Japanese prefectures analyzed 7 socioeconomic outcomes, but more data is better, so I contacted Ken Kura, the author of the previous study who is a Japanese native, and asked him to locate more data for me. He sent me a file with 31 variables, including those found in his published paper. The variables from the previous paper are listed below. The first line is the variable name, and the second line is a brief description:

1. Latitude
   Latitude.
2. Height
   Height at age 17.
3. IQ
   IQ score. Estimated from scholastic achievement tests.

4. Skin.color
   Skin color (brightness).
5. Income
   Average per capita income.
6. Labor.participation
   Labor participation rate.
7. Homicide
   Homicide rate.
8. Infant.death
   Infant mortality rate.
9. Divorce
   Divorce rate.
10. Fertility
    Total fertility rate.
11. Suicide
    Suicide rate.

The explanations for these can be found in the previous paper (Kura, 2013).

The new variables from Kura are:

1. Gini.income
   GINI of income (i.e. a measure of inequality, larger values mean more inequality).
2. Gini.asset
   GINI of assets.
3. Unemployment
   Unemployment rate.
4. Welfare.use
   Welfare use rate, type 1.
5. Welfare.use2
   Welfare use rate, type 2.
6. Felony
   Felony rate.
7. Abortions
   Abortion rate.
8. Physicians
   Physicians rate.
9. Pharmacists
   Pharmacists rate.

10. Voter.turnout.upper
Voter turnout, upper house.
11. Voter.turnout.lower
Voter turnout, lower house.
12. Marriages
Marriage rate.
13. Education.9.years
Percentage who has completed 9 years of education.
14. Education.12.years
Percentage who has completed 12 years of education.
15. Obesity
Obesity rate.
16. Smoking
Smoking rate.
17. Drinking
Drinking rate.
18. Verbal
Mean verbal test score.
19. Math
Mean math test score.
20. Science
Mean science test score.

Most of the data were averaged over a couple of recent years. Details about this can be found in the supplementary material (*S_factor_Japan_project.ods*).

2.2. Data from the Japanese statistics agency

Because an initial analysis of Kura's data gave decidedly unexpected results and because of some oddities with the data[3], I decided to download additional data myself. Variables were selected and downloaded from the English-language section of the Japanese statistics bureau's website (http://www.stat.go.jp/english/). The selection criteria were that variables must 1) concern an important socioeconomic outcome, and 2) not be strongly reliant on local natural environment (e.g. presence of water for fishing).

The list of variables below were included. The first line is the variable name given by me, the second is the description from the website:

1. Low.edu
Ratio of people having completed up to elementary or junior high school only.

3 The abortion variable has a max-min ratio of 145, meaning that the prefecture with the most abortions per capita has 145 as many of that with the fewest. For libraries (in the second dataset), the value is 100.

2. High.edu
   Ratio of people having completed up to colleges and universities.
3. Foreigners
   Ratio of population of foreigners (per 100,000 persons).
4. Fertility
   Total fertility rate.
5. Marriages
   Rate of marriages (per 1,000 persons).
6. Divorces
   Rate of divorces (per 1,000 persons).
7. Income
   Prefectural income per person.
8. Income.growth
   Annual increase rate of prefectural income.
9. Consumer.price.index
   Regional difference index of consumer prices [general: average of 51 cities = 100]
10. Financial.potential
    Index of financial potential.
11. In.work.male
    Labour force participation rate [male].
12. In.work.female
    Labour force participation rate [female]
13. Unemployment.male
    Unemployment rate [male]
14. Unemployment.female
    Unemployment rate [female]
15. Tertiary.industry
    Ratio of persons employed in the tertiary industry
16. Libraries
    Libraries (per 1,000,000 persons)
17. Museums
    Museums (per 1,000,000 persons)
18. Flush.toilet
    Ratio of dwellings with flush toilet
19. Piped.water

Ratio of households covered by piped water supply system

20. Hospitals
General hospitals (per 100,000 persons)
21. Physicians
Physicians working at medical establishments (per 100,000 persons)
22. Nurses
Nurses working at medical establishments (per 100,000 persons)
23. Life.expect.male
Life expectancy [0 year old, male]
24. Life.expect.female
Life expectancy [0 year old, female]
25. Suicides
Suicides (per 100,000 persons)
26. Infant.mortality
Infant death rate (per 1,000 live births)
27. Unemployment.benefits
Ratio of recipients of benefits of employment insurance
28. Criminal.offenses
Recognitions of criminal offenses (per 1,000 persons)
29. Mean.air.temp
Yearly average of air temperature
30. Mean.humidity
Yearly average of relative humidity
31. Sunshine
Yearly sunshine hours
32. Precipitation
Yearly precipitation
33. Population
Percentage distribution by prefecture

For almost all the variables, multiple years of data were available. I downloaded only the three most recent datapoints almost all of which were from between 2000 and 2013, and most were from 2005 and 2010. However, they were not consistently available in any particular years, so conducting a longitudinal study akin to the study of Brazilian states (Kirkegaard, 2015f) was not easy and was not done.

