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Article in Mankind Quarterly · February 2020

DOI: 10.46469/mq.2020.60.3.3

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MANKIND QUARTERLY 2020 60:3 327-351

Public Preferences and Reality: Crime Rates among 70 Immigrant Groups in the Netherlands

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We estimated crime rates among 70 origin-based immigrant groups in the Netherlands for the years 2005-2018. Results indicated that crime rates have overall been falling for each group in the period of study, and in the country as a whole, with about a 50% decline since 2005. Immigrant groups varied widely in crime rates, with East Asian countries being lower and Muslim countries, as well as Dutch (ex-)colonial possessions in the Caribbean, being higher than the natives. We found that national IQ and Muslim percentage of population of the origin countries predicted relative differences in crime rates, *r*'s = .64 and .45, respectively, in line with previous research both in the Netherlands and in other European countries. Furthermore, we carried out a survey of 200 persons living in the Netherlands to measure their preferences for immigrants for each origin country in terms of getting more or fewer persons from each country. Following Carl (2016), we computed a mean opposition metric for each country. This correlated strongly with actual crime rates we found, *r*'s = .46 and .57, for population weighted and unweighted results, respectively. The main outliers in the regression were the Dutch (ex-)colonial possessions, and if these are excluded, the correlations increase to .68 and .66, respectively. Regressions with plausible confounders (Muslim percentage, geographical fixed effects) showed that crime rates continued to be a useful predictor of opposition to specific countries. The results were interpreted as being in line with a rational voter preference for less crime-prone immigrants.

Key Words: Immigration, Crime, Netherlands, Stereotype accuracy

Western European countries are seeing levels of immigration that are unprecedented in the last hundreds of years. Generally speaking, immigrants as a whole perform below the level of the natives in terms of income, education, crime rates, use of benefits etc. (Andersson & Jespersen, 2018; MG, 2015, 2016; D. Murray, 2017; Roth, 2010; Sanandaji, 2017; Sarrazin, 2012). Causes of such social performance gaps are heavily debated both in the academic literature and society in general (Hesson, 2019; Pickering & Ham, 2015; Salmi et al., 2015). Unfortunately, determining the causes of performance gaps is difficult for a number of reasons. First, the case-level data for studying immigrant crime are not generally available for researchers since these depend on government data protected by privacy regulations, or only available by application limited to university employed researchers which requires an arduous process. Thus, most data published for public use are aggregated statistics. Second, most such published government aggregated statistics and studies do not distinguish between immigrant groups by country of origin, which would allow for using origin country characteristics as predictors (Borjas, 2016; Hamilton & Hummer, 2011). For instance, many reports group together all immigrants into categories such as EU-origin or Western immigrants, whose definitions can both change over time (as EU membership changes) and between reports. However, in recent years, a number of datasets that disaggregate by country of origin have become available for many countries.

A number of studies have been done using these national origin datasets. Most of them use national IQ as a predictor. The idea with this is that immigrant populations are at least roughly representative of their origin countries in terms of intelligence, and thus one can approximate the average intelligence levels of immigrant groups by using (the estimate of) their home country average. This method is more dubious when the data include second and later generation immigrants, as these are generally found to have better cognitive scores than first generation immigrants (Rindermann & Thompson, 2016; Robie et al., 2017; but see Kirkegaard, 2013), suggesting environmental causation of between country gaps and biasing the estimates of between group gaps in the host country. In the same way, some studies have used the Muslim % of the home country as a best guess for the prevalence of this religious affiliation among the immigrants and their descendants. With regards to predictive analysis using country of origin variables, Kirkegaard (2017) presented a preliminary meta-analysis of results from studies covering six host countries (Denmark, Norway, Sweden, Finland, Germany, and the Netherlands), all of which are located in Northern Europe. He found that national IQ predicted individual outcomes (e.g. crime rate) or a general social outcome or status composite (SES/S factor) with correlations of .40 to .62, with a mean of .51 (n = 16). For Muslim %, the values ranged from .18 to .76, with a mean of .55. The summary of results is shown in Figure 1. Other researchers analyzing data for the US have also found national IQs to be useful in analysis of immigrant data (Jones & Schneider, 2010; Vinogradov & Kolvereid, 2010; Whitaker, 2018).

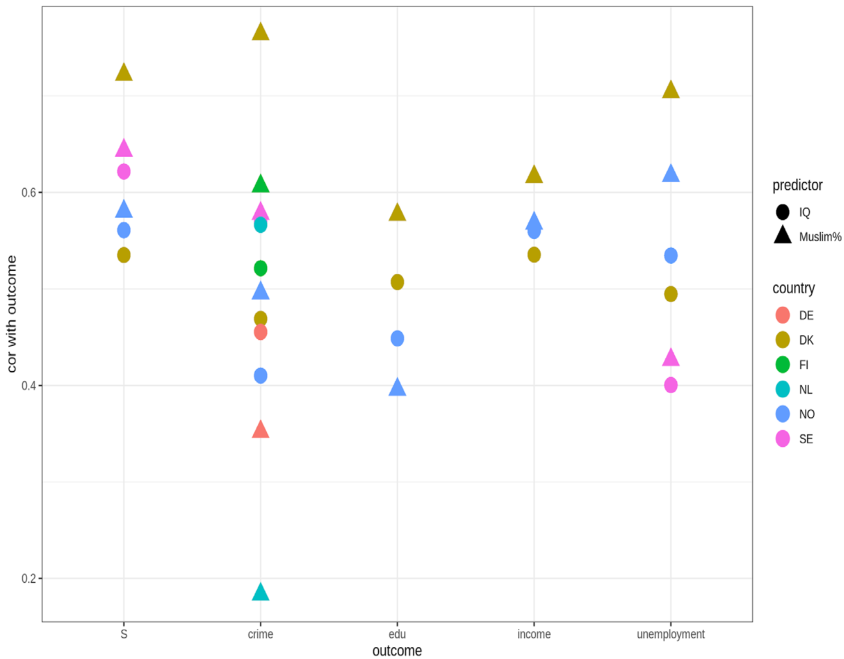

Figure 1. *Summary of meta-analysis of country of origin predictive studies. From Kirkegaard (2017).*

Decades of research in sociology, criminology and differential psychology show that higher intelligence causes better outcomes in general, whether these relate to education, income, health, unemployment or criminality. 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 (Hill et al., 2019). In line with expectations, it is well established that immigrant populations in Western countries in general have below native levels of average intelligence (Kirkegaard, 2019b; Rindermann & Thompson, 2016; Robie et al., 2017) and that these are related to their origin countries' level of ability. Putting these facts together, it was predicted that national IQs would predict variation in crime rates among immigrant groups.

