What Happened to Brussels? The Big Decline and Muslim Immigration

Emil O. W. Kirkegaard*
Ulster Institute for Social Research, London, UK

Baptiste Dumoulin**
Independent Researcher, Belgium

* Email: emil@emilkirkegaard.dk
**Email: BaptisteDumoulin@hotmail.com

We examined regional inequality in Belgium, both in the 19 communes of Brussels and in the country as a whole (n = 589 communes). We find very strong relationships between Muslim% of the population and a variety of social outcomes such as crime rate, educational attainment, and median income. For the 19 communes of Brussels, we find a correlation of -.94 between Muslim% and a general factor of socioeconomic variables (S factor) based on 22 diverse indicators. The slope for this relationship is -7.52, meaning that a change in S going from 0% to 100% Muslim corresponds to a worsening of overall social well-being by 7.52 (commune-level) standard deviations. For the entire country, we have data for 8 measures of social inequality. Analysis of the indicators shows an S factor which is very similar to the one from the Brussels data only based on the full set of indicators (*r*'s = .98). In the full dataset, the correlation between S and Muslim% is -.52, with a slope of -8.05. Adding covariates for age, population density, and spatial autocorrelation changes this slope to -8.77. Thus, the expected change going from a 0% to 100% Muslim population is -8.77 standard deviations in general social well-being. We discuss our findings in relation to other research on immigration and social inequality, with a focus on the causal influence of intelligence on life outcomes in general.

Key words: Belgium, Brussels, Inequality, Immigration, Muslim, Islam, Income, Crime, S factor, Spatial autocorrelation, Intelligence

Northwest European countries have received large numbers of non-European immigrants beginning approximately in the 1960s. In every country, some immigrant groups have fared poorly, and this has resulted in strong public opposition to immigration among the natives such that most elections in the past two decades have been strongly focused on the immigration question (Kaufman, 2019; D. Murray, 2017; Roth, 2010; Sanandaji, 2017; Sarrazin, 2012). It has been noted many times, however, that immigrants are not all alike, but outcomes differ by country of origin (Adsera & Chiswick, 2006; Beenstock et al., 2001; Borjas, 2016; Boyd & Thomas, 2002; Jones & Schneider, 2010; Osili & Paulson, 2008; Vinogradov & Kolvereid, 2010). Many previous studies have examined the relative social performance or well-being — measured as income, educational attainment, crime rate, unemployment etc. — of immigrant groups according to country of origin (Jones & Schneider, 2010; Kirkegaard, 2015a; Kirkegaard & Becker, 2017; Kirkegaard & Fuerst, 2014; Vinogradov & Kolvereid, 2010). These studies show that immigrant populations usually, but not always, perform below the native population. Furthermore, country of origin characteristics such as Muslim percentage of the population and average intelligence in the country (measured as IQ or as scores on scholastic achievement tests such as PISA) strongly predict outcomes (mean absolute correlation around .60) and plausibly serve as causal variables that country of origin is a proxy of (Kirkegaard & de Kuijper, 2020).

In the Belgian context, the capital of Brussels (Bruxelles) saw the relative wealth of its inhabitants reduced dramatically in about 50 years, shown in Figure 1 (Ashworth et al., 2003; Van Hamme, 2015). In this same period, the population composition of the city changed drastically from mostly natives, or at least persons of European ancestry, to now being approximately 25% Muslim of mostly non-European ancestry. The wealth index (the ratio of average earnings in a given unit in Belgium compared to the Belgian mean) in the Belgian capital declined from about 150 in the early 1970s to 79 in 2015, meaning that the relative prosperity of the Brussels region is today half of what it was 50 years before. This decline in well-being is very noticeable to the inhabitants and is strongly concentrated in neighborhoods with more immigrants. However, we are not aware of any published academic work statistically examining the relationships between immigrant populations, or Muslims in particular, and well-being in Brussels or Belgium at large, though it has been mentioned occasionally (Corijn & Ven, 2013, Chapter 5). The purpose of the present study is to fill this gap in the literature.

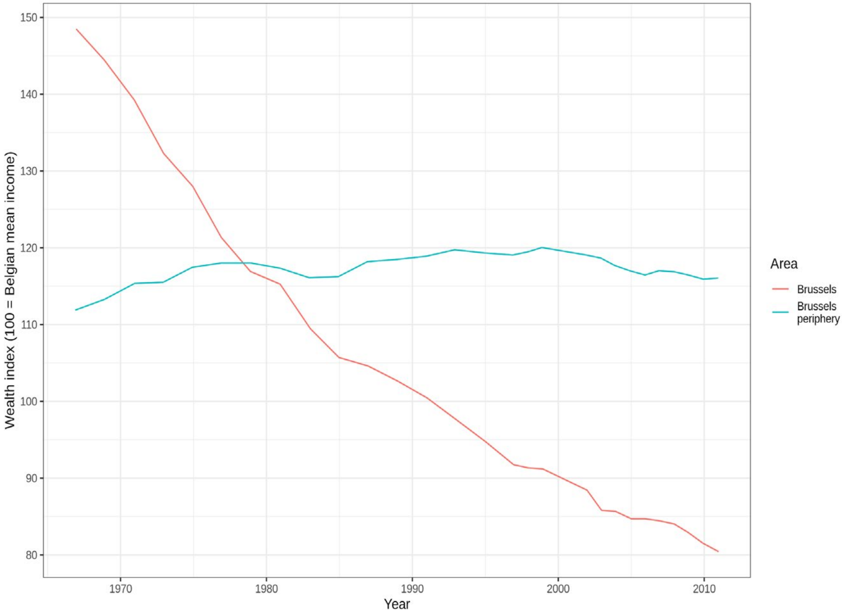

Figure 1. *Timeline of Brussels wealth index compared to surrounding areas, 1967-2011 (data from Van Hamme, 2015).*

Data

We compiled data from a number of sources for this study since a collection of suitable data was not available at a single source. Some variables were available for many years, and others only for a single year. For each variable, we attempted to pick a single year of data closest to the mean of a given dataset, or averaged surrounding years of data if the data were noisy. The details of the data sources and their years are given in the supplementary materials. Generally speaking, the data sources were governmental sources such as national or local government web portals. As such, they are considered to have high validity.

One data source, however, warrants some discussion here. Government population records give the number of persons by citizenship in each municipality from 1989 to 2019. We estimated Muslim% for each municipality using the Muslim prevalence in origin countries in 2010 as estimated by Pew Research (Pew Research Center, 2011). However, we found that this method did not work as expected because many immigrants change their citizenship, and their children may be born with Belgian citizenship, thus being counted as natives and non-Muslims in these data. This problem has been noted by others as well e.g.

"Official statistics do not provide a good reflection of people's ethnic origins in Brussels." (Corijn & Ven, 2013, Chapter 5) and was confirmed by a government employee by email. This results in many estimates of Muslim% actually *decreasing* while in reality they are increasing. Figure 2 shows the estimated Muslim% using this method.

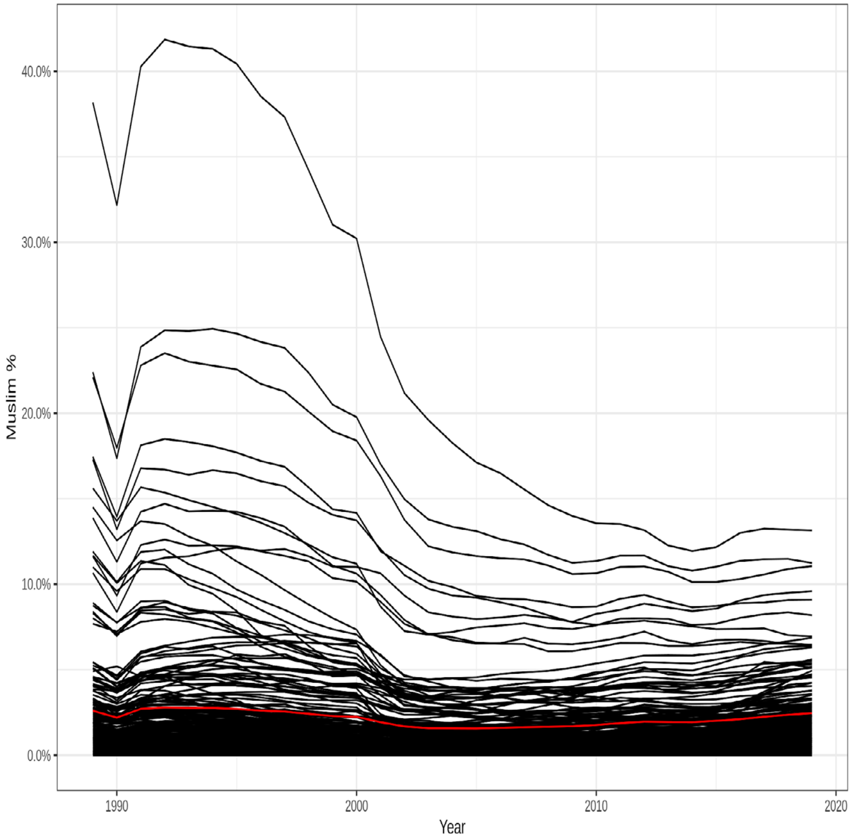

Figure 2. *Muslim% in Belgium as estimated by citizenship and country of origin Muslim%. Each black line is a commune (n = 589). The red line shows the entire country.*

Because of this issue, we sought a different source of Muslim% estimates. We found public estimates by Belgian sociologist Jan Hertogen (Dutch speaker) who runs the website http://www.npdata.be/ ("Non-Profit Data"). He has published estimated Muslim% for the years 2011, 2013, 2015-2017 (Hertogen, 2017). His values are based on the same citizenship data we obtained, but he makes adjustments to correct for the people who changed their citizenship, as well as their children. According to his 2011 estimates, Belgium was 6.3% Muslim while for Brussels it was 22.4%. Pew Research estimated the country value at 6.0% for 2010 (Pew Research Center, 2011), so the estimates are closely in line. Figure 3 shows his estimates, used in this study. All data used in the study are available for reuse in the supplementary materials at https://osf.io/ja6ce/.

