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Immigrant crime in Germany 2012-2015

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Abstract
Number of suspects per capita were estimated for immigrants in Germany grouped by citizenship (n=83). These were correlated with national IQs (r=-.53) and Islam prevalence in the home countries (r=.49). Regression analyses revealed that the mean age and sex distribution of the groups in Germany were confounds.

The German data lacked age and sex information for the crime data and so it was not possible to adjust for age and sex using subgroup analyses. For this reason, an alternative adjustment method was developed. This method was tested on the detailed Danish data which does have the necessary information to carry out subgroup analyses. The new method was found to give highly congruent results with the subgrouping method.

The German crime data were then adjusted for age and sex using the developed method and the resulting values were analyzed with respect to the predictors. They were moderately to strongly correlated with national IQs (.46) and Islam prevalence in the home country (.35). Combining national IQ, Islam% and distance to Germany resulted in a model with a cross-validated r^2 of 20%, equivalent to a correlation of .45. If two strong outliers were removed, this rose to 25%, equivalent to a correlation of .50.

Key words: crime, immigrants, country of origin, Germany, Muslim, Islam, cognitive ability, intelligence, IQ

1. Introduction

A number of previous studies have examined whether immigrant characteristics (scores on cognitive tests, etc.) and socioeconomic outcomes (educational attainment, income, crime rates, etc.) are predictable from country of origin characteristics (André, Dronkers, & Need, 2014; Dronkers & Kornder, 2015; Dronkers, Levels, & Heus, 2014; Fuerst, 2012; Fuerst & Kirkegaard, 2014; Jones & Schneider, 2010; Kirkegaard, 2014a, 2014b, 2015b, 2015a; Kirkegaard & Fuerst, 2014). These studies have found that country of origin characteristics strongly (r's .4 to .8; no meta-analysis exists) predict immigrant characteristics/outcomes in the receiving countries.

In 2010 Thilo Sarrazin published the book *Deutschland schafft sich ab* (*Germany abolishes itself*) claiming that Muslim immigrant groups were overrepresented in the crime statistics in Germany: “(...) 70 to 80 % of all

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problems with immigrants in the areas of education, labor market, welfare and crime can be traced back to this group [Muslims].” (Sarrazin, 2012, p. 215, our translation). The book caused a major debate in the media. As justification for his claim about the high crime rates for Muslims, Sarrazin cites, among other things, a number that 20% of crime in Berlin is committed by a group of about 1000 Turkish and Arab youths (p. 297). Such data, however, is insufficient to establish his strong claim. Sarrazin furthermore complains that the official statistics lump all immigrants together instead of splitting them by country of origin. This makes it very difficult to find patterns in the data and obscures the high or low performance of some groups which are grouped together.

Since Sarrazin’s book was published detailed data for immigrant crime in Germany have been published, and as such, the purpose of this study was to extend the previous studies of immigrant performance to a new country, Germany, and to bring some light on Sarrazin's claim regarding Muslim immigrants.

2. Data

Data were compiled from multiple official statistical datasets.

2.1. Crime data

The German Federal Police Office (Bundeskriminalamt – BKA) publishes yearly data on the number of suspects per citizenship, *Straftaten und Staatsangehörigkeit nichtdeutscher Tatverdächtiger* (Offenses and nationality of non-German suspects). This data are broken down into a very large number of crime categories (about 1000) that varies slightly by year (as laws change). The data are (currently) available for the years 2012-2015. There are reports available from before 2012 but they do not seem to have detailed spreadsheets accompanying them, making them difficult to use for detailed study. The publications from before the publication of Sarrazin (2012) do have some citizenship-based data but only for a more limited number of countries (see e.g. Table T71 and T75 in Bundeskriminalamt, 2010), and thus could not easily have been used by Sarrazin.

The data from 2012 to 2015 were merged into one dataset. There were data for 208 citizenships (including wildcards).

There were no data for Germans, so these were obtained from *Polizeiliche Kriminalstatistik 2014* (Table T8 – T12).

2.2. Census data

The crime data are given in raw counts, not rates (per capita numbers). To calculate rates, one needs population counts for the same citizenship x year combinations. Citizenship population data were downloaded from the German Federal Office of Statistics (Statistisches Bundesamt) for the same years (2012-2015) in the dataset *Bevölkerung und Erwerbstätigkeit - Ausländische Bevölkerung, Ergebnisse des Ausländerzentralregisters* (Population and employment - Foreign population, results of the foreigners' register; Table 4). These datasets were merged as before. There were data for 85 citizenships (including wildcards). The data only included foreign populations and thus not Germans. Data for Germans were filled in from *Bevölkerung und Erwerbstätigkeit - Vorläufige Ergebnisse der Bevölkerungsfortschreibung auf Grundlage des Zensus* (Population and employment - Provisional results of the population update on the basis of the census; Table 4.1).

Based on these data, we calculated mean age, male% and population growth (2012-2015) of each group to use as auxiliary variables.

2.3. Former countries

A few former countries – Soviet Union, Czechoslovakia, Yugoslavia – were represented in both the population data and crime data. However, the numbers were not comparable because the crime data filed persons under the new countries in most cases while the census data did not. Using the data thus results in extremely low crime rates (1/1000 of the other countries). For this reason, these cases were excluded leaving 83 cases (country groups) with matching population and crime data.

2.4. Crime rates

The crime rate for a given group was calculated as the mean number of suspects in the years 2012-2015 divided by the mean number of persons 2012-2015.

The calculated crime rates are problematic for multiple reasons. First, they rely on citizenship data, rather than country of origin data. Persons can change citizenship and so move between categories. The rates at which persons from different countries change citizenships to German are not probably the same, and this will introduce noise in the data depending on whether these rates are correlated with other variables.

Second, the population data only includes persons officially living in Germany while the crime data includes persons not living in Germany. Thus, there is a mismatch in populations to the extent that some groups have more tourists or illegal immigrants than others.

Relative crime rates were calculated by dividing the crime rates by the crime rate for Germans. Since these are linear transformations, they do not alter correlations/standardized betas which are scale independent.

2.5. Country of origin data

Country of origin data was copied from the international megadataset (https://osf.io/zdcbq/). We included:

- Islam prevalence in % (Pew Research Center, 2011).
- Cognitive ability on the IQ scale (Lynn & Vanhanen, 2012). This was slightly modified in a few cases, see the datafile for details.
- Latitude/longitude of capitals. This was used to calculate the distance to Germany.[3] Data were scraped from Wikipedia and based on the capitals of each country.

There were a few missing datapoints. These were filled in on an *ad hoc* basis. For instance, the Palestinian territories had no official capital and thus no latitude/longitude in our dataset. This was filled in based on Ramallah, the *de facto* capital of the Fatah faction. Similar choices were made for the other cases, see the code file for details.

3. Analyses of unadjusted crime rates in Germany

All analyses were done in R.

3.1. Weights

It is unclear whether weights should be used or not. There are reasons for and against. In favor of using weights one can observe that numbers for smaller groups have more sampling error. It is standard meta-analytic practice

3 There are several ways to calculate great circle distances, but differences are very small. We used the Haversine formula because this is the default of *distm* function from the **geosphere** package (Hijmans, Williams, & Vennes, 2016).

to weigh studies after their estimated sampling error (Hunter & Schmidt, 2004; Rothstein, Borenstein, Hedges, & Higgins, 2013). One can also argue that smaller groups are more likely to have strong selection effects which introduces noise into the relationships, and for that reason should be given less weight. Against weighing, it can be said that each group represents one datapoint in the analysis at this level of analysis, no matter its size (Pesta, 2016). See also discussion in Fuerst and Kirkegaard (2016).

In this dataset, the largest group was Germans with a population of about 73.7 million. The smallest group was Liechtensteiners with a population of only 245. If one used n-weighting, the German group would be weighted about 300k times more than the Liechtenstein group, thus making it effectively irrelevant. As a compromise, we transformed the population size to reduce the disparity. Using the square root, the weights ratio was reduced to 550. These weights were used in the analyses.

3.2. Correlation analysis

The correlations between the variables are shown in Table 1.