The use of Muslim% as a predictor in the literature is not founded upon an equally strong theoretical or empirical basis, but is included because many commentators have noted that Muslim groups in particular tend to perform poorly (but see Kuran, 2018; Rindermann, 2018, sec. 4.4.3; Sarrazin, 2018). In fact, origin country Muslim% often predicts social outcomes better than does national IQ, and sometimes is a stronger predictor in multiple regression, though because of the collinearity and limited sample sizes, these regressions give very imprecise estimates (Kirkegaard & Fuerst, 2014).

The reason for this predictive validity is unclear. First, it could be because Islam teaches Muslims to act in a hostile manner towards non-Muslims, which would result in a prediction of high outgroup crime rates but not e.g. high unemployment rates (unless these are interpreted as economic aggression) or crimes against other Muslims (unless from another variant of Islam, Shia vs. Sunni vs. Alevism). Second, it could be because Muslim faith is correlated with other traits that are causal for general social performance, such as interpersonal trust, work ethic, mental well-being, or clannishness (Carl, 2017; Schulz et al., 2019). The question is difficult to examine without the use of individual-level datasets that also contain measures of potential confounders, especially intelligence, and mediators, such as educational attainment. The authors have been looking for such datasets for a number of years without luck. At present, the authors do not advance any particular model for why the relationship exists, but we include the predictor because of its potential causality and evident predictive validity, and hope that future studies might clarify its role in the nomological network.

The reasons for the present study were two-fold. First, we are only aware of one published study that examined immigrant groups in the Netherlands grouped by country of origin (Kirkegaard, 2015). This study however relied on old and limited data from a Dutch language report that examined data from 2002 (Blom et al., 2005), whose reliability was questionable. Thus, there was a need to further investigate immigrant crime in the Netherlands. The previous study found that crime rates among the 57 origins studied were highly predictable from national IQ (*r* = -.80) and moderately by Muslim % (*r* = .34). Second, the British intelligence researcher and sociologist Noah Carl was recently the target of a harassment campaign by left-wing activists and eventually fired from his job as a research fellow at the University of Cambridge (Lehmann, 2019). One of the complaints against him was that he had investigated the relationship between immigrant crime rates by country of origin and public preferences regarding further immigration from the same countries. Carl (2016) found that the crime rates correlated *r* = .69 with net opposition (defined below) to immigration from the countries, which suggests that public stereotypes about immigrant groups are both fairly accurate and taken into account when forming immigration political preferences. However, no published replication currently exists of his finding, so we additionally sought to replicate it for the Netherlands.

Data

We used publicly available data about registered suspects among persons living in the Netherlands (https://opendata.cbs.nl/statline/#/CBS/nl/dataset/81959NED/table?ts=1569478057921). These data are compiled and published by CBS (Centraal Bureau voor de Statistiek, Central Bureau of Statistics), which is the official government body that publishes statistics for the Netherlands. These were divided into groups by country of origin. Country of origin was defined as including both first and second generation immigrants, i.e. persons who themselves were born elsewhere, or whose parents were born elsewhere (exception being if someone is born elsewhere but both parents are Dutch, for instance, as part of longer foreign stays or medical tourism). Using these, we calculated per capita suspect rates using population counts from https://opendata.cbs.nl/statline/#/CBS/nl/dataset/37325/table?ts=1566221048639 . The population count data were limited to persons aged 12 to 45, which is the range who commits most recorded crimes. We used all available years of data, spanning 2005 to 2018. In total, we have data from 70 immigrant countries as well as the natives. Thus, we have a total of 994 country-years of data, which is based on 8.3 million person-years of data. The new estimates were strongly correlated with those used in the previous study: the correlation with the best estimate from the previous study was .96. Furthermore, we downloaded data split by generation, so as to investigate any potential confounding by distribution of immigrant generation. Finally, we found another variable concerning arrests that ran from 2005 to 2014. Since it had less data, we used it only for robustness testing.

For country of origin variables, we used national IQs from Lynn and Vanhanen's 2012 dataset (Lynn & Vanhanen, 2012). This dataset has been extensively used by other researchers for both country level analyses and immigrant studies. Recently, German political scientist David Becker undertook an independent analytic replication of the estimates by obtaining copies of each original source and redoing all the calculations previously done by Richard Lynn and colleagues. His work is presented in Lynn and Becker (2019) and is continuously updated at http://viewoniq.org (currently in version 1.3.3). Many other sets of estimates have been produced by others, most importantly Heiner Rindermann (2018). However, we used the 2012 dataset because, as of writing, it is more comprehensive than the 2019 recalculation (see discussion in Kirkegaard, 2019c). For estimates of the proportion of Muslims in each group, we used estimates from Pew Research (Pew Research Center, 2011). Countries with missing data were imputed based on neighboring or component countries as done in previous research (Kirkegaard & Becker, 2017).

We were unable to find a published survey with information about which countries of origin Dutch people prefer and dislike as immigrants in their country. For this reason, we sought to do our own small survey. Sample size was not crucial for this because the differences between countries were expected to be large, and we were only interested in estimating the mean preference for each country. Using Prolific (https://www.prolific.co/) (Palan & Schitter, 2018), we polled approximately 200 persons living in the Netherlands with regards to their preferences for immigration from 68 immigrant countries we had crime data from. We skipped two countries that no longer exist (Soviet Union and Czechoslovakia) as well as the Netherlands itself, which isn't an immigrant origin (and thus one cannot have immigration preferences for it).

For each country of origin, subjects were asked "Thinking about people who want to come and live in the Netherlands from different countries, to what extent should people from the following countries be allowed to come and live in the Netherlands?" with the available options of "none", "fewer", "same", and "more" (all in Dutch). This is the same format as used by YouGov when collecting the data that Noah Carl used (Smith, 2016). Finally, we re-weighed the results by party vote in the last election because our survey was tilted towards immigrant friendly voters (e.g. Greens got 36% of the votes in our survey but 9.1% in the 2017 general election). This re-weighting did not affect the relative differences much (r = .95 before and after). Prolific keeps track of whether their users provide good data, and removes persons who provide poor data (i.e. click through surveys very fast/at random). To ensure our participants were paying attention to our somewhat tedious survey (they had to answer ~70 similar questions in a row, one for each origin), we included two attention checks in the country list that asked participants to select a particular response, and excluded participants who failed these (n = 20, ~10%). This exclusion did not alter results noticeably.

Results

The differences in crime (suspect) rate by country of origin were large. The lowest rate was seen for Northeast Asian countries, with Japan having a relative rate of 0.21 to that of Dutch natives, while Netherlands Antilles had a relative rate of 3.81. Thus, the relative difference between the most and least criminal groups was about a factor of 17. Figure 2 shows a world map with the estimated crime rates.