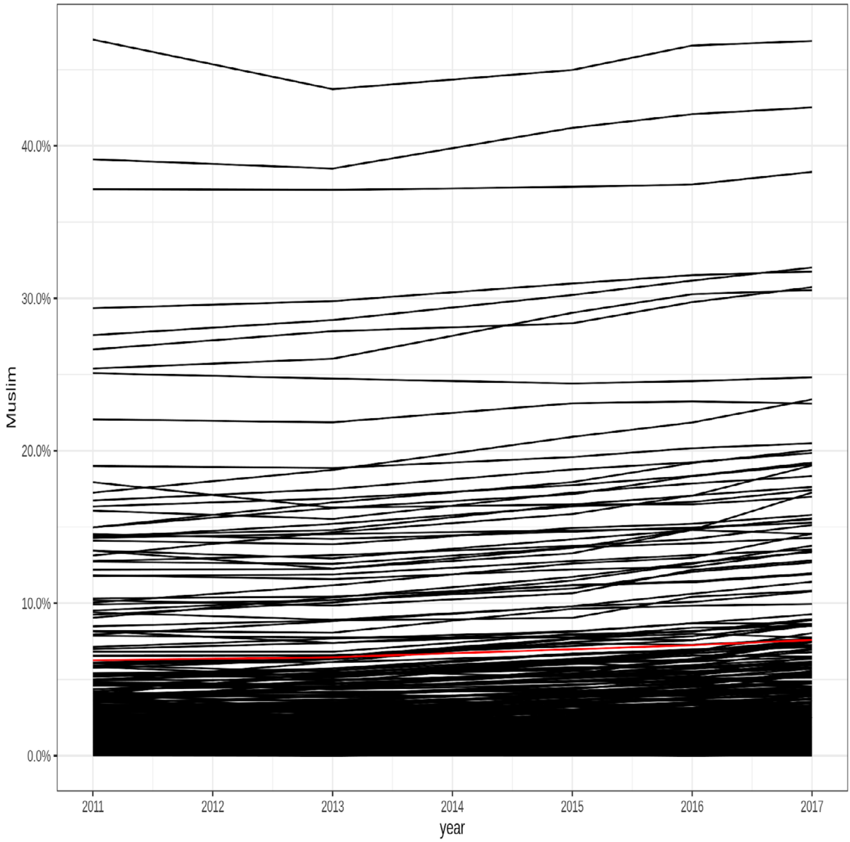

Figure 3. *Muslim% in Belgian communes as estimated by Jan Hertogen. Each black line is a commune (n = 589). The red line shows the entire country.*

Analyses

Analyses are first presented for the Brussels region where we have the most detailed data. The units are relatively homogenous in terms of population density and geographical factors that might distort the results. After this we expand our scope to the entirety of Belgium and assess whether the results are in line with those from the capital region. Figure 4 shows a reference map of Belgium with provinces and communes.

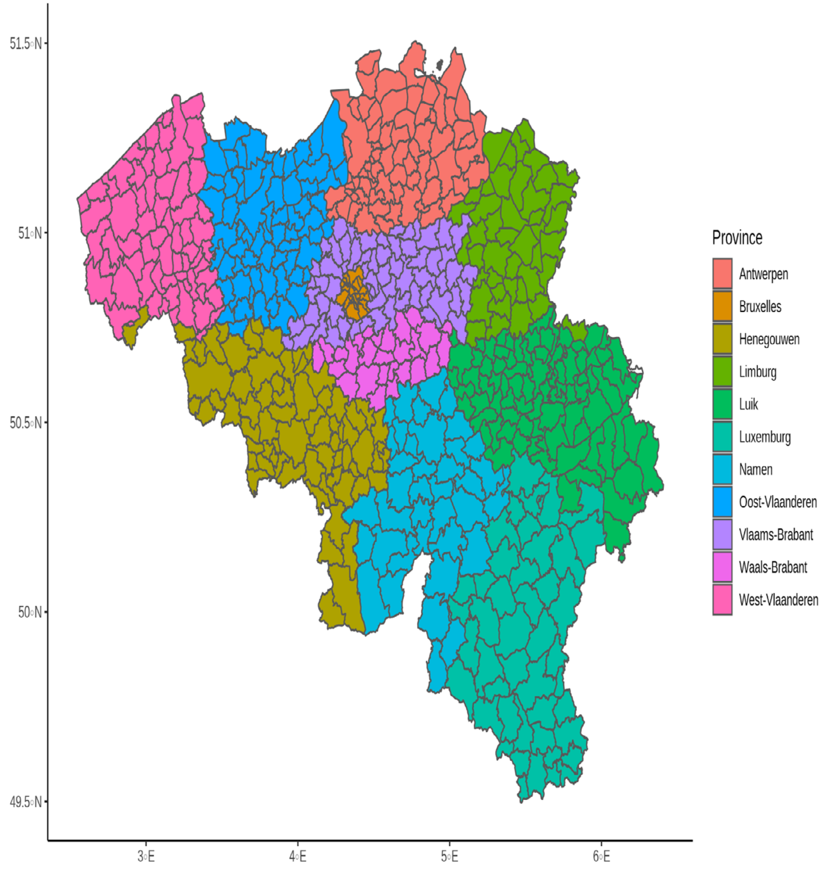

Figure 4. *Map of Belgium showing the division into provinces and communes.*

Brussels

We factor analyzed the available 22 indicators of well-being. A very strong (76% of variance) general factor was found. We used extensive method variation to check if this was robust to choice of factor analytic method and factor scoring method, and we found that it was (all method variations resulted in factor scores that correlated near 1.00), see statistical output for details. Figure 5 shows the estimated factor loadings across 3 weighing method variations.

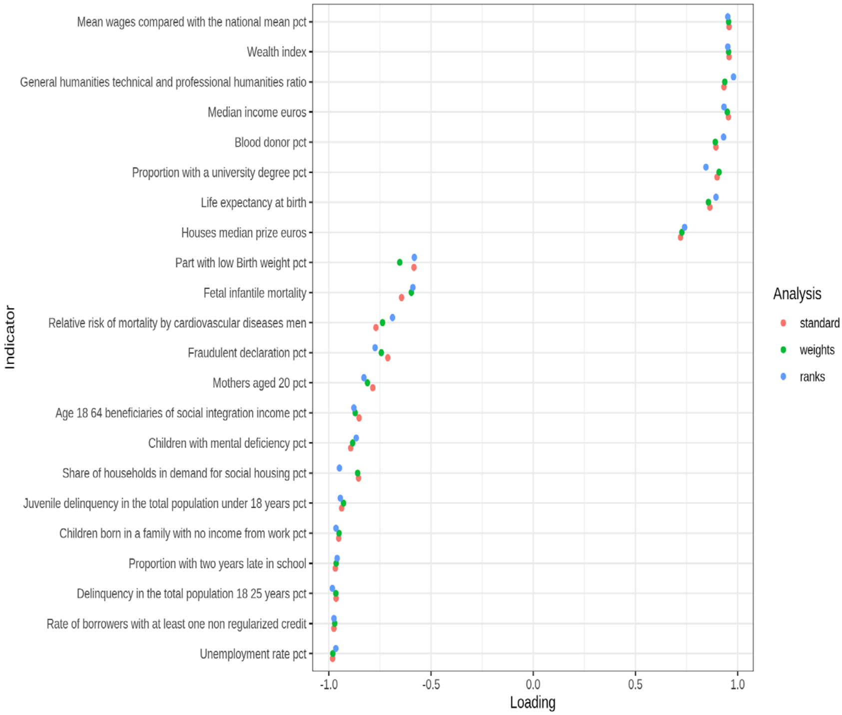

Figure 5. *General socioeconomic factor (S) loadings across three methods of estimation.*

In the figure, standard is the default settings used by *fa()* from the **psych** package (Revelle, 2020). This is the combination of unweighted least squares for the factor loadings estimation, and the regression method for scoring. The weights analysis was done using the square root of population size as weights, and finally the rank analysis was done using rank-transformed data. Inspection of the factor loadings showed that they conformed to the usual interpretation: desirable indicators had positive loadings and undesirable indicators negative loadings (Pesta et al., 2010). This allows for a simple interpretation of the resulting scores as a clean measure of social well-being or generalized socioeconomic status, termed the S factor (see e.g. Kirkegaard, 2014a; Kirkegaard & Fuerst, 2017 for other examples of such factor analyses). Figure 6 shows the scatterplot between Muslim% and the S factor, while Figure 7 shows a map of Brussels with the S factor score. The supplementary materials have maps of Brussels with each variable. For comparison, Figure 8 shows a similar map of Brussels with percentage of Muslims.