	Relative crime rate, Germany	**Relative crime rate, Denmark**	**IQ**	**Muslim %**	**Mean age**	**Male %**	**Distance to Germany**
Relative crime rate, Germany		0.66	-0.53	0.49	-0.53	0.39	-0.11
Relative crime rate, Denmark	0.69		-0.49	0.59	-0.45	0.55	-0.16
IQ	-0.67	-0.68		-0.26	0.58	-0.29	-0.29
Muslim%	0.49	0.84	-0.59		-0.45	0.49	-0.07
Mean age	-0.68	-0.54	0.66	-0.47		-0.22	-0.25
Male%	0.33	0.44	-0.29	0.39	-0.24		-0.23
Distance to Germany	0.17	0.15	-0.41	0.16	-0.47	-0.16	

Table 1: Intercorrelations between variables. Weighted correlations below the diagonal (square root of population).

Relative crime rates for the groups in Denmark were included as a comparison and will be discussed further in Section 5.

It can be seen that cognitive ability was negatively related to crime rates while Muslim% was positively.

Using weights did not make much difference for the German results, and so was not done for further analyses.

Figure 1 shows a scatterplot between cognitive ability and the relative crime rate.

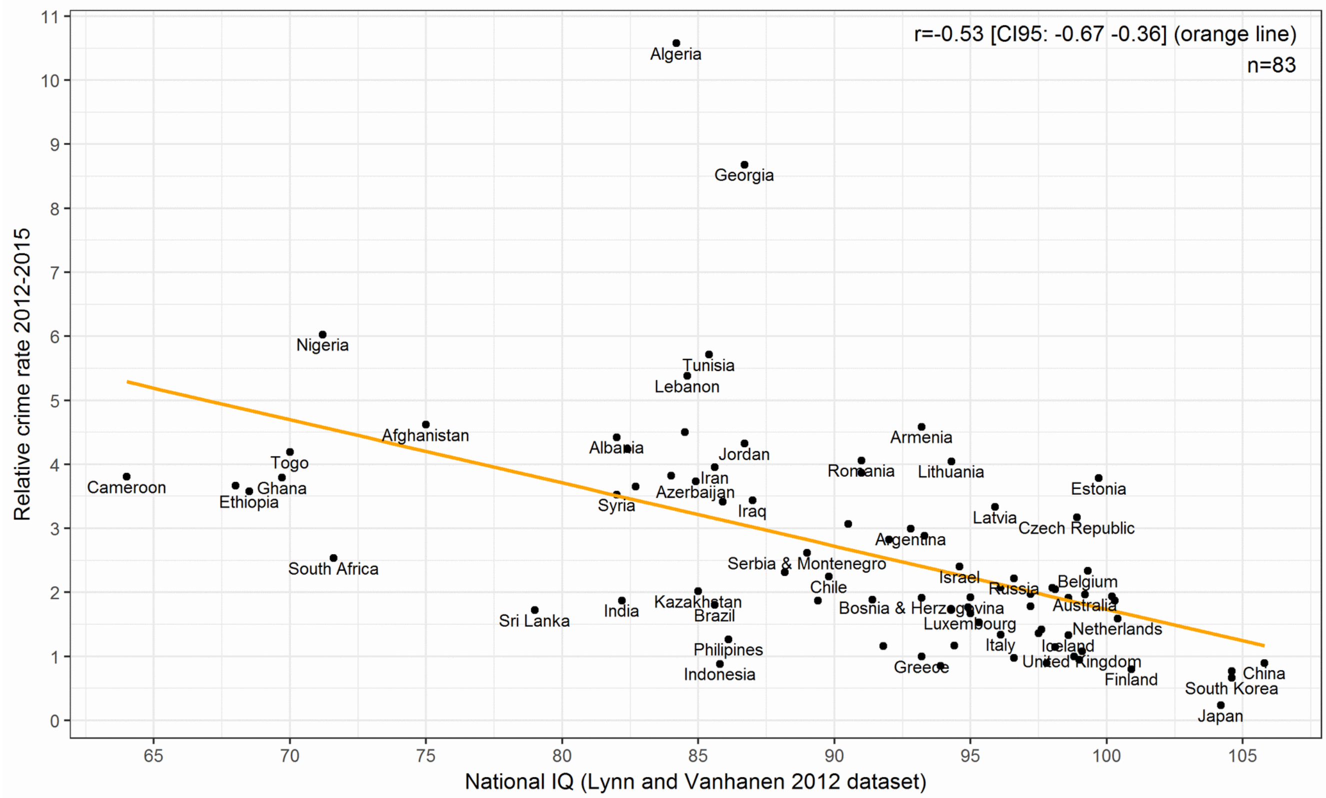

Figure 1: National IQ of origin country and relative crime rate in Germany.

As has been found before, the groups with the highest crime rates are usually not the Sub-Saharan African countries though these have the lowest estimated levels of cognitive ability (see Rindermann (2013)). This may be because of positive selection from these countries or the combined effect of lowish (relative to German norms) cognitive ability and a high prevalence of Muslims for the MENAP countries.[4]

Figure 2 shows a scatterplot between Islam prevalence in the home country and the relative crime rate.

4 MENAP = Middle East, North Africa and Pakistan.

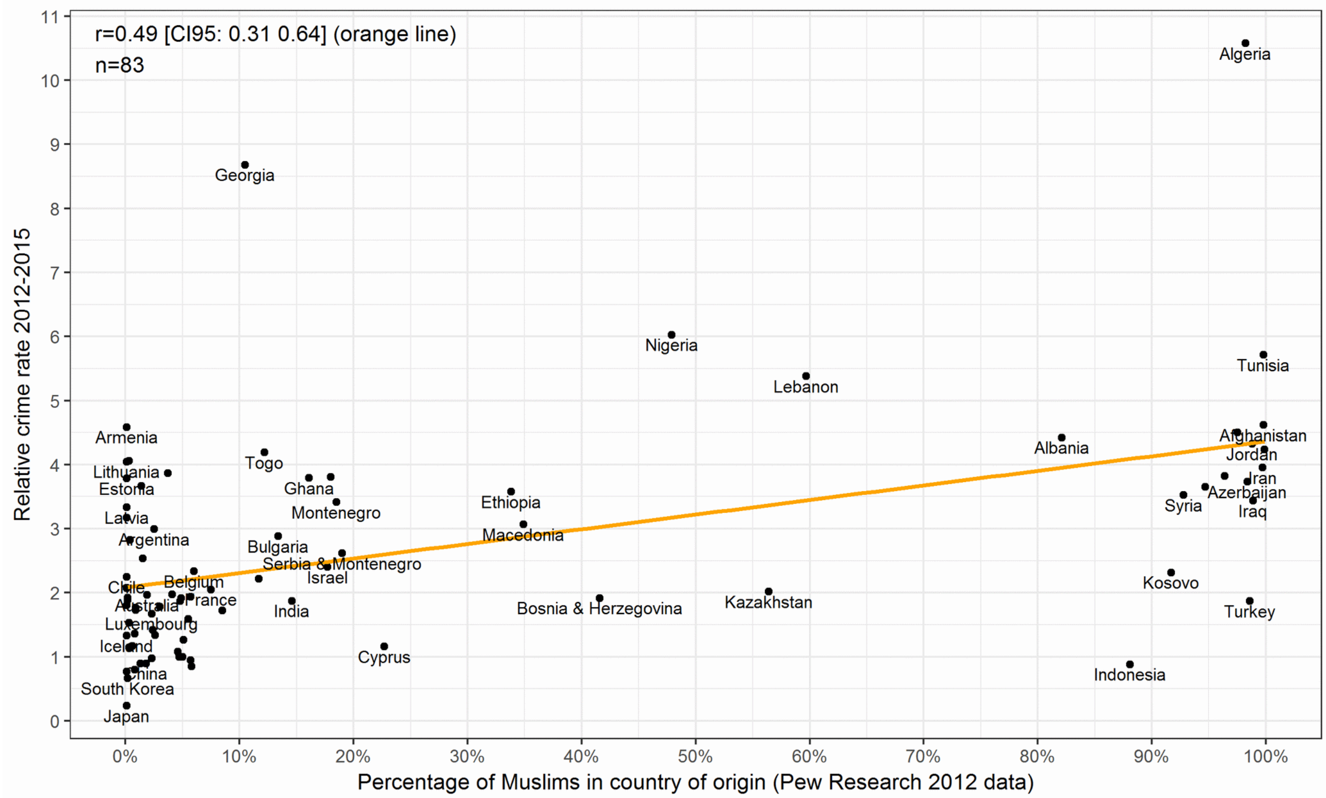

Figure 2: Islam prevalence in origin country and relative crime rate in Germany.

