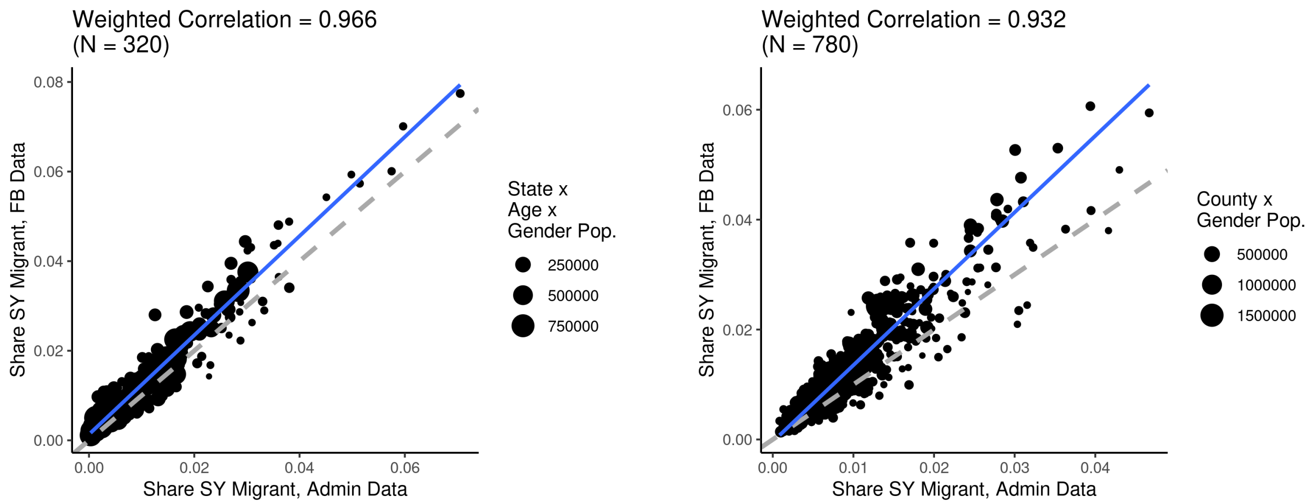
# 1 Additional Figures and Tables

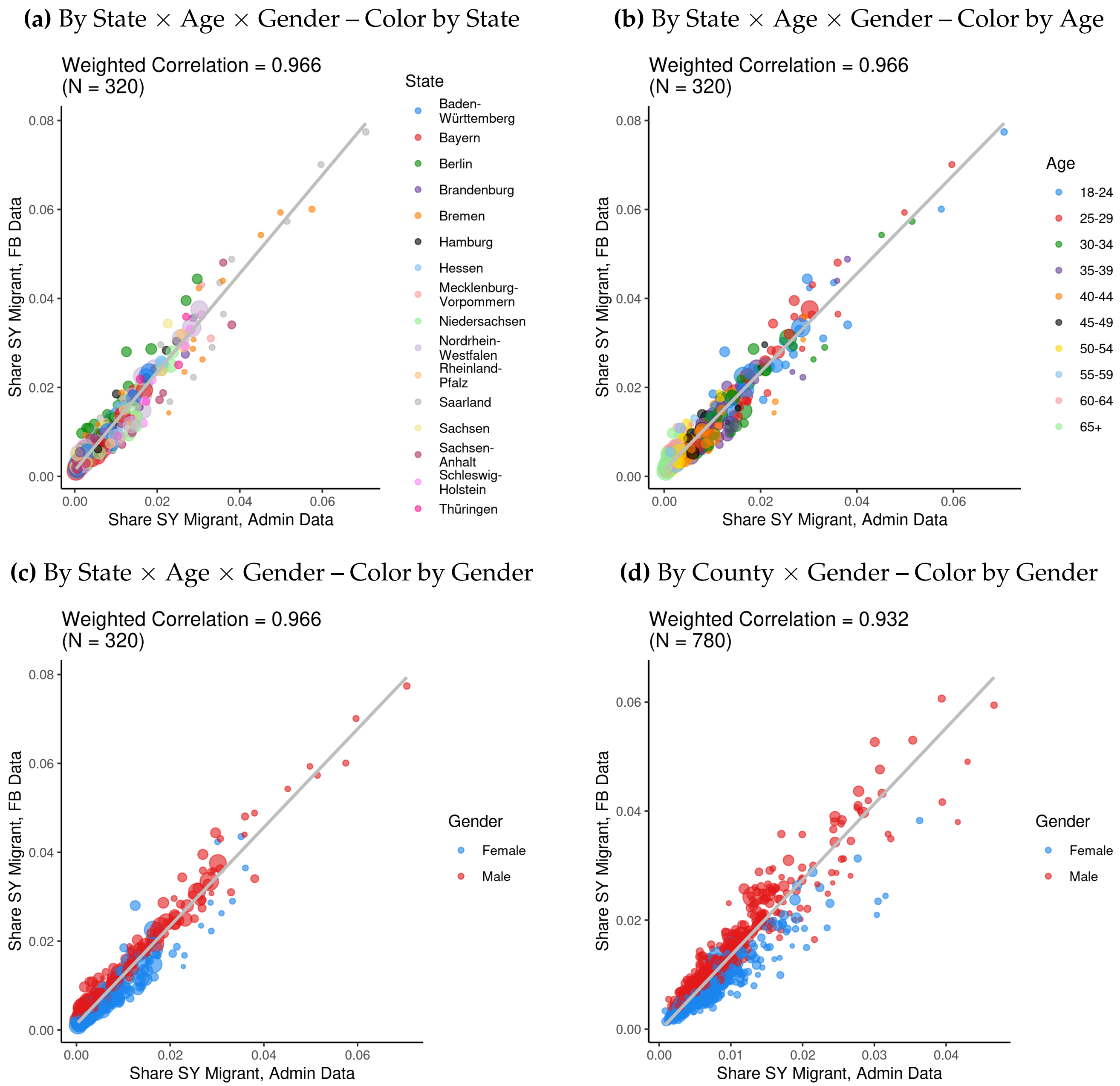
**Figure A1:** Syrian Migrant Sample vs. Admin Data