A composite dataset was created by merging the two datasets, yielding 63 variables in total. For identification, "_A" and "_B" were added to the variables names, where the first indicates that the data is from Kura and the second that it is from myself.

3. Redundant variables

Some of the variables were clearly overlapping between the two datasets, e.g. marriage rate. However, it is possible that data error had been introduced at some point. Thus, these pairs were left in and were filtered out as part the regular quality control.

When one extracts a general factor from a dataset, it will be influenced to some degree by the variables it is extracted from. If these variables are not representative of the domain, the general factor will include some group factor variance. To avoid this, I developed an algorithm for removing duplicates and near-duplicates from datasets before extracting a general factor (Kirkegaard, In review). Briefly put, the algorithm removes variables until no pair correlate above a certain threshold. No study has examined what a good threshold would be, but .90 has been used (by me) in earlier studies and was used here for consistency.

The output of the algorithm is shown below:

```
The following variable pairs had stronger intercorrelations than |0.9|:
                      Var1                   Var2      r
2207          Physicians_A           Physicians_B  0.999
1395           Marriages_A            Marriages_B  0.995
1480              Income_A               Income_B  0.963
832   Voter.turnout.lower_A Voter.turnout.upper_A  0.942
1872    Unemployment.male_B Unemployment.female_B  0.939
1841         Unemployment_A Unemployment.female_B  0.938
1300             Low.edu_B             High.edu_B -0.915
2287           Hospitals_B               Nurses_B  0.901
The following variables were excluded:
Physicians_B, Marriages_B, Income_B, Voter.turnout.upper_A, Unemployment.female_B,
High.edu_B, Nurses_B
```

The first three pairs are variants of the same variable that are slightly different due to the data coming from different years. There were three unemployment variables, one with both genders, and one for each gender. However, they all correlated near unity, so only the gender-combined one was kept. In some rare cases, variables can be drastically different by gender, so one should not average them before checking their correlations. In the case of low and high education, we see a very strong negative relationship as expected.

After the exclusions, there were 44 socioeconomic variables left. However, some of these were clearly (near-)duplicates that did not reach the threshold:

- Suicide_A and Suicides_B, r = .887
- Fertility_A and Fertility_B, r = .820
- Felony_A and Criminal.offenses_B, r = .872
- Infant.death_A and Infant.mortality_B, r = .727

We see that the first three of these narrowly missed the threshold (all r's ≥ .82), while there seems to be something wrong with the infant data.[4] Upon investigating the issue, Kura and I found that the problem is due to two things: first, that the averages are based on slightly different years.[5] Second, the year-to-year intercorrelations are near-zero, averaging only .17. Thus, it seems that Japanese health care is so good that differences between prefectures almost only reflect unstable variation.

4. Reliability of factor extraction across methods

In most cases, different methods for factor extraction and scoring yield near-identical results. However, sometimes they yield radically different results. For this reason, it is a good idea to examine consistency across methods which can be a sign of data error or violated statistical assumptions.

I extracted one factor from the dataset using every combination of factor extraction and scoring methods available in the *fa()* function from the *psych* package for R (Revelle, 2015). Factor score reliability was strong across methods but not always near unity. The mean correlation was .96 and the smallest was
.82.

All further extractions were done with least squares and Bartlett's scoring method (Revelle, 2015).

5. Indicator sampling reliability

Theoretically, one can think of S as being the general factor extracted from a complete collection (population) of socioeconomic indicators (compare with (Ashton, Lee, & Vernon, 2001; Jensen, 1998, p. 31)). If there is a general factor of such a collection, then it should not depend strongly on which exact indicators one extracts it from. It should to a large degree be *indifferent to the indicator* (Jensen, 1987, 1998, p. 32). Thus, one can assess the existence and reliability of a hypothetical factor by repeatedly sampling indicators, extracting factors and correlating them (Kirkegaard, In review). This method was implemented by randomly splitting the dataset into two halves (i.e. each with half the indicators), factor analyzing each half separately and then correlating the factor scores. This was done 1000 times. Figure 2 shows a density-histogram of the results.

4 An earlier version of the analysis used infant data averaged from fewer years, which produced a correlation between the two of only about .5.