The crime rate for Turkey (1.87) is not particularly high compared to the cluster of Northwestern European countries and their offshoots in the bottom left corner (mean 1.60).[5] This is in contrast to the earlier cited claim that 20% of crime in Berlin is committed by a fairly small population of Turkish and Arab youths. Indonesia, a country with about 88% Muslims, is in fact below Germany itself (0.88) and roughly half of the Northwestern European countries. On the other hand, Algeria has an extremely high rate of 10.60.

Both scatterplots indicate that there is clearly something more going on than just cognitive ability or Islam. It can be seen in Table 1 that several other variables are candidates for explaining some of the variance. First, younger people commit more crimes, with the peak being around age 15-25.[6] Based on this, one might hypothesize that age differences between the populations in Germany explain some of the variation. This is supported by the correlation of -.53 with crime rates.

Second, men commit most crime. Exactly how much depends on the type of crime, but a typical overall figure is around 85% (yielding a relative rate (M/F) of about 5.7). As such, one would expect populations that with more males to have higher crime rates. Again the correlation supports this idea, r=.39 between male% and crime rates.

Third, one might propose that traveling is difficult and this is a rough function of the distance.[7] Thus, the further immigrants have to travel to get to Germany, the more select they should be. There was little support for this as the direction of effect depended on the use of weights and was of small size.

5 These are Denmark, Sweden, Norway, Finland, Iceland, United Kingdom, Netherlands, Luxembourg, Belgium, Switzerland, Liechtenstein, Austria, and France as well as the offshoots Australia, New Zealand, United States, and Canada.

6 The exact peak age is difficult to determine and probably varies with the nature of the crime (Barnes, Jorgensen, Pacheco, & TenEyck, 2015; Ulmer & Steffensmeier, 2015).

7 Aside from the distance, various natural barriers may also have some effect such as mountain ranges and oceans (Hall, 1904).

3.3. Regression analysis

Cognitive ability, Muslim%, mean age and sex distribution were found to be correlated with each other to various degrees and with the raw crime rate in Germany. Thus, one might wonder how they are best combined and what this reveals for the relative validity of each predictor. To examine this, we fit an OLS regression model with these predictors to the data. Results are shown in Table 2.

Predictor	**Beta**	**SE**	**CI lower**	**CI upper**
IQ	-0.31	0.11	-0.52	-0.09
Muslim%	0.15	0.11	-0.06	0.36
Male%	0.10	0.10	-0.10	0.30
Mean age	-0.32	0.11	-0.53	-0.10
Distance to Germany	-0.23	0.09	-0.42	-0.05

Table 2: OLS regression results. Outcome: unadjusted relative crime rate in Germany. n=83. r^2 = .47, r^2-cv = .39.[8] *CI = 95% analytic confidence interval.*

IQ and mean age kept their above chance levels of predictive validity, while Muslim% and male% did not. Not too much can be made of such results because the sample size is small (n=83), which means that OLS regression with multiple predictors gives unreliable results. This can be seen in the fact that the cross-validated r^2 was 17% smaller than the r^2.

4. Adjusting for age

Including mean age as a predictor is likely to lead to overestimates of its true causal effects. This is because the mean age of a population (including immigrant populations) is itself a consequence of other properties of the population as well as its immigration history. The effect size in a regression of mean age is thus not just the true causal effect of age, but also indirect statistical signal of other variables with which mean age is correlated.[9] If these other variables are absent from the regression (omitted variable bias), or are measured with error, spurious signal will be associated with the age variable in multivariate analysis (Westfall & Yarkoni, 2016).

Including mean age as a covariate is one way of adjusting for age, but there are others. Kirkegaard and Fuerst (2014) used age-based subgroup analyses to correct for the differential age distribution of immigrant groups in Denmark. Specifically, they looked only at the crime rates for persons in two age brackets: 15-19 and 20-29. Data for other age brackets were available, but because their analysis was done semi-manually using spreadsheets, using all the data would have been very time consuming.

The German data, however, lacks age and sex information for the crime data, so the subgroup method cannot be used. Instead, we developed an alternative adjustment method based on the relative criminality of the different age brackets. To test that the method worked as intended, it was tested on the detailed Danish data.

8 Cross-validated r^2 values were calculated by 200 runs of the 10-fold method (James, Witten, Hastie, & Tibshirani, 2013).

9 The mean age of a population is a function of among other things the fertility, age at first birth and lifespan of the population. All are these are known to be related to cognitive ability and educational attainment (particularly in women). Thus, treating mean age of a population as an exogenous variable is problematic (Arden et al., 2016; Meisenberg, 2009; Meisenberg & Kaul, 2010).

4.1. Method examples: hypothetical data

Before presenting the analyses of the full Danish data, we present simplified examples of the proposed method.[10] The method relies upon the assumption that the age-crime relationship is constant across human populations. That is, while one population may be more criminal than another, the relative risk of crime between age brackets is constant. E.g. that 15-19 year olds commit 5 times as many crimes as 70-79 year olds in all populations. If this assumption can be made, then one can adjust for age without having age information about crime rates, as long as one has this about the population. Table 3 shows basic crime data for the Danish population along with relative risk in relation to the youngest age group. The source of the data will be explained in Section 5.

Age band	Population%	Crime rate	Crime rate rr
15-19	7.62%	0.0386	1
20-29	14.46%	0.0527	1.365
30-39	17.24%	0.0419	1.085
40-49	18.53%	0.0378	0.979
50-59	17.67%	0.0248	0.642
60-69	15.18%	0.0146	0.378
70-79	9.31%	0.0071	0.184

Table 3: Crime data for the Danish population. 2000, 2002, 2004-2015. rr = relative risk in relation to the 15-19 age bracket.

The overall crime rate can be found simply by calculating the dot product of the population and crime rate columns and is .032. One can also compare specific age brackets. For instance, 15-19 years olds are about 5.44 times as criminal as 70-79 year olds according to these data (1/.184).

Consider now a hypothetical population that by age is just as criminal as the Danish population, but happens to have more young persons. Table 4 shows the numbers for this population.

Age band	Population%	Crime rate	Population relative proportion
15-19	20.00%	0.0386	2.625
20-29	25.00%	0.0527	1.729
30-39	20.00%	0.0419	1.160
40-49	15.00%	0.0378	0.809
50-59	10.00%	0.0248	0.566
60-69	7.00%	0.0146	0.461
70-79	3.00%	0.0071	0.322

Table 4: Hypothetical population with more young persons but the same age-related crime rate.

We see that this population has quite a few more young persons, and thus an overall higher crime rate of .039. In relative terms, this is 1.21 the Danish rate. To calculate the adjustment factor to use, one calculates what the crime rate would have been if this population had the same age-related crime rates as the Danish population, and

10 Unknown to the authors at development, a similar method was used in a Swedish-language analysis of immigrant crime in Sweden (Ahlberg, 1996).

divides this value by the Danish crime rate. In this example, this value is also 1.21. We then divide the observed crime rate or the relative risk by the same value and obtain a value of 1.00. In other words, we find that this population is exactly as criminal as the Danish population when age has been taken into account. This is of course what we had assumed in this scenario.

Table 5 shows another hypothetical population.

Age band	**Population%**	**Crime rate**	**Population relative proportion**
15-19	20.00%	0.0772	2.625
20-29	25.00%	0.1054	1.729
30-39	20.00%	0.0838	1.160
40-49	15.00%	0.0756	0.809
50-59	10.00%	0.0496	0.566
60-69	7.00%	0.0292	0.461
70-79	3.00%	0.0142	0.322

Table 5: Hypothetical population with more young persons and a higher age-related crime rate.

As can be seen, this population has as many young persons as that before, but the age-related crime rates are also higher. The total crime rate for this population is .077, or 2.41 times the Danish overall rate. How much of this increase is due to the different population structure and how much is due to the higher age-related crime rate? We calculate what the total crime rate would have been given the population structure and the *Danish* crime rates, and then divide this value by the Danish total crime rate. This gives us a value of 1.21. Thus, to get the adjusted total rate, we divide the observed rate by the adjustment factor which gives 2.00 (2.41/1.21). Thus, after taking age into account, this population is twice as criminal as the Danish population, a fact which can also quickly be verified by noticing that the crime rates are exactly twice as large for each age group compared to the Danish ones.

These examples may seem trivial, but the point is that this method can be used when one does not know the crime rate by age brackets for the subgroup. One only needs to know these for the total or host population, and be able to make the assumption that the crime-age relationship is approximately the same across groups.