**(a)** By State × Age × Gender    **(b)** By County × Gender




**Note:** Figures show the shares of the primary sample of Facebook users that are also in the Syrian migrant sample (on the y-axis), against shares of the population that are Syrian from administrative data (on the x-axis). The size of each dot is proportional to the true population it represents. The solid blue lines are from weighted linear regressions. The dashed grey line is the line $y = x$. Panel (a) plots these shares by state × age × gender. The age groups are 18-24, 25-29, 30-24, 35-39, 40-44, 45-49, 50-54, 55-50, 60-64, and 65+. There are 16 states X 10 age groups X 2 genders = 320 observations. Panel (b) plots these shares by county × gender. Admin data is unavailable for 11 counties. There are 390 counties X 2 genders = 780 observations.

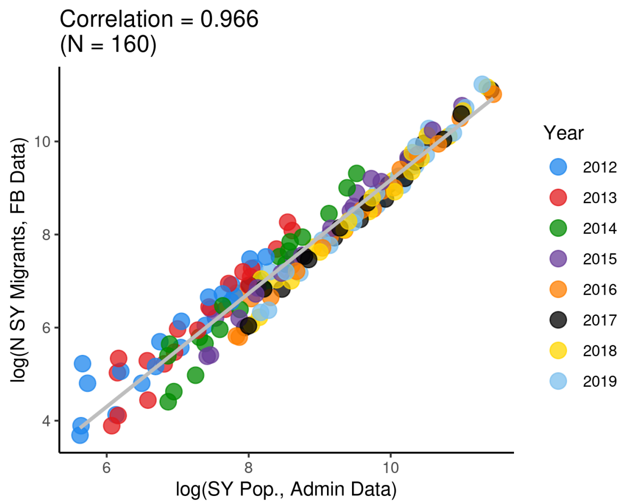
**Figure A2:** Syrian Migrant Sample vs. Admin Data



