Statistical Power in Immigration–Crime Studies: A Comment on Riaz (2026)

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Abstract

Riaz (2026) argues that regional studies of immigration and crime lack statistical power because aggregate crime rates dilute the contribution of immigrants: even the composition effect of adding a group with a higher crime rate can be detected only if that rate is implausibly high relative to natives'. His power simulation for the refugee immigration shock in German counties in 2014–2016 implies that a first-difference design reaches 80 per cent power only if refugees offend at least 15 times as often as natives. I show that this result rests on the calibrated residual volatility in county crime changes, which comes almost entirely from immigration-law offences, recorded in a few counties on the Austrian border. These offences record the act of migration rather than offending by immigrants, and most studies exclude them. Without them, the residual volatility falls by a factor of 9.1, and the design reaches 80 per cent power at an immigrant–native crime rate ratio of 2.64, below the ratio of about 5.2 observed for asylum seekers in 2016 suspect data.

Keywords: immigration; crime; refugees; statistical power; police crime statistics; Germany

1 Introduction

Riaz (2026) argues that studies of the effect of local immigration on local crime rates are underpowered, as aggregate crime statistics dilute the contribution of immigrants. He examines the design that underlies much of this literature, a regression of the change in a region's crime rate on the (exogenous) change in its immigrant share. Most such studies fail to reject the null that immigration does not increase crime, but also rely on immigration shocks that are modest relative to the native population. Riaz therefore asks whether these designs have sufficient power to detect even the compositional effect of adding a group with a higher crime rate, assuming that the crime rates of the pre-existing population do not respond to the inflow. He calculates the minimum detectable crime rate ratio, the smallest ratio of the immigrant to the native crime rate that the design detects with 80 per cent power at the 5 per cent level. In a Monte Carlo simulation calibrated to crime data and the refugee inflow across German counties in 2014–2016 (an increase in the refugee share of about one percentage point, with a standard deviation of 0.68 percentage points), the design reaches 80 per cent power only if refugees offend at least 15 times as often as natives. He concludes that many null results in this literature are "null by design".

In this comment, I show that this result rests on the crime measure used to calibrate the residual volatility, the variation in county crime changes that the refugee inflow does not explain. Riaz's measure of total recorded crime includes immigration-law offences, mainly unauthorized entry and stay, which were recorded in a few counties on the Austrian border where refugees crossed into Germany, and which most German studies exclude. Without these offences, the design reaches 80 per cent power at an immigrant–native crime rate ratio of 2.64 for the 2014–2016 inflow, below the ratio of about 5.2 observed for asylum seekers in 2016 suspect data. My comment covers a case with a large migration shock, the case that Riaz presents as most favourable to these designs: I do not dispute his analytic argument or that his concern is valid for smaller shocks.

2 Original simulation

2.1 Setup

Riaz simulates a first-difference design across $n = 390$ counties, $\Delta y_i = r\,\Delta S_i + \Delta\varepsilon_i$, estimated by OLS with an intercept. Here Δy_i is the change in crimes per inhabitant, ΔS_i the change in the refugee share, and $r = c_I - c_N$ the difference between the immigrant and native crime rates. The baseline crime rate c_N is calibrated as the 2014 crime rate, the population-weighted mean of county crimes per inhabitant. Immigration shocks are drawn as $\Delta S_i \sim N(\bar{S}, (CV \cdot \bar{S})^2)$, where $\bar{S}$ is the mean shock and CV its coefficient of variation, matching the refugee inflow into German counties in 2014–2016, and idiosyncratic noise as $\Delta\varepsilon_i \sim N(0, \sigma^2_{\Delta\varepsilon})$. The minimum detectable crime rate ratio is then $c_I/c_N \approx 1 + 2.8\,\sigma_{\Delta\varepsilon}/(CV\,\bar{S}\sqrt{n}\,c_N)$.

Riaz calibrates the residual volatility $\sigma_{\Delta\varepsilon}$ as the standard deviation of the residuals from an OLS regression of the observed 2014–2016 change in county crime rates on the observed change in the refugee share, with total recorded crime in the police crime statistics (*Polizeiliche Kriminalstatistik*, PKS) as the outcome (Riaz 2026, SI Section E). His replication package contains the parameter values but not the code that produces them. I reconstructed them from the public PKS county tables and Federal Statistical Office data (Appendix Table A1), matching his sample size, the mean and dispersion of the shock, and $\sigma_{\Delta\varepsilon}$ to the sixth decimal (Table 1, columns 1 and 2).[1]

2.2 The role of immigration-law offences in the calibration

The total recorded crime data used to calibrate the simulation parameters include immigration-law offences, that is, offences against residence, asylum and freedom-of-movement law (PKS key 725000), which mainly consist of unauthorized entry and stay. Almost all suspects in these offences are non-Germans (Bundeskriminalamt 2017a, p. 16). The PKS county tables record 155,850 such offences in 2014, 2.6 per cent of all 6.03 million recorded offences, and 486,631 in 2016, 7.7 per cent of 6.29 million, while crime excluding them fell.