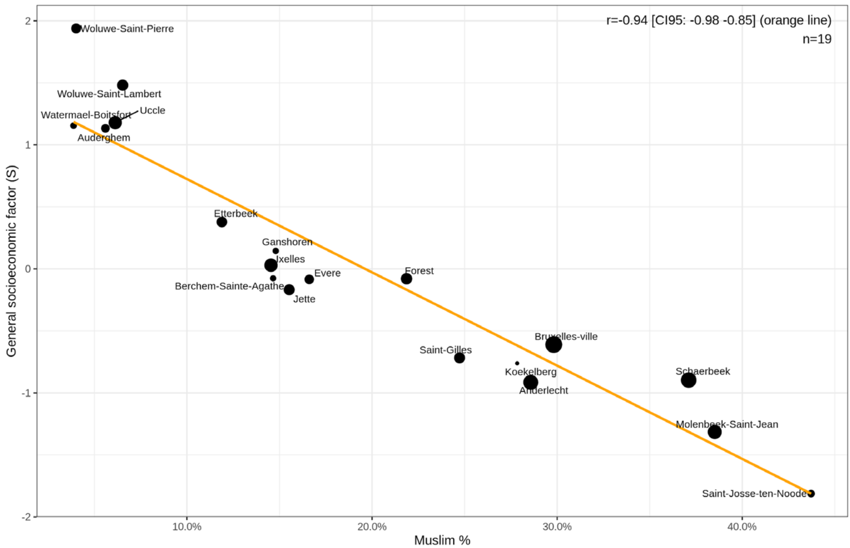

Figure 6. *Scatterplot of communes of Brussels showing Muslim% and general socioeconomic factor (S). Weighted by the square root of population size.*

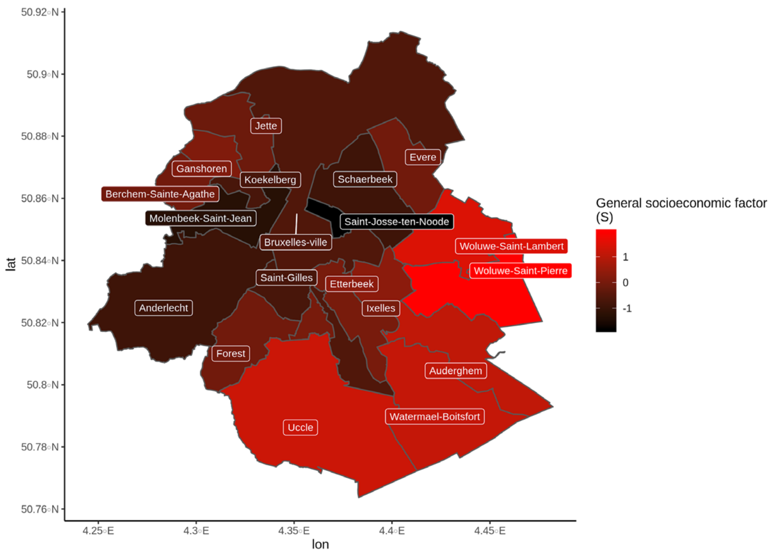

Figure 7. *Map of Brussels showing variation in general socioeconomic factor (S) score.*

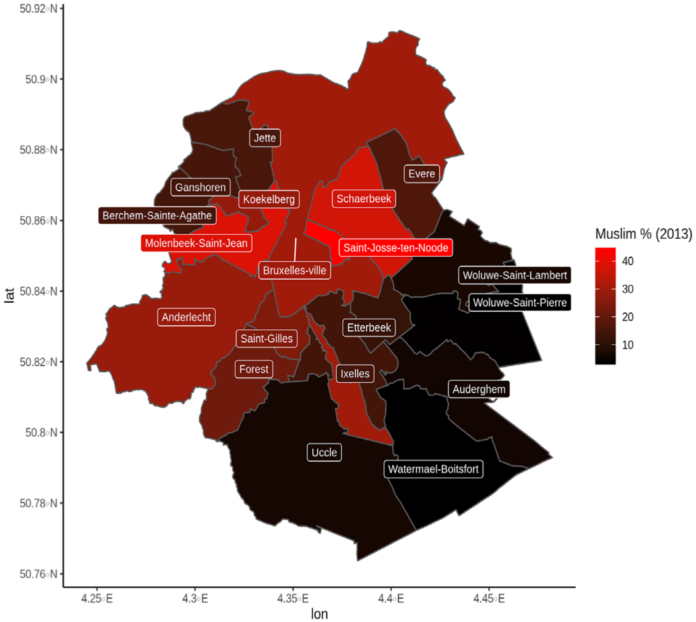

Figure 8. *Map of Brussels showing variation in Muslim%.*

The scatter plot shows an extremely strong negative correlation such that the greater the Muslim% in a city district, the worse the social well-being. The relationship between Muslim% and every indicator of S was very strong, as shown in Table 1. The relationship to the S factor was 'S-loaded' in that the social indicators that were more strongly related to the S factor also had a stronger relationship to Muslim%, $r = .92$, shown in Figure 9.

Table 1. *Correlation between Muslim% and well-being indicators. Weighted by the square root of population.*

Variable	Correlation with Muslim %
Wealth index	-0.94
Wage index	-0.94
Share of households in demand for social housing % (2012)	0.84
Unemployment rate (2012)	0.96
Median income in Euro (2012)	-0.90
18-64 year old beneficiaries of social integration income % (2012)	0.90
Delinquent population aged <18 years %	0.89
Delinquent population aged 18-25 years %	0.91
University degree %	-0.80
Low birth weight %	0.50
Life expectancy at birth	-0.73

Variable	Correlation with Muslim %
Children born in a family with no income from work %	0.96
Median house price in Euro	-0.65
Fraudulent insurance declarations %	0.68
Rate of borrowers with bad credit	0.89
"Mothers <20 years % (2009-2013)	0.83
Infant mortality (2009-2013)	0.62
Proportion two years late in school (2013-2014)	0.93
Special education mental deficiency % (2013-2014)	0.80
Relative risk of mortality by cardiovascular diseases, men (2009-2013)	0.56
General humanities to technical and professional humanities ratio in education	-0.86
Blood donor %	-0.85
General socioeconomic factor (S)	-0.94

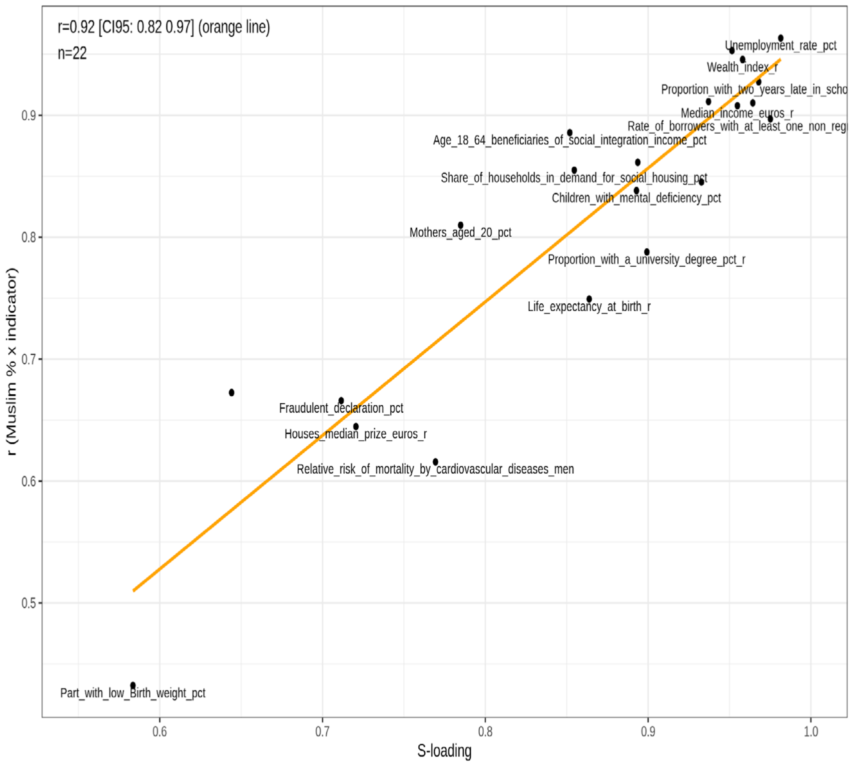

Figure 9. *Jensen's method used on Muslim% and general socioeconomic status (S factor). Note that indicators with negative loadings were reversed to avoid variance inflation (Kirkegaard, 2016b), and are marked with "_r".*

This Jensen pattern[1] suggests that whatever it is Muslim% relates to, it is something that relates chiefly to the joint variation of a broad variety of indicators of well-being. This pattern has previously been found for immigrant group differences in Denmark (Kirkegaard, 2014b), and for a variety of predictors at the national level (Kirkegaard, 2014a).

Instead of looking at the S factor, which is a unitless metric, we can also examine specific indicators. Table 2 shows regression results for selected indicators, as well as S itself. Because all the units are part of Brussels, we considered it unnecessary to control for e.g. population density.

Table 2. *Summary of regression results for general socioeconomic status (S factor), median income, educational attainment, and unemployment rate. Weighted by the square root of population. * = p <.01, ** = p < .005, *** = p < .001. B coefficients with standard errors in parentheses.*

Predictor/Model	Median income	Unemployment rate	Uni degree	S factor
Intercept	23106*** (553)	11.82*** (0.850)	14.56*** (1.27)	1.48*** (0.16)
Muslim%	-19357*** (2304)	48.36*** (3.542)	-29.01*** (5.30)	-7.52*** (0.65)
R^2 adj.	0.795	0.912	0.616	0.881
N	19	19	19	19

Belgium

In the analyses above, we saw that the association of social outcomes with Muslim% in Brussels is very strong. However, it is not certain that it will hold up for the country at large. To examine this, we computed a general socioeconomic factor score from 8 available indicators for each commune: median income reported (2016), mean income reported (2016), income inequality (2016), total crime rate (average of 2009-2016), violent crime rate (average of 2009-2016), life expectancy (2014), proportion of population with a university degree (2011), and unemployment rate (average of 2009-2016). The general factor showed very little method variance, accounted for 47% of the variance, and showed a similar loading pattern as that found for Brussels. The factor scores derived from the Brussels area communes correlated .98 with those for the same units derived from the full country analysis, and .98 with those derived from the full set of 22

[1] The concept was named *Jensen effect* by Phil Rushton for the analogous finding where g-loadings of intelligence tests relate to the strength of tests' relationship with other variables (Rushton, 1998), but we have generalized it here to any factor.

indicators used in the analysis above. Figure 10 shows the scatterplot of Muslim% and the S factor score for all communes. Figures 11 and 12 show maps of Belgium colored by S factor score and Muslim%. The supplementary materials contain maps for every other variable. It can be seen that for Belgium as a whole, Muslim% is correlated with worse outcomes, though not as strongly as for just the municipalities of Brussels. Table 3 shows the correlation matrix between the primary variables.