4.2. Method example: Danes and non-Danes

As before, we demonstrate the method, but this time we analyze real data, namely that for Danes and non-Danes in Denmark. Table 6 shows data for all non-Danes in Denmark.

Age band	Population%	Crime rate	Population relative proportion	Crime rate rr
15-19	8.43%	0.0671	1.106	1
20-29	24.89%	0.0700	1.721	1.043
30-39	23.65%	0.0552	1.372	0.823
40-49	19.14%	0.0496	1.033	0.739
50-59	12.53%	0.0351	0.709	0.523
60-69	7.57%	0.0201	0.499	0.300
70-79	3.79%	0.0095	0.407	0.142

Table 6: Crime data for all non-Danes in Denmark: 2000, 2002, 2004-2015. rr = relative risk in relation to the 15-19 age bracket.

We see that this population has, relative to the Danish, more people in the age brackets spanning 15 to 49 years and one would thus expect the total crime rate to be higher for this population. The total crime rate for non-Danes is in fact .052 which is 1.62 that of the Danish rate. The expected increase due to the age structure is, as before, found by calculating the dot product of the Danish crime rate column and the non-Danish population% column, and then dividing this value by the Danish crime rate. This value is 1.19. The age-adjusted crime rate is thus 1.37 (1.62/1.19). Therefore, we find that about 40% of the increased crime rate was due to having a younger population.

How well does this value correspond to the value found using the subgroup method? To obtain the value adjusted for age using the subgroup method, one calculates the relative risk of crime for each age bracket (non-Dane/Dane), and then calculates the population-sized weighted mean. This value turns out to be 1.37 as well, though the results do differ if one inspects more decimals (1.3661 vs. 1.3724). Thus, the proposed age correction method was validated on the simple Danish vs. non-Danish comparison.

Note that the relative risk column is somewhat different from the Danish one shown in Table 3. The correlation between them is, however, quite high (r=.97). The group of all non-Danes is a very heterogeneous group whose country of origin composition also depends on the age bracket. This violation of origin homogeneity by age bracket seems a likely explanation for the somewhat different relative risk vectors. We will return to this matter in Section 5.4.

5. Adjusting for age and sex: validation on the full Danish data

After having shown on simple datasets that the proposed age adjustment method gives results highly congruent with the subgroup based method, we move on to analyze the full Danish dataset. This is a larger validation test of the proposed method. Unlike before, we also correct for the sex distribution. This is a simple extension of the above method where we calculate the crime rates for each sex x age combination and use this vector to adjust the observed crime rates.

5.1. Data

The **dkstat** package for R was used to access the API of the Danish statistics agency (Danmarks Statistik, http://dst.dk/).

Crime data from the *STRAFNA1* table and population data from the *FOLK2* table were used.[11] The crime data concern the number of persons found guilty of a crime. The crime data cover the years 2000-2015 (except 2001 and 2003), while the population data cover the period 1980-2016. We used only the overlapping years, yielding 14 years of data.

5.2. Methods

The former Yugoslavia has two entries in the Danish data that correspond to the country as it was before and after the secession of many of its members in 1991-1992.[12] The data for these two countries were merged and treated as one country. Most of the persons from this combined country were from the pre-split variant.

The crime data were given in age brackets, while the population data were given by single years. Thus, we aggregated the population data to cover the same age brackets.

For a brief period, the minimal age of criminal responsibility was lowered from 15 to 14. However, very few convicted persons were of this age and it was excluded to simplify the analyses.

Since we were not interested in historical trends, we summed the data across the years.[13] We calculated the conviction rate by dividing the number of convictions by the population size. This was done separately for each age bracket x country of origin combination.

Lastly, we calculated the adjusted conviction rates using the two methods described above.

5.3. Correlations

Table 7 shows the intercorrelations between the uncorrected and corrected crime variables as well as with the two main predictor variables.

	Crime rate	**Crime rate SG**	**Crime rate PS**	**Male%**	**Mean age**	**IQ**	**Muslim%**
Crime rate	1.00	0.95	0.98	0.37	-0.60	-0.49	0.76
Crime rate SG	0.95	1.00	0.98	0.26	-0.43	-0.41	0.67
Crime rate PS	0.98	0.98	1.00	0.25	-0.50	-0.47	0.73
Male%	0.37	0.26	0.25	1.00	-0.08	-0.18	0.32
Mean age	-0.60	-0.43	-0.50	-0.08	1.00	0.51	-0.46
IQ	-0.49	-0.41	-0.47	-0.18	0.51	1.00	-0.44
Muslim%	0.76	0.67	0.73	0.32	-0.46	-0.44	1.00

Table 7: Intercorrelations between crime variables and predictor variables in the Danish dataset. Weighted correlations below the diagonal. SG = subgroup method. PS = population structure method.

All the crime variables correlated close to 1.00 indicated that age and sex adjustment was fairly unnecessary for

11 STRAFNA1: Persons guilty in crimes by type of offence, type of decision, national origin, country of origin, age and sex. FOLK2: Population 1. January by sex, age, ancestry, country of origin and citizenship. Note that this table has since been depublished due to privacy concerns. We were able to secure a reduced copy from the DST which allowed for our analyses to be reproduced.

12 I.e. Yugoslavia proper – Serbia (with Kosovo), Montenegro, Bosnia, Herzegovina, Croatia, Macedonia, and Slovenia – and the reduced Yogoslavia (Federal Republic of Yogoslavia) consisting of just Serbia (with Kosovo) and Montenegro.

13 Temporal patterns can be of interest (Pinker, 2012), but due to the small populations of many country of origin groups, such patterns would be lost in the noise.

the sake of doing correlational analyses. The crime variables were also about equally strongly related to cognitive ability and Islam prevalence. As expected, mean age was more strongly related to the uncorrected crime variable, but this difference was small (-.60 vs. -.43 and -.50).

The conclusion of this analysis is that mean age and male% can show moderate to strong correlations to outcomes *even when one can be sure that they have close to no true causal effect*.

5.4. Assumption check: age and sex brackets and crime rates

As mentioned before, the proposed adjustment method depends on the assumption that the age-crime rate relationship is the same, or at least very similar between groups (Barnes, Jorgensen, Pacheco, & TenEyck, 2015; Ulmer & Steffensmeier, 2015). One can test this on the Danish data to some degree because we have access to crime rates across 7 age brackets for 70 groups. This robustness check is limited by the fact that many of these groups are fairly small and are unlikely to be a random sample of the persons from their countries of origin. Furthermore, though we have data for multiple years, these data are quasi-longitudinal and semi-non-independent because they involve the same persons from year to year.

Figure 3 shows the age-crime relationship for every group. Only male groups were used to avoid male% influencing the results and to avoid excessive sampling error associated with use of the female, much less crime prone groups.