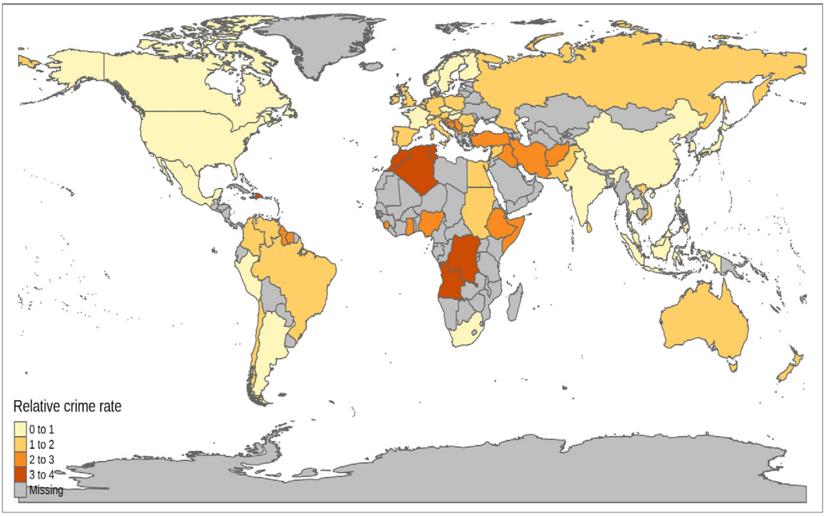

Figure 2. *World map of relative crime (suspect) rates among immigrant groups in the Netherlands by origin country (native = 1). Averaged from 2005 to 2018. Grey indicates no data (few immigrants in the Netherlands).*

Crime rates are generally falling in Western countries despite the influx of above average crime rate immigrants, and indeed have been generally falling for centuries (Pinker, 2012). This outcome is due to the fact that the crime rate among the natives is falling sufficiently fast to offset the increase from immigration, so that the net effect is negative (decreasing). Figures 3 and 4 show the timeline of crime rates and relative rate versions for the 10 largest groups.

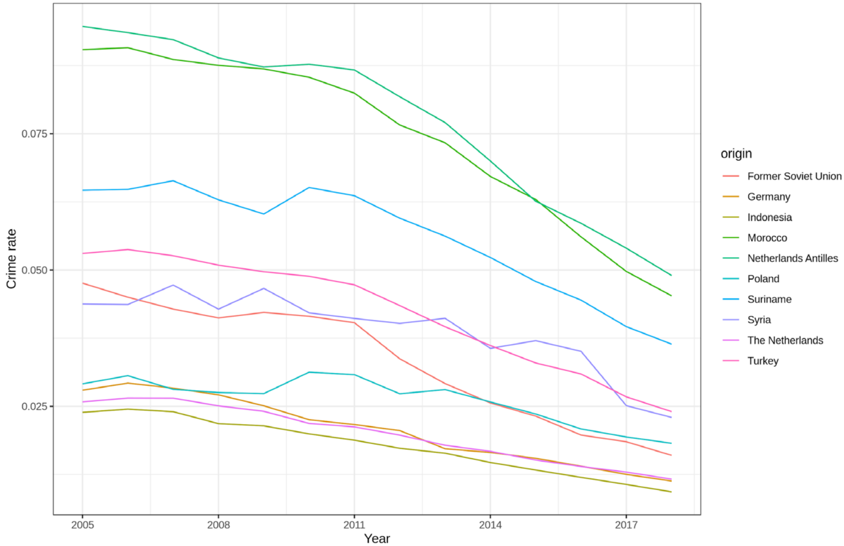

Figure 3. *Timeline of crime (suspect) rates in the Netherlands by origin group, 10 largest groups.*

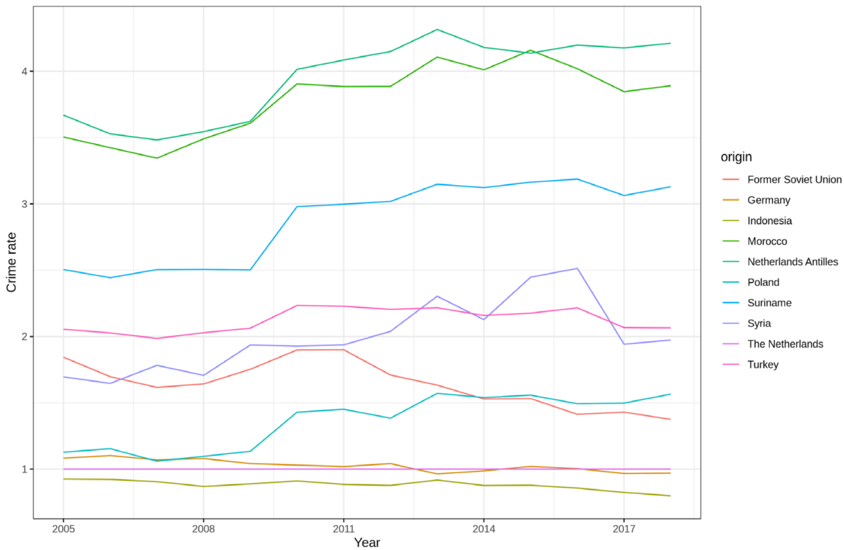

Figure 4. *Timeline of relative crime (suspect) rates in the Netherlands by origin group, 10 largest groups. The Netherlands = 1.*

In the period of study, the crime rate fell by 51% in the population as a whole, and by an average of 50% within each origin group from 2005 to 2018. Still, the relative group differences stayed approximately the same over the period of study, *r* = .93 between 2005 and 2018 crime rates. This can also clearly be seen in Figure 4 (above). The reason for the uptick in crime in 2010 is not known. Figures 5 and 6 show the scatterplots for the two national-level predictors and the crime rates.

The two predictors are correlated in the present sample (*r* = -.42, but only -.27 worldwide), and thus their individual effect size is likely overestimated from the bivariate analyses. For this reason, we fit a regression model with both predictors. Adjusted R^2 was strong at .41 (i.e. model R = .64). In the weighted model, the effect of IQ was stronger than that of Muslim origin: $\beta IQ = -0.61$ (SE = 0.12, $p<.0001$), $\beta Muslim\% = 0.16$ (SE = 0.10, $p = .12$). In the unweighted model, Muslim% did a little better (model adj. $R^2 = .45$, $\beta IQ = -0.57$ with $p<.0001$, $\beta Muslim\% = 0.20$ with $p = .04$).