[1] The only parameter I do not match exactly is the baseline crime rate c_N. The difference is only 0.09 per cent.

Most of the increase was recorded at points of entry on the Austrian border. Berchtesgadener Land, Rosenheim district, Rottal-Inn and Passau city, which together hold only 0.65 per cent of the population, recorded 56 per cent of the increase in these offences. In Berchtesgadener Land, recorded crime rose from 0.09 to 1.03 crimes per inhabitant (an increase of 1,096 per cent), while crime excluding immigration-law offences was 0.047 in 2014 and 0.046 in 2016. Figure 1 shows the consequence for the changes in county crime rates, and Appendix Table B1 lists the counties with the largest relative increases. The standard deviation of the change in crime rates across counties is 0.052 crimes per inhabitant (against a 2014 average crime rate of 0.074), and it is driven largely by these four counties. They have the four largest absolute increases and account for 96 per cent of the squared residuals, Berchtesgadener Land alone for 84.5 per cent. Dropping the four counties while keeping all crimes reduces the standard deviation of the changes from 0.052 to 0.0093. Excluding immigration-law offences yields a standard deviation of only 0.0057; the long right tail in Figure 1 disappears.

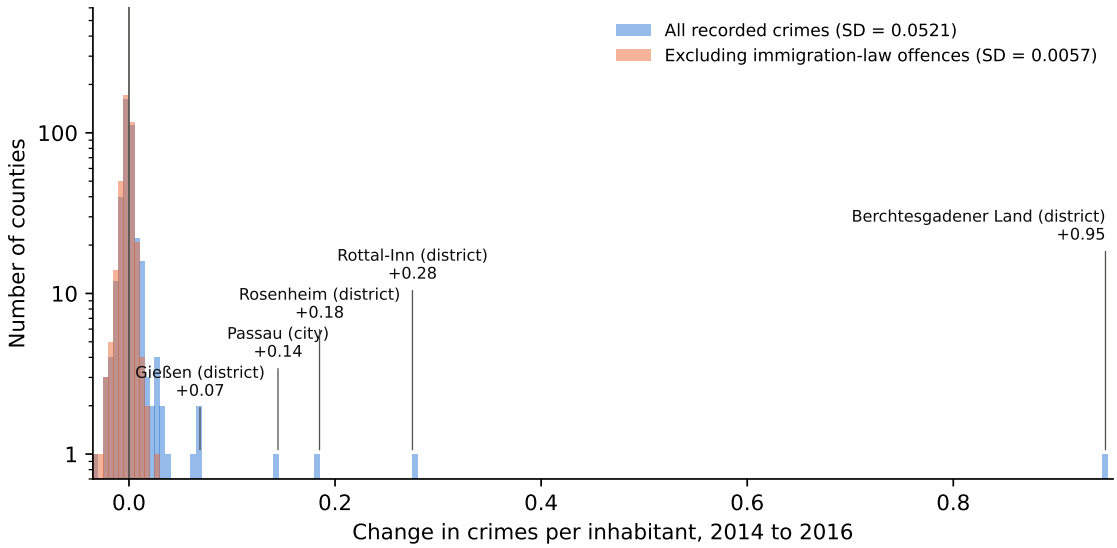


Figure 1: Changes in county-level crime rates, 2014–2016

Notes: Distribution of the 2014–2016 change in recorded crimes per inhabitant across the 390 counties in Riaz's sample, with and without immigration-law offences (offences against residence, asylum and freedom-of-movement law). Bins are 0.005 wide; the vertical axis is logarithmic. The labelled counties have the five largest changes in all recorded crimes; excluding immigration-law offences, their changes lie between −0.001 and 0.005. Sources: Appendix Table A1.

