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Educational attainment, income, use of social benefits, crime rate and the general socioeconomic factor among 71 immmigrant groups in Denmark

Emil O. W. Kirkegaard[1]
John Fuerst

Abstract
We obtained data from Denmark for the largest 71 immigrant groups by country of origin. We show that three important social-economic variables are highly predictable from the Islam rate, IQ, GDP and height of the countries of origin. We further show that there is a general socio-economic factor and this too is very predictable.

Keywords: National IQs, group differences, country of origin, Denmark, immigration

1 Introduction

In our previous paper[1] we introduced the spatial transferability hypothesis, which is the proposition that when people migrate to other countries, they retain their traits, whether personality, cognitive or other. The corollary of this is that the known correlates of g are also retained such as average education levels. We have previously shown this to be true for fertility and crime rates in Denmark[2], crime rates in Norway[3], GMAT, TOEFL, GRE, PISA and GPA in the U.S[4, 5]. In this paper we examine new data from Denmark about educational level, income and use of social benefits.

2 Datasets and methods

We bought three new datasets for Denmark from the official Danish statistics agency (Danmarks Statistik, http://dst.dk). All datasets concern the 71 largest immigrant groups by country of origin that one of us previously examined with respect to crime rates. All datasets contain data from 2012 only. Dataset 1 contains information about the highest level of formal education reached by immigrant groups and is divided into age groups (15-19, 20-29, 30-39, 40-49, 50-59, >60). Dataset 2 contains the mean income levels per group and by age groups. Dataset 3 contains the percentage of the groups who are on social benefits by age groups.

Our analysis strategy was similar to those used in previous studies. First, we extracted the data of interest and imported it into SPSS where we performed the statistical analyses.

[1]Corresponding author: emil@emilkirkegaard.dk

We extracted mean income levels for all age groups, percentage who have long tertiary education (lang videregående uddannelse) for age groups 20-29 and 30-39, percentage who has only basic schooling (all age groups), percentage on social benefits (all age groups).

The predictor variables were: 1) Lynn and Vanhanen's national IQs as given in [6] with an estimate of the former Yugoslavia's IQ from [7], 2) national GDPs per capita from the International Monetary Fond (2013) via Wikipedia[8, 9], 3) national rates of belief in Islam from Pew Research via Wikipedia[10, 11], 4) the average heights from Wikipedia[12].

3 Educational attainment

Correlational analysis of the proportion who have only basic schooling is shown in Table 1, while Table 2 shows the similar analysis for proportion who have long tertiary educational degrees.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	Basic_school_15_19	Basic_school_20_29	Basic_school_30_39	Basic_school_40_49	Basic_school_50_59	Basic_school_60plus
LV2012IQ		1	.612	-.486	.548	-.127	-.544	-.488	-.465	-.418	-.215
	Sig. (2-tailed)		.000	.000	.000	.298	.000	.000	.000	.000	.073
	N	205	182	68	53	69	70	70	70	70	70
GDPIMF2013		.719	1	-.414	.643	-.173	-.496	-.522	-.541	-.480	-.242
	Sig. (2-tailed)	.000		.001	.000	.172	.000	.000	.000	.000	.052
	N	182	186	65	52	64	65	65	65	65	65
Islam		-.571	-.453	1	-.421	.221	.592	.587	.489	.508	.384
	Sig. (2-tailed)	.000	.000		.002	.075	.000	.000	.000	.000	.001
	N	68	65	68	53	66	67	67	67	67	67
Height		.578	.675	-.325	1	-.036	-.467	-.476	-.500	-.472	-.222
	Sig. (2-tailed)	.000	.000	.018		.802	.000	.000	.000	.000	.113
	N	53	52	53	53	51	52	52	52	52	52
Basic_school_15_19		-.188	-.147	.085	-.004	1	.300	.220	.155	.136	.079
	Sig. (2-tailed)	.121	.246	.495	.979		.012	.069	.204	.264	.521
	N	69	64	66	51	69	69	69	69	69	69
Basic_school_20_29		-.620	-.554	.549	-.561	.262	1	.854	.782	.693	.488
	Sig. (2-tailed)	.000	.000	.000	.000	.029		.000	.000	.000	.000
	N	70	65	67	52	69	70	70	70	70	70
Basic_school_30_39		-.699	-.665	.574	-.508	.233	.844	1	.915	.838	.576
	Sig. (2-tailed)	.000	.000	.000	.000	.054	.000		.000	.000	.000
	N	70	65	67	52	69	70	70	70	70	70
Basic_school_40_49		-.674	-.650	.547	-.582	.116	.773	.898	1	.923	.710
	Sig. (2-tailed)	.000	.000	.000	.000	.341	.000	.000		.000	.000
	N	70	65	67	52	69	70	70	70	70	70
Basic_school_50_59		-.571	-.576	.484	-.506	.095	.675	.802	.909	1	.814
	Sig. (2-tailed)	.000	.000	.000	.000	.439	.000	.000	.000		.000
	N	70	65	67	52	69	70	70	70	70	70
Basic_school_60plus		-.352	-.302	.327	-.230	.056	.494	.556	.702	.769	1
	Sig. (2-tailed)	.003	.014	.007	.100	.650	.000	.000	.000	.000	
	N	70	65	67	52	69	70	70	70	70	70