5 Kura's variable is based on the years 2005-2014 while my variable is based on the years 2005, 2010 and 2013.

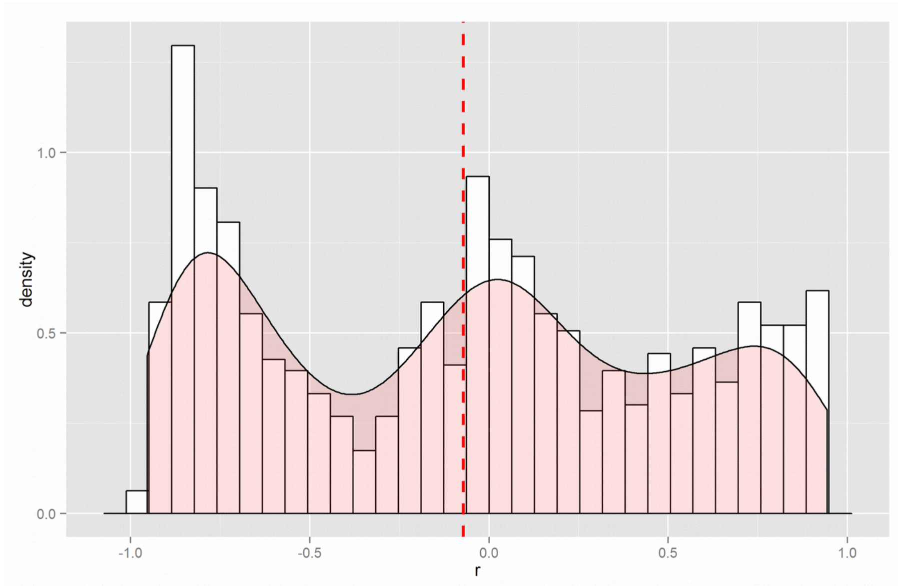

Figure 2: Indicator sampling reliability. 1000 runs. The red line gives the mean correlation.

Because factors can be reversed, values that fall away from 0 are evidence of factor reliability. One can create a numeric measure of this by choosing a threshold for an acceptable reliability correlation, e.g. .50, and then finding the fraction of scores such that |r| > .50 In the present case, this number was .539. This does reveal some structure. A simulation with the same number of cases and indicators but using random, normally distributed scores, found a value of 0, that is, none of the 1000 runs produces a correlation |r|>.5.

Still, the results are strikingly weak compared to the country-level S factor, where 100% of the correlations were above the threshold (Kirkegaard, In review). There does not seem to be a reliable S factor across Japanese prefectures.

6. Mixedness

When extracting a factor structure from a dataset that has a latent structure, generally cases fit the factor structure. However, it is possible that some cases have patterns that are strongly incongruent with the overall structure in the data. Such cases are said to be *highly mixed* or *structural outliers* (Kirkegaard, In review, 2015d). Several methods have been developed to try to identify such cases, see (Kirkegaard, In review) for discussion.

Each of the earlier developed methods was used to examine if any cases showed strong mixedness. There were no cases of strong outliers. There was only moderate correlational agreement (mean r = .40; range .19-.63) across methods indicating a lack of clear outliers aside from sampling error.

No action was taken in relation to the mixedness results.

7. Factor loadings

A general factor was extracted using both standard interval-level data and using rank-level data. The reason to use the second is that it is thought to be robust to non-linearity and outliers in the dataset.

Figure 3 shows the loadings.

