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Crime, income, educational attainment and employment among immigrant groups in Norway and Finland

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Abstract
I present new predictive analyses for crime, income, educational attainment and employment among immigrant groups in Norway and crime in Finland. Furthermore I show that the Norwegian data contains a strong general socioeconomic factor (S) which is highly predictable from country-level variables (National IQ .59, Islam prevalence -.71, international S factor .72, GDP .55), and correlates highly (.78) with the analogous factor among immigrant groups in Denmark.

Keywords: National IQ, intelligence, group differences, country of origin, Norway, Finland, Denmark, immigration, crime, spatial transferability hypothesis, income, employment, educational attainment, general socioeconomic factor, Islam

1 Introduction

Recent studies show that criminality and other useful socioeconomic traits such as educational attainment among immigrant groups is predictable from country level variables[1, 2, 3, 4]. This study attempts to replicate and generalize these findings.

The theoretical impetus for testing country-level predictors is the spatial transferability hypothesis.[5] In brief, it proposes that 1) a country's performance on a variety of metrics is due to some degree to the psychological makeup of its inhabitants; 2) people retain their psychological attributes to some degree, as reflected on psychological tests, when they migrate; and 3) the psychological attributes of groups determine to some degree their relative performance on a variety of socioeconomic variables, such as crime, educational attainments, income, and employment rate, in the countries that receive them.

For instance, when people from a poorer country move to a wealthier country, they will tend to be relatively poor in that country as well. This is because part of the reason the country is poor is that the people living there are low in general intelligence. When they move to a new country, they will generally still be low in the relevant behavioral traits, and this will cause them to be relatively poor in that country as well. This is of course still allowing for other causes (e.g. culture or religion people tend to bring with them, time preference, impulse control, anger threshold, monotony avoidance, affective empathy) as well as improvements on an absolute scale. Somalis living in Denmark are far richer than those who have stayed behind in Somalia, but they are nonetheless poorer than ethnic Danes, just as Somalia is poorer as a whole than Denmark.

One way of testing the spatial transferability hypothesis involves looking at immigrant performance on a variety of measures grouped by country of origin, and then checking how predictable this performance is from country-level variables such as national IQ and national prevalence of Islam. In this study I explore a number of datasets in this fashion.

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2 Dataset 1: Norway and Finland

Skardhamar et al (2014)[6] presented new crime data for immigrant groups by country and macro-region of origin for Norway and Finland and compared the two countries. Their main findings are shown in Figures 1 and 2.

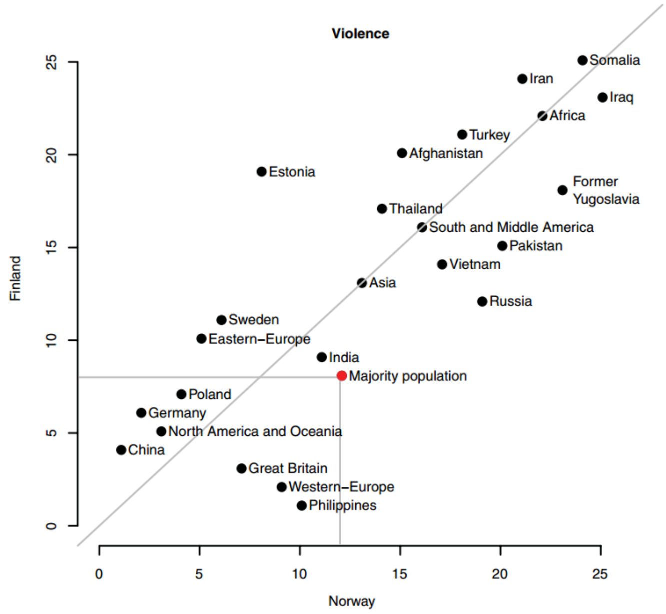

Figure 1: Violent crime in Norway and Finland by country of origin. From [6]