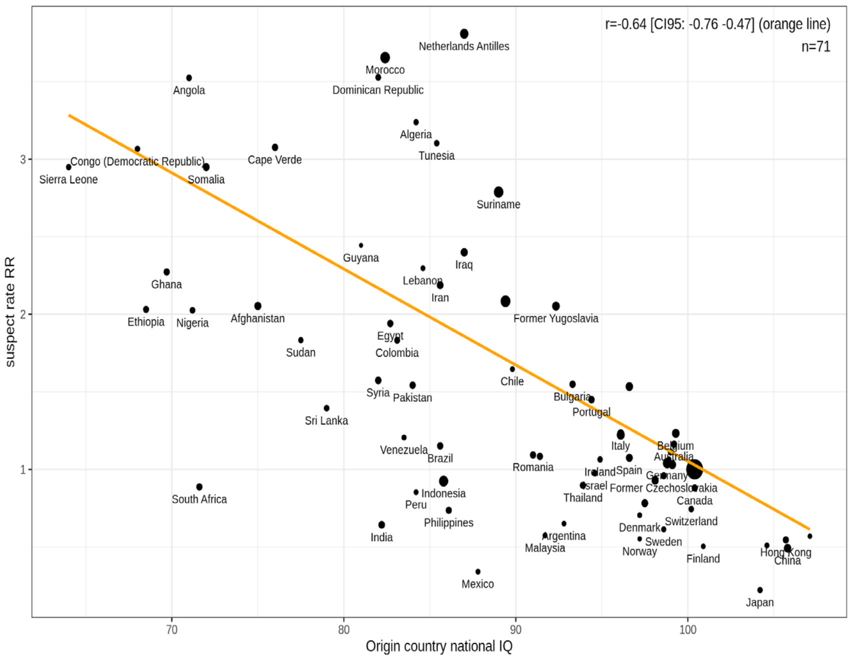

Figure 5. *Scatterplot of national IQ of origin country and relative crime rate among origin groups in the Netherlands, 2005-2018. Weighted by the square root of population size.*

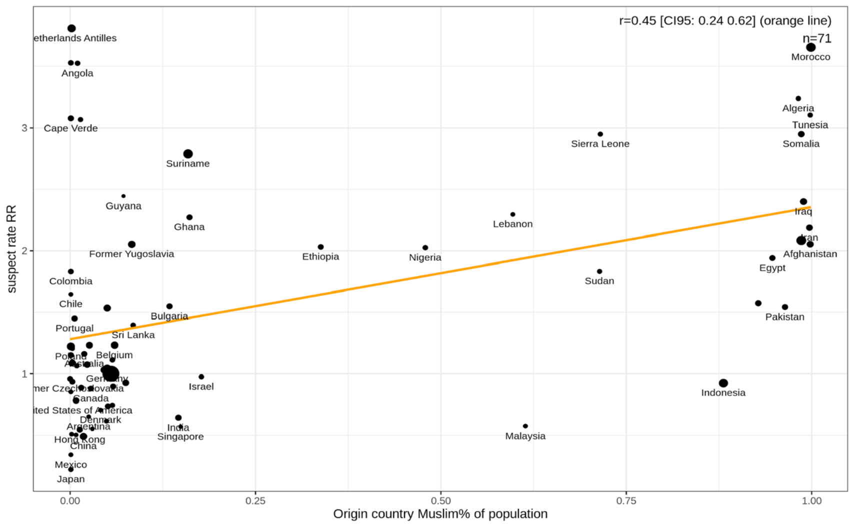

Figure 6. *Scatterplot of Muslim percentage of origin country and relative crime rate among origin groups in the Netherlands, 2005-2018. Weighted by the square root of population size.*

Figure 7 shows the scatterplot of crime rates and mean opposition. The results replicate the general result found by Carl (2016). Suriname and Netherlands Antilles stand out as strong outliers with large populations in the Netherlands. Suriname is a former Dutch colonial possession in the north of South America (gained independence in 1975), and Netherlands Antilles is a current Dutch colonial possession consisting of several small islands north of Suriname. A third ex-colonial possession is Indonesia, which has a low relative crime rate (0.92, below natives) and faces low net opposition. However, even this country still has a negative residual (standardized residuals are -1.96, -2.17, and -0.08 for Suriname, Netherlands Antilles, and Indonesia, respectively). Thus, it appears that people living in the Netherlands are willing to grant persons from these countries relatively more or easier entrance to the Netherlands. If the colonial origins are excluded, the correlations increase to .68 and .66, weighted and unweighted, respectively. Another pattern that stands out is the dual clusters of countries in the left. The bottom cluster consists of other traditional west European countries (before the fall of USSR), while the upper one appears to be a remainder category of countries that are more culturally distant but about equally low in crime rates.

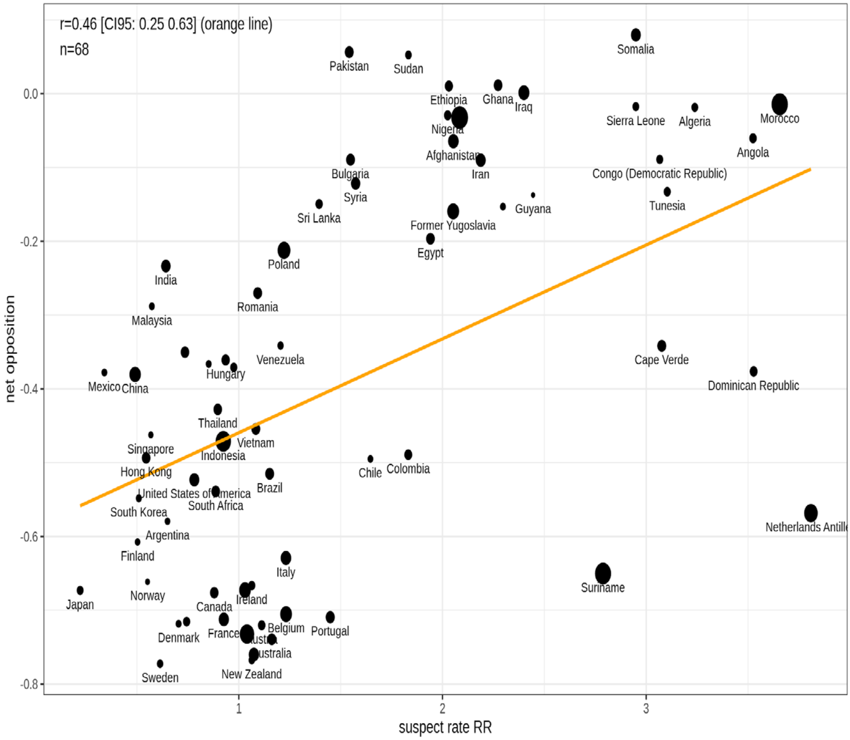

Figure 7. *Scatterplot of relative crime rate and net opposition to origin groups. Weighted by the square root of population size. Unweighted r = .57.*

We can combine these insights into a series of regression models, the results of which are summarized in Table 1. Colonial is a dummy variable for whether the origin country is Suriname, Netherlands Antilles, or Indonesia. We included regional dummies, one based on continents and one based on macroregions. The macroregions were copied from a previous study and based on UN classifications (Kirkegaard, 2019a). Maps with the classification schemes are given in the appendix. Because of the central role of Islam/Muslims in public debate, we included this variable in the regressions. We did not include national IQs as these have at best a minor role in public debates about immigration in Europe.