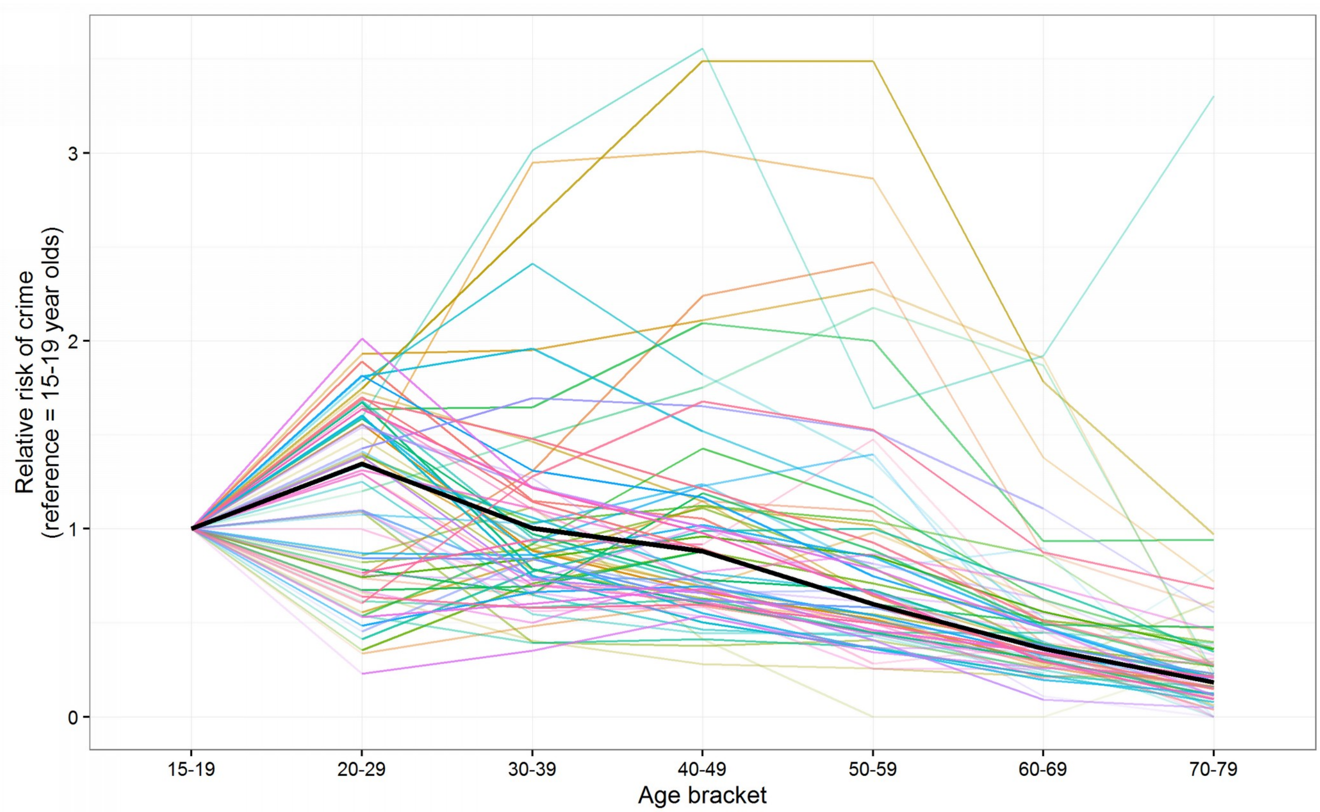

Figure 3: Age-crime rate by age brackets and country of origin. Each color is a country of origin group. The black line is the total group (all countries as a single group). Relative rate calculated as compared to the youngest group.

As can be seen, there are both similarities and irregularities. The highest crime rate was found among the 20-29 year olds. In interpreting the data, it should be remembered that the samples are quite small for some groups, and thus one would not expect perfect results *even if the age-crime rate relationship was universal*.

The assumption was mathematically examined by correlating every pair of countries' age-crime vectors with each other. If the age-crime relationship is universal *and there is no sampling error*, the intercorrelations between these should be 1. To the degree there is sampling error or variation in the relationship, the mean of the intercorrelations will move towards 0. Figure 4 shows a density histogram of the intercorrelations.

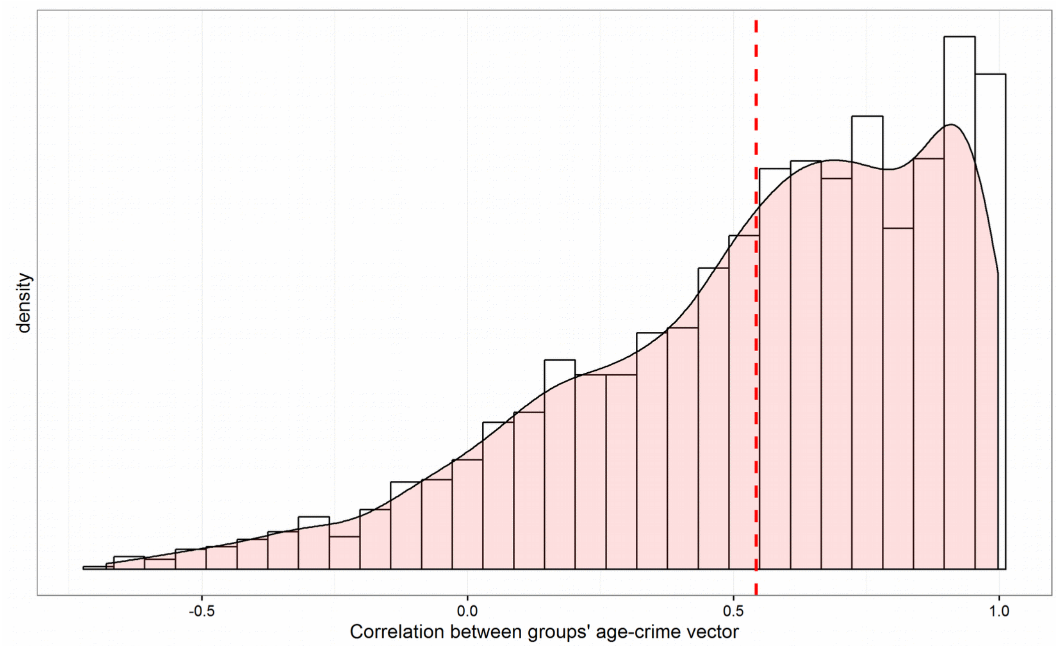

Figure 4: Intercorrelations between age-crime rate vectors for 70 groups. The vertical line marks the mean.

As can be seen, the correlations were strongly pushed towards 1, with a mean of .54 and median of .61. Insofar as deviation from 1 is due to sampling error, one would expect the correlations between the larger populations to be closer to 1. Figure 5 shows the relationship between population size and the correlation of the age-crime rate vector with the Danish one.

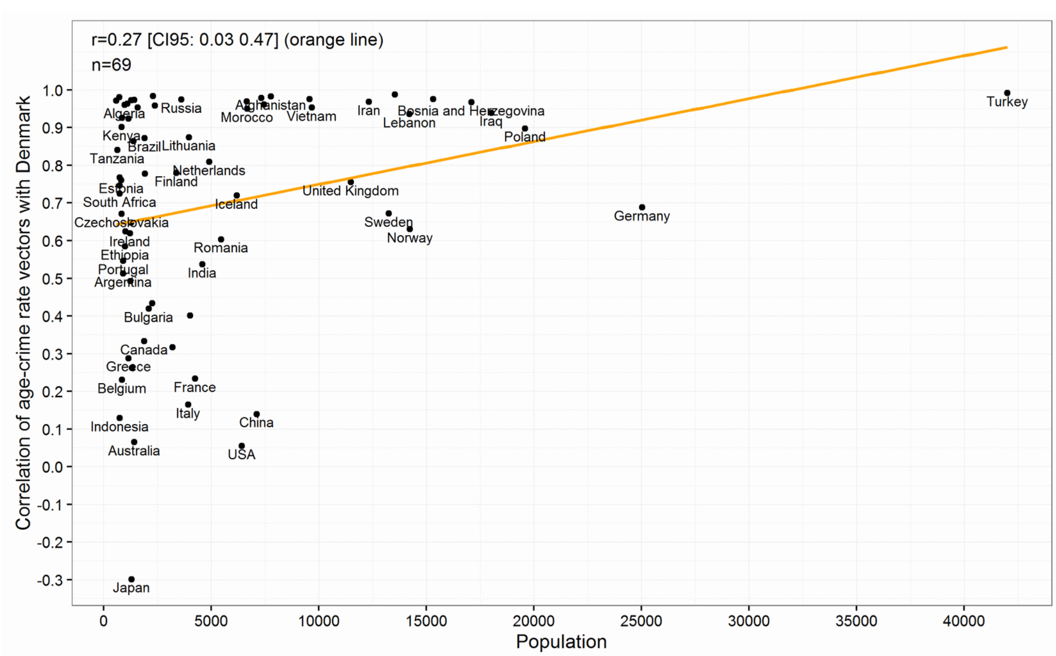

Figure 5: Scatterplot of population size and the correlation of the age-crime rate vector with the Danish vector.

We see a positive relationship as expected. In fact all the correlations are positive except for Japan. The Japanese group in Denmark is the least criminal group (relative crime rate 0.29), which increases the sampling error of the age-crime rate vector. Additionally, it is a very small group, with only 1300 persons on average in the studied time period. Furthermore, it is very female-skewed (male% = 31). Since these vectors are only based on male data, this adds extra sampling error. For example, there are only on average 12.1 men in the 70-79 age group who committed an average of 0.31 crimes.

Still, we can see that even for some quite large and similar populations such as Germans, the vector correlation is not quite 1.0, but only about .7. Such a value may have resulted from age-related differential immigration. If, for instance, younger groups tend to be exchange students (smarter and thus less crime prone), while the older tend to be semi-manual laborers (more crime prone), a deviation from a correlation of 1.0 is expected.

In general, however, the assumption is acceptably close to reality.

6. Re-analysis of German data with adjusted crime rates

Having validated the proposed method for adjusting crime data for age and sex distribution on the detailed Danish data, we now return to the analysis of the German data presented in this study.