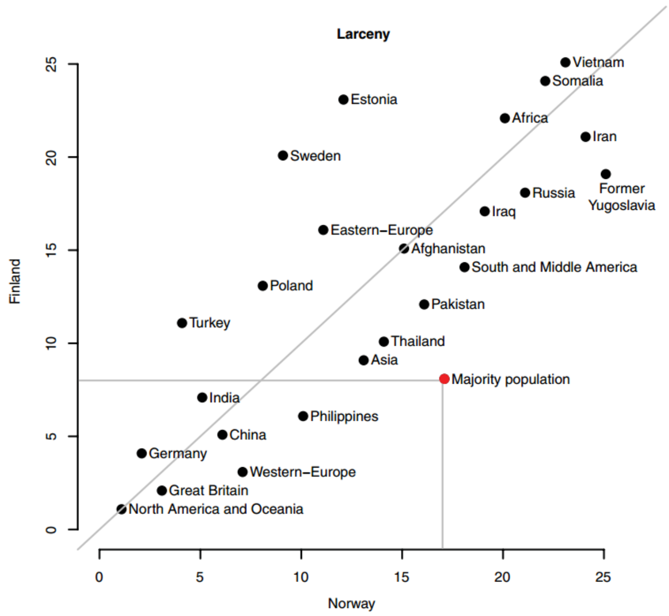

Figure 2: Property crime (larceny) in Norway and Finland by country of origin. From [6]

These findings indicate that people from the same areas of origin are similarly disposed to criminal behavior in Norway and Finland.

3 Dataset 2-4: Norway

I took a closer look at Statistisk Sentralbyrå's (SSB) [2] website for data that could be useful for testing the spatial transferability hypothesis. To be useful, the data must concern a variable of considerable

[2] The official statistics bureau of Norway. http://www.ssb.no/

social interest and contain information on immigrant group performance by country of origin with at least a small sample (my threshold was => 10) of countries.

I did a search for "landbakgrunn" (country background) on the website, limited the results to publicly available datasets ("statistikbanken") and looked through all 124 results. I identified three useful datasets:

1) Income after tax, measured as a percent of the national mean (income index).[3] No information about age is given. I included all available countries (N=23). Generally, SSB limits the available countries to the ones with samples large enough to give reliable results.

2) Registered unemployed persons by sex aged 15-74, as a percent of the working population.[4] As before I included all available countries (N=120) and both sexes separately.

3) Tertiary educational attainment per capita for persons aged 16 and above in 2013.[5] This table was in absolute numbers, so I supplemented it with the population size by country of origin to calculate a pseudo per capita value.[6] The reason it is a pseudo per capita is that population sizes were not available by age groups, so I had to use the entire age group, even though the educational attainment data concerned only people aged 16 and above. This introduces error if the age structures are different between groups. The data are also not broken down by gender, so there is possibly gender ratio bias as well.

The first variable includes all groups with a population >= 200 (N=118). The second only includes groups with >= 1000 to reduce sampling error (N=67).

4 Predictive analyses

All analyses were done with R.[7]

The primary question was whether crime was predictable from country-level variables as previously found. To test this, I used the following predictors in a correlation analysis:

- Prevalence of Islam (as estimated by the Pew Research Center).[7]
- Lynn and Vanhanen's national IQs with changes based on the work of Jason Malloy. When a value is changed, it is noted in the datafile.[8, 9]
- Altinok's educational achievements.[10]
- The World Bank's GDP per capita (2013).[11]
- Kirkegaard's country-level general socioeconomic factor scores.[12]

Table 1 shows the correlations of interest. Generally, all predictors did well when two conditions were satisfied: 1) the sample of countries was large enough to have significant inter-country variation, and 2) the sample of countries was not so large as to introduce significant sampling error in estimates. The reason this introduces error is that the more countries covered in a variable means that the value must be based on a smaller sample of persons from that country.