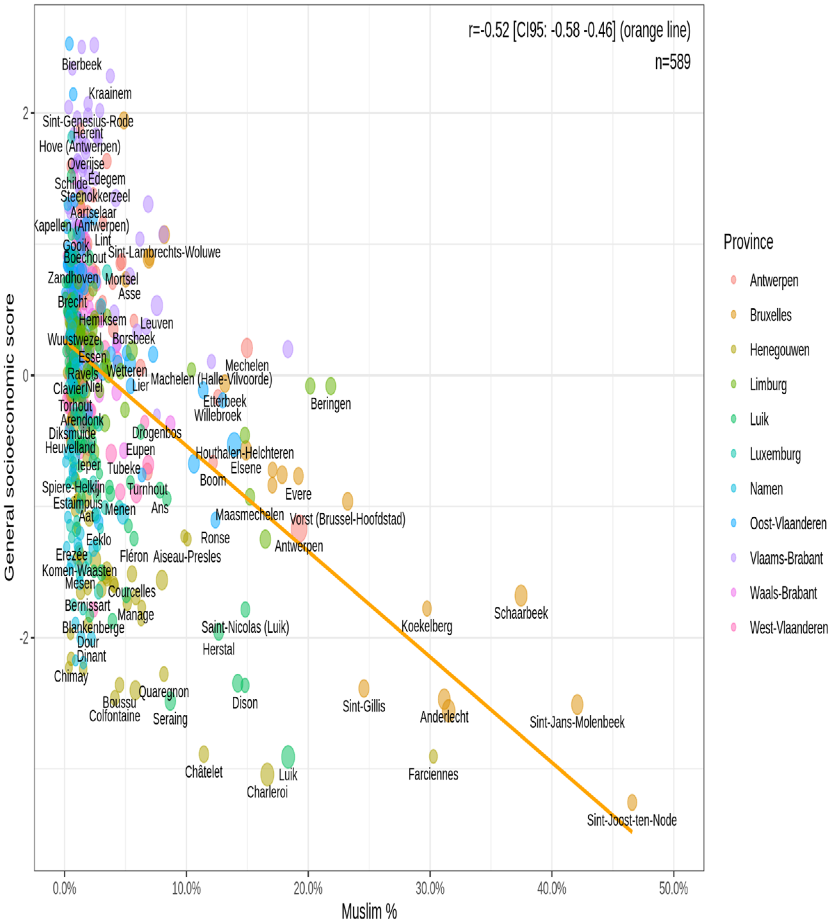

Figure 10. *Scatterplot of Muslim% and general socioeconomic factor (S factor). Weighted by the square root of population.*

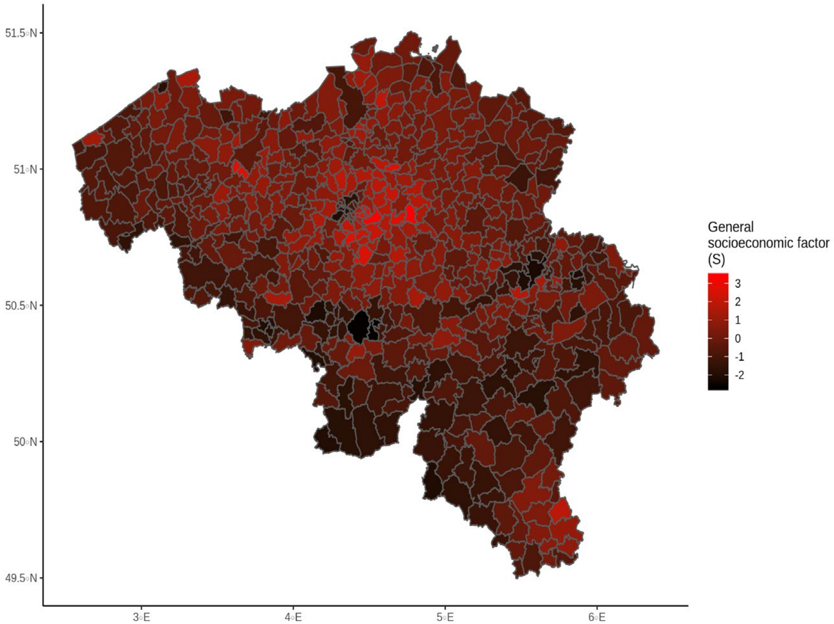

Figure 11. *Map of Belgian communes showing variation in general socioeconomic status (S) factor scores.*

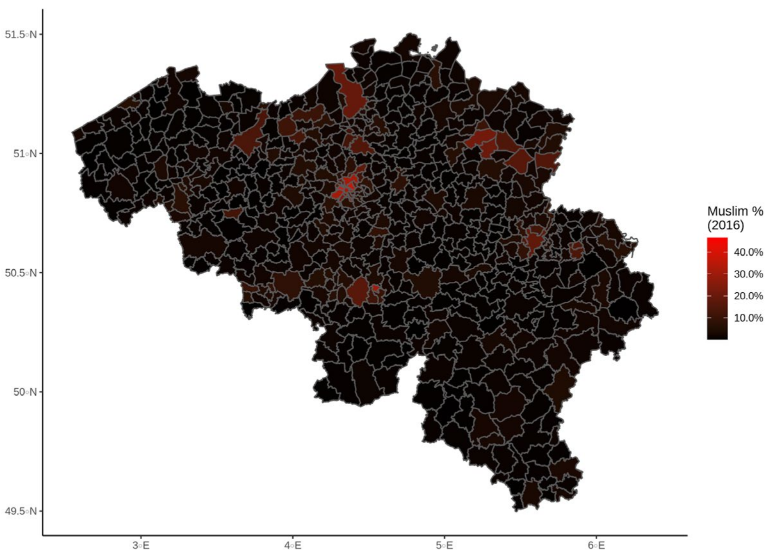

Figure 12. Map of Belgian communes showing variation in Muslim %.

Table 3. *Correlation matrix for primary variables for Belgian municipalities, n = 561-589. Values below diagonal are weighted by the square root of population. S = general social well-being.*

	S	Muslim%	Median income	Mean income	Income inequality
S		-0.41	0.88	0.88	0.48
Muslim %	-0.52		-0.37	-0.24	0.05
Median income	0.89	-0.51		0.85	0.26
Mean income	0.87	-0.32	0.83		0.59
Income inequality	0.40	0.13	0.19	0.58	
Crime rate	-0.65	0.63	-0.50	-0.27	0.07
Violent crime rate	-0.81	0.49	-0.58	-0.45	-0.16
Life expectancy	0.64	-0.15	0.49	0.53	0.32
Higher educ. %	0.59	-0.06	0.45	0.77	0.86
Unemployment	-0.81	0.72	-0.74	-0.51	0.04

Table 3. *Correlation matrix for primary variables for Belgian municipalities, n = 561-589. Values below diagonal are weighted by the square root of population. S = general social well-being.*

	Crime rate	Violent crimes	Life expect.	Higher edu. %	Unempl.
S	-0.61	-0.79	0.61	0.65	-0.78
Muslim %	0.56	0.40	-0.10	-0.08	0.62
Median income	-0.43	-0.54	0.45	0.50	-0.67
Mean income	-0.27	-0.45	0.47	0.78	-0.48
Income inequality	-0.03	-0.24	0.28	0.86	-0.05
Crime rate		0.85	-0.28	-0.10	0.68
Violent crime rate	0.88		-0.47	-0.31	0.73
Life expectancy	-0.28	-0.47		0.35	-0.53
Higher educ. %	-0.02	-0.24	0.41		-0.19
Unemployment	0.70	0.72	-0.53	-0.15	

To understand whether the pattern was plausibly causal, we fit a series of regression models adding potential confounders. In the second model step, we add the traditional controls: age, and population density. We used natural splines to adjust for any nonlinear effects of these (Harrell, 2015, 2019). For the third step, we add the spatial lag, i.e. the outcome variable as predicted by spatial data. Concretely, we used spatial k nearest neighbor regression by averaging the values of the three nearest neighboring units (Anselin & Bera, 1998; Kirkegaard, 2015b; Pesta et al., in review see spatial statistics supplement). The position of each commune was calculated by the centroid of their polygons. The autocorrelations for the main variables are shown in Table 4 (each variable correlated with its own lag).

Table 4. *Spatial autocorrelation (SAC r) for the main variables in the country-wide dataset. Unweighted correlations.*

Variable	SAC r
General socioeconomic factor	0.74
Life expectancy	0.58
Mean income	0.79
Median income	0.77
Income inequality	0.76
Muslim%	0.73
Crime rate	0.47
Violent crime rate	0.50
Unemployment	0.83
Population density	0.82
Age 65 and above %	0.71
Age 0-19 %	0.79

The autocorrelation results confirm the usual expectations: everything close to each other is more similar (spatially autocorrelated, SAC), and the mean/median SAC are .70/.75. This has come to be called *Tobler's first law of geography* (for historical review, see Tobler, 2004; and for a powerful modern illustration, see Li et al., 2014), though it relates back to Francis Galton, and the problem is known also as *Galton's problem* (Eff, 2004). As many have noted (Gelade, 2008; Hassall & Sherratt, 2011), when SAC is present, datapoints are not fully independent and then residuals from models will usually also be SAC which violates the assumption of most regression methods. The regression results are shown in Table 5.