Because $\sigma_{\Delta\varepsilon}$ is the standard deviation of the residuals after regressing Δy_i on ΔS_i,

the calibration is meant to count as residual volatility only the variation in crime that the local refugee inflow does not explain. Yet this step does not remove the influence of immigration-law offences at the border. They are recorded where refugees crossed the border, whereas ΔS_i measures where refugees lived at the end of the year, after their distribution across Germany, so the increases in the border counties are unrelated to those counties' own refugee shares.[2] Hence, the immigration-related offences at the border also strongly impact the calibration of $\sigma_{\Delta\varepsilon}$.

Table 1 shows that excluding immigration-law offences reduces the residual volatility $\sigma_{\Delta\varepsilon}$ from 0.052 to 0.0057. These values are almost identical to the standard deviations of the raw changes reported above, because the change in the refugee share explains almost none of the variation in crime changes. Appendix Table B2 also shows that in a period without many newly arriving asylum applicants, 2017–2019, the residual volatility in changes in crime rates both including and excluding immigration-law offences is low. With all recorded crimes, it is 0.0067 in that period, close to the value of 0.0057 that I obtain for 2014–2016 without immigration-law offences.

Table 1: Calibration of the first-difference design

	Riaz (2026)	Reconstruction	
		All crimes	Excl. immigration law
	(1)	(2)	(3)
Baseline crime rate 2014, c_N	0.0743	0.0742	0.0723
Residual volatility, $\sigma_{\Delta\varepsilon}$	0.0521	0.0521	0.0057
Minimum detectable c_I/c_N	15.5	15.5	2.64

Notes: All columns use the same 390 counties and the same immigration shock: an average county change in the refugee share of 1.0 percentage point between 2014 and 2016, with a standard deviation of 0.68 percentage points. Column 1 reports the values in Riaz's replication file. Columns 2 and 3 reconstruct the calibration from public data, using all recorded crimes or excluding immigration-law offences. The minimum detectable ratio is the immigrant–native crime ratio detected with 80 per cent power at the 5 per cent level, computed from the formula in Section 2.1 for the 2014–2016 shock.

[2]Once they have submitted their asylum claims, asylum seekers are dispersed and receive permission to reside for the duration of the asylum procedure (*Aufenthaltsgestattung*, § 55 AsylG), so they can no longer commit most immigration-law offences.

3 Excluding immigration-law offences

One might object that immigration-law offences are offences committed by immigrants and therefore belong in the immigrant crime rate c_I. Excluding them, however, does not remove the effect that the design is meant to detect. That effect concerns offences that natives and immigrants can both commit, such as theft or assault, whereas immigration-law offences record the border crossing itself, in the county where it took place. Even if one counted them as offending by immigrants, they would not enter the design as a signal: they were recorded in a few border counties, not in the counties whose refugee share rose, so they add to the residual volatility rather than to the slope.

The residual volatility in Riaz's calibration is therefore specific to this setting: the refugee inflow and the way immigration law records it. Using the same data would still be defensible if most studies did so, because the power calculation would then describe the designs actually used. Table 2 shows that they do not. Regional studies of the post-2014 refugee inflow in Germany exclude these offences, because only foreigners can commit them and because they record the act of migration rather than offending after arrival. The exception, Maghularia and Uebelmesser (2023), notes that its highest crime rate, in Berchtesgadener Land in 2016, reflects the refugee inflow at the Austrian border (p. 489), but does not adjust for this in the analysis.[3] Crime excluding immigration-law offences is thus the outcome that most studies of the inflow use, and the appropriate one for calibrating $\sigma_{\Delta\varepsilon}$.

4 Simulation without immigration-law offences

I rerun Riaz's Monte Carlo simulations with his data-generating process, number of draws and test, varying only c_N and $\sigma_{\Delta\varepsilon}$. I reproduce his Figure 2 in Panel A of Figure 2 using slightly different axis ranges and show the results of the simulation based on the calibration without immigration-law offences in Panel B. Under his calibration (Panel A), 80 per cent power at Germany's 2014–2016 immigration shock of one percentage point requires an

[3] The Federal Criminal Police Office also explicitly reports totals without these offences (Bundeskriminalamt 2017b, p. 5).