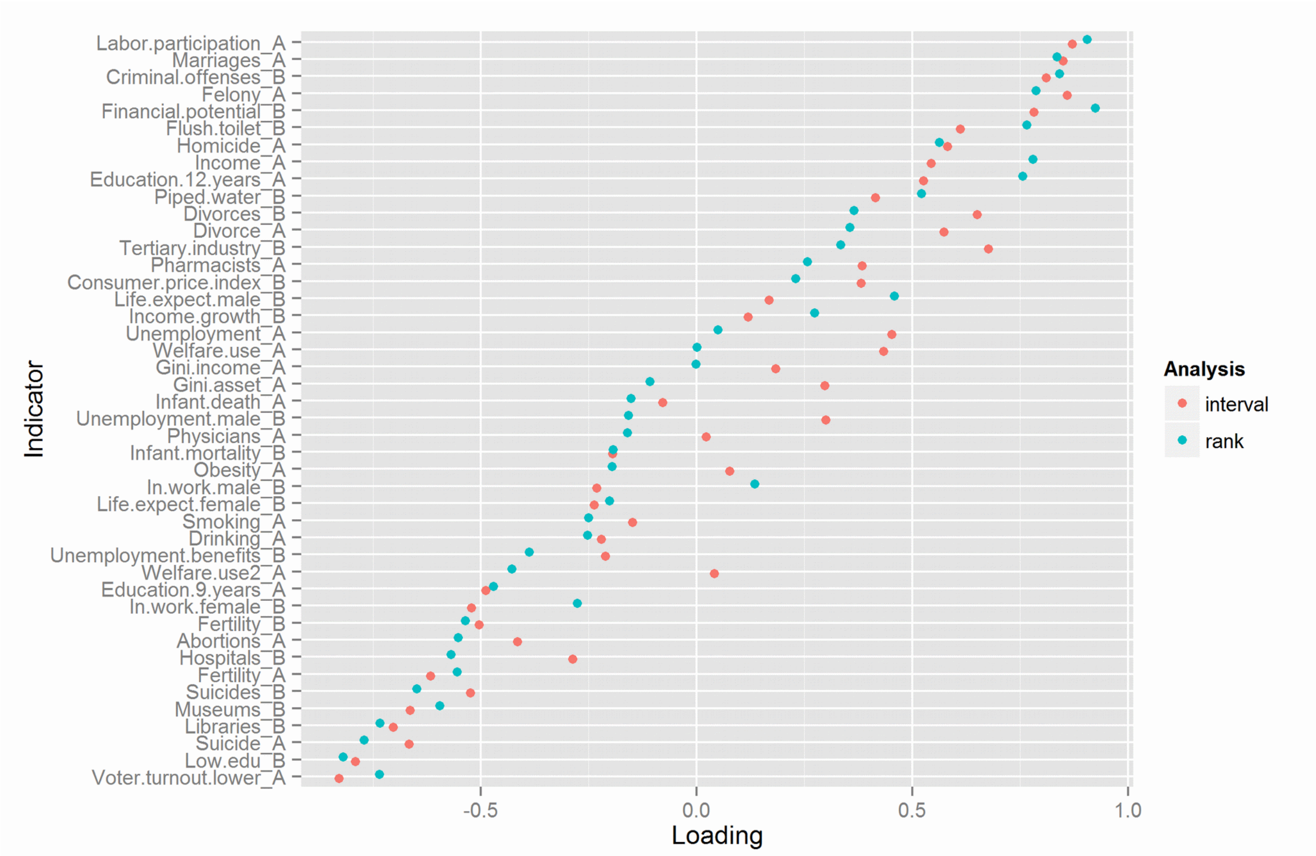

Figure 3: Loadings on the first factor.

If there is no clear S factor, as the indicator sampling reliability analysis suggests, then we should also fail to observe the usual pattern of loadings: that generally desirable outcomes have positive loadings and conversely for generally undesirable outcomes. While some indicators have expected loadings, a large number do not: 1) three crime variables have strong positive loadings, 2) two divorce indicators have strong positive loadings, 3) unemployment has a near-zero loading, 4) Physicians and Hospitals have negative loadings, 5) Museums and Libraries have negative loadings, 6) Life.expect.female has a negative loading but the male version has a positive, and 7) voter turnout has the strongest negative loading of all, which is strange because it usually has a positive loading.

The strange negative loading of Education.9.years seems to be due to a fluke from a strong ceiling effect, as all prefectures have values very close to 100%.

In general, the picture is very muddled at best, similar to the results from the indicator sampling reliability analysis.

8. Relationships to cognitive ability

Still, we might be curious as to whether the 'S' factor correlates with cognitive ability as found in all previous studies. Kura's dataset contains both his estimated IQ scores from the previous study (Kura, 2013) as well as three scholastic achievement scores (math, language and science). Factor analysis of the three achievement scores reveal a G factor (aggregate-level g factor) and each indicator loaded strongly on it (all loadings >.90), as one would expect (Rindermann, 2007). The scores from this factor were used as the measure of cognitive ability. Figure 4 shows a scatterplot between cognitive ability and 'S'.

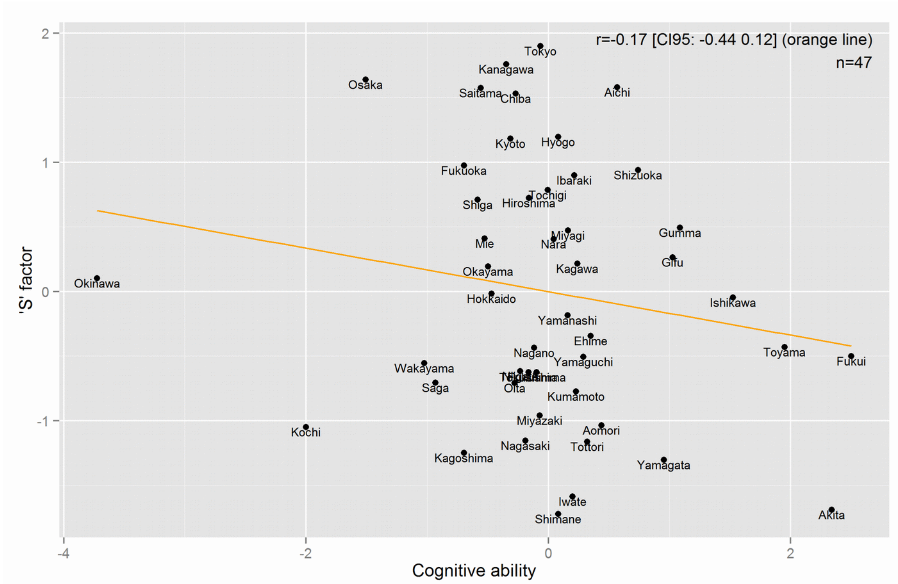

Figure 4: Scatterplot of cognitive ability and 'S' factor scores.