Across the three outcomes, we see that there are large effects of Muslim%. For S factor, the simple model suggests a -8.05 SD decrease in general well-being by increasing the Muslim% from zero to 100%. Adding age and population density controls (betas are not shown because nonlinear) increases this estimate to a 12.80 SD decrease. However, adding the spatial lag in Model 3 reduces it to an 8.77 SD decrease. For income, we see weaker results compared to those from Table 2, based on just the 19 communes of Brussels. This is not surprising because much income variation is linked to population density — cities and city-adjacent areas are richer on average (cf. Figure 11). However, mass immigration has primarily been to the cities as well. This migration pattern results in cities now being a mix of above average natives (and other Europeans), and generally low-status immigrants. This creates a particularly large contrast among city communes, and thus the large slope seen. Consistent with this, the slope increases in Model 2 when we add covariates which include a control for population density. Finally, in Model 3, the slope shrinks to -6.8k. Thus, if we imagined two counterfactual Belgiums, one with 0% and one with 100% Muslims, the one with 100% would be €6,800 lower in median income. For crime rate, we see that Model 1 has a slope of 3.76, thus an increase in Muslim% to 100% from 0% would result in a 376%points increase in crime rate (the intercept is 0.65, so this would be an increase of 478%). This value is reduced to 224%points in Model 2, and 198%points in Model 3. Surprisingly, the lag variable is weaker for the crime model than for the other two, despite the fact that one might expect contagious effects of crime.

Table 5. *Regression models for general socioeconomic status (S factor) for Belgian municipalities. Weighted by the square root of population. * $p < .01$, ** $p < .005$, *** $p < .001$. Standard errors in parentheses.*

Predictor/Model	**1**	**2**	**3**
		outcome = S	
Intercept	0.27*** (0.046)	3.13 (1.540)	3.89*** (1.135)
Muslim%	-8.05*** (0.55)	-12.80*** (0.95)	-8.77*** (0.72)
S lag			0.73*** (0.033)
age & population density	no	yes	yes
R^2 adj.	0.268	0.384	0.666
N	589	589	589
		outcome = median income	
Intercept	18699*** (58)	16681*** (1065)	4478*** (905)
Muslim%	-9909*** (694)	-12608*** (1250)	-6788*** (914)
median income lag			0.77*** (0.032)
age & population density	no	yes	yes
R^2 adj.	0.256	0.378	0.691
N	589	589	589
		outcome = crime rate relative rate (country = 1)	
Intercept	0.65*** (0.016)	1.37*** (0.283)	0.71 (0.292)
Muslim%	3.76*** (0.194)	2.24*** (0.335)	1.98*** (0.326)
crime rate RR lag			0.38*** (0.058)
age & population density	no	yes	yes
R^2 adj.	0.393	0.537	0.568
N	582	582	582

As a robustness test, we residualized the S indicator variables for age and population density before conducting the factor analysis. This would theoretically allow one to leave out the age and population density variables in the regression models, and might affect the structure of the S factor. However, we found that the S factor scores from this approach correlated r = .90 with those from the standard approach, and we did not investigate it further.

Finally, we examined whether the Jensen pattern was also present for the country as a whole, as it was for the Brussels region (cf. Figure 9). This analysis presents the difficulty that we know that age distribution and population density confound the pattern. For this reason, we introduce a new variant on the method by using metrics from regression models. Specifically, we fit a regression model for each S indicator as the outcome with and without Muslim%, along with the age and density controls. We saved the model R^2 gain from adding the Muslim% predictor, as well as the slope of this predictor. Finally, we reverse the negative S indicators as normally done. Table 6 shows the resulting values from this approach, and Table 7 shows their correlations.

Table 6. *Expanded Jensen method results for Belgian general socioeconomic status indicators, and Muslim% as predictor.*

Indicator	Reversed	Loading	r (indicator * Muslim%)	r (indicator * Muslim%), weighted	Partial r^2	Δ r^2	Slope
Median income	no	0.83	-0.37	-0.51	0.13	0.13	-10.38
Mean income	no	0.85	-0.24	-0.32	0.19	0.19	-12.06
Income inequality	no	0.46	0.05	0.13	0.10	0.09	-8.52
Crime rate	yes	0.57	-0.56	-0.63	0.08	0.08	-9.73
Violent crime rate	yes	0.76	-0.40	-0.49	0.11	0.11	-10.46
Life expectancy	no	0.59	-0.10	-0.15	0.04	0.03	-4.46
Higher education %	no	0.62	-0.08	-0.06	0.16	0.17	-11.43
Unemployment %	yes	0.74	-0.62	-0.71	0.07	0.08	-8.72

Table 7. *Correlations among variables from Table 6. Pearson correlations above, and Spearman correlations below the diagonal.*

	Loading	r (indicator * Muslim%)	r (indicator * Muslim%), weighted	Partial r^2	Δ r^2	Slope
Loading		-0.46	-0.56	0.51	0.53	-0.50
r (indicator x Muslim%)	-0.31		0.99	0.21	0.15	0.18
r (indicator x Muslim%), weighted	-0.33	0.98		0.17	0.12	0.18
Partial r^2	0.60	0.29	0.26		1.00	-0.87
Δ r^2	0.60	0.29	0.26	1.00		-0.90
Slope	-0.69	0.05	0.02	-0.90	-0.90	

Though we only have 8 S indicators, we see evidence of values in the expected direction. The correlations vary somewhat, but average |.50| across methods. Note that since the correlations and slopes are signed, negative values are expected, i.e., the variables with stronger loadings, have a stronger negative relationship with Muslim %.

Discussion

We studied regional (subnational) inequality in Belgium using a rich dataset of communes (n = 589). Our main goal was to examine to what degree inequality between communes could be explained by the population proportions of Muslims. In particular, we were interested in the explanation for the relative decline of Brussels. It has generally been found in regional research that capital cities or areas are unusually high in general well-being (Fuerst & Kirkegaard, 2016). However, in Belgium the exact opposite is the case, raising the question of why this is so (Ashworth et al., 2003).

In all models, we find large, statistically certain (low p values) effects of Muslim% of the population. For the models of Brussels, we did not utilize any controls since the communes are already very similar in plausible exogenous confounders we could control for. For the regressions using the complete dataset, our addition of a spatial lag control is of note. A spatial lag controls for *unmeasured* confounders. These are variables that cause S and that are correlated with Muslim% but are not entirely caused by it (Rohrer, 2018), to the extent that they are spatially autocorrelated (Baller et al., 2001; Jerrett et al., 2003; Kühn, 2007; Pesta et al., in review, spatial statistics supplement). As we saw in Table 4, most of our variables are very highly spatially autocorrelated (mean r = .70). We can probably expect plausible unobserved or partially observed confounders to be so as well, thus being at least partially accounted for by our spatial lag control. The remaining estimates in the full models are still quite large and socially significant. For instance, going from a 0% to 100% Muslim population would yield an estimated increase in the crime rate of about 200%points, cf. Table 5, column 3.[2] However, the slopes were often weaker when we added spatial lag control compared to only the classic controls. The interpretation of this is tricky. Decreases in slopes from adding spatial lags can indicate a successful control for unmeasured confounding variables, but it can also indicate measurement error in

---

[2] The association of Muslim immigrants with crime is long-standing and of great interest to the public according to survey data. While associations in the USA are weaker, they are quite strong in European countries (Ahlberg, 1996; Carl, 2016; Junger & Polder, 1992; Kirkegaard, 2014b; Kirkegaard & Becker, 2017; Kirkegaard & de Kuijper, 2020; Skardhamar et al., 2014).

the predictor. Our estimates of Muslim% are certainly not without error, especially when comparing units close in proximity, so by this reason alone we expected some decrease in the slope. Furthermore, the sizable betas of some of the spatial lag variables (e.g. .73 for S factor in Table 5, Model 3) could also suggest that there are contagion effects, i.e. that neighboring units affect each other's well-being. For instance, having a neighboring commune or city district with many criminals probably means at least some of them will cause crime in your neighborhood, which causes an assortment of problems downstream, such as decreasing house prices and increased spending on local police or private guards. These effects would eventually show up in the various well-being indicators and thus the S factor. However, when we actually model the crime rate itself, it shows only a moderately strong beta for the spatial lag (.38) which suggests this particular contagion effect is not strong, at least for our data. In the same vein, crime rate actually has the weakest SAC of our variables, .47, cf. Table 4. These results seem to speak against the spatial contagiousness or roaming criminals models (Loftin, 1986; Mennis & Harris, 2013; Osorio, 2015).

The main focus of this investigation was our overall measure of general social well-being, or general socioeconomic factor. However, most research focuses on particular indicators of this general factor, and it is worth reviewing some of this to see whether it is congruent with our findings. Among the indicators used for Brussels, we have the rate of fraudulent insurance declarations, which shows a correlation to Muslim% of .68. This finding is in line with results by Carl (2017) who found that in the United Kingdom, the population proportion of Pakistanis and Bangladeshis (both Muslim populations) was a strong predictor of electoral fraud. He interpreted this in line with a history of cousin marriages promoting ethnocentric behavior resulting in relatively stronger distrust and hostility towards outsiders, including scamming behaviors (Schulz et al., 2019; Woodley & Bell, 2013).