The age brackets between the population data for foreigners and the crime rates for Germans did not match. We estimated the rates for the age brackets found in the foreigner data by weighted means. For instance, the age bracket 15-19 was estimated by 4 parts the 14-17 rate + 2 parts the 18-20 rate.

6.1. Unadjusted and adjusted crime rates

How do the unadjusted and adjusted crime rates compare in Germany? Figure 6 shows the scatterplot.

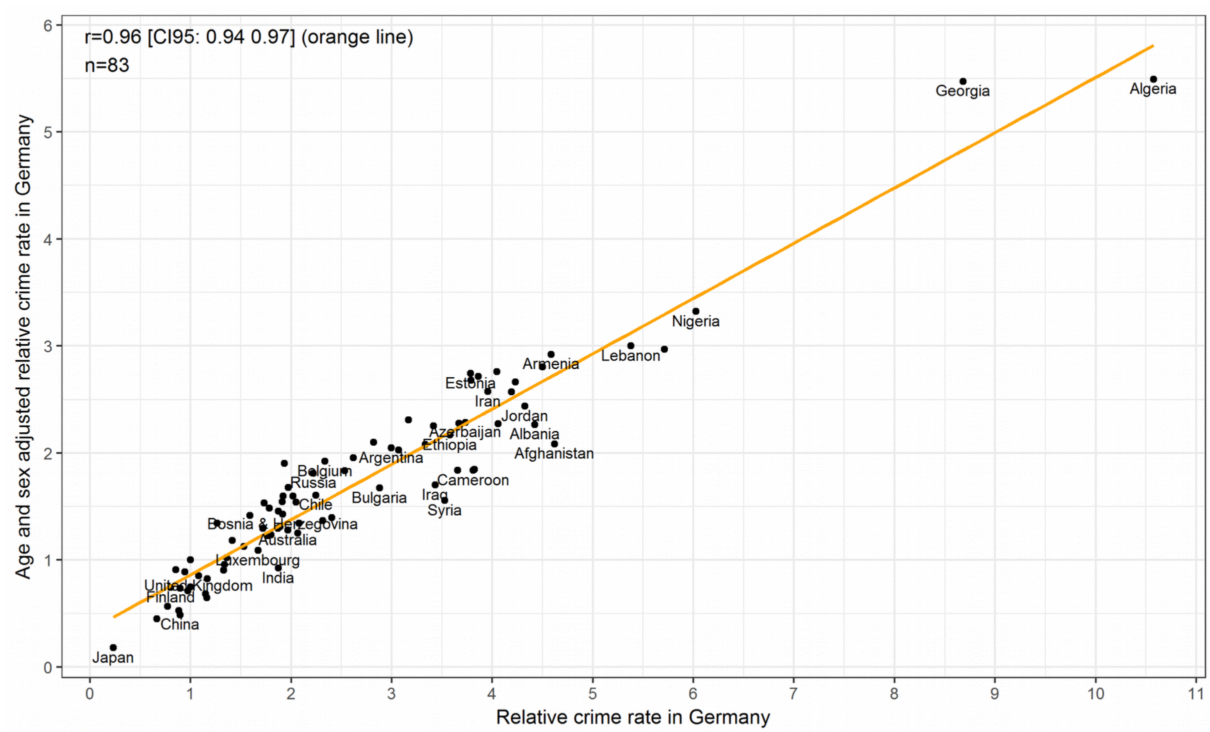

Figure 6: Adjusted and unadjusted relative crime rates in Germany.

As with the Danish data, we observe that the relative difference between the countries did not change much despite larger differences in mean age and male% (r=.96; Danish r=.98[14]). However, as with the Danish data, it can be seen that some of the very large disparities were strongly reduced in size by the adjustment, most obvious for the two outliers of Algeria and Georgia with relative crime rates of 10.6 and 8.7, which were reduced to 5.5 and 5.5, respectively. Overall, the standard deviation of relative crime rates decreased from 1.70 to 0.92 (Danish: 0.86 to 0.65).

Turks, the largest immigration population in Germany (1.5 million in these data), had an adjusted crime rate of 1.30, thus being similar to groups such as Poles (1.34), Vietnamese (1.31), Sri Lankans (1.29) and Australians (1.28). Therefore, the numbers do not fit well with narrative reports of rampant crime in this population.

6.2. Comparison with Denmark

Previous studies have shown that country of origin group crime rates correlate substantially across host countries, suggesting a common cause. For instance, Skardhamar et al. (2014) reported crimes rates for 25 groups in both Norway and Finland. Although they did not report the correlation, the correlation between the violent crime rates is .85. Kirkegaard (2014b) reported a correlation of crime rates between Denmark and Norway of about .75. Are the German data congruent with these findings? Figure 7 shows the scatterplot of the adjusted crime rates for Denmark and Germany. We see substantial agreement in the relative criminality between the two countries. The observed differences may reflect differences in immigrant selection, sampling error and different crime measures (guilty verdicts vs. suspects), but it is difficult to say how important each factor is.

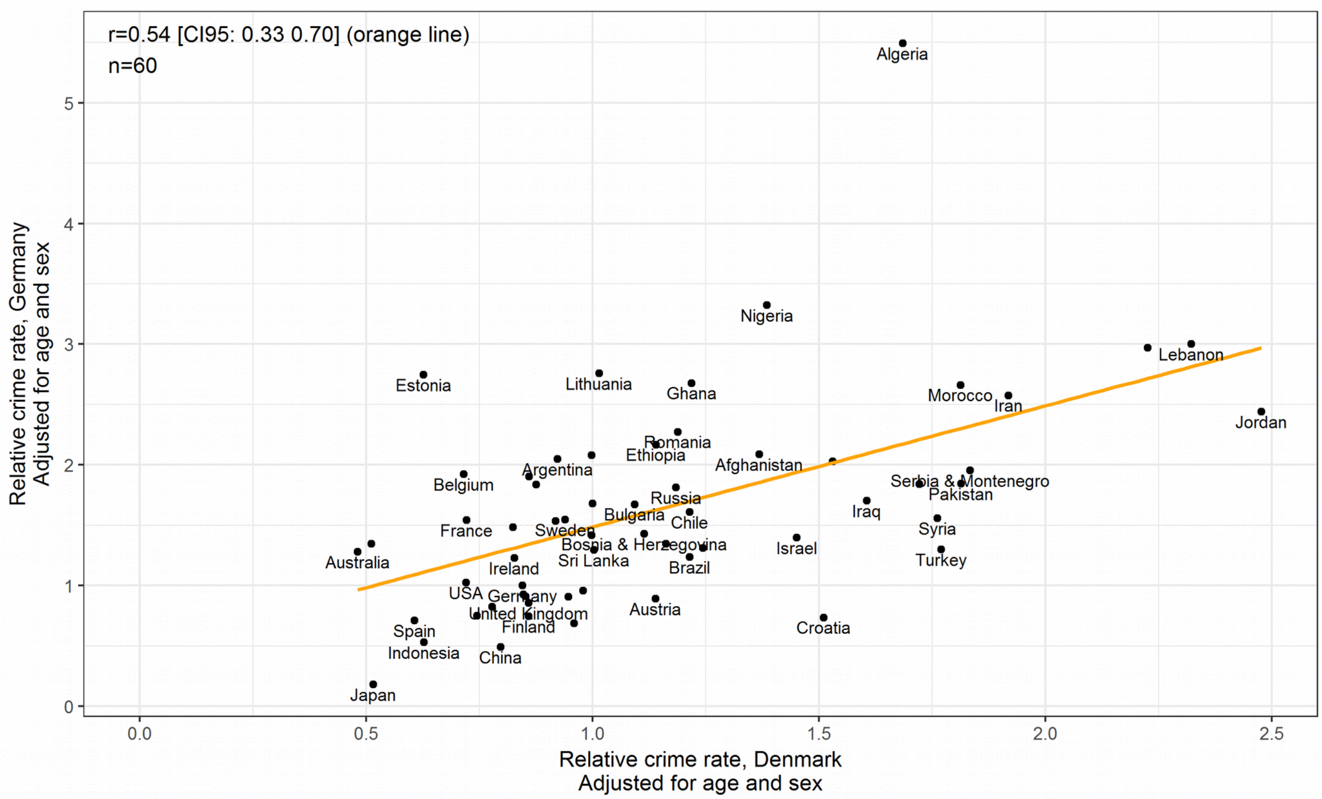

Figure 7: Age and sex adjusted relative crime rates in Denmark and Germany.