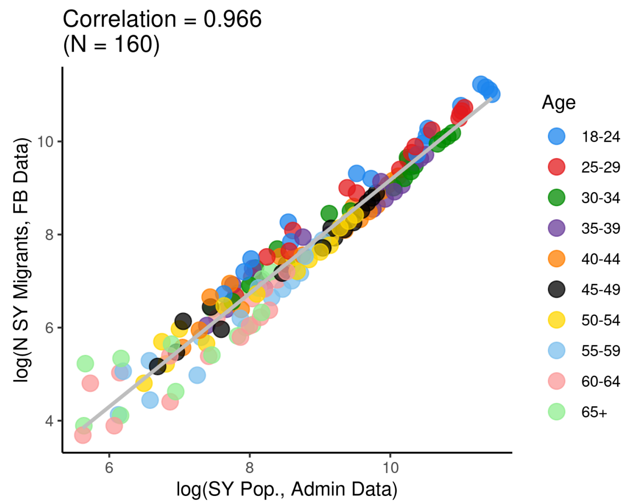

**Note:** Figures show the shares of the primary sample of Facebook users that are also in the Syrian migrant sample (on the y-axis), against shares of the population that are Syrian from administrative data (on the x-axis). The size of each dot is proportional to the size of the population it represents. The solid grey lines are from weighted linear regressions. Panels (a), (b), and (c) plot these shares by state, age, and gender. The age groups are 18-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-50, 60-64, and 65+. There are 16 states × 10 age groups × 2 genders = 320 observations. Panel (d) plots these shares by county and gender. Administrative data is unavailable for 11 counties. There are 390 counties × 2 genders = 780 observations. Panel (a) colors observations by state; panel (b) colors by age; and panels (c) and (d) color by gender.