Table 1: Predictors and basic schooling.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	Long_tert_edu_20_29	Long_tert_edu_30_39	Long_tert_edu_40_49	Long_tert_edu_50_59	Long_tert_edu_60plus
LV2012IQ		1	.612	-.486	.548	.385	.459	.547	.380	.037
	Sig. (2-tailed)		.000	.000	.000	.001	.000	.000	.001	.762
	N	205	182	68	53	70	70	70	70	70
GDPIMF2013		.719	1	-.414	.643	.402	.528	.517	.393	.024
	Sig. (2-tailed)	.000		.001	.000	.001	.000	.000	.001	.848
	N	182	186	65	52	65	65	65	65	65
Islam		-.571	-.453	1	-.421	-.432	-.543	-.493	-.357	-.176
	Sig. (2-tailed)	.000	.000		.002	.000	.000	.000	.003	.154
	N	68	65	68	53	67	67	67	67	67
Height		.578	.675	-.325	1	.355	.437	.516	.330	.120
	Sig. (2-tailed)	.000	.000	.018		.010	.001	.000	.017	.397
	N	53	52	53	53	52	52	52	52	52
Long_tert_edu_20_29		.535	.520	-.474	.424	1	.740	.471	.266	.132
	Sig. (2-tailed)	.000	.000	.000	.002		.000	.000	.026	.277
	N	70	65	67	52	70	70	70	70	70
Long_tert_edu_30_39		.559	.530	-.454	.437	.848	1	.760	.594	.411
	Sig. (2-tailed)	.000	.000	.000	.001	.000		.000	.000	.000
	N	70	65	67	52	70	70	70	70	70
Long_tert_edu_40_49		.646	.580	-.522	.528	.689	.837	1	.801	.491
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000		.000	.000
	N	70	65	67	52	70	70	70	70	70
Long_tert_edu_50_59		.525	.426	-.402	.388	.456	.669	.820	1	.589
	Sig. (2-tailed)	.000	.000	.001	.005	.000	.000	.000		.000
	N	70	65	67	52	70	70	70	70	70
Long_tert_edu_60plus		.055	-.017	-.162	.011	.288	.428	.501	.560	1
	Sig. (2-tailed)	.651	.894	.189	.941	.016	.000	.000	.000	
	N	70	65	67	52	70	70	70	70	70

Table 2: Predictors and long tertiary education.

For the proportion who have only basic schooling, it is clear that age matters. First, at age 15-19 most people have not have enough time to finish secondary education and so clear patterns do not yet emerge. Second, the correlations diminish towards the older groups probably because they immigrated too late to the country and so have not taken advantage of the Danish education system which presumably in many cases is of higher quality than the one in the home country.

The picture is much the same for the proportions who have attained long tertiary degrees except that the first age group is missing. This is because there were no data for it as no one in that age group has attained long tertiary education. For the rest of the age groups, it is very similar to before.

From the correlations it was apparent that there might be a general education factor. We performed principle component analysis (PCA) to extract latent variables. The component loadings are shown in Table 3. The first component was a large general factor while PC2 was not readily interpretable.

	Component	
	1	2
Basic_school_15_19	.210	.533
Basic_school_20_29	.846	.373
Basic_school_30_39	.917	.170
Basic_school_40_49	.922	-.053
Basic_school_50_59	.917	-.174
Basic_school_60plus	.770	-.453
Long_tert_edu_20_29	-.587	-.614
Long_tert_edu_30_39	-.849	-.301
Long_tert_edu_40_49	-.892	.056
Long_tert_edu_50_59	-.813	.346
Long_tert_edu_60plus	-.590	.527
Var%	61.387328	14.1677

Table 3: Factor loadings of income variables.

The correlations with predictors is shown in Table 4. All four predictors performed similarly for this variable which is surprising given that height seems to have no conceptual relevance to education.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	PC1EdAtt	PC2EdAtt
LV2012IQ		1	.612	-.486	.548	-.494	-.223
	Sig. (2-tailed)		.000	.000	.000	.000	.066
	N	205	182	68	53	69	69
GDPIMF2013		.719	1	-.414	.643	-.527	-.217
	Sig. (2-tailed)	.000		.001	.000	.000	.086
	N	182	186	65	52	64	64
Islam		-.571	-.453	1	-.421	.570	.215
	Sig. (2-tailed)	.000	.000		.002	.000	.083
	N	68	65	68	53	66	66
Height		.578	.675	-.325	1	-.492	-.111
	Sig. (2-tailed)	.000	.000	.018		.000	.438
	N	53	52	53	53	51	51
PC1EdAtt		-.641	-.599	.530	-.561	1	.000
	Sig. (2-tailed)	.000	.000	.000	.000		1.000
	N	69	64	66	51	69	69
PC2EdAtt		-.265	-.261	.104	-.172	.016	1
	Sig. (2-tailed)	.028	.037	.406	.226	.898	
	N	69	64	66	51	69	69

Table 4: Predictors and the latent educational attainment variable.