6.3. Correlation analysis

In Section 3.2 we saw that some country of origin variables were able to predict differences in crime rates in Germany when using unadjusted crime rates. Do they retain their predictive validity after adjustment? Table 8

14 The adjusted numbers from the Danish data based on the same method were used to avoid method variance.

shows the predictor correlations.

Predictor	Crime rate DE	Crime rate DK	Crime rate DE adj.	Crime rate DK adj.
IQ	-0.53	-0.49	-0.46	-0.47
Muslim%	0.49	0.76	0.35	0.73
Mean age	-0.53	-0.45	-0.37	-0.40
Male%	0.39	0.55	0.22	0.47
Distance to Germany	-0.11	-0.16	-0.16	-0.17

Table 8: Correlations of predictors and crime rates for Denmark and Germany. Adjusted values are adjusted for age and sex. N's = 83 (Germany), 70 (Denmark).

We see that the correlations were generally similar before and after adjustment. Given the small sample sizes, some of the variation seen may be the result of chance variation. For instance, Muslim% was a worse predictor in Germany after adjustment (.49 to .35), but not so in Denmark (.76 to .73).

Figures 8 and 9 replicate the scatterplots for relative crime rates in Germany and the two primary predictors, national IQ and Muslim%.

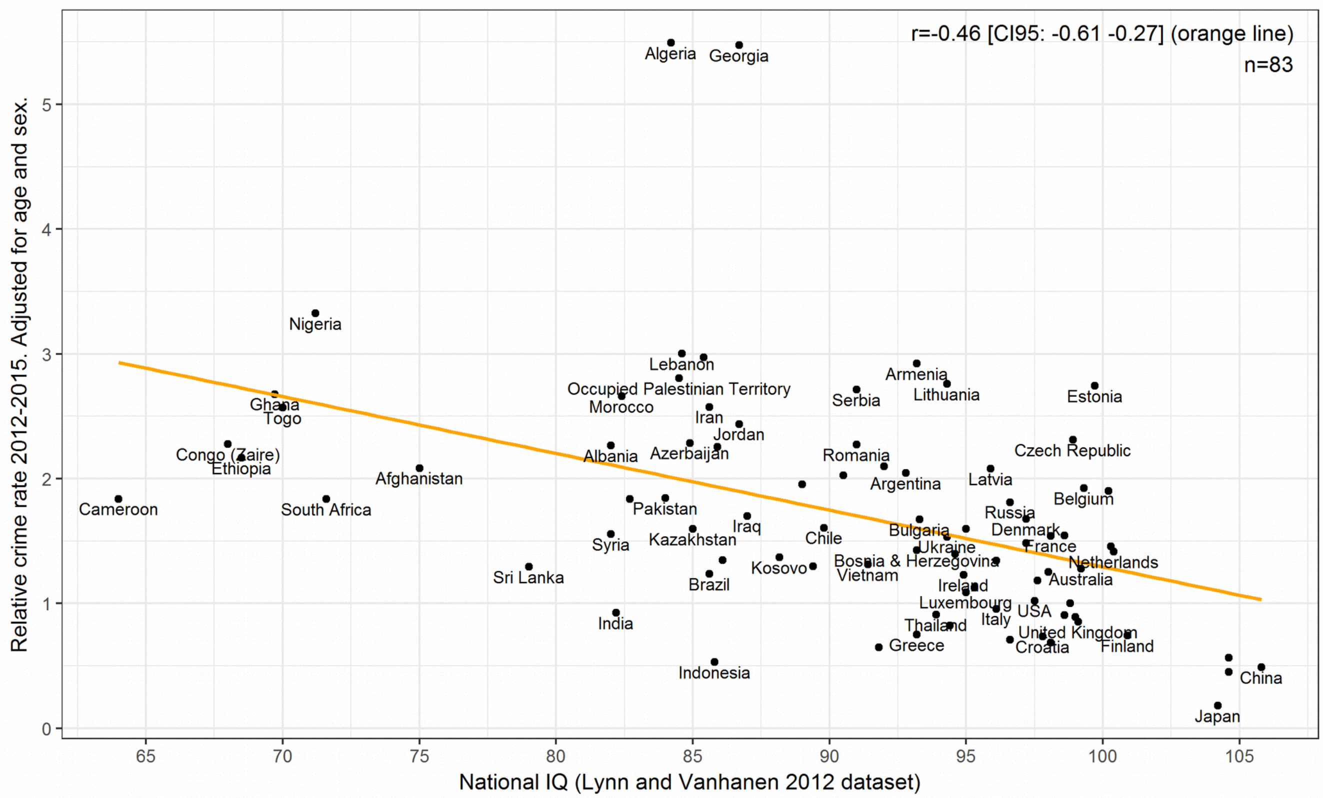

Figure 8: National IQ of origin country and adjusted relative crime rate in Germany.

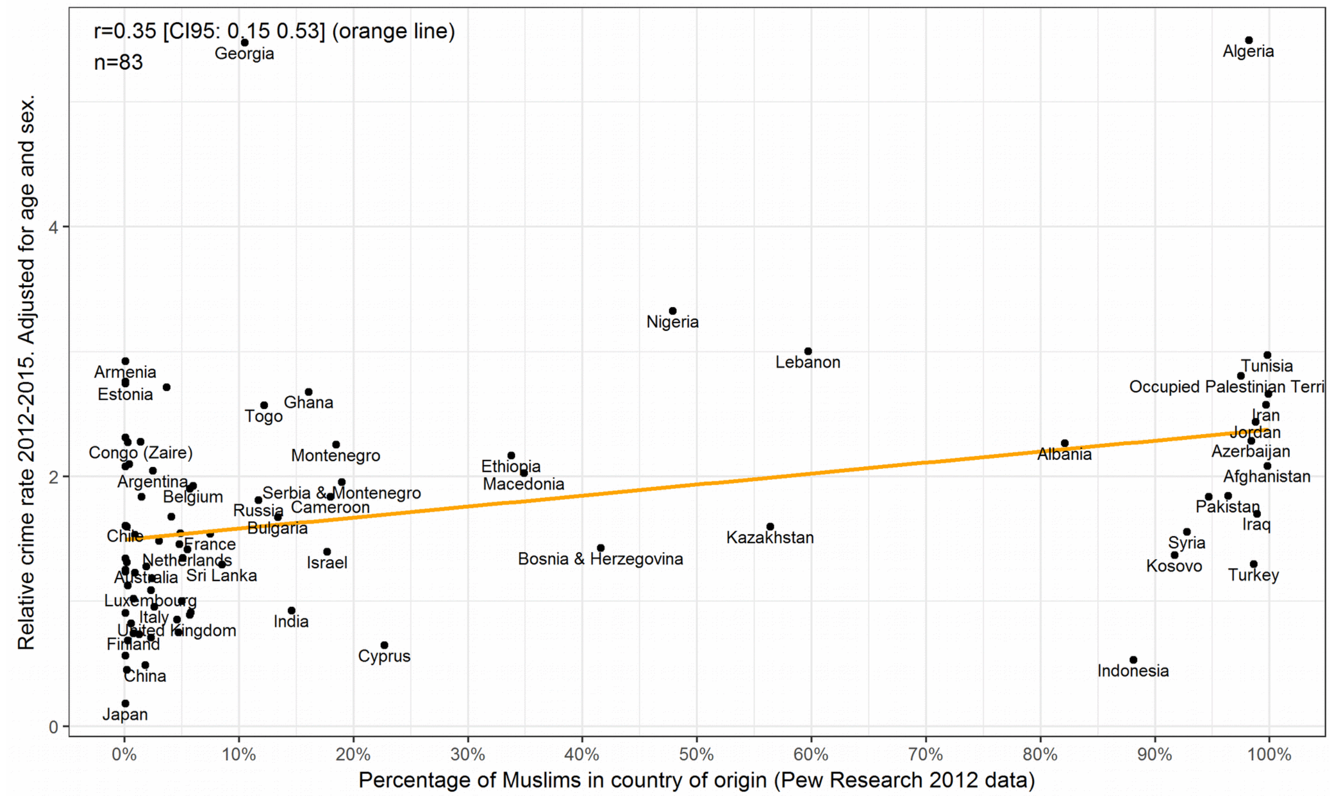

Figure 9: Islam prevalence in origin country and adjusted relative crime rates in Germany.