Table 1. *Model results for predicting public net opposition to immigration from particular origin countries. N = 68. Numerical variables are standardized, value in parentheses = standard error. * = p<.01, ** = p<.005, *** = p<.001.*

Predictor/Model	1	2	3	4	5
Intercept	-0.07 (0.114)	0.08 (0.107)	-0.01 (0.083)	-0.37* (0.136)	-0.88*** (0.129)
Suspect rate	0.44*** (0.105)	0.55*** (0.097)	0.33*** (0.081)	0.37*** (0.099)	0.21 (0.089)
Colonial		-1.32*** (0.308)	-1.20*** (0.236)	-1.20*** (0.248)	-1.12*** (0.233)
Muslim			0.50*** (0.074)	0.27* (0.094)	0.35*** (0.096)
UN_continent=Europe				0 (ref)	
UN_continent=Africa				0.66 (0.269)	
UN_continent=Americas				0.18 (0.249)	
UN_continent=Asia				0.83*** (0.222)	
UN_continent=Oceania				-0.71 (0.514)	
UN_macroregion=N & W Europe + offshoots					0 (ref)
UN_macroregion=Caribbean					0.89 (0.394)
UN_macroregion=Latin America					0.85*** (0.223)
UN_macroregion=Africa					1.55*** (0.245)
UN_macroregion=Eastern Asia					0.95*** (0.256)
UN_macroregion=Eastern Europe					1.71*** (0.225)
UN_macroregion=MENA					1.18*** (0.291)
UN_macroregion=South-Eastern Asia					1.11*** (0.240)
UN_macroregion=Southern Asia					1.47 (0.276)
UN_macroregion=Southern Europe					0.54 (0.221)
R^2 adj.	0.198	0.365	0.628	0.697	0.841
N	68	68	68	68	68

First, we see that in all models, higher crime rate predicts more opposition (all betas are positive). As expected, adding the colonial dummy increased the beta for crime rate (β = 0.44→0.55, models 1→2). Second, Muslim% was also a predictor beyond the crime rates (β = 0.27 to 0.50, models 3-5). Adding controls for continents decreased the effect size for Muslim% (β = 0.50→0.27, model 3→4) but not crime rate (β = 0.33→0.37). Adding macroregions decreased the effect size of both crime rate (β = 0.33→0.21, model 3→5) and Muslim percentage (β = 0.50→0.35). Not too much can be made of some of the smaller changes because the standard errors are fairly large given the sample size of 68.

As a robustness test, we examined the correlations using the crime rates computed for each immigrant generation. Table 2 shows the correlations among the variables.

Table 2. *Correlations among main variables. 1st and 2nd refer to immigrant generations. Prop 2nd = proportion of population who is second generation immigrant. Weighted correlations below the diagonal.*

	Suspect rate	Suspect rate 1st	Suspect rate 2nd	Muslim	IQ	Net opposition	Prop 2nd
Suspect rate		0.96	0.90	0.44	-0.66	0.57	-0.08
Suspect rate 1st	0.95		0.80	0.39	-0.66	0.58	-0.24
Suspect rate 2nd	0.91	0.76		0.43	-0.59	0.58	-0.09
Muslim	0.45	0.27	0.43		-0.42	0.66	-0.07
IQ	-0.64	-0.56	-0.55	-0.52		-0.71	0.30
Net opposition	0.46	0.41	0.53	0.68	-0.63		-0.48
Prop 2nd	-0.02	-0.19	-0.02	0.10	0.18	-0.43	

The results broken down by immigrant generation were quite similar, sometimes a bit weaker. This does not necessarily imply a confound because the correlations by generation are based on smaller samples which produce noisier estimates for each origin group, and thus weaker correlations.

We conducted several other robustness tests. First, we compared results using Rindermann's national IQ estimates. These were calculated independently from Lynn and Becker's calculations, and give more weight to the scholastic ability (school) tests such as PISA. The results however were mostly the same. Second, we computed a raw version of the net opposition metric, without weighting to control for over-sampling of left-wing voters. This however correlated .96 with the weighted version and did not produce any notable differences. Third, we examined the main scatterplots for evidence of nonlinearity. However, the results indicated a general lack of nonlinearity in that the error bars of the smoothed fit (LOESS) almost always overlapped the linear fit. Fourth, by reviewer request, we fit models containing an interaction term between colonial status and crime rate. These models produced similar results for our main variable of interest (crime rate) and varying estimates for colonial heritage and its interaction with crime rate, but with large standard errors which limit their interpretation. Fifth, we ran the regressions without the imputed Muslim%. This did not result in any notable differences. Sixth, we ran analyses with our alternative crime measure, arrest rates. However, these correlated .995, so the results were practically identical. Full output from these robustness tests can be found in the supplementary materials.

Discussion

We found that differences in crime rates between origin-based immigration groups were large, up to a factor of 17 between the most criminal (Netherlands Antilles) and the least (Japan). The relative differences in crime rates were well-predicted by the origin characterstics of national IQ and Muslim percentage as well as their combination, as found in many previous studies (Kirkegaard, 2017) as well as the previous Dutch study (Kirkegaard, 2015). Population-wide, the crime rate has been decreasing in the Netherlands and many other countries for hundreds of years (Pinker, 2012). This decrease still seems to be happening in northern and western European countries despite growing immigrant populations with above average crime rates. This seeming contradiction is explained in part by the aging of the native populations combined with the lower crime rates of the elderly, which more than offsets the increase from the rising numbers of younger and more crime-prone immigrants. However, some categories of crime show some recent upticks in relation to the migrant wave of 2015-2017, in particular rapes and other violent crimes (Pallesen, 2018; Sanandaji, 2017).

We furthermore conducted a replication study of Carl (2016), who studied the relationship between crime rates and immigrant preferences. Specifically, Carl reasoned that sensible voters would base their immigration preferences partly on variables such as crime rates, and to the extent voters are aware of real group differences in crime rates, their preferences will be correlated with the real crime rates. He found this to be the case (r = .69) for the United Kingdom using two surveys with an overlapping set of 23 countries of origin. In the present study, we had access to a much larger set of 68 countries. We also find that our estimated crime rates are moderately strongly related to immigrant preferences, population weighted r = .46 and unweighted r = .57. The pattern was weaker than the UK results, mainly due to the Dutch colonial (ex-)possessions. The public seems to be willing to grant these some leeway with allowing immigration despite the high crime rates of some of them, perhaps as a sort of reparation payment. We furthermore ran a number of regressions to see if the predictive power of crime rate was merely due to some obvious confounding factor. However, we found that it retains much validity in the face of plausible confounders. A diagram of our conceptual causal model is shown in Figure 8.