**Figure A3:** Syrian Migrant Sample vs. Admin Data – By Age × Gender × Year

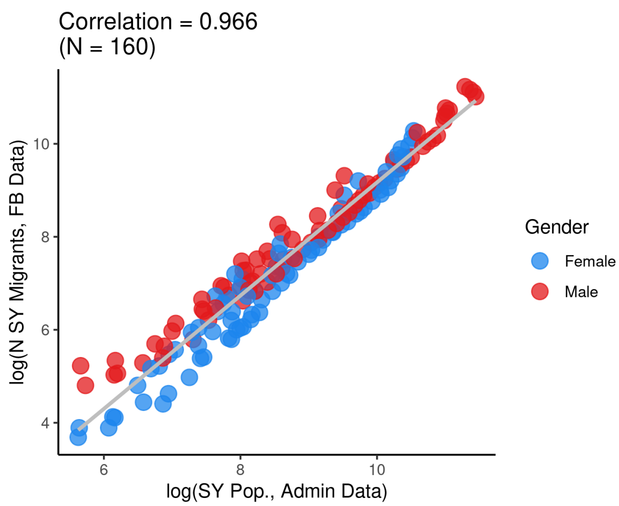
**(a)** Color by Year




**(b)** Color by Age

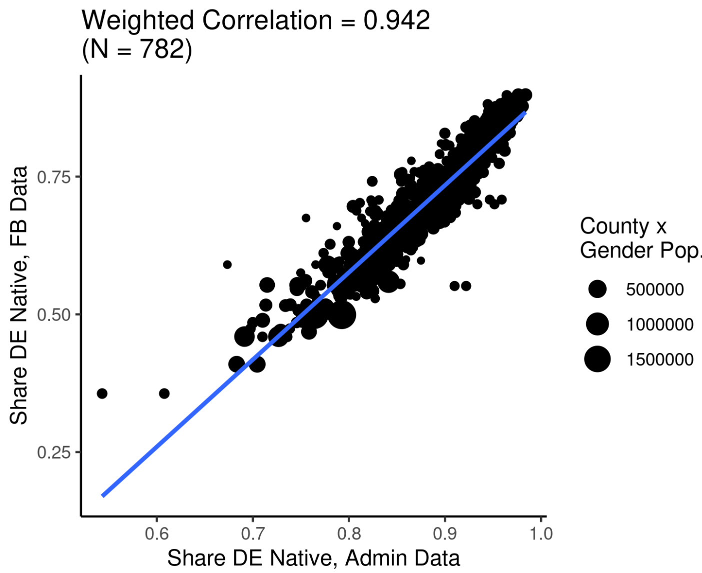



**(c)** Color by Gender



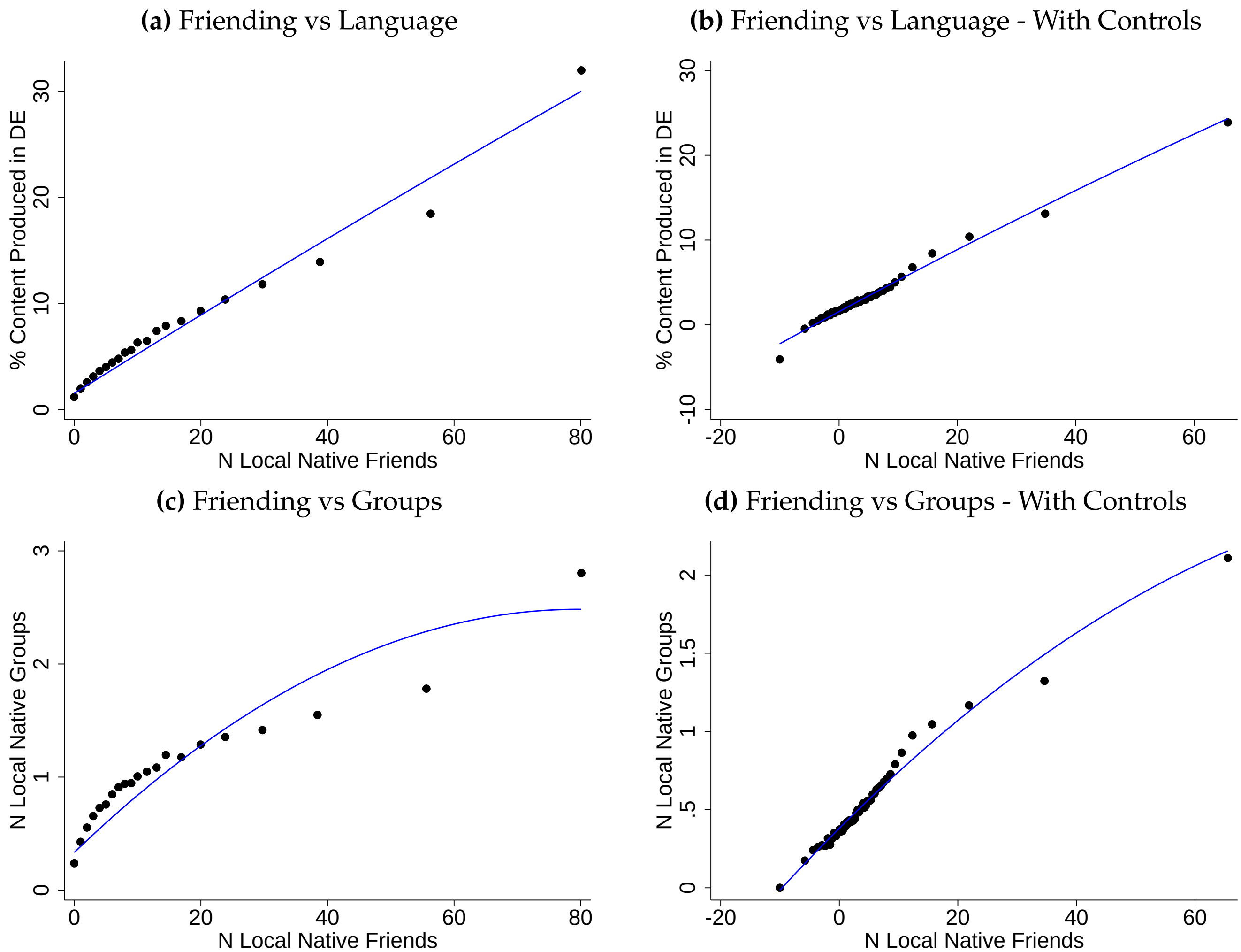

**Note:** Figure shows the number of users in our Syrian migrant sample using Facebook in Germany by the end of each year from 2012 to 2019 (on the y-axis), against analogous measures of Syrian migrant population from German administrative data (on the x-axis). Each observation is an age by gender by year group. The age groups are the same as those used in Figure A1. Both axes are transformed by the natural logarithm. The solid grey line is from a linear regression. Observations are colored by year in panel (a), age in panel (b), and gender in panel (c).