Lynn (2020) reviewed findings on race differences in blood donation, as a measure of altruism. He finds that overall European-descent ('whites') have more blood donors per capita than the 5 other racial/ancestry groups considered, including East Asians. He did not find a study that included Middle Easterners or Muslims in particular, but one German study compared immigrants to natives and found that the native blood donor rate was slightly less than twice that of immigrants, perhaps a majority of which are Muslims (Boenigk et al., 2015). Thus the rank order does not follow the usual IQ order entirely, as the results suggest that East Asians are less altruistic than Europeans despite superior average intelligence. In fact, inspection of country-level data about foreign aid suggests the same. The largest 10 donor countries in terms of % of GNI to foreign aid are all European, mainly Northern European (see appendix for details). These various results fit well with our finding of a negative correlation between blood donations and Muslim% of -.85 among the Brussels communes (Table 1).

Among the Brussels communes we found that the proportion of students in special education for the mentally retarded or who are otherwise educationally backwards has a strong relationship to Muslim%, $r = .80$ (Table 1).[3] This result fits well with cognitive testing results from Belgium. PISA studies provide us with data, shown in Tables 8A-C (Jacobs et al., 2007; Lafontaine et al., 2017).

Table 8A. *Scholastic ability results from PISA 2003 by origin group: natives versus first and second generation immigrants. The standard deviation for natives is around 90.*

Origin	Science	Reading	Math	Problem solving
Natives	524	523	545	540
1st	416	407	437	447
2nd	435	439	454	445

Table 8B. *Scholastic ability results from PISA 2003 by national origin.*

Mother's origin	French area	Dutch area
Natives	514	567
France	409	
Netherlands		521
Other EU countries	476	469
Eastern Europe	508	479
Turkey	430	414
Maghreb	434	452
Africa (non-Maghreb)	429	454
Other countries	437	456

[3] To be sure, we checked the criteria used for this classification (https://www.vaph.be/professionelen/mdt/mdv/modules/verstandelijke-handicap). The diagnoses are primarily based on low IQ scores on standardized tests (Wechsler, SON-R and others), but also based on behavioral and learning problems in school (Deblonde et al., 2020). Race differences in rates of mental retardation are well known and relate to the difference in average intelligence and thus also the proportion that are below a given threshold (Jensen, 1969; Yeargin-Allsopp et al., 1995).

Table 8C. *Scholastic ability results from PISA 2015 by origin group: natives versus first and second generation immigrants.*

Group	Science	Reading	Math
	French area and Brussels		
Natives	499	496	502
1st	438	440	443
2nd	459	465	465
	Dutch area		
Natives	529	523	534
1st	419	427	425
2nd	448	427	425
	German area		
Natives	511	508	510
1st	457	455	456
2nd	472	470	470

We see that substantial cognitive gaps exist, whether the data concern reading comprehension, mathematics, science or problem solving; whether it is in French, Dutch, or German speaking areas; and whether it was measured in 2003 or 2015. Additionally, Klein et al. (2007) tested 69 sub-Saharan Africans living in Belgium on a reduced form of the Cattell test as part of a stereotype threat study (study participation rate was 15%). They obtained an IQ score of 81. However, when the necessary adjustment for the Flynn effect is applied, this results in an estimate of roughly 70 (see the appendix for details of calculation). Rindermann & Thompson (2016) calculated an overall IQ metric score of 92 for Belgian immigrants relative to natives' 100 based on various waves of scholastic testing data. The standard deviation for the PISA scale among natives is approximately 90, so the gaps we see in Table 8 are congruent with Rindermann and Thompson's results.

The presence of a substantial cognitive gap is important because of the evidence that intelligence gaps are the primary cause of scholastic ability gaps and of later social inequality. Evidence for this claim comes from many research designs including prospective studies, which rule out reverse causation, sibling studies, which rule out any confounder that differs between families (Frisell et al., 2012; Hegelund et al., 2018, 2019; Herrnstein & Murray, 1994; C. Murray, 2002), and GWASs that allow for functional analysis of genetic causes of intelligence and outcomes, as well as studies using polygenic scores constructed from them (Belsky et al., 2016; Hill et al., 2019; Lee et al., 2018). Thus, generally, one would expect cognitive gaps to result in social gaps. The various estimates of cognitive gaps summarized above are therefore a likely cause of immigrant-native gaps in social outcomes. Unfortunately, evidence to directly test this mediation is generally lacking. One exception is the study by Nordin & Rooth (2007), which examines income gaps between natives and various second generation immigrants in Sweden. They used IQ data from the Swedish military draft test taken at age 18, and income data from the national register. They found that 66% of the native income advantage over those from "outside Europe" could be explained by the test score gap (their Table 2, column 2). There will be some measurement error in the IQ test, so if this were accounted for, the true mediation % will be higher. Nevertheless, it is a plausible lower bound estimate. In their model that includes family background (a composite of parental years of schooling and annual income), they found that 88% of the gap could be explained. However, including family background in a regression is causally ambiguous because of its genetic correlations with offspring personality traits. It would be informative to replicate this study in other countries. The most likely candidates would be other Nordic countries with similar existing datasets. Preferably, one would include measures of Muslim religious beliefs to gauge their potential causal effects, controlling for intelligence. Using a sibling design would allow for a natural adjustment for any parental effects. It is unfortunate that Hegelund et al. (2019), who conducted a sibling study for IQ and social outcomes in Denmark, did not examine the question about immigrants more closely.

Our results from Jensen's method, i.e., the positive relations between S factor loadings and measures of strength of association with Muslim%, adds plausibility to the above interpretation of causality mediated by intelligence. This is because the same analysis has been done with intelligence as the predictor in other studies, and very strong Jensen patterns were also found for this variable (Kirkegaard, 2014a, 2016a). This essentially serves as a kind of fingerprint of the causal variable involved. This kind of interpretation has also been advocated with regard to genetic causation of other group gaps (Metzen, 2012; Rushton & Jensen, 2010).

Limitations

Perhaps the most important confounding variable is that many Muslims are first generation and relatively recent immigrants. It is well known that it takes a number of years for immigrants to 'catch-up' to their maximal social performance level (Boyd & Thomas, 2002; Hu, 2000; Husted et al., 2001). Unfortunately, we do not have any good estimates of this confounding factor (e.g. mean duration of stay) or any suitable proxy such as proportion of Muslims who are first generation in each commune. The causal route of this factor would probably mainly be language proficiency, unless the migrant happens to speak the same language in his home country, e.g. due to colonial heritage. It will probably also relate to broad cultural knowledge, and perhaps education in the host country (especially for younger immigrants).

Our estimates of Muslim% of the population were less than ideal. However, one cannot argue that our findings are questionable because the Muslim estimates were produced by political opponents of immigration of Muslims. The sociologist who produced them is clearly left-leaning. His website features a quote by Karl Marx, and he often is critical towards claims by Belgian nationalists (who are critical of Muslims). Thus, our results cannot be explained by the estimates being purposefully or inadvertently produced to make Muslims look bad, quite the opposite. This being said, future research should attempt to find ways to estimate population proportions more effectively, especially when the governments seem uninterested or actively hostile to doing so (e.g. in France where such statistics are illegal for the government to collect).

One promising route for Belgium is to use data from first names. The Belgian statistics agency (StatBel) publishes counts of first names for newborns and the total population for every commune (https://statbel.fgov.be/en/open-data?category=214). With these, one could assign every name to a probable origin using databases of known names (such as https://www.behindthename.com/), perhaps augmented by machine learning methods. Better yet would be to convince or pay for StatBel to compute ancestries for each commune. This can be done accurately using a recursive method that relies on having an accurate population register. With this method, one begins with every person alive, and asks if one has data about their parents or not. If yes, then one asks whether one has data about the parents' parents or not. At some point, no further data are available about parents. Then one asks whether the person was born in Belgium, and if not, where they were born. Then one assigns the ancestry of the origin to the person this way. Finally, one averages the ancestry of all ancestors to estimate the ancestry of living persons. The result will be a quite accurate estimate of the population level ancestry, insofar as country of origin is concerned. This method has been used in Denmark recently, with results forthcoming.

Thus to answer our question in the title of the paper. The big decline of Brussels is mainly due to large-scale low-intelligence immigration to the capital region. The immigrants have generally not been selected for their ability to contribute to Belgian society, and originated from second- and third-world countries. Furthermore, they are mainly Muslims, and across the world, adherents of this faith generally perform relatively poorly compared to other groups, both in Muslim majority and non-Muslim majority countries (Kuran, 1997).

Supplementary material and acknowledgments

Supplementary materials including code, high quality figures and data can be found at https://osf.io/ja6ce.

References

Adsera, A. & Chiswick, B.R. (2006). Are there gender and country of origin differences in immigrant labor market outcomes across European destinations? *Journal of Population Economics* 20: 495. https://doi.org/10.1007/s00148-006-0082-y

Ahlberg, J. (1996). *Invandrares och invandrares barns brottslighet: En statistisk analys [Immigrants' and immigrants' children's crime: A statistical analysis]*. Brottsförebyggande rådet (BRÅ).

Anselin, L. & Bera, A.K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In: A. Ullah (ed.), *Handbook of Applied Economic Statistics*.

Ashworth, J., Geys, B. & Heyndels, B. (2003). Income tax base evolution in Brussels 1980-1999: The budgetary value of the rich. In: E. Witte, A. Alen, H. Dumont, P. Vandernoot & R. De Groof (eds.), *De Brusselse negentien gemeenten en het Brussels model*.