Not only do we not find a strong positive correlation, we find a weak negative one. The relationship also fails Jensen's method (coefficient = -.19; with reversing (Kirkegaard, In review)).[6]

Still, while there seems to be no S factor in this dataset, it is possible that some of the indicators have interesting relationships to cognitive ability as found by the previous study (Kura, 2013). Table 1 shows the correlations between cognitive ability and the other variables.

Variable	**Correlation with cognitive ability**	**Variable**	**Correlation with cognitive ability**
Verbal_A	0.98	S_B	-0.09
Science_A	0.98	High.edu_B	-0.1
IQ_A	0.96	Nurses_B	-0.11
Math_A	0.92	Life.expect.female_B	-0.12
Height_A	0.55	Population_B	-0.16
Latitude_A	0.54	Fertility_B	-0.17
Education.9.years_A	0.48	S_AB	-0.17
Skin.color_A	0.48	S_A	-0.17

6 Jensen's method (method of correlated vectors, named after the great psychologist Arthur Jensen) consists of correlating the factor loadings of indicators with their relationships to some criterion variable. The reasoning is that if the relationship between the factor scores and the criterion variable is real, then (everything else equal) the indicators that have stronger loadings on the factor (i.e. are better measures of it) should be more strongly related to the criterion variable than those with weaker loadings. For more details, see (Jensen, 1998; Kirkegaard, In review).

In.work.male_B	0.47	Labor.participation_A	-0.18
In.work.female_B	0.43	Physicians_A	-0.18
Voter.turnout.lower_A	0.35	Hospitals_B	-0.18
Museums_B	0.29	Consumer.price.index_B	-0.19
Voter.turnout.upper_A	0.26	Physicians_B	-0.19
Libraries_B	0.26	Pharmacists_A	-0.2
Suicide_A	0.24	Piped.water_B	-0.22
Abortions_A	0.24	Sunshine_B	-0.26
Mean.humidity_B	0.24	Gini.income_A	-0.29
Precipitation_B	0.21	Unemployment.benefits_B	-0.29
Income_A	0.19	Criminal.offenses_B	-0.3
Education.12.years_A	0.19	Marriages_A	-0.39
Low.edu_B	0.19	Obesity_A	-0.4
Income_B	0.18	Felony_A	-0.41
Drinking_A	0.15	Marriages_B	-0.43
Suicides_B	0.15	Homicide_A	-0.45
Life.expect.male_B	0.11	Divorce_A	-0.46
Foreigners_B	0.09	Tertiary.industry_B	-0.5
Fertility_A	0.07	Mean.air.temp_B	-0.51
Income.growth_B	0.07	Unemployment_A	-0.54
Infant.mortality_B	0.07	Welfare.use_A	-0.55
Financial.potential_B	0.01	Welfare.use2_A	-0.59
Flush.toilet_B	-0.01	Gini.asset_A	-0.61
Infant.death_A	-0.06	Unemployment.male_B	-0.64
Smoking_A	-0.09	Unemployment.female_B	-0.65
		Divorces_B	-0.72

Table 1: Correlations between cognitive ability and other variables. N=47.

A comparison with the results from Kura's study (Table 2 in that paper) shows strong agreement (Kura, 2013), that is, we both find negative correlations to homicide and divorce rate, and positive correlations to latitude, height and skin brightness.

9. Robustness check

Because the results were so at odds with prior research, the probability of data or analysis error or some other detectable anomaly was thought to be high. For this reason, additional checks were run.

9.1. Parallel analysis of the sub-datasets

To assess the robustness of the results, I carried out all analyses in parallel on the three datasets (combined, Kura's and mine). Results did not generally change. As might be expected due to the very poor indicator sampling reliability, the 'S' factors from the two datasets correlated poorly, r=.18 and neither were substantially related to cognitive ability (also shown in Table 1).

9.2. Different duplicate variable threshold

It is possible that group factor variance were strongly coloring the first factors. To see if this could be avoided, the analyses were re-run with lower thresholds (.70 and .80) for excluding 'duplicated' or overlapping variables, but the results were very similar.