4 Income

Correlations with predictors and average income levels are shown in Table 5. It is apparent that early income levels are not very predictable but later incomes are. Oddly national IQs (NIQ) did not predict income after age 60, but GDP and Islam continued to have sizable correlations. As might be expected from the conceptual link, GDP was strongest predictor of income levels, but height also performed well.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	Income_15_19	Income_20_29	Income_30_39	Income_40_49	Income_50_59	Income_60
LV2012IQ		1	.612	-.486	.548	-.083	-.127	.549	.566	.479	.064
	Sig. (2-tailed)		.000	.000	.000	.594	.297	.000	.000	.000	.614
	N	205	182	68	53	44	69	70	70	70	65
GDPIMF2013		.719	1	-.414	.643	-.218	-.395	.654	.735	.699	.360
	Sig. (2-tailed)	.000		.001	.000	.176	.001	.000	.000	.000	.005
	N	182	186	65	52	40	64	65	65	65	60
Islam		-.571	-.453	1	-.421	.081	-.049	-.608	-.606	-.598	-.564
	Sig. (2-tailed)	.000	.000		.002	.612	.692	.000	.000	.000	.000
	N	68	65	68	53	42	67	67	67	67	62
Height		.578	.675	-.325	1	-.014	-.087	.474	.453	.325	.167
	Sig. (2-tailed)	.000	.000	.018		.942	.542	.000	.001	.019	.250
	N	53	52	53	53	30	52	52	52	52	49
Income_15_19		-.147	-.287	.205	-.046	1	.633	.075	-.065	-.110	-.208
	Sig. (2-tailed)	.340	.073	.192	.809		.000	.629	.673	.476	.197
	N	44	40	42	30	44	44	44	44	44	40
Income_20_29		-.166	-.356	-.006	-.126	.664	1	.153	-.077	-.179	-.060
	Sig. (2-tailed)	.173	.004	.962	.373	.000		.210	.530	.141	.638
	N	69	64	67	52	44	69	69	69	69	64
Income_30_39		.666	.654	-.493	.514	-.028	.147	1	.915	.822	.557
	Sig. (2-tailed)	.000	.000	.000	.000	.857	.227		.000	.000	.000
	N	70	65	67	52	44	69	70	70	70	65
Income_40_49		.674	.715	-.550	.491	-.204	-.087	.906	1	.919	.612
	Sig. (2-tailed)	.000	.000	.000	.000	.185	.475	.000		.000	.000
	N	70	65	67	52	44	69	70	70	70	65
Income_50_59		.599	.664	-.489	.327	-.261	-.203	.778	.909	1	.695
	Sig. (2-tailed)	.000	.000	.000	.018	.087	.095	.000	.000		.000
	N	70	65	67	52	44	69	70	70	70	65
Income_60		.225	.351	-.484	.143	-.332	-.083	.529	.665	.695	1
	Sig. (2-tailed)	.072	.006	.000	.326	.036	.513	.000	.000	.000	
	N	65	60	62	49	40	64	65	65	65	65

Table 5: Predictors and income.

As before we did a PCA to extract latent variables. 2 components were extracted. The first one was interpretable as a latent middle adulthood income variable with high loadings on income after age 20. The second was interpretable as an early income signaling those who go out of school early to earn money. Factor loadings are shown in Table 6. Correlations with predictors are shown in Table 7.

	Component	
	1	2
Income_15_19	-.150	.892
Income_20_29	-.080	.904
Income_30_39	.916	.268
Income_40_49	.975	.052
Income_50_59	.976	-.020
Income_60	.866	-.081
Variance Explained	58.71%	28.24%

Table 6: Factor loadings of income variables.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	Latent_adult_income	Latent_early_income
LV2012IQ		1	.612	-.486	.548	.565	.043
	Sig. (2-tailed)		.000	.000	.000	.000	.793
	N	205	182	68	53	40	40
GDPIMF2013		.719	1	-.414	.643	.820	-.221
	Sig. (2-tailed)	.000		.001	.000	.000	.196
	N	182	186	65	52	36	36
Islam		-.571	-.453	1	-.421	-.698	-.107
	Sig. (2-tailed)	.000	.000		.002	.000	.523
	N	68	65	68	53	38	38
Height		.578	.675	-.325	1	.540	-.002
	Sig. (2-tailed)	.000	.000	.018		.003	.992
	N	53	52	53	53	28	28
Latent_adult_income		.661	.697	-.613	.580	1	.000
	Sig. (2-tailed)	.000	.000	.000	.001		1.000
	N	40	36	38	28	40	40
Latent_early_income		-.019	-.195	.002	-.034	-.035	1
	Sig. (2-tailed)	.908	.254	.991	.862	.831	
	N	40	36	38	28	40	40

Table 7: Predictors and the latent income variables.

Latent early income was not very predictable while latent adult income was highly predictable. Perhaps not surprisingly, GDP was the strongest correlate of latent income variables.

5 Use of social benefits

Social benefits in Denmark include both a stipend for students and various payouts for people who for some reason cannot or won't work and receives money from the state to support themselves. The supplementary material has a detailed description of this variable (in Danish).