Table 2: Treatment of immigration-law offences in regional studies of immigration and crime in Germany

Study	Period	Immigrant group	Immigration-law offences	Stated reason
Panel A. Studies covering the 2014–2016 refugee inflow				
Dehos (2021, p. 8)	2010–2015	Asylum seekers, recognized refugees	Excluded	Undocumented entry or stay is itself an offence; natives cannot commit them
Gehrsitz and Ungerer (2022, pp. 600, 615)	2013–2017	Refugees	Excluded	Entry over land violates the Dublin Regulation; the rise in crime disappears without them
Maghularia and Uebelmesser (2023, p. 489)	2008–2019	Foreigners	Included	–
Lange and Sommerfeld (2024, p. 7)	2013–2018	Refugees	Excluded	Administrative offences that only immigrants can commit
Huang and Kvasnicka (2026, p. 13)	2014–2016	Refugees	Excluded	–
Panel B. Studies of other periods				
Piopiunik and Ruhose (2017)	1996–2005	Ethnic German repatriates	Included	Not applicable: the immigrants are German citizens
Adema and Alipour (2025, p. 2)	2018–2023	Foreigners, protection seekers	Excluded	Only foreigners can commit them

immigrant–native crime rate ratio of 15.5. Without immigration-law offences (Panel B), the threshold is only 2.64. This shows that a much smaller crime rate ratio can be detected using these data.

Is a detectable crime rate ratio of 2.64 small or large for the 2014–2016 refugee inflow? As a benchmark, I compare the suspect rate of asylum seekers with that of the rest of the population in 2016 in Appendix C. Asylum seekers were suspected of a crime 5.2 times as often as everyone else, which would have been large enough to detect, with 80 per cent power, an inflow with mean 0.39 and standard deviation 0.27 percentage points.

At the benchmark ratio of 5.2 and the 2014–2016 shock, the two calibrations lead to opposite conclusions. Under Riaz's calibration, the design detects the benchmark ratio with probability 12 per cent (Panel A); without immigration-law offences, it does so with probability more than 99 per cent (Panel B), and still with 94 per cent at a shock of half the size. Riaz's concern does apply to smaller inflows. For the increase in the refugee share

between 2017 and 2019, whose standard deviation across counties was 0.24 percentage points, even the recalibrated design detects the benchmark ratio with a probability of only 71 per cent.

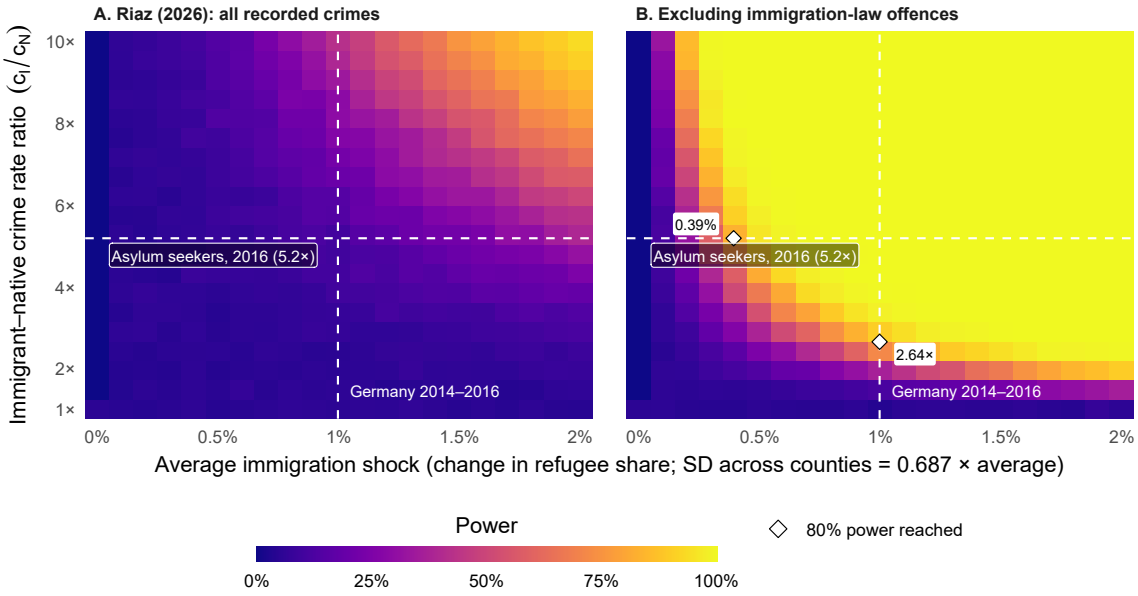


Figure 2: Power of the first-difference design under two calibrations

Notes: Each cell shows the share of 1,000 simulated datasets in which a two-sided test of a zero slope rejects at the 5 per cent level, in a regression of the change in crimes per inhabitant on the change in the refugee share across 390 counties. Panel A uses Riaz's calibration; Panel B excludes immigration-law offences (Table 1). The horizontal line marks the suspect rate of asylum seekers relative to that of the rest of the population in 2016 (Appendix C); the vertical line marks the average 2014–2016 shock. Diamonds mark where power reaches 80 per cent, computed from 10,000 simulated datasets; in Panel A this happens outside the plotted range, at 15.5 on the vertical line and at 3.5 percentage points on the horizontal line.