6.4. Regression analysis

As in Section 3.3, the crime rates were regressed on the predictors. The difference is that here we used the adjusted crime rates and did not include the mean age and male% predictors because we know the statistical effects from these are spurious. Table 9 shows the results.

Predictor	Beta	SE	CI lower	CI upper
IQ	-0.45	0.11	-0.67	-0.24
Muslim%	0.14	0.11	-0.08	0.35
Distance to Germany	-0.26	0.10	-0.46	-0.07

Table 9: Adjusted relative crime rates in Germany. Regression results. r^2 = .30, r^2-cv = .20. n=83.

The results mirror those from before. IQ remains a strong predictor in multiple regression, while Muslim% does not. Distance to Germany seems to have some validity. This is most plausibly interpreted as a proxy for migrant selection effects.

6.5. Robustness checks

To assess robustness, a few method variations were tried.

6.5.1. Outlier removal

Georgia and Algeria were clear outliers in many of the analyses, suggesting that perhaps something is wrong with these datapoints. We therefore reran the main analyses without them. Table 10 shows the resulting primary correlations.

Predictor	Crime rate DE	Crime rate DK	Crime rate DE adj.	Crime rate DK adj.
IQ	-0.62	-0.49	-0.52	-0.46
Muslim%	0.53	0.76	0.36	0.73
Mean age	-0.60	-0.45	-0.38	-0.39
Male%	0.40	0.53	0.20	0.45
Distance to Germany	-0.10	-0.16	-0.16	-0.16

Table 10: Correlations of predictors and crime rates for Denmark and Germany. Adjusted values are adjusted for age and sex. N's = 81 (Germany), 68 (Denmark). Outliers removed.

By comparing the numbers with those in Table 8 it can be seen that the correlations were not strongly affected by the outliers being removed. As expected based on Figure 8, the (German) IQ correlations improved because the two outliers were disrupting the general trend. There was little effect on the Muslim correlations because the outliers had opposite effects as seen in Figure 9.

The regression results were similar with only small changes (βIQ = -.54, βMuslim% = .11, βDistance = -.29, r^2-cv = .25).

6.5.2. Data transformation

Noah Carl suggested attempting to normalize the crime rates using a log (1 + crime rate) transformation. Figure 10 shows the distribution of the adjusted relative crime rates in Germany.

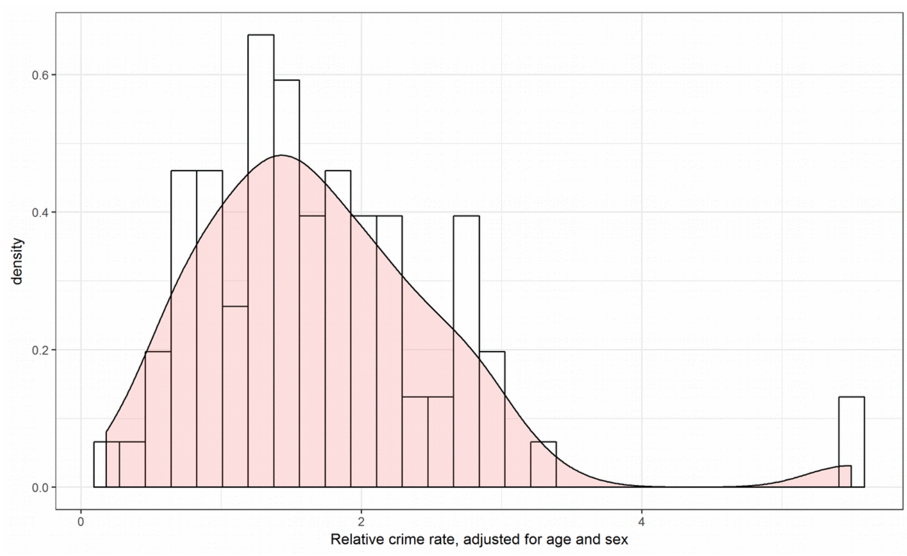

Figure 10: Distribution of age and sex adjusted relative crime rates.

As can be seen, the distribution is quite normal aside from the two outliers. Consequently, little is gained by further trying to normalize it. The correlation of before and after log transformation values was .97, (.99 if the outliers were removed as well).

7. Discussion and conclusion

We observed large differences between crime rates of immigrant groups in Germany (Section 3). These differences were reduced by about half (standard deviation of relative crime rates from 1.70 to 0.92) when adjustments were made for differential age and sex structures, but the relative differences between the crime rates were very similar (r=.96) (Section 6.1).

To some extent, the differences in crime rates could be predicted by country of origin variables (Section 6.3). In particular origin country national IQ (Lynn & Vanhanen, 2012), Muslim% (in the origin country) and distance from Germany seemed to be useful predictors. When combined in a regression model, Muslim% ceased to have much predictive validity while the others retained theirs (Table 9). When we adjust for overfitting by use of cross-validation, the r^2 was 20%, equivalent to a correlation of .45; a fairly accurate prediction. If we allow for exclusion of two strong outliers, the cross-validated explained variance increased to 25% equivalent to a correlation of .50 (Section 6.5.1).

The crime rates in Germany were similar to those seen in the high quality Danish dataset (Section 6.2), both before and after adjustment was made for age and sex (r's .66 and .53, n=60). In fact, they were also similar to those seen in Norway, Finland and the Netherlands (Kirkegaard, 2014a, 2015a; Skardhamar et al., 2014). Among selected crime variables, the mean/median correlation was .72/.76 (n's 16 to 60, median 20).[15] This suggests a common cause of the crime rates, which was supported by the finding that country of origin predictor correlations were similar for the German and Danish data as well (Table 8).

We propose a simple demographic model to account for these data: the spatial transferability model (Fuerst & Kirkegaard, 2014). When groups of persons migrate from one country to another, they tend to keep their psychological profile, and cultural practices and beliefs. The psychological profile of a population is expected to predict the relative socioeconomic performance of that group relative to other groups in the same society, in the same way as has been found at the individual level. Thus, since cognitive ability has consistently been found to be negatively related to crime (Frisell, Pawitan, & Långström, 2012; Herrnstein & Murray, 1994; Ttofi et al., 2016), then if groups differ on this trait (on average), then the groups' crime rates are expected to differ as well, all else equal. We offer no particular causal model of the predictive validity of Muslim% in the home land because there is insufficient research on this variable in our opinion. The validity may be due to inherent anti-non-Muslim beliefs of Islam, teachings of Muslim scholars/imams which are not necessarily part of the religion, or the variable may in fact be non-causal and the validity is due to some unmeasured confound, cultural or genetic. We hope that further research can clarify the issue, which will require individual-level data (e.g. (Khattab, 2009)).

The present study is limited by the available data. The German data is based on suspects, not arrests or guilty verdicts. This has both advantages and disadvantages. The advantage of using suspects is that there are more suspects than persons found guilty of crime by a court which means that the base rate is higher and thus estimates are more precise. The disadvantage is that any bias in the police force will be reflected in the suspicion rates. It's unclear which direction such bias might be in. It would be informative to gather data on self-reported crime rates by country of origin groups, though it should be noted that there is evidence that crime prone groups also give more false answers when self-reporting criminal history (Fendrich & Johnson, 2005).[16]

15 The variables were not entirely comparable. For Norway and Finland, we used the violent crime odds ratio which was adjusted for age and sex. For the Netherlands, we used the total population values (suspects per capita) as no adjusted values were available and analyses in this paper shows them to be mostly unnecessary for the purposes of correlations. For Denmark and Germany, the adjusted relative rates were used as before.

16 Note that this does not necessarily mean that there is differential lying although that would be consistent with the reported relationship between higher cognitive ability and honesty (Ruffle & Tobol, 2016), it could mean poor memory.

In the same vein, although we were able to find crime data for about 200 countries of origin (more or less the entire world), we were only able to find matching population count data for 85 countries, and we could thus only analyze these groups. We were unable to find outcome data for other variables such as income, education or use of welfare benefits, and thus were unable to do a cross-outcome analysis as has been previously done (Kirkegaard, 2014a; Kirkegaard & Fuerst, 2014).

A major limitation of this study is that it is based on citizenship data, not country of origin data per se. As mentioned earlier, persons can change citizenship and thus move between categories. To the extent that this happens differentially for the groups, it will introduce bias in the data. Persons may also hold multiple citizenships, and it's not clear how this affects the results.

Supplementary material and acknowledgments

Project files including data files, analyses code and high quality figures are available at https://osf.io/rswyv/.

Open peer review available at https://openpsych.net/forum/showthread.php?tid=296.

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