Like before, we performed a correlation analysis with the variables for each age group and the predictors. It is shown in Table 8.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	Social_benefits_16_19	Social_benefits_20_29	Social_benefits_30_39	Social_benefits_40_49	Social_benefits_50_59	Social_benefits_60plus
LV2012IQ		1	.612	-.486	.548	-.424	-.492	-.433	-.482	-.465	-.429
	Sig. (2-tailed)		.000	.000	.000	.005	.000	.000	.000	.000	.001
	N	205	182	68	53	43	69	70	70	70	54
GDPIMF2013		.719	1	-.414	.643	-.306	-.469	-.403	-.438	-.486	-.536
	Sig. (2-tailed)	.000		.001	.000	.059	.000	.001	.000	.000	.000
	N	182	186	65	52	39	64	65	65	65	50
Islam		-.571	-.453	1	-.421	.533	.670	.704	.710	.684	.747
	Sig. (2-tailed)	.000	.000		.002	.000	.000	.000	.000	.000	.000
	N	68	65	68	53	41	67	67	67	67	52
Height		.578	.675	-.325	1	-.276	-.250	-.173	-.251	-.192	-.293
	Sig. (2-tailed)	.000	.000	.018		.156	.074	.221	.073	.172	.059
	N	53	52	53	53	28	52	52	52	52	42
Social_benefits_16_19		-.457	-.338	.463	-.192	1	.776	.687	.629	.613	.533
	Sig. (2-tailed)	.002	.035	.002	.328		.000	.000	.000	.000	.002
	N	43	39	41	28	43	43	43	43	43	32
Social_benefits_20_29		-.634	-.584	.624	-.255	.730	1	.950	.909	.892	.776
	Sig. (2-tailed)	.000	.000	.000	.068	.000		.000	.000	.000	.000
	N	69	64	67	52	43	69	69	69	69	53
Social_benefits_30_39		-.547	-.491	.600	-.178	.720	.947	1	.963	.933	.848
	Sig. (2-tailed)	.000	.000	.000	.207	.000	.000		.000	.000	.000
	N	70	65	67	52	43	69	70	70	70	54
Social_benefits_40_49		-.683	-.646	.644	-.404	.797	.888	.903	1	.963	.883
	Sig. (2-tailed)	.000	.000	.000	.003	.000	.000	.000		.000	.000
	N	70	65	67	52	43	69	70	70	70	54
Social_benefits_50_59		-.635	-.580	.611	-.252	.755	.837	.843	.934	1	.926
	Sig. (2-tailed)	.000	.000	.000	.072	.000	.000	.000	.000		.000
	N	70	65	67	52	43	69	70	70	70	54
Social_benefits_60plus		-.487	-.505	.587	-.197	.620	.713	.772	.820	.866	1
	Sig. (2-tailed)	.000	.000	.000	.211	.000	.000	.000	.000	.000	
	N	54	50	52	42	32	53	54	54	54	54

Table 8: Predictors and use of social benefits.

Height is not a good predictor of the use of social benefits, IQ and GDP were both good predictors and Islam came out ahead again. Intercorrelations of the use of social benefits were high indicating a latent variable. We used PCA to extract latent variables. Loadings are shown in 9

	Component
	1
Social_benefits_16_19	.770
Social_benefits_20_29	.956
Social_benefits_30_39	.982
Social_benefits_40_49	.981
Social_benefits_50_59	.972
Social_benefits_60plus	.906
Variance Explained	86.67%

Table 9: Factor loadings for social benefits variables.

PCA resulted in only one factor. Correlations with predictors is shown in Table 10.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	PC1SocialBenefits
LV2012IQ		1	.612	-.486	.548	-.580
	Sig. (2-tailed)		.000	.000	.000	.001
	N	205	182	68	53	32
GDPIMF2013		.719	1	-.414	.643	-.511
	Sig. (2-tailed)	.000		.001	.000	.005
	N	182	186	65	52	29
Islam		-.571	-.453	1	-.421	.850
	Sig. (2-tailed)	.000	.000		.002	.000
	N	68	65	68	53	31
Height		.578	.675	-.325	1	-.403
	Sig. (2-tailed)	.000	.000	.018		.063
	N	53	52	53	53	22
PC1SocialBenefits		-.658	-.520	.653	-.377	1
	Sig. (2-tailed)	.000	.004	.000	.084	
	N	32	29	31	22	32

Table 10: Predictors and the latent social benefit variables.

6 General socioeconomic factor

In the previous paper about immigrant groups in Norway[3], one of us noted that there might be a general socioeconomic factor of how well a group does in a country. That would be the case if there were correlations between the various socioeconomic variables. It is not immediately obvious that this will be true. Perhaps some immigrant groups high relatively high crime rates but also have relatively high average incomes (like men compared with women). In the Norwegian data, this idea could not be properly tested because there were only two different socioeconomic variables making PCA impossible.

The present study has adequate data to answer the question. We ran a PCA on all the manifest variables previously mentioned as well as the two crime variables for age groups 15-19 and 20-29 from the previous study.

The results of the PCA are shown in Table 12. PC1 was a large general factor while the other factors were not clearly interpretable nor were there any theoretically expected interpretations.

	Component			
	1	2	3	4
Social_benefits_16_19	.585	.482	.160	.063
Social_benefits_20_29	.881	.325	.191	.106
Social_benefits_30_39	.890	.361	.187	.064
Social_benefits_40_49	.899	.313	.202	-.050
Social_benefits_50_59	.914	.217	.262	-.104
Social_benefits_60plus	.907	.010	.239	-.088
All_crime_age_15_19	.848	.158	.178	.033
All_crime_age_20_29	.889	.157	.230	.024
Income_15_19	.277	-.565	.465	.464
Income_20_29	.040	-.597	.591	.042
Income_30_39	-.756	-.409	.262	.129
Income_40_49	-.832	-.297	.100	.173
Income_50_59	-.875	-.214	-.033	.258
Income_60	-.837	-.124	-.102	.234
Basic_school_15_19	.114	.437	-.593	.481
Basic_school_20_29	.859	-.009	-.327	.207
Basic_school_30_39	.963	-.059	-.123	-.006
Basic_school_40_49	.838	-.361	-.276	-.157
Basic_school_50_59	.761	-.442	-.298	-.235
Basic_school_60plus	.616	-.601	-.330	-.146
Long_tert_edu_20_29	-.689	.028	.062	-.568
Long_tert_edu_30_39	-.850	.198	.092	-.313
Long_tert_edu_40_49	-.805	.468	.064	-.124
Long_tert_edu_50_59	-.681	.585	.115	-.002
Long_tert_edu_60plus	-.487	.680	.060	.143
Variance Explained	58.32%	14.40%	7.14%	5.03%

Table 11: Factor loadings of all socioeconomic variables.