5 Conclusion

Riaz's point that aggregate designs dilute group differences is important, and researchers should consider the effect sizes their designs can detect. How severe the problem is, however, depends on the volatility of the outcome. In his Monte Carlo simulation calibrated to German data, the residual volatility comes almost entirely from immigration-law offences recorded in four border counties, offences that natives cannot commit and that most German studies exclude. With the standard outcome, the first-difference design detects an immigrant crime rate of 2.64 rather than 15.5 times the native rate at a shock like Germany's in 2014–2016, below the ratio of about 5.2 observed for asylum seekers in 2016 police data.

The compositional effect of the 2014–2016 refugee inflow on county crime rates was therefore probably large enough to be detected. This raises the question of why most studies of the inflow find no significant effect on crime. Two explanations are consistent with both findings. First, refugees may commit offences outside the county to which they were assigned, which presents an inherent limitation of local-inflow studies. Second, the criminal behavior of natives and of earlier immigrants may respond to the inflow, offsetting the compositional effect of adding a group with a higher crime propensity.

Two caveats apply to this reanalysis. First, I keep Riaz's stylized calibration and data-generating process; in settings with measurement error and heterogeneous effects the minimum detectable ratio can be larger, while the inclusion of controls could increase it (by absorbing variation in the immigration shock) or decrease it (by absorbing residual variation in the outcome). Second, designs with smaller immigration shocks, fewer units or noisier crime rates may indeed be underpowered. The minimum detectable ratio is the right tool to assess them, but it has to be computed from the outcome a study actually uses.

Data availability statement

The data, code, log files and replication instructions are available at https://jopieadema.github.io/replication/replication_riaz.zip.

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Use of artificial intelligence. The author used Claude Opus 5.5 (Anthropic), accessed through Claude Code in October 2026, to download and process the public data, to write and check the analysis code, and to edit the text. The author checked all results against the source data and takes full responsibility for the content of this article.

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Competing interests

The author declares none.

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Appendix A. Data sources

Table A1: Data sources

Variable	Source	Years
Panel A. Calibration (Tables 1, B1 and B2; Figures 1 and 2)		
Recorded crimes by county, all offences and immigration-law offences (key 725000)	Federal Criminal Police Office, PKS county tables, cases (Table 01)	2014, 2016, 2017, 2019
Population by county	Federal Statistical Office, GENESIS table 12411-0015	31 Dec. 2014, 2016, 2017, 2019
Refugees (protection seekers) by county	Federal Statistical Office, GENESIS table 12531-0040 (Central Register of Foreigners)	31 Dec. 2014, 2016, 2017, 2019
Calibration values of Riaz (2026)	Riaz's replication package, Harvard Dataverse, doi:10.7910/DVN/FJFWEI	2014–2016
Panel B. 2016 benchmark (Appendix C)		
Suspects in Germany by residence status, excluding immigration-law offences (key 890000)	Federal Criminal Police Office, PKS standard table 61	2016
Population of Germany	Federal Statistical Office, *Statistischer Bericht Schutzsuchende 2025*, table 12531-01	31 Dec. 2016
Asylum procedures pending and asylum applications in Germany	Federal Office for Migration and Refugees, *Das Bundesamt in Zahlen 2016*, pp. 10, 56, 60	31 Dec. 2015, 2016
Panel C. Distance to the border (Table B1)		
County boundaries	Eurostat GISCO, NUTS 2016, 1:1 million	2016

Notes: Immigration-law offences are offences against residence, asylum and freedom-of-movement law. The years 2017 and 2019 are used only for the 2017–2019 immigration shock in the text and for Table B2. Police and GENESIS data are used under the Data licence Germany – attribution – version 2.0 (dl-de/by-2-0); © EuroGeographics for the administrative boundaries.

Appendix B. Immigration-law offences and residual volatility

Table B1 lists the counties with the largest percentage increase in recorded crime between 2014 and 2016, with and without immigration-law offences. Table B2 repeats the calibration for the two-year window 2017–2019, after the large refugee inflow across the border had ended.