Findings of note include: Violent crime was easier to predict than property crime, just as in the Danish dataset.[1] The poor predictive performance of Altinok with the crime and income variables seems to be due to sampling error. The educational attainment variable which includes only large samples ("Tert. Ed. Att. Big") had higher correlations than the one with smaller samples too. This

[3] Tabell: 10489: Innvandreres inntekt etter skatt per forbruksenhet, etter landbakgrunn

[4] Tabell: 07117: Registrerte arbeidsledige 15-74 år, etter landbakgrunn og kjønn. Absolutte tall og i prosent av arbeidsstyrken

[5] Tabell: 09623: Innvandrere 16 år og over, etter utdanningsnivå og landbakgrunn. Absolutte tall

[6] Tabell: 05184: Innvandrere, etter kjønn og landbakgrunn

[7] R is a free, powerful, easy to use programming language designed for data mining and statistics. See http://www.r-project.org/

is probably because the smaller ones introduced sampling error. Islam was a better predictor of female unemployment than of male, which may be related to the role of women in Islam.

	ViolentCrimeNO	ViolentCrimeFI	LarcenyNO	LarcenyFI	Tert. Ed. Att.	Tert. Ed. Att. Big	Unemployment men	Unemployment women	Income
IQ	-0.63	-0.64	-0.38	-0.29	0.35	0.47	-0.5	-0.43	0.61
n	20	19	20	19	117	67	119	119	23
Altinok	-0.24	-0.14	-0.14	0.19	0.31	0.41	-0.49	-0.46	0.29
n	14	13	14	13	92	54	95	95	15
Islam	0.82	0.83	0.52	0.25	-0.26	-0.37	0.45	0.68	-0.52
n	19	18	19	18	118	67	120	120	23
GDP (log)	-0.33	-0.07	-0.26	-0.06	0.33	0.46	-0.44	-0.36	0.64
n	17	16	17	16	103	58	105	105	20
S.scores	-0.59	-0.38	-0.4	0.04	0.35	0.41	-0.5	-0.53	0.64
n	16	15	16	15	103	58	105	105	18

Table 1: Correlation matrix for country-level predictors and socioeconomic variables.

4.1 Differential predictive ability of predictors

Are some predictors just generally better at predicting than others, or is there an interaction effect between predictor and variables? To investigate this, I correlated the prediction vectors (rows in Table 1) for each predictor with each other predictor. Correlations at ±1 indicate that predictor performance is general, while correlations near ±0 indicate specificness. The results are shown in Table 2.

Var	Altinok.cors	Islam.cors	GDP.cors	S.cors
IQ.cors	0.83	-0.99	0.93	0.96
Altinok.cors		-0.86	0.9	0.92
Islam.cors			-0.92	-0.97
GDP.cors				0.97

Table 2: Correlation matrix of predictor vectors.

Surprisingly, even though there were problems with small sample sizes of the predictive correlations and the length of the vectors (N=9), the results strongly suggest that what is well-predicted by one predictor is also well-predicted by other predictors, no matter which two were compared. This indicates that we are dealing with general phenomena and is evidence against more specific theories of causation.

5 A general socioeconomic factor among immigrant groups in Norway

Similarly to my previous study of immigrant groups in Denmark[3], I wanted to investigate the possibility of a general socioeconomic factor at the group level (S factor).[12] To do this, I used all the variables concerning Norway except for the educational attainment with smaller groups to avoid duplicating variables.

5.1 Handling missing values

Factor analytic methods require that there are no missing values. The easiest and most common way to deal with this is to limit the data to the subset with complete cases. This, however, produces biased results if the data are not missing completely at random, which they rarely are. Furthermore, it heavily reduces sample sizes. Lastly, it wastes non-redundant information and potentially resources spent gathering it. If a case has values for 5 out of 6 chosen variables, removing the case wastes 5 pieces of useful information.[13, 14, 15, 16] Table 3 shows the distribution of missing values.

Number of missing values	0	1	2	3	4	6
Number of cases	15	3	8	41	61	141

Table 3: The distribution of missing values in the Norwegian dataset.

For the above reasons, I used four methods for handling missing cases: 1) complete cases only (N=15), 2) using multiple imputation[8] to impute data to cases with 1 or fewer missing values (N=18), 3) imputing data in cases with 2 or fewer missing values (N=26), 4) imputing data in cases with 3 or fewer missing values (N=67). Table 4 shows description statistics for each dataset. The imputed datasets are similar to both the full datasets and the complete cases although there were changes in both the skew and kurtosis.