Table 12 shows the predictors correlations with the general socioeconomic factor. Islam was an very good predictor while IQ and GDP were merely good and height still good but somewhat worse. However, due to the number of missing values for some countries, we reran the PCA without the four variables that had the lowest sample size (income 15-19, social benefits 15-19, social benefits >60). This increased the sample size from 31 to 63. The correlation between the two components was .999 so clearly the removed variables were not important. Correlations with predictors did not change much with the new PC (also shown in Table 12). The appendix has a list of the 63 countries and their factor scores.

Intercorrelations. Pearson above diagonal, Spearman below.		LV2012IQ	GDPIMF2013	Islam	Height	PC1General SES31	PC1General SES63
LV2012IQ		1	.612	-.486	.548	-.624	-.583
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	205	182	68	53	31	63
GDPIMF2013		.719	1	-.414	.643	-.664	-.705
	Sig. (2-tailed)	.000		.001	.000	.000	.000
	N	182	186	65	52	28	58
Islam		-.571	-.453	1	-.421	.824	.776
	Sig. (2-tailed)	.000	.000		.002	.000	.000
	N	68	65	68	53	30	61
Height		.578	.675	-.325	1	-.551	-.525
	Sig. (2-tailed)	.000	.000	.018		.008	.000
	N	53	52	53	53	22	48
PC1General SES31		-.725	-.693	.643	-.661	1	.999
	Sig. (2-tailed)	.000	.000	.000	.001		.000
	N	31	28	30	22	31	31
PC1General SES63		-.735	-.779	.629	-.596	.991	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	63	58	61	48	31	63

Table 12: Predictors and the general socioeconomic latent variable.

7 Multiple regression

We tested whether predictors could be combined to improve the prediction of the general socioeconomic factor with multiple regression. Results are shown in Table 13.

Model	R	R^2	R^2 adjusted
Islam+IQ+GDP+height	.844	.712	.685
Islam+IQ+GDP	.845	.714	.698
Islam+IQ	.825	.680	.669
Islam+GDP	.845	.713	.703
IQ+GDP+height	.735	.540	.508
IQ+GDP	.710	.505	.487
IQ+height	.628	.395	.368
GDP+height	.734	.539	.518
IQ	.583	.340	
GDP	.705	.497	
Islam	.776	.601	

Table 13: Multiple regression results.

Like previously found in the studies of crime in Denmark and Norway[2, 3], IQ and GDP did not show independent effects. This is to be expected if there is a causal relationship between the two (in either direction or both). Some regression plots of interest are shown in Figures 1 - 5.

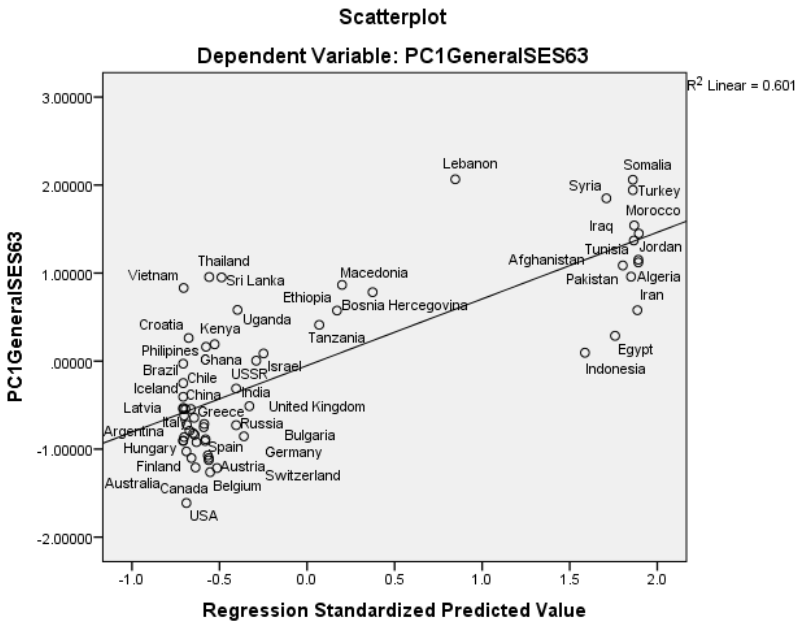

Figure 1: Regression plot for Islam on the general socioeconomic factor.

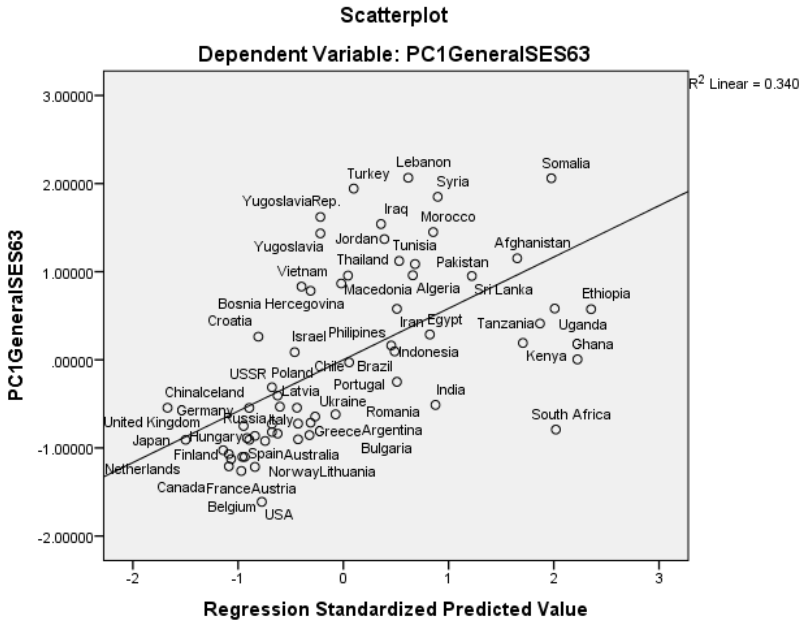

Figure 2: Regression plot for IQ on the general socioeconomic factor.