Table B1: Counties with the largest relative increase in recorded crime, 2014–2016

County	Crimes per inhabitant 2014	Crimes per inhabitant 2016	Change (%)	Within 25 km of border	Share of squared residuals (%)
Panel A. All recorded crimes					
Berchtesgadener Land (district)	0.086	1.034	1,096	✓	84.5
Rottal-Inn (district)	0.029	0.304	955	✓	7.0
Rosenheim (district)	0.067	0.252	277	✓	3.1
Passau (district)	0.038	0.103	173	✓	0.4
Passau (city)	0.108	0.253	134	✓	1.8
Five counties combined					96.9
Panel B. Excluding immigration-law offences					
Wesermarsch (district)	0.059	0.086	46		6.6
Kyffhäuserkreis	0.057	0.075	30		2.8
Harburg (district)	0.055	0.070	29		2.4
Lindau (Bodensee) (district)	0.040	0.048	21	✓	0.7
Ilm-Kreis	0.059	0.071	19		1.3
Five counties combined					13.7

Notes: The five counties with the largest percentage increase in recorded crimes per inhabitant between 2014 and 2016, among the 390 counties in Riaz's sample. Panel A uses all recorded crimes, as in Riaz (2026); Panel B excludes immigration-law offences, that is, offences against residence, asylum and freedom-of-movement law. A county is within 25 km of the border if any part of it lies within 25 km of a neighbouring country (Eurostat NUTS 2016 boundaries, 1:1 million). The last column gives each county's share of the sum of squared residuals from a regression of the change in crimes per inhabitant on the change in the refugee share across all 390 counties, using the outcome of the respective panel. Sources: Federal Criminal Police Office, PKS county tables 2014 and 2016; Federal Statistical Office, population and refugee statistics.

Table B2: Residual volatility during and after the refugee inflow

	2014–2016 (1)	2017–2019 (2)
Counties	390	390
Mean change in refugee share	0.0100	0.0015
SD of change in refugee share	0.0068	0.0024
Residual volatility $\sigma_{\Delta\varepsilon}$, all crimes	0.0521	0.0067
Residual volatility $\sigma_{\Delta\varepsilon}$, excl. immigration law	0.0057	0.0062

Notes: Calibration of the first-difference design for two two-year windows: 2014–2016, the window in Riaz (2026), and 2017–2019, after the inflow across the border had ended. Both columns use the same 390 counties as Table 1. The change in the refugee share is the change in protection seekers per inhabitant at 31 December. The residual volatility $\sigma_{\Delta\varepsilon}$ is the standard deviation of the residuals from a regression of the change in crimes per inhabitant on the change in the refugee share, using all recorded crimes or excluding immigration-law offences, that is, offences against residence, asylum and freedom-of-movement law. Column 1 repeats the values in Table 1, columns 2 and 3. Sources: Federal Criminal Police Office, PKS county tables 2014, 2016, 2017 and 2019; Federal Statistical Office, population and refugee statistics.

Appendix C. The 2016 benchmark

The power calculation asks whether the first-difference design could detect the compositional effect of the refugee inflow if it were the only channel at work, that is, if the crime rates of natives and earlier immigrants did not respond to the inflow. Whether the detectable crime rate ratio is small or large therefore depends on the actual ratio of the crime rate of asylum seekers to that of the rest of the population. This appendix estimates that ratio, c_I/c_N, the quantity on the vertical axis of Figure 2, from police suspect statistics for 2016.

Of the 2,022,414 suspects registered in 2016, excluding immigration-law offences, 137,385, or 6.79 per cent, were recorded by the police as asylum seekers. I approximate the number of asylum seekers in 2016 by the 364,664 procedures pending at the Federal Office for Migration and Refugees and the 58,974 asylum cases pending at administrative courts at the end of 2015, plus the 722,370 first applications filed in 2016 (Bundesamt für Migration und Flüchtlinge 2017, pp. 10, 56, 60). These 1,146,008 asylum seekers equal 1.39 per cent of the population, so their suspect rate is 11.99 per cent. The suspect rate of everyone else, the remaining suspects divided by the population minus asylum seekers, is 2.32 per cent. The ratio of the two rates, 5.18, is my estimate of c_I/c_N. The translation from suspects to recorded offences assumes that asylum-seeker suspects and other suspects are registered for the same number of offences on average. This count of asylum seekers is conservative, because it probably overestimates their number. It treats every applicant as present for the whole year, although many arrived during 2016 and some received a protection status or another decision during it, and the court figures also include cases on the revocation of a protection status, whose plaintiffs are not asylum seekers. A count that is too high lowers the suspect rate of asylum seekers and slightly raises that of everyone else, so the benchmark probably underestimates c_I/c_N.