Var name	Dataset	n	mean	sd	min	max	skew	kurtosis
Violent crime	Full	26	1.31	0.87	0.2	3.2	0.55	-0.83
	Complete cases	15	1.41	0.99	0.2	3.2	0.39	-1.25
	Impute 1	18	1.33	0.93	0.2	3.2	0.57	-0.94
	Impute 2	26	1.28	0.81	0.2	3.2	0.7	-0.27
	Impute 3	67	1.23	0.63	0.2	3.2	1.05	1.41
Larceny	Full	26	0.77	0.56	0.1	2	0.56	-1.09
	Complete cases	15	0.78	0.55	0.2	1.6	0.38	-1.74
	Impute 1	18	0.72	0.53	0.1	1.6	0.55	-1.42
	Impute 2	26	0.69	0.56	-0.29	1.96	0.62	-0.58
	Impute 3	67	0.69	0.34	0.1	1.6	0.71	0.19
Tert. ed. att.	Full	67	0.12	0.08	0.01	0.31	0.42	-0.91
	Complete cases	15	0.1	0.07	0.01	0.23	0.39	-1.32
	Impute 1	18	0.1	0.07	0.01	0.23	0.5	-1.12
	Impute 2	26	0.09	0.07	0.01	0.24	0.75	-0.63
	Impute 3	67	0.12	0.08	0.01	0.31	0.42	-0.91
Unemployment, men	Full	120	7.05	4.18	1.38	22.08	1.26	1.69
	Complete cases	15	7.4	5.36	2.68	22.08	1.38	1.18
	Impute 1	18	7.31	4.89	2.68	22.08	1.57	2.16
	Impute 2	26	6.88	4.3	2.66	22.08	1.8	3.72
	Impute 3	67	6.81	4.11	1.66	22.08	1.39	2.18
Unemployment, women	Full	120	7.5	4.97	1.32	31.82	1.92	5.11
	Complete cases	15	8.9	6.2	1.98	22.42	0.83	-0.58
	Impute 1	18	8.17	5.93	1.9	22.42	1.03	-0.04
	Impute 2	26	7.4	5.25	1.56	22.42	1.3	1.14
	Impute 3	67	7.41	5.39	1.32	31.82	1.97	5.23
Income	Full	23	79.86	14.58	53.25	108.25	-0.01	-0.92
	Complete cases	15	78.78	14.78	53.25	108.25	0.19	-0.78
	Impute 1	18	82.4	16.3	53.25	112.29	0.11	-0.95
	Impute 2	26	79.09	13.9	53.25	108.25	0.13	-0.75
	Impute 3	67	81.71	13.86	31.96	108.25	-0.76	0.95

Table 4: Descriptive stats by dataset.

KMO tests showed that all datasets were suitable to factor analysis, KMO's 68-75. Note that multiple imputation is probabilistic and does not result in the same imputation every time. Therefore, any researcher replicating the analysis may find that the numbers deviate somewhat from the shown results.

[8] I used the VIM package 4.00. The irmi() function imputes values.[17] I used the default settings. http://cran.r-project.org/web/packages/VIM/index.html

5.2 Number of factors to extract

To find out how many factors to extract, I ran nScree() from the nFactors package.[9] For each dataset, all four tests within that function suggested to extract only 1 factor.

5.3 Strength of the general factor

Previous studies have shown that principal component analysis tends to overestimate factor loadings when used on a small number of variables, but that other factor methods yield very similar results.[12, 18, 19, 20] I used minimum residuals (the default) to extract the first factor from each dataset.[10]

Revelle and Wilt[21] showed that one cannot solely rely on the size of the first factor in a normal analysis as a measure of the strength of the general factor. They advocated five other methods, of which I have used four here: 1) hierarchical omega and its asymptotic value, 2) the amount of variance accounted for by the first factor in a Schmid-Leiman transformation, 3) the explained common variance, and 4) the squared multiple correlation of regression the first factor on the original variables.[11] Table 5 shows the comparison statistics.