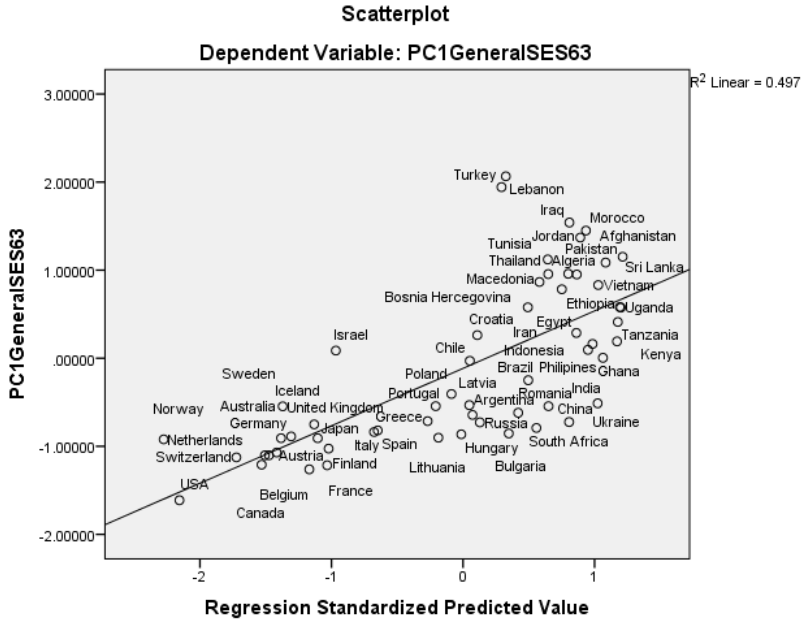

Figure 3: Regression plot for GDP on the general socioeconomic factor.

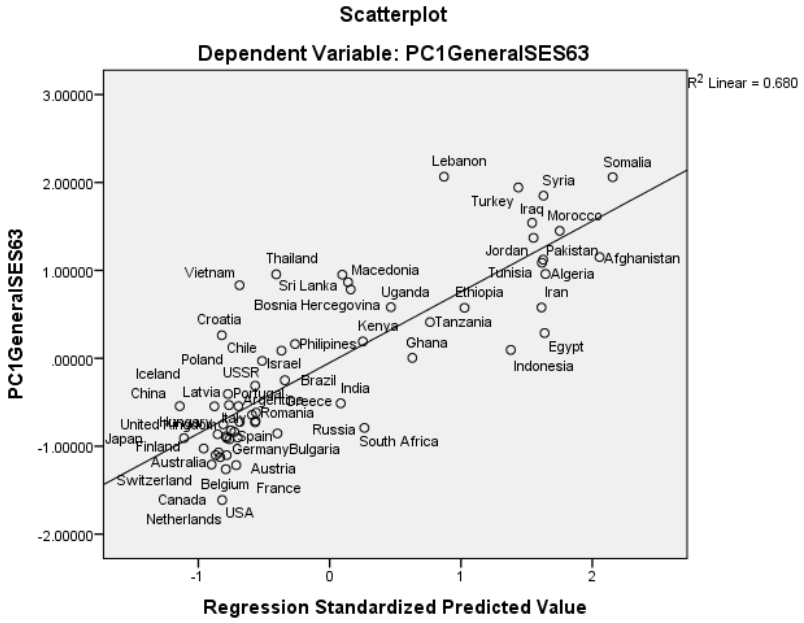

Figure 4: Regression plot for Islam+IQ on the general socioeconomic factor.

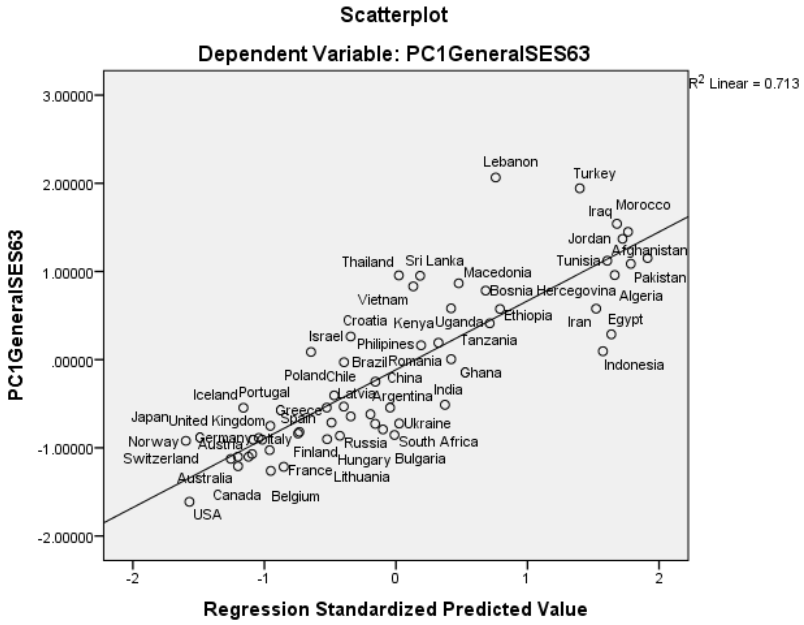

Figure 5: Regression plot for Islam+GDP on the general socioeconomic factor.