Baller, R.D., Anselin, L., Messner, S.F., Deane, G. & Hawkins, D.F. (2001). Structural covariates of U.S. county homicide rates: Incorporating spatial effects. *Criminology* 39: 561-588. https://doi.org/10.1111/j.1745-9125.2001.tb00933.x

Beenstock, M., Chiswick, B.R. & Repetto, G.L. (2001). The effect of linguistic distance and country of origin on immigrant language skills: Application to Israel. *International Migration* 39(3): 33-60. https://doi.org/10.1111/1468-2435.00155

Belsky, D.W., Moffitt, T.E., Corcoran, D.L., Domingue, B., Harrington, H., Hogan, S., Houts, R., Ramrakha, S., Sugden, K., Williams, B.S., Poulton, R. & Caspi, A. (2016). The genetics of success: How single-nucleotide polymorphisms associated with educational attainment relate to life-course development. *Psychological Science* 27: 957-972. https://doi.org/10.1177/0956797616643070

Boenigk, S., Mews, M. & de Kort, W. (2015). Missing minorities: Explaining low Migrant blood donation participation and developing recruitment tactics. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations* 26(4): 1240-1260. https://doi.org/10.1007/s11266-014-9477-7

Borjas, G.J. (2016). *We Wanted Workers: Unraveling the Immigration Narrative*, 1st edition. W.W. Norton & Co.

Boyd, M. & Thomas, D. (2002). Skilled immigrant labour: Country of origin and the occupational locations of male engineers. *Canadian Studies in Population* 29: 71-99. https://doi.org/10.25336/P6X60F

Carl, N. (2016). Net opposition to immigrants of different nationalities correlates strongly with their arrest rates in the UK. *Open Quantitative Sociology & Political Science*. https://openpsych.net/paper/48

Carl, N. (2017). Ethnicity and electoral fraud in Britain. *Electoral Studies* 50: 128-136. https://doi.org/10.1016/j.electstud.2017.09.011

Corijn, E. & van de Ven, J. (eds.) (2013). *The Brussels Reader (Urban Notebooks): A Small World City to Become the Capital of Europe*. ASP.

Deblonde, N., Gheysen, T., Gysen, E., Lebeer, J., Maes, B., Schittekatte, M. & Verlinde, L. (2020). *Classificerend Diagnostisch Protocol Verstandelijke Beperking*. https://portaal.kwaliteitscentrumdiagnostiek.be/wp-content/uploads/2020/05/CDP_Verstandelijke_Beperking_FINAAL_v25.pdf

Eff, E.A. (2004). Does Mr. Galton still have a problem? Autocorrelation in the Standard Cross-Cultural Sample. *World Cultures*. http://capone.mtsu.edu/eaeff/downloads/SAS2001.pdf

Frisell, T., Pawitan, Y. & Långström, N. (2012). Is the association between general cognitive ability and violent crime caused by family-level confounders? *PLoS ONE* 7(7): e41783. https://doi.org/10.1371/journal.pone.0041783

Fuerst, J. & Kirkegaard, E.O.W. (2016). Admixture in the Americas: Regional and national differences. *Mankind Quarterly* 56: 255-373. https://doi.org/10.46469/mq.2016.56.3.2

Gelade, G.A. (2008). The geography of IQ. *Intelligence* 36: 495-501. https://doi.org/10.1016/j.intell.2008.01.004

Harrell, F.E. (2015). *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis*, 2nd ed. Springer.

Harrell, F.E. (2019). *rms: Regression Modeling Strategies* (5.1-3.1) [Computer software]. https://CRAN.R-project.org/package=rms

Hassall, C. & Sherratt, T.N. (2011). Statistical inference and spatial patterns in correlates of IQ. *Intelligence* 39: 303-310. https://doi.org/10.1016/j.intell.2011.05.001

Hegelund, E.R., Flensborg-Madsen, T., Dammeyer, J. & Mortensen, E.L. (2018). Low IQ as a predictor of unsuccessful educational and occupational achievement: A register-based study of 1,098,742 men in Denmark 1968-2016. *Intelligence* 71: 46-53. https://doi.org/10.1016/j.intell.2018.10.002

Hegelund, E.R., Flensborg-Madsen, T., Dammeyer, J., Mortensen, L.H. & Mortensen, E.L. (2019). The influence of familial factors on the association between IQ and educational and occupational achievement: A sibling approach. *Personality and Individual Differences* 149: 100-107. https://doi.org/10.1016/j.paid.2019.05.045

Herrnstein, R.J. & Murray, C.A. (1994). *The Bell Curve: Intelligence and Class Structure in American Life*. Simon & Schuster.

Hertogen, J. (2017). *PEW-onderzoek: % moslims in 2050 (BuG 374)*. http://www.npdata.be/BuG/374-Moslims/Moslims.htm

Hill, W.D., Davies, N.M., Ritchie, S.J., Skene, N.G., Bryois, J., Bell, S., Angelantonio, E.D., Roberts, D., … & Deary, I.J. (2019). Genome-wide analysis identifies molecular systems and 149 genetic loci associated with income. *Nature Communications* 10(1): 1-16. https://doi.org/10.1038/s41467-019-13585-5

Hu, W.-Y. (2000). Immigrant earnings assimilation: Estimates from longitudinal data. *American Economic Review* 90(2): 368-372. https://doi.org/10.1257/aer.90.2.368

Husted, L., Skyt Nielsen, H., Rosholm, M. & Smith, N. (2001). Employment and wage assimilation of male first-generation immigrants in Denmark. *International Journal of Manpower* 22(1/2): 39-71. https://doi.org/10.1108/01437720110386377

Jacobs, D., Rea, A. & Hanquinet, L. (2007). *Performances des élèves issus de l'immigration en Belgique selon l'étude PISA: Une comparaison entre la Communauté Française et la Communauté Flamande*.

Jensen, A.R. (1969). How much can we boost IQ and scholastic achievement? *Harvard Educational Review* 39: 1-123.

Jerrett, M., Burnett, R., Willis, A., Krewski, D., Goldberg, M., DeLuca, P. & Finkelstein, N. (2003). Spatial analysis of the air pollution–mortality relationship in the context of ecologic confounders. *Journal of Toxicology and Environmental Health, Part A* 66: 1735-1778. https://doi.org/10.1080/15287390306438

Jones, G. & Schneider, W.J. (2010). IQ in the production function: Evidence from immigrant earnings. *Economic Inquiry* 48: 743-755. https://doi.org/10.1111/j.1465-7295.2008.00206.x

Junger, M. & Polder, W. (1992). Some explanations of crime among four ethnic groups in the Netherlands. *Journal of Quantitative Criminology* 8: 51-78. https://doi.org/10.1007/BF01062759

Kaufman, E. (2019). *Whiteshift: Populism, Immigration and the Future of White Majorities.* Penguin Books.

Kirkegaard, E.O.W. (2014a). The international general socioeconomic factor: Factor analyzing international rankings. *Open Differential Psychology*. https://doi.org/10.26775/ODP.2014.09.08

Kirkegaard, E.O.W. (2014b). Crime, income, educational attainment and employment among immigrant groups in Norway and Finland. *Open Differential Psychology*. http://openpsych.net/ODP/2014/10/crime-income-educational-attainment-and-employment-among-immigrant-groups-in-norway-and-finland/

Kirkegaard, E.O.W. (2015a). Crime among Dutch immigrant groups is predictable from country-level variables. *Open Differential Psychology*.

Kirkegaard, E.O.W. (2015b). Some methods for measuring and correcting for spatial autocorrelation. *The Winnower*. https://thewinnower.com/papers/2847-some-methods-for-measuring-and-correcting-for-spatial-autocorrelation

Kirkegaard, E.O.W. (2016a). Inequality across US counties: An S factor analysis. *Open Quantitative Sociology & Political Science*. http://openpsych.net/OQSPS/2016/05/inequality-across-us-counties-an-s-factor-analysis/

Kirkegaard, E.O.W. (2016b). Some new methods for exploratory factor analysis of socioeconomic data. *Open Quantitative Sociology & Political Science* 1(1). https://openpsych.net/paper/47

Kirkegaard, E.O.W. & Becker, D. (2017). Immigrant crime in Germany 2012-2015. *Open Quantitative Sociology & Political Science* 1(1). https://doi.org/10.26775/OQSPS.2017.02.11

Kirkegaard, E.O.W. & de Kuijper, M. (2020). Public Preferences and Reality: Crime Rates among 70 Immigrant Groups in the Netherlands. *Mankind Quarterly* 60: 327-351. https://doi.org/10.46469/mq.2020.60.3.3

Kirkegaard, E.O.W. & Fuerst, J. (2014). Educational attainment, income, use of social benefits, crime rate and the general socioeconomic factor among 70 immigrant groups in Denmark. *Open Differential Psychology*. https://openpsych.net/paper/21

Kirkegaard, E.O.W. & Fuerst, J. (2017). Admixture in Argentina. *Mankind Quarterly* 57: 542-580. http://mankindquarterly.org/archive/issue/57-4/4

Klein, O., Pohl, S. & Ndagijimana, C. (2007). The influence of intergroup comparisons on Africans' intelligence test performance in a job selection context. *Journal of Psychology* 141: 453-468. https://doi.org/10.3200/JRLP.141.5.453-468

Kühn, I. (2007). Incorporating spatial autocorrelation may invert observed patterns. *Diversity and Distributions* 13: 66-69. https://doi.org/10.1111/j.1472-4642.2006.00293.x

Kuran, T. (1997). Islam and underdevelopment: An old puzzle revisited. *Journal of Institutional and Theoretical Economics* 153: 41-71.

Lafontaine, D., Crépin, F. & Quittre, V. (2017). *Les compétences des jeunes de 15 ans en sciences, en mathématiques et en lecture. Résultats de l'enquête PISA 2015 en Fédération Wallonie-Bruxelles*.

Lee, J.J., Wedow, R., Okbay, A., Kong, E., Maghzian, O., Zacher, M., Nguyen-Viet, T.A., Bowers, P., … & Cesarini, D. (2018). Gene discovery and polygenic prediction from a 1.1-million-person GWAS of educational attainment. *Nature Genetics* 50: 1112-1121. https://doi.org/10.1038/s41588-018-0147-3

Li, T.J.-J., Sen, S. & Hecht, B. (2014). Leveraging advances in natural language processing to better understand Tobler's first law of geography. *Proceedings of the 22nd ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems - SIGSPATIAL '14*, 513–516. https://doi.org/10.1145/2666310.2666493

Loftin, C. (1986). Assaultive violence as a contagious social process. *Bulletin of the New York Academy of Medicine* 62: 550-555.