Dataset	**Var% MR**	**Var% MR SL**	**Omega h.**	**Omega h. a.**	**ECV**	**R2**
NO Complete cases	0.68	0.65	0.87	0.91	0.78	0.98
NO Impute 1	0.66	0.62	0.86	0.9	0.74	0.96
NO Impute 2	0.64	0.60	0.85	0.89	0.75	0.95
NO Impute 3	0.63	0.59	0.82	0.87	0.73	0.99
DK complete cases	0.57	0.51	0.83	0.85	0.68	0.99
DK impute 4	0.55	0.51	0.86	0.88	0.73	0.99
International S factor	0.43	0.35	0.76	0.77	0.51	0.81
Cognitive data		0.33	0.74	0.79	0.57	0.78
Personality data		0.16	0.37	0.48	0.34	0.41

Table 5: Measures of general factor strength. The cognitive and personality data is from Revelle and Wilt (2013)[21], the international S factor data is from Kirkegaard (2014)[12], and the Danish comparison data is from a reanalysis of the datasets from Kirkegaard and Fuerst (2014)[3] presented in the next subsection.

The data makes it clear that the S factors at the group-level among immigrants in Norway and Denmark are very strong, even compared to the international S factor and the g factor of cognitive ability in 5 classic datasets. The imputation of data had little effect on the measures of general factor strength but seemed to make the S factors somewhat weaker.

5.4 Reanalysis of immigrant performance in Denmark

I used the same methods on this dataset[3] as I did on the Norwegian ones discussed above, so I will keep the description short.

There were a few missing values in the dataset. I used two methods to deal with this: 1) complete cases (N=31), and 2) imputation via the VIM package for cases with 4 or fewer missing values (N=70). Table 6 shows the distribution of missing values.

Number of missing values	0	1	2	3	4	23
Number of cases	31	9	23	6	1	1

Table 6: Distribution of missing values in the Danish dataset.

[9] Version 2.3.3 http://cran.r-project.org/web/packages/nFactors/index.html

[10] I used the fa() function from Psych package. http://cran.r-project.org/web/packages/psych/index.html Version: 1.4.8.11

[11] I used the omega() function from Psych package to extract the information.

I analyzed the data with the fa() and omega() functions.

6 Predictive analyses of S scores

I wanted to know how well S factor scores in Norway are predictable from the predictor variables. Table 7 shows the correlation matrix.

Variable	DA S imp.	NO S complete	NO S imp. 1	NO S imp. 2	NO S imp. 3
National IQ	0.54	0.72	0.73	0.66	0.59
Altinok	0.55	0.26	0.31	0.2	0.6
Islam	-0.71	-0.79	-0.79	-0.72	-0.71
log(GDP)	0.51	0.35	0.4	0.44	0.55
National S	0.54	0.7	0.71	0.63	0.72
DA S imp.		0.91	0.91	0.79	0.78
NOS complete			1	0.99	0.99
NO S imp. 1				0.99	0.99
S imp. 2					0.99

Table 7: Correlation matrix of predictor variables and S factor scores in Denmark (with imputed values) and the four Norwegian datasets with varying amounts of imputation.

The results indicate that S factor scores are about equally predictable by predictor values in the full Danish and Norwegian datasets. The size of the correlation decreases with the amount of imputation and increasing sample size. This may be because the imputation introduces error or that the correlations are artificially high due to sampling error.

7 Discussion

The simple predictive analyses gave results similar to those found earlier. They serve as a successful replication and generalization.

The analyses of general factor strength show that the S factors are generally very strong, often surpassing even the g factor. This is due in part to the grouped nature of the data as group correlations tend to go towards 1 when there aren't sampling errors.[22]

Generally the results strongly confirm the spatial transferability hypothesis as forwarded by Fuerst and Kirkegaard (2014)[5].