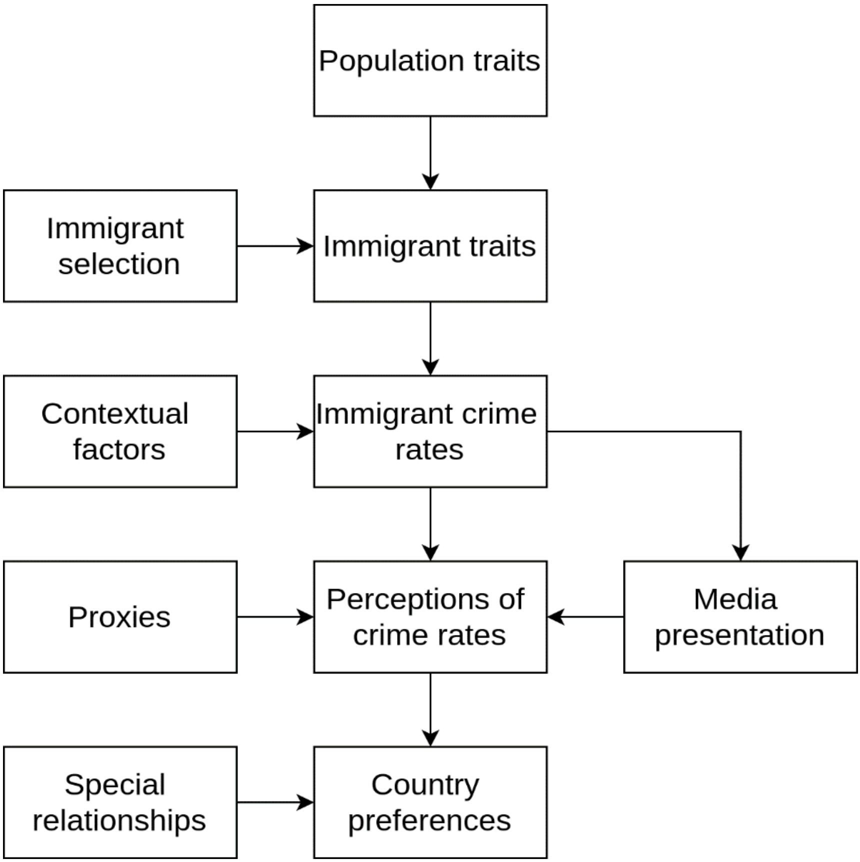

Figure 8. *Conceptual causal model of immigrant crime rates, perceptions and preferences.*

In the model, origin populations are assumed to vary in traits such as intelligence, time-preference, testosterone level and so on. These traits are then brought with the immigrants when they migrate to a new country (spatial transferability), modified by selection effects. After this, the different immigrant groups in the destination country also vary in their traits, and this gives rise to variations in crime rates, which are also influenced by contextual factors such as age and sex composition, duration of stay, cultural conflicts and so on. These real differences in crime rates then give rise to stereotypes, understood as subjective perceptions about group differences (Jussim, 2018). The perceptions are also caused by media reports and various proxies. Few people memorize detailed reports of crime rates, so they rely on proxies such as geographical location of countries or their wealth levels. Finally, these perceptions cause people to modify their preferences for immigrants from specific countries, which is also affected by special relationships between the countries (e.g. colonial history). The current study did not measure all the relevant variables, but focused on three of the variables in the main (middle column) pathway, and showed that they were related as expected from the model. Furthermore, the addition of detailed geographical proxies (model 5 in Table 1) reduced the relationship between crime rates and preferences, in line with the model (since people rely on proxies in part).

Limitations

First, we only investigated one broad outcome, crime, whereas many others are possible (e.g. use of social welfare) and plausibly affect public perception as well. However, according to survey data from the UK cited by Carl (2016), violent crime proneness is the most important variable people consider.

Second, related to the first, crime rates are difficult to estimate empirically since these are rare events (being the suspect of a crime) and thus unstable in small populations. Furthermore, insofar as the goal is to estimate criminal propensity of a population, one will need to adjust for the age and sex distributions of the population which are generally considered exogenous variables. It was not possible to do so completely in our data. We used population data for age 12-45 since this is the main age span where people commit crimes, but a prior study of Danish and German data showed that more detailed adjustments matter little for *relative* differences in crime rates between immigrant populations (Kirkegaard & Becker, 2017). The very strong correlation of our crime rates with those from the prior study ($r = .96$) suggests age and sex confounding is not a large problem in this case either.

Third, our survey of Dutch persons to estimate the immigration preferences was smaller than typical public surveys owing to cost limitations, and furthermore was not politically representative. We adjusted for the political representation using the party vote in the last election, but this did not seem to affect results much. It is possible it was unrepresentative in other ways we did not study. We did not have age, sex, education information about the subjects, so we were unable to calculate representativeness in terms of these.

Fourth, our use of national origin country-level data assumes that the immigrant groups are representative of their origin populations, and that we have reliable estimates of the origin country's characteristics themselves. The estimates of national IQs, based on Richard Lynn's work, have in particular been questioned (Hunt & Sternberg, 2006; Wicherts et al., 2010). Recently, however, David Becker independently redid all the data extraction from the original sources as well as every calculation (Flynn effect adjustment, age adjustments, quality weights etc.). His work is described in a recent book coauthored with Lynn (Lynn & Becker, 2019). Generally speaking, the estimates can be considered quite reliable for many countries, but not all, and much work remains to be done examining questionable aspects of measurement invariance (Dutton et al., 2018; Kirkegaard, 2019c).

Aside from the question of the country estimates, it is well known that immigrants tend to be self-selected on traits evident inside their countries of origin (non-random emigration) (Aksoy & Poutvaara, 2019; Connor, 2019; Hamilton & Hummer, 2011; Knudsen, 2019) and in their choice of destination country, and by the need to obtain legal rights to live in the destination country (non-random immigration). It is possible to account for some such selectivity factors, for instance using the Brain Drain dataset (https://www.iab.de/en/daten/iab-brain-drain-data.aspx), but it requires a more complex approach than used here and is left for future research (see for example Fuerst & Kirkegaard, 2014). It should be noted, however, that selection would probably have to be unrealistically strong to overcome the national differences (see also Pesta et al. (2019) with regards to potential immigrants and GRE testing scores). Furthermore, selection that is similar across sending countries (e.g. everybody sends elites, say, the top 5%) does not alter conclusions from the kinds of analyses in this study since they don't affect relative differences between groups, only the intercept. This conclusion depends on the additional assumption of equal variances across sending countries, which is known not to be entirely true (Kirkegaard & Tranberg, 2015; Meisenberg, 2008; Rindermann, 2018, Chapter 8). However, generally speaking, the point stands that for selection to notably affect the results, it must be in the form of differential selection, either from the sending countries themselves (e.g. country A sends higher class people and country B sends lower class people), or among incoming immigrants in the host country (e.g. a host country decides to accept higher class people from country A but lower class from country B).