9.3. Controlling for population density or population

During the peer review process L. J. Zigerell suggested that population density or total population might be obscuring the results. To test this, I created parallel versions of the dataset with controls. This was done simply by regressing (linear regression) each indicator on the control variable and saving the residuals. Then each control variable was used with three modes: 1) untransformed, 2) log transformed and 3) square root transformed. This was done to make the distribution more normal and suitable for the linear model used for the control. The population data was copied from Wikipedia ("List of Japanese prefectures by population," 2015).

To see if an S factor could be consistently measured in the datasets, I used indicator sampling reliability like before. Then I calculated the proportion of correlations with an absolute value above .5. Table 2 shows the results:

Control method	Proportion with |r| > .50
Standard	0.526
Pop. density	0.603
Pop. density (log)	0.931
Pop. density (sqrt)	0.907
Population	0.783
Population (log)	0.793
Population (sqrt)	0.837

Table 2: Indicator sampling reliability and control methods.

Surprisingly, most of the controls worked very well. The data controlled for log population density had the strongest indicator sampling reliability, and the scores from that were used for the following analyses. Figure 5 shows the distribution of reliability correlations for the chosen control method.

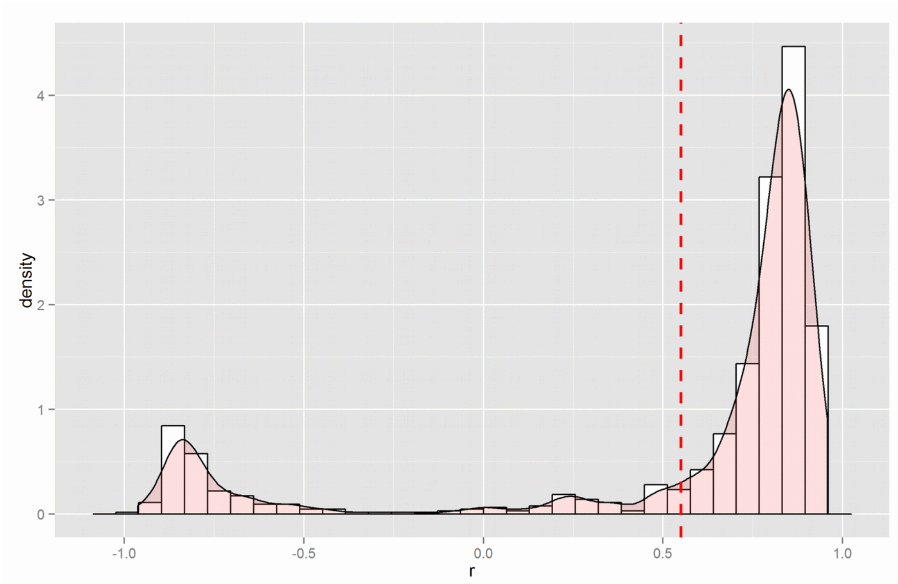

Figure 5: Indicator sampling reliability for the dataset corrected for log population density. 1000 runs. The red line gives the mean correlation.

Below, I repeat the other analyses from before on the corrected dataset. Figure 6 shows the loadings plot.