Lynn, R. (2020). Racial and ethnic differences in altruism assessed by blood donation. *Mankind Quarterly* 60: 539-550. https://doi.org/10.46469/mq.2020.60.4.6

Mennis, J. & Harris, P. (2013). Spatial contagion of male juvenile drug offending across socioeconomically homogeneous neighborhoods. In: M. Leitner (ed.), *Crime Modeling and Mapping Using Geospatial Technologies*, pp. 227-248. Springer Netherlands. https://doi.org/10.1007/978-94-007-4997-9_10

Metzen, D. (2012). *The causes of group differences in intelligence studied using the method of correlated vectors and psychometric meta-analysis*. Masters Thesis, Univ. of Amsterdam.

Murray, C. (2002). IQ and income inequality in a sample of sibling pairs from advantaged family backgrounds. *American Economic Review* 92: 339-343.

Murray, D. (2017). *The Strange Death of Europe: Immigration, Identity, Islam*, 1st edition. Bloomsbury Continuum.

Nordin, M. & Rooth, D.-O. (2007). *Income gap between natives and second generation immigrants in Sweden: Is skill the explanation?* (SSRN Scholarly Paper ID 984423). Social Science Research Network. https://papers.ssrn.com/abstract=984423

Osili, U.O. & Paulson, A. (2008). What can we learn about financial access from U.S. immigrants? The role of country of origin institutions and immigrant beliefs. *World Bank Economic Review* 22: 431-455. https://doi.org/10.1093/wber/lhn019

Osorio, J. (2015). The contagion of drug violence: Spatiotemporal dynamics of the Mexican war on drugs. *Journal of Conflict Resolution* 59: 1403-1432. https://doi.org/10.1177/0022002715587048

Pesta, B.J., Fuerst, J.G.R., Lasker, J. & Kirkegaard, E.O.W. (in review). County-level USA: No robust relationship between geoclimatic variables and intelligence.

Pesta, B.J., McDaniel, M.A. & Bertsch, S. (2010). Toward an index of well-being for the fifty U.S. states. *Intelligence* 38: 160-168. https://doi.org/10.1016/j.intell.2009.09.006

Pew Research Center (2011). *Table: Muslim Population by Country*. Pew Research Center. http://www.pewforum.org/2011/01/27/table-muslim-population-by-country/

Revelle, W. (2020). *psych: Procedures for Psychological, Psychometric, and Personality Research* (1.9.12.31) [Computer software]. https://CRAN.R-project.org/package=psych

Rindermann, H. & Thompson, J. (2016). The cognitive competences of immigrant and native students across the world: An analysis of gaps, possible causes and impact. *Journal of Biosocial Science* 48: 66-93. https://doi.org/10.1017/S0021932014000480

Rohrer, J.M. (2018). Thinking clearly about correlations and causation: Graphical causal models for observational data. *Advances in Methods and Practices in Psychological Science* 1(1): 27-42. https://doi.org/10.1177/2515245917745629

Roth, B.M. (2010). *The Perils of Diversity: Immigration and Human Nature*, 1st edition. Washington Summit.

Rushton, J.P. (1998). The "Jensen effect" and the "Spearman-Jensen hypothesis" of Black-White IQ differences. *Intelligence* 26: 217-225. https://doi.org/10.1016/S0160-2896(99)80004-X

Rushton, J.P. & Jensen, A.R. (2010). The rise and fall of the Flynn effect as a reason to expect a narrowing of the Black–White IQ gap. *Intelligence* 38: 213-219. https://doi.org/10.1016/j.intell.2009.12.002

Sanandaji, T. (2017). *Massutmaning: Ekonomisk politik mot utanförskap och antisocialt beteende*. Kuhzad Media.

Sarrazin, T. (2012). *Deutschland schafft sich ab: Wie wir unser Land aufs Spiel setzen*, 1. Aufl. Dt. Verl.-Anst.

Schulz, J.F., Bahrami-Rad, D., Beauchamp, J.P. & Henrich, J. (2019). The Church, intensive kinship, and global psychological variation. *Science* 366: 707. https://doi.org/10.1126/science.aau5141

Skardhamar, T., Aaltonen, M. & Lehti, M. (2014). Immigrant crime in Norway and Finland. *Journal of Scandinavian Studies in Criminology and Crime Prevention* 15: 107-127. https://doi.org/10.1080/14043858.2014.926062

Tobler, W. (2004). On the First Law of Geography: A reply. *Annals of the Association of American Geographers* 94: 304-310. https://doi.org/10.1111/j.1467-8306.2004.09402009.x

Van Hamme, G. (2015). *Inégalités et flux entre Bruxelles et sa périphérie*. https://docplayer.fr/62414320-Inegalites-et-flux-entre-bruxelles-et-sa-peripherie.html

Vinogradov, E. & Kolvereid, L. (2010). Home country national intelligence and self-employment rates among immigrants in Norway. *Intelligence* 38: 151-159. https://doi.org/10.1016/j.intell.2009.09.004

Woodley, M.A. & Bell, E. (2013). Consanguinity as a major predictor of levels of democracy. A study of 70 nations. *Journal of Cross-Cultural Psychology* 44: 263-280. https://doi.org/10.1177/0022022112443855

Yeargin-Allsopp, M., Drews, C.D., Decouflé, P. & Murphy, C.C. (1995). Mild mental retardation in black and white children in metropolitan Atlanta: A case-control study. *American Journal of Public Health* 85: 324-328. https://doi.org/10.2105/ajph.85.3.324

Appendix

Spatial units merged

One can see the old NIS on Esperanto Wiki (click the change language function)

- Nevele (44049) was merged into Deinze (44083)
- Knesselare (44029) was merged into Aalter (44084)
- Effective 1 January 2019, Waarschoot (44072), Lovendegem (44036) and Zomergem (44085) were merged into the new municipality of Lievegem (44085).

Klein et al. (2007) calculation

David Becker suggested the following calculation (email Jan 30, 2018). The context is that Richard Lynn calculated an IQ of 70 for this in his *Race Differences in Intelligence* book. He writes as a comment:

I only have German norms of the CFT-20 and CFT-3. Don't know which CFT they have used and if I could apply norms from the German version on raw scores from the other. But let's try it:

If assumed mean age is 32.30y and mean score is 19.94, CFT-20 would give an IQ of 81 (10th German percentile). CFT-3 doesn't have norms for >19y olds.

Year of standardization is 1977, the year of measurement is ~2006 (or earlier). Pietschnig & Voracek (2015) calculated a FLynn-Effect/y at the CFT-20 in Germany of 0.6 between 1977 and 1995. Therefore, the IQ inflation would be between 17.4 (29y from 1977 to 2006) and 10.8 (18y from 1977 to 1995). Second value is more likely because no FE-data is available in this case after 1995.

In addition, 1.20 IQ must be deducted because norms are from Germany and Germany is 1.20 IQ below the UK (this part of the method is questionable). Overall, 12 IQ (10.8+1.20) must be deducted from the score of 81, which would give the sample a final IQ of 69 or 70.2 without country-correction. This is very close to Richard's 70.

National foreign aid rates, % of GNI

These were computed based on OECD data (n = 44) at https://data.oecd.org/oda/net-oda.htm. Country-years with missing data were filled with 0%, i.e. no aid that year. The table below shows the averages across years. In the last 10 years, a few Muslim countries (United Arab Emirates and Turkey) have started donating.

Rank	Country ISO-3	1960-2017	Country ISO-3	2008-2017
1	NOR	0.78	SWE	1.05
2	SWE	0.75	NOR	1.01
3	NLD	0.74	LUX	1.00
4	DNK	0.70	DNK	0.83
5	FRA	0.55	NLD	0.72
6	BEL	0.49	ARE	0.69
7	GBR	0.42	GBR	0.61
8	AUS	0.40	FIN	0.51
9	DEU	0.38	BEL	0.50
10	LUX	0.38	CHE	0.46
11	CAN	0.35	DEU	0.46
12	DAC	0.33	IRL	0.44
13	FIN	0.32	LIE	0.44
14	CHE	0.28	FRA	0.42
15	NZL	0.26	TUR	0.39
16	USA	0.25	AUT	0.32
17	JPN	0.24	AUS	0.31
18	IRL	0.23	DAC	0.30
19	AUT	0.22	CAN	0.29
20	ITA	0.20	ESP	0.27
21	ESP	0.14	NZL	0.27
22	PRT	0.14	ISL	0.26
23	ARE	0.12	PRT	0.23
24	TUR	0.09	ITA	0.20
25	LIE	0.08	JPN	0.20
26	ISL	0.07	USA	0.19
27	GRC	0.06	MLT	0.18
28	KOR	0.04	GRC	0.15
29	CZE	0.03	SVN	0.14
30	MLT	0.03	EST	0.13
31	SVN	0.03	KOR	0.13
32	EST	0.03	CZE	0.13
33	CYP	0.03	LTU	0.12
34	HUN	0.03	CYP	0.11
35	LTU	0.03	HUN	0.11
36	SVK	0.02	SVK	0.10
37	ISR	0.02	POL	0.10
38	POL	0.02	ROU	0.09
39	TWN	0.02	ISR	0.08
40	LVA	0.02	LVA	0.08
41	ROU	0.02	BGR	0.08
42	BGR	0.01	TWN	0.08
43	RUS	0.01	RUS	0.04
44	THA	0.01	THA	0.02