8 Partial correlations

Another way to test the robustness of two variables is to calculate the partial correlations controlling for other variables. Specifically, we wanted to know whether the validity of IQ was due to Islamic countries have low IQs or whether it had independent validity. Results are shown in Table 14. The predictive validity of national IQs and GDPs cannot be explained as being wholly due to the indirect effects of Islam nor can Islam's predictive validity be explained as being wholly due to IQ and GDP.

Predictor	Controlling for	r with general socioeconomic factor
IQ	Islam	-0.487
GDP	Islam	-0.592
Islam	IQ, GDP	0.67

Table 14: Partial correlations.

9 Pearson vs. Spearman correlations

We note that while other predictors tended to outperform national IQs with Pearson correlations, the Spearman correlations were systematically higher often making national IQs the best predictor. The scatter plots do seem to indicate some non-linearity for IQ as the worst performing groups have IQs in the mid 80s. Jensen wrote that criminals average IQs around 88-90 while Herrnstein et al reported 92 as the average, so perhaps this is some of the explanation[13, 14].

10 The predictive ability of Islam

A reviewer suggested that Islam's predictive ability is due to other facts having to do with the MENAP countries (Middle East, North Africa, Pakistan). If so, then it should not be a predictor if we look at Europeans only. The regression plot in Figure 6 shows that this does not seem to be the case. If anything Islam is a better predictor within the sample of European countries of origin although this was due to two countries Bosnia Herzegovina and Macedonia.

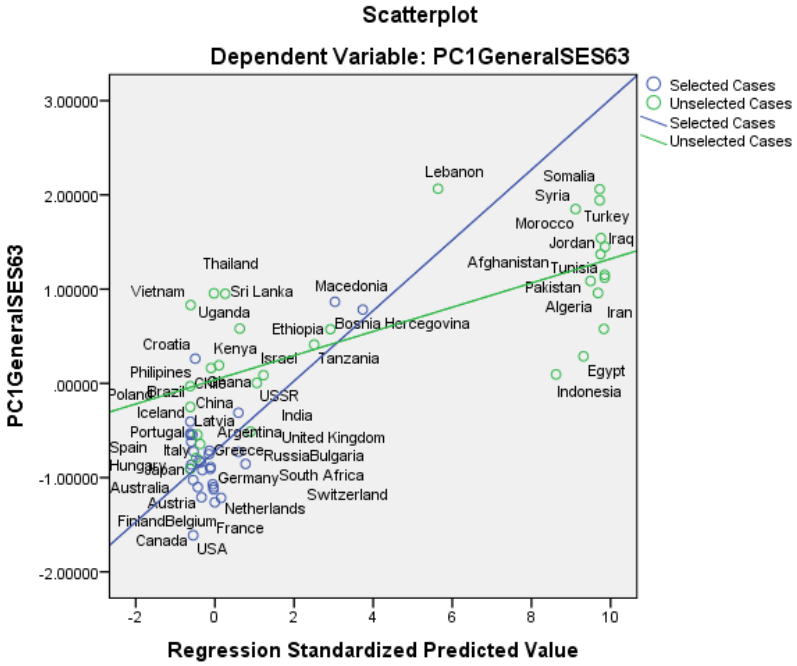

Figure 6: Regression plot for Islam on the general socioeconomic factor for Europeans vs. non-Europeans.

11 Discussion and conclusion

We have shown that how well an immigrant group does in 4 different areas of society is to a high degree predictable from their country of origin. Furthermore, we have shown that these can be seen as part of a more general socioeconomic factor that broadly measures how well a group does in Denmark.

One might wonder what the effects of migrant generation are. The datasets employed here do not break the variables down by immigrant generation. However, the reports *Immigrants in Denmark 2013* (*Invandrere i Danmark 2013[15]*) and *PISA Ethnic 2012* (*PISA Etnisk 2012*[16]) does break down some variables per generation (first and second). The first report does not group immigrants by their country of origin, but by macro-origin: western vs. non-western. Perhaps surprisingly, crime rates are higher in the second generation as shown in Figure 7.

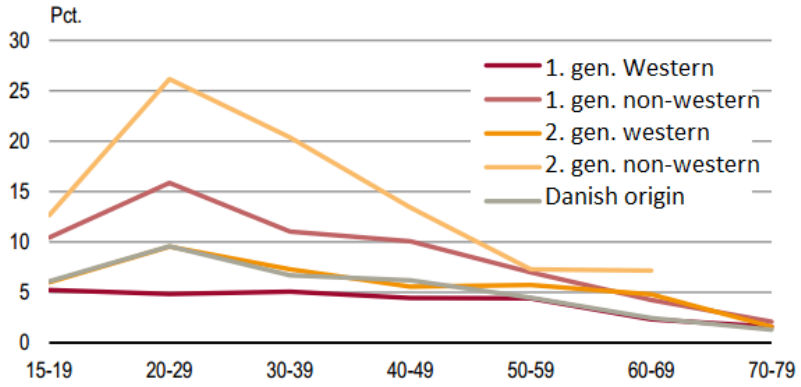

Figure 7: Crime rate for men per macro-origin, generation and age group, 2012. Adapted from Figure 5.3 in [15].

However, employment rate and percentage on social benefits improves from the first to second generation without reaching native levels see Figure 8 and 9.