Supplementary materials

R analysis code and full dataset are available at https://osf.io/46pwz/ and at https://rpubs.com/EmilOWK/Dutch_immigrant_crime_2019.

Acknowledgements

We wish to thank an anonymous sponsor without whom this research would not be possible. The sponsor had no influence on the study design or publication.

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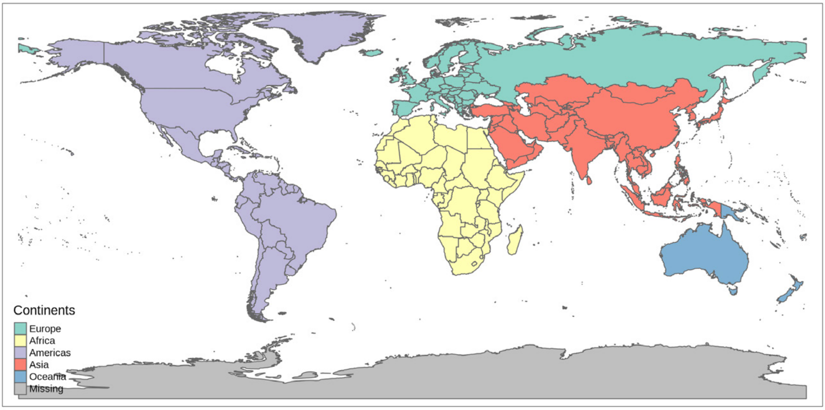
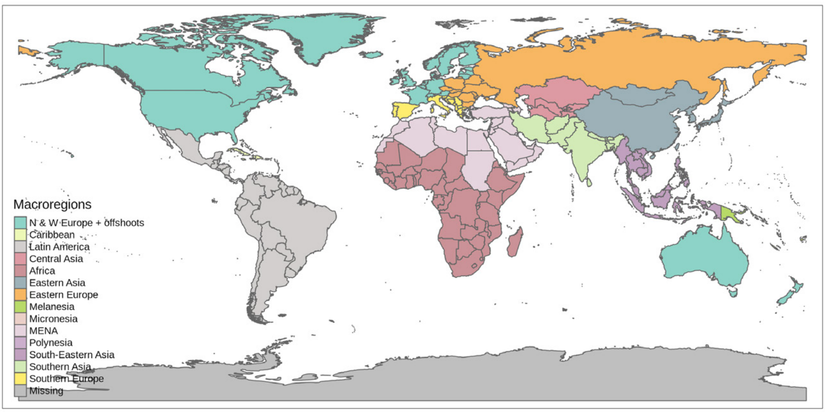
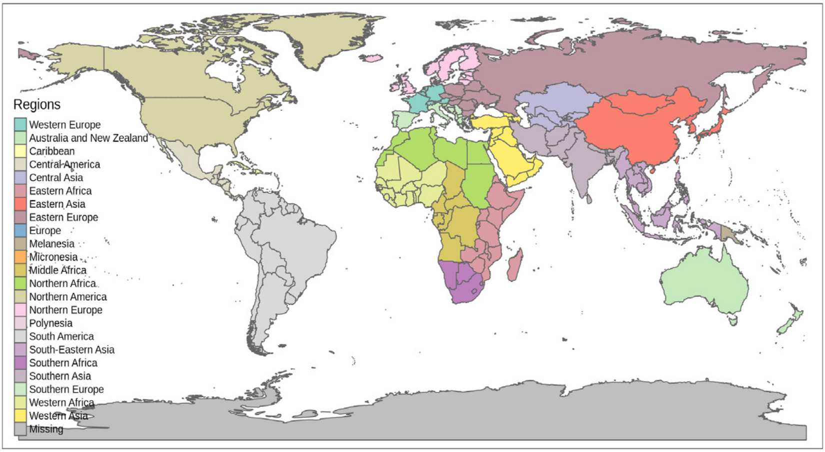
Appendix

Maps of regional coding. Continents and regions are given by the UN, and macroregions are an aggregate based on the UN regions. The regions were not used in this study, but given here for reference.







Main data table. *Average values across years given for population and crime rates.*

Origin	Cont.	Macroreg.	Pop.	Sus rate	Sus rate RR	Sus rate 1st RR	Sus rate 2nd RR	Muslim	IQ	Net opp
Afghanistan	Asia	S. Asia	25016.14	0.04	2.05	2.1	1.37	1	75	-0.06
Algeria	Africa	MENA	4219.5	0.07	3.24	2.73	3.64	0.98	84.2	-0.02
Angola	Africa	Africa	5755.86	0.07	3.52	3.65	2.76	0.01	71	-0.06
Argentina	Americas	Latin America	2669	0.01	0.65	0.26	1.24	0.02	92.8	-0.58
Australia	Oceania	N & W Europe + offshoots	10573	0.02	1.16	0.36	1.53	0.02	99.2	-0.74
Austria	Europe	N & W Europe + offshoots	5951.36	0.02	1.11	0.77	1.33	0.06	99	-0.72
Belgium	Europe	N & W Europe + offshoots	41977.07	0.02	1.23	0.95	1.42	0.06	99.3	-0.71
Brazil	Americas	Latin America	11406	0.02	1.15	1.07	1.39	0	85.6	-0.52
Bulgaria	Europe	E. Europe	11523.07	0.03	1.55	1.48	3.01	0.13	93.3	-0.09
Canada	Americas	N & W Europe + offshoots	9540.14	0.02	0.88	0.41	1.13	0.03	100.4	-0.68
Cape Verde	Africa	Africa	11495.93	0.06	3.08	2.44	3.52	0	76	-0.34
Chile	Americas	Latin America	2752.79	0.03	1.65	1.17	2.16	0	89.8	-0.49
China	Asia	E. Asia	36051.57	0.01	0.49	0.48	0.51	0.02	105.8	-0.38
Colombia	Americas	Latin America	7189.14	0.04	1.83	1.66	2.27	0	83.1	-0.49