Limitations include the small sample sizes and the lack of adjustment for age and sex for some of the variables. This probably introduces some bias in an unknown direction. Note however that the Danish data is age-controlled, and yet the results are very similar to the Norwegian ones, showing that bias due to age is unlikely to be a large source of error.

8 Supplementary material

All datasets and source code are available in the submission thread at the *Open Differential Psychology* forum. Most of the data used in the study can be found in version 1.5 of the Worldwide Megadataset.

The appendix contains a list of S scores by group in Norway and Denmark.

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9 Appendix

Name	ID	S Factor in NO	S factor in DK
Afghanistan	AFG	-1.09	-1.38
Argentina	ARG		0.75
Australia	AUS	1.03	1.13
Austria	AUT	1.02	0.95
Burundi	BDI	-0.54	
Belgium	BEL	1.16	1.09
Bulgaria	BGR	0.17	0.81
Bosnia and Herzegovina	BIH	0.49	-0.91
Brazil	BRA	-0.34	0.46
Canada	CAN	1.03	1.14
Switzerland	CHE	1.13	1.12
Chile	CHL	0.25	0.28
China	CHN	0.61	0.63
Congo Rep.	COG	-1.07	
Colombia	COL	0.26	
Czech Republic	CZE	0.43	0.25
Germany	DEU	1.04	0.85
Denmark	DNK	1	
Algeria	DZA	-1.52	-0.78
Egypt Arab Rep.	EGY		-0.24
Eritrea	ERI	-0.43	
Spain	ESP	0.52	0.79
Estonia	EST	0.19	0.72
Ethiopia	ETH	-0.16	-0.59
Finland	FIN	0.78	0.89
France	FRA	0.97	1.1
United Kingdom	GBR	1.14	0.85
Ghana	GHA	0.03	0.16
Gambia The	GMB	-0.84	

Greece	GRC	0.61	0.61
Croatia	HRV	0.54	-0.12
Hungary	HUN	0.45	0.84
Indonesia	IDN	0.33	0.13
India	IND	0.63	0.53
Ireland	IRL		0.88
Iran Islamic Rep.	IRN	-0.35	-0.69
Iraq	IRQ	-2.26	-1.65
Iceland	ISL	0.76	0.55
Israel	ISR		-0.06
Italy	ITA	0.86	0.77
Jordan	JOR		-1.19
Japan	JPN		1.02
Kenya	KEN	-0.24	0.09
Kosovo	KSV	-0.43	
Kuwait	KWT		-2.62
Lebanon	LBN	-1.03	-2.03
Sri Lanka	LKA	-0.14	-0.75
Lithuania	LTU	-0.08	0.9
Latvia	LVA	0.06	0.68
Morocco	MAR	-0.63	-1.03
Macedonia FYR	MKD	-0.19	-0.44
Myanmar	MMR	-0.27	-1.81
Nigeria	NGA	-0.53	0.34
Netherlands	NLD	1.11	1.12
Norway	NOR		0.84
Nepal	NPL	0.75	
Pakistan	PAK	-0.87	-0.68
Peru	PER	0.1	
Philippines	PHL	0.58	0.36
Poland	POL	-0.02	0.46
Portugal	PRT	0.54	0.63
West Bank and Gaza	PSE	-3.8	
Romania	ROU	0.31	0.7
Russian Federation	RUS	-0.44	0.45
Sudan	SDN	-1.52	
Somalia	SOM	-3.06	-2.05
Serbia	SRB	0.46	-1.93
USSR	SUN		0.17
Slovak Republic	SVK	0.42	
Sweden	SWE	1.03	0.77
Syrian Arab Republic	SYR	-1.62	-2
Thailand	THA	-0.03	-0.23
Tunisia	TUN		-0.82
Turkey	TUR	-0.52	-1.42
Tanzania	TZA		-0.25
Uganda	UGA		-0.34
Ukraine	UKR	0.34	0.69
United States	USA	0.97	1.26
Vietnam	VNM	-0.11	-0.58

Former Yugoslavia2	YU2		-1.61
Former Yugoslavia	YUG		-1.25
South Africa	ZAF		0.73