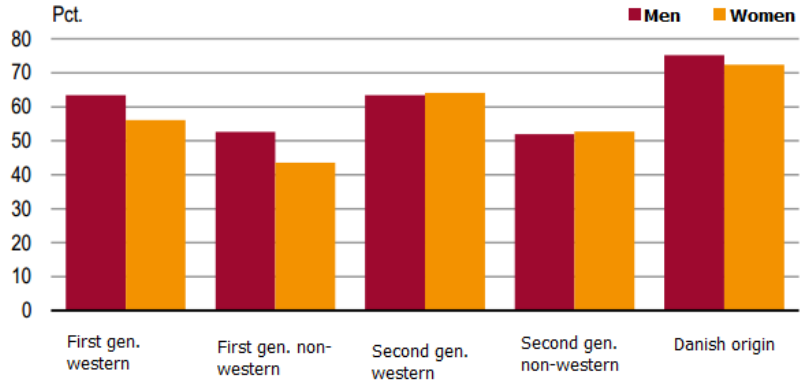

Figure 8: Employment rate by macro-origin and generation. Adapted from Figure 2.3 in [15].

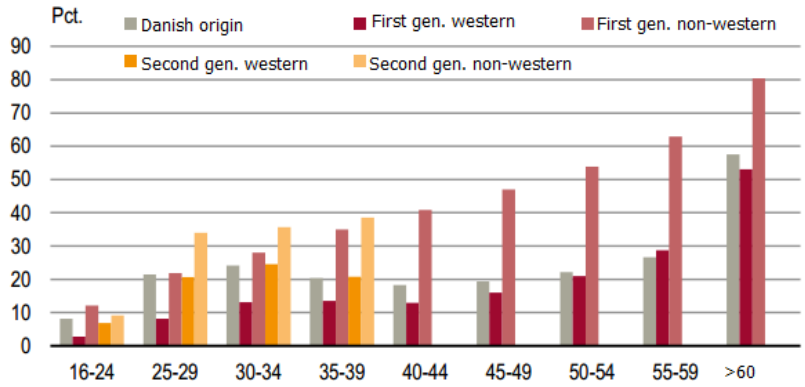

Figure 9: Percentage on social benefits by macro-origin, age group and generation. Adapted from Figure 4.1 in [15]

In the second report average scores by immigrant generation are reported as shown in Table 15. The PISA scores improve about 20 points from first to second generation, but are still 61 below children of Danish origin. This should be seen in the light of the estimate of the total immigrant population in Denmark's IQ at 89.9[7], which is about .67 d lower than Native Danish if it is assumed to be 100. The PISA SD is around 80, so d of the second gen. immigrant and Danish origin gap is about .76.

Origin	**PISA Score**
All origins	500
Danish origin	508
First gen. immigrants	428
Second gen. immigrants	447

Table 15: PISA scores by generation and origin. Adapted from Table 2.2 in [16]

There is not yet reliable data for third generation due to small samples[15].

11.1 Future studies

Future studies should replicate the analyses done here, especially with regards to the existence of general socioeconomic factors in diverse immigrant populations.

Further studies are also needed of the predictive abilities of various country level variables for immigrant populations in other countries. Especially interesting would be an analysis of immigrant populations in an Islamic country.

11.2 Error sources

The crime data from Denmark used spanned multiple years (2000-2012) while the three new datasets concern 2012 data only. This might introduce error.

Lynn and Vanhanen's national IQs are estimates based on data from numerous years and are probably not representative of the current average IQ in the country's as of 2012. Similarly for other predictors.

There is no way to detect selective migration which can both increase and decrease correlations. This is true for selection immigration due for race (e.g. Latin America, South Africa, USA) or whichever traits cause the patterns we report in the study.

Principle components analysis tends to overestimate the amount of variance explained by the latent trait a bit, so the real values are somewhat smaller, compare with [17].

12 Acknowledgment and funding

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13 Appendix - list of countries of origin by general socioeconomic latent variable in Denmark

Note that the factor is negatively coded, so those with the highest score are those who perform the worst.

Country	**Score on the general socioeconomic factor**
Lebanon	2.06574
Somalia	2.06059
Turkey	1.94332
Syria	1.84938
Yugoslavia, Republic	1.62137
Iraq	1.54085
Morocco	1.44991
Yugoslavia	1.43415
Jordan	1.37048
Afghanistan	1.15156
Tunisia	1.12141
Pakistan	1.08631
Algeria	0.95893
Thailand	0.95542
Sri Lanka	0.95115
Macadonia	0.86555
Vietnam	0.83137
Bosnia-Hercegovina	0.78319
Uganda	0.58149
Iran	0.57854
Ethiopia	0.57487
Tanzania	0.41146
Egypt	0.28731

Croatia	0.26194
Kenya	0.19122
Philippines	0.16204
Indonesia	0.09543
Israel	0.08693
Ghana	0.00465
Chile	-0.02897
Brazil	-0.24962
Soviet Union	-0.31177
Poland	-0.40592
India	-0.51208
Latvia	-0.53251
Portugal	-0.54386
China	-0.5447
Iceland	-0.54589
Romania	-0.61938
Argentina	-0.64445
Greece	-0.71416
Ukraine	-0.72463
Russia	-0.72804
United Kingdom	-0.751
South Africa	-0.79153
Spain	-0.81968
Italy	-0.83756
Bulgaria	-0.85429
Hungary	-0.8639
Germany	-0.88794
Lithuania	-0.90211
Sweden	-0.90745
Japan	-0.90857
Norway	-0.9214
Finland	-1.02674
Netherlands	-1.07091
Australia	-1.10136
Austria	-1.10213
Switzerland	-1.12573
Canada	-1.20867
France	-1.21555
Belgium	-1.26163
USA	-1.61244