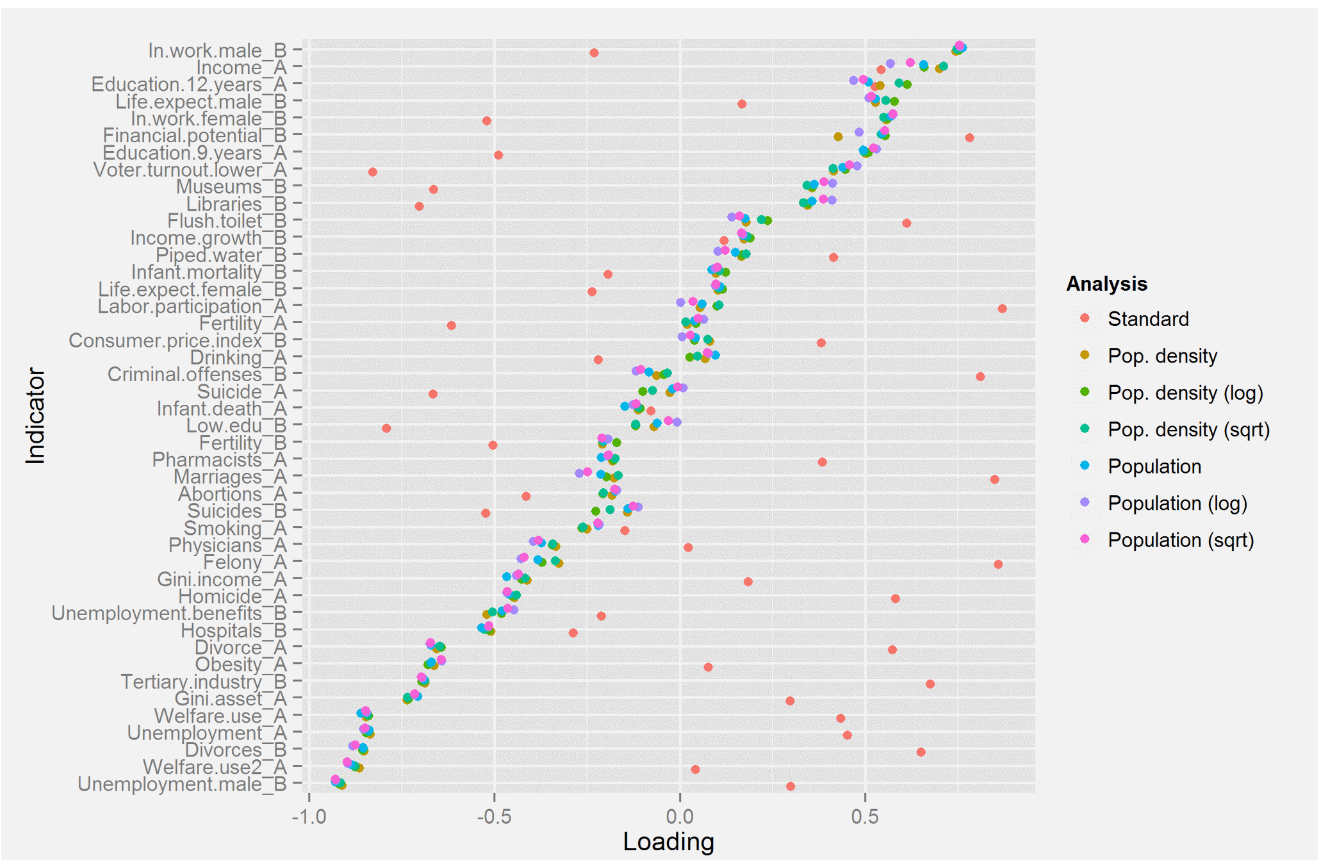

Figure 6: First factor loadings with population controls. Indicators are sorted by the loadings from the pop. density (log) analysis.

Clearly, there were many large changes in S loadings before and after implementing the control. All the controlled analyses had nearly identical loadings. Examining the indicators with large changes generally shows that the indicators with loadings in unexpected directions changed after the control. For instance, Unemployment.male_B changed from slightly positive to very negative, and Felony_A from very positive to moderately negative. Not all changes were improvements. For instance, labor participation_A decreased from having a strong positive loading to have a very weak positive loading.

Figure 7 shows the scatterplot of cognitive ability and the corrected S scores.

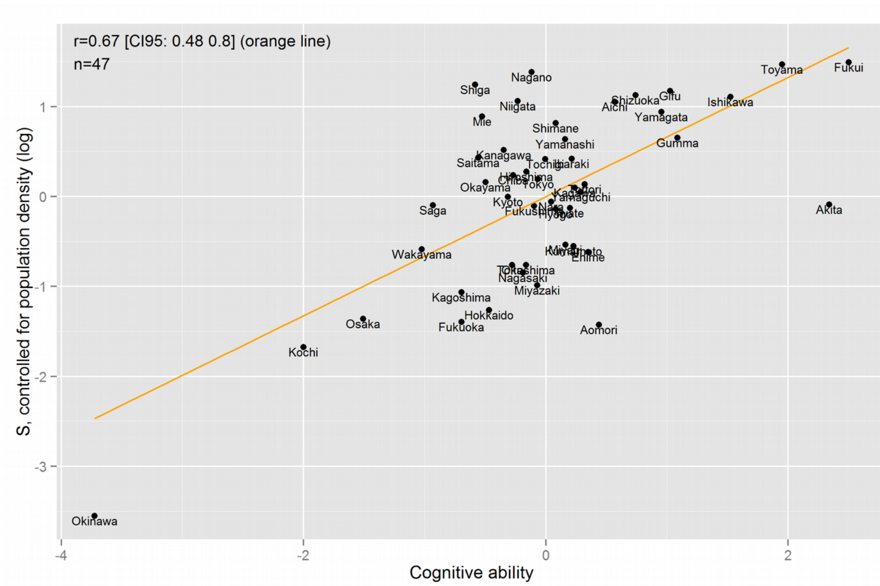

Figure 7: Scatterplot of cognitive ability and S scores from the corrected analysis.

Now we see the expected pattern. Okinawa is an outlier, but it is reasonably close to the regression line. If Okinawa is excluded, the correlation decreases to .54 [95CI: .29 to .72].

Figure 8 shows Jensen's method applied as before.