Origin	Cont.	Macroreg.	Pop.	Sus rate	Sus rate RR	Sus rate 1st RR	Sus rate 2nd RR	Muslim	IQ	Net opp
Congo (D. R.)	Africa	Africa	4618.14	0.06	3.07	3.29	2.49	0.01	68	-0.09
Denmark	Europe	N & W Europe + offshoots	2965.07	0.01	0.7	0.39	1.1	0.04	97.2	-0.72
Dominican Republic	Americas	Caribbean	6864.57	0.07	3.53	3.25	4.35	0	82	-0.38
Egypt	Africa	MENA	10597.86	0.04	1.94	1.4	2.6	0.95	82.7	-0.2
Ethiopia	Africa	Africa	8016.57	0.04	2.03	1.72	3.04	0.34	68.5	0.01
Finland	Europe	N & W Europe + offshoots	2604.14	0.01	0.5	0.16	1.18	0.01	100.9	-0.61
Former Czechoslovakia	Europe	E. Europe	8049.86	0.02	0.96	0.84	1.32	0	98.6	
Former Soviet Union	Europe	E. Europe	36559.14	0.03	1.53	1.53	1.61	0.05	96.6	
Former Yugoslavia	Europe	S. Europe	43570.57	0.04	2.05	1.84	2.49	0.08	92.33	-0.16
France	Europe	N & W Europe + offshoots	21128.21	0.02	0.93	0.68	1.26	0.08	98.1	-0.71
Germany	Europe	N & W Europe + offshoots	107339.5	0.02	1.04	0.73	1.27	0.05	98.8	-0.73
Ghana	Africa	Africa	10561	0.05	2.27	1.62	3.42	0.16	69.7	0.01
Guyana	Americas	Latin America	2099.79	0.05	2.44	1.91	2.82	0.07	81	-0.14
Hong Kong	Asia	E. Asia	9935	0.01	0.55	0.46	0.59	0.01	105.7	-0.49
Hungary	Europe	E. Europe	8932.21	0.02	0.94	0.78	1.34	0	98.1	-0.36
India	Asia	S. Asia	14997.43	0.01	0.64	0.44	1.51	0.15	82.2	-0.23
Indonesia	Asia	S.E. Asia	147590.21	0.02	0.92	0.46	0.97	0.88	85.8	-0.47
Iran	Asia	S. Asia	18965.86	0.04	2.19	2.22	1.98	1	85.6	-0.09
Iraq	Asia	MENA	29432.5	0.05	2.4	2.41	2.35	0.99	87	0
Ireland	Europe	N & W Europe + offshoots	4658.93	0.02	1.06	0.58	1.6	0.01	94.9	-0.67
Israel	Asia	MENA	4900	0.02	0.98	0.75	1.31	0.18	94.6	-0.37
Italy	Europe	S. Europe	23803.36	0.02	1.23	0.8	1.63	0.03	96.1	-0.63
Japan	Asia	E. Asia	4322.5	0	0.22	0.14	0.59	0	104.2	-0.67
Lebanon	Asia	MENA	2913.29	0.05	2.3	2.19	2.5	0.6	84.6	-0.15
Malaysia	Asia	S.E. Asia	2840.79	0.01	0.57	0.34	0.81	0.61	91.7	-0.29
Mexico	Americas	Latin America	2914.29	0.01	0.34	0.32	0.41	0	87.8	-0.38
Morocco	Africa	MENA	199533.64	0.07	3.66	2.49	4.74	1	82.4	-0.01
Netherlands Antilles	Americas	Caribbean	81888.5	0.08	3.81	4.4	2.98	0	87	-0.57
New Zealand	Oceania	N & W Europe + offshoots	3428.21	0.02	1.06	0.4	1.44	0.01	98.9	-0.77
Nigeria	Africa	Africa	5698.14	0.04	2.03	1.91	2.28	0.48	71.2	-0.03
Norway	Europe	N & W Europe + offshoots	2245.07	0.01	0.55	0.21	1.05	0.03	97.2	-0.66
Pakistan	Asia	S. Asia	11386.14	0.03	1.54	1.26	1.94	0.96	84	0.06

Origin	Cont.	Macroreg.	Pop.	Sus rate	Sus rate RR	Sus rate 1st RR	Sus rate 2nd RR	Muslim	IQ	Net opp
Peru	Americas	Latin America	2908	0.02	0.85	0.61	1.46	0	84.2	-0.37
Philippines	Asia	S.E. Asia	9719.86	0.01	0.74	0.47	1.27	0.05	86.1	-0.35
Poland	Europe	E. Europe	61822.07	0.02	1.22	1.2	1.42	0	96.1	-0.21
Portugal	Europe	S. Europe	12607.5	0.03	1.45	1.42	1.51	0.01	94.4	-0.71
Romania	Europe	E. Europe	10918.64	0.02	1.09	1.03	1.61	0	91	-0.27
Sierra Leone	Africa	Africa	4261.57	0.06	2.95	2.98	2.4	0.72	64	-0.02
Singapore	Asia	S.E. Asia	2429.36	0.01	0.57	0.24	0.87	0.15	107.1	-0.46
Somalia	Africa	Africa	17921.36	0.06	2.95	2.8	4.12	0.99	72	0.08
South Africa	Africa	Africa	10580.64	0.02	0.89	0.69	1.14	0.02	71.6	-0.54
South Korea	Asia	E. Asia	3059.43	0.01	0.51	0.24	1.52	0	104.6	-0.55
Spain	Europe	S. Europe	21226.57	0.02	1.07	0.65	1.52	0.02	96.6	-0.76
Sri Lanka	Asia	S Asia	5509.64	0.03	1.39	1.3	1.69	0.08	79	-0.15
Sudan	Africa	MENA	3998.5	0.04	1.83	1.8	2.23	0.71	77.5	0.05
Suriname	Americas	Latin America	182732.79	0.06	2.79	2.47	3.01	0.16	89	-0.65
Sweden	Europe	N & W Europe + offshoots	3577.36	0.01	0.61	0.45	0.92	0.05	98.6	-0.77
Switzerland	Europe	N & W Europe + offshoots	5092.64	0.02	0.74	0.61	0.88	0.06	100.2	-0.72
Syria	Asia	MENA	13836	0.03	1.57	1.5	2.29	0.93	82	-0.12
Thailand	Asia	S.E. Asia	9868.64	0.02	0.9	0.66	1.87	0.06	93.9	-0.43
Netherlands	Europe	N & W Europe + offshoots	4826127	0.02	1			0.06	100.4	
Tunisia	Africa	MENA	4871.14	0.06	3.1	2.63	3.46	1	85.4	-0.13
Turkey	Asia	MENA	230197	0.04	2.08	1.57	2.55	0.99	89.4	-0.03
UK	Europe	N & W Europe + offshoots	39369	0.02	1.03	0.71	1.37	0.05	99.1	-0.67
USA	Americas	N & W Europe + offshoots	18612.29	0.02	0.78	0.55	1.21	0.01	97.5	-0.52
Venezuela	Americas	Latin America	3378.5	0.02	1.21	1.32	1.05	0	83.5	-0.34
Vietnam	Asia	S.E. Asia	11108.5	0.02	1.08	1.14	1	0	91.4	-0.45

Cont.= UN continent; Macroreg.= UN macroregion; Sus. = Suspect; Net opp. = Net opposition.