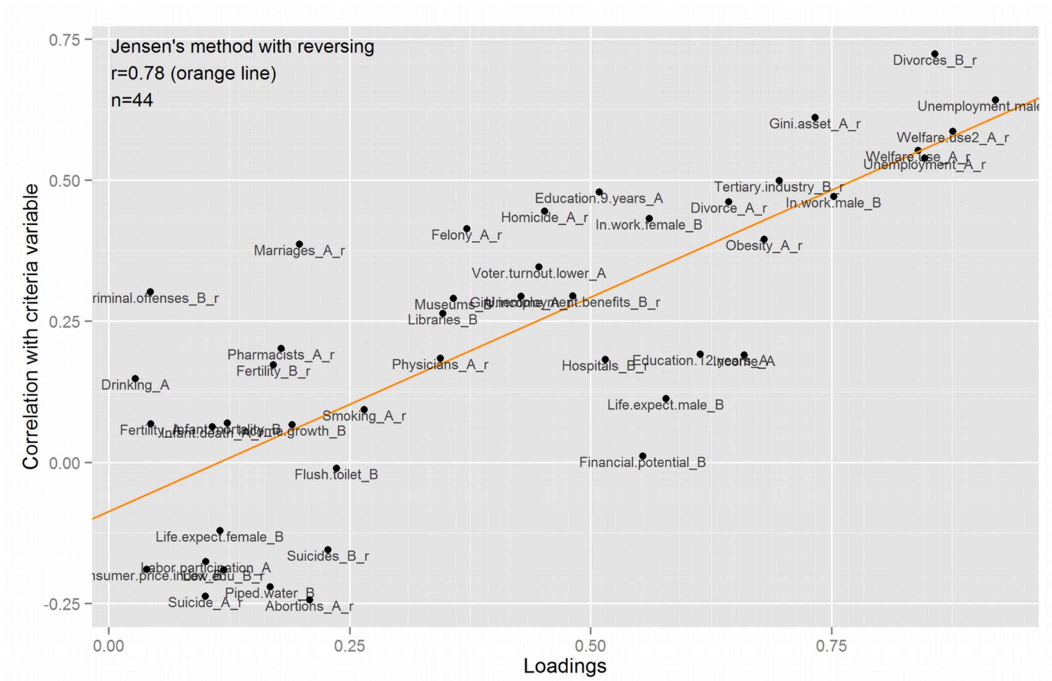

Figure 8: Jensen's method with reversing for the corrected S factor. The suffix "_r" means that the variable was reversed.

And again, we see familiar results. Cognitive ability is more strongly related to the socioeconomic variables that are more strongly related to other socioeconomic variables (=higher S loading).

Additionally, I tried the same analyses as above with ranked data. This produced similar but slightly weaker results (cognitive ability x S = .56, Jensen's coef. = .70). This could but does not necessarily mean that non-linearity or outliers were inflating the results; it may be that transforming the data to a lower level of measurement (ordinal from interval) obscures important patterns.

10. Discussion and conclusion

The results from Japanese prefectures are markedly different from those from other studies in that from the uncorrected data, no clear S could be extracted, the loadings did not generally fit the S factor pattern (good outcomes with positive loadings, bad outcomes with negative loadings) and if one tried extracting factor scores anyway, they did not correlate substantially with cognitive ability.

However, in an exploratory (unplanned) analysis, it was found that if one removes the effect of (the log of) population density, the usual S factor study pattern emerges: the loadings go in expected directions, S can be reliably extracted from different samples of indicators, S correlates strongly with cognitive ability, and Jensen's method indicates that the relationship is due mostly to S, not other variance.

Thus it would seem that Japan is odd in that the large differences in population density between the prefectures almost totally obscure the S pattern (Tokyo has a population density 92 times that of Hokkaido). Previous S factor studies did not correct for population density even when marked differences were present[7] and still found relatively pure S factors that correlated strongly with cognitive

7 For instance, for the United States, New Jersey has a population density 931 times larger than that of Alaska and 202 times larger than that of Wyoming. Numbers from Wikipedia ("List of U.S. states by population density," 2015).

ability, so it is somewhat of a mystery why the control would be needed for Japanese prefectures. It would be worthwhile to re-do all the previous 'state'-level S factor studies with a similar control for population density and see how this affects the results. Finally, during the review, Noah Carl pointed out that Lynn (1979) employed a similar control and observed that this can have large effects (see also Kirkegaard (2015g) for a reanalysis that study).

Strengths of the study include the relatively large number of cases (N=47), large number of indicators (N=44) and the good quality of the cognitive ability estimates. With the caveat that the control for population density was unplanned, the results conform to the pattern found in previous studies.

Supplementary material and acknowledgments

Open peer review thread: http://openpsych.net/forum/showthread.php?tid=260

Supplementary material including datasets and R code: https://osf.io/4bw8u/files/

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