**Figure A4:** Native German Sample vs Admin Data



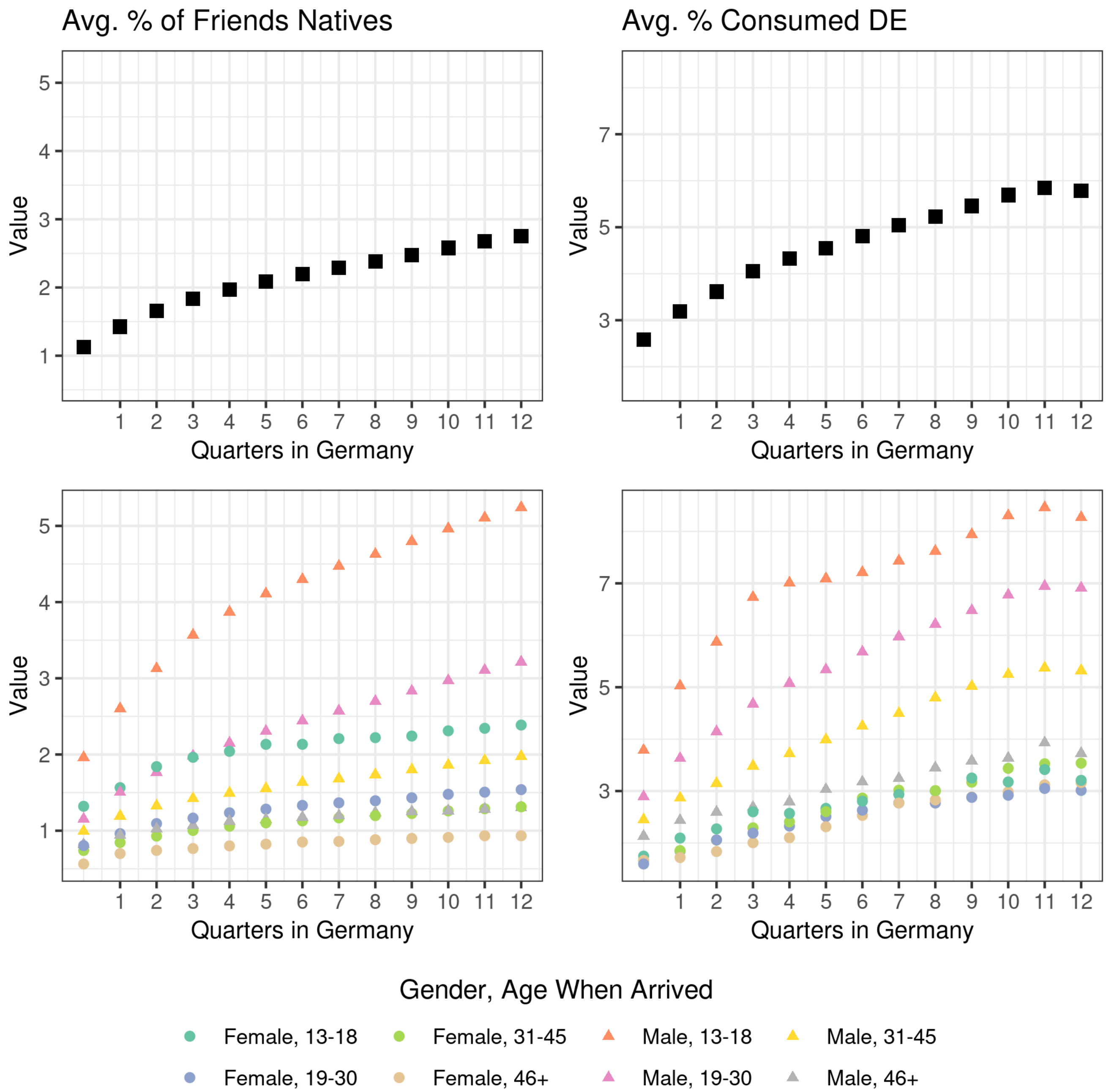

**Note:** Figure shows the shares of the primary sample of Facebook users that are also in the German native sample (on the y-axis), against shares of the population that are native from administrative data (on the x-axis). Each observation is a county by gender group. The size of each dot is proportional to the true population it represents. The solid blue lines are from weighted linear regressions. Admin data is unavailable for 10 counties. There are 391 counties $\times$ 2 genders = 782 observations.

**Figure A5:** Relationship Between Integration Outcomes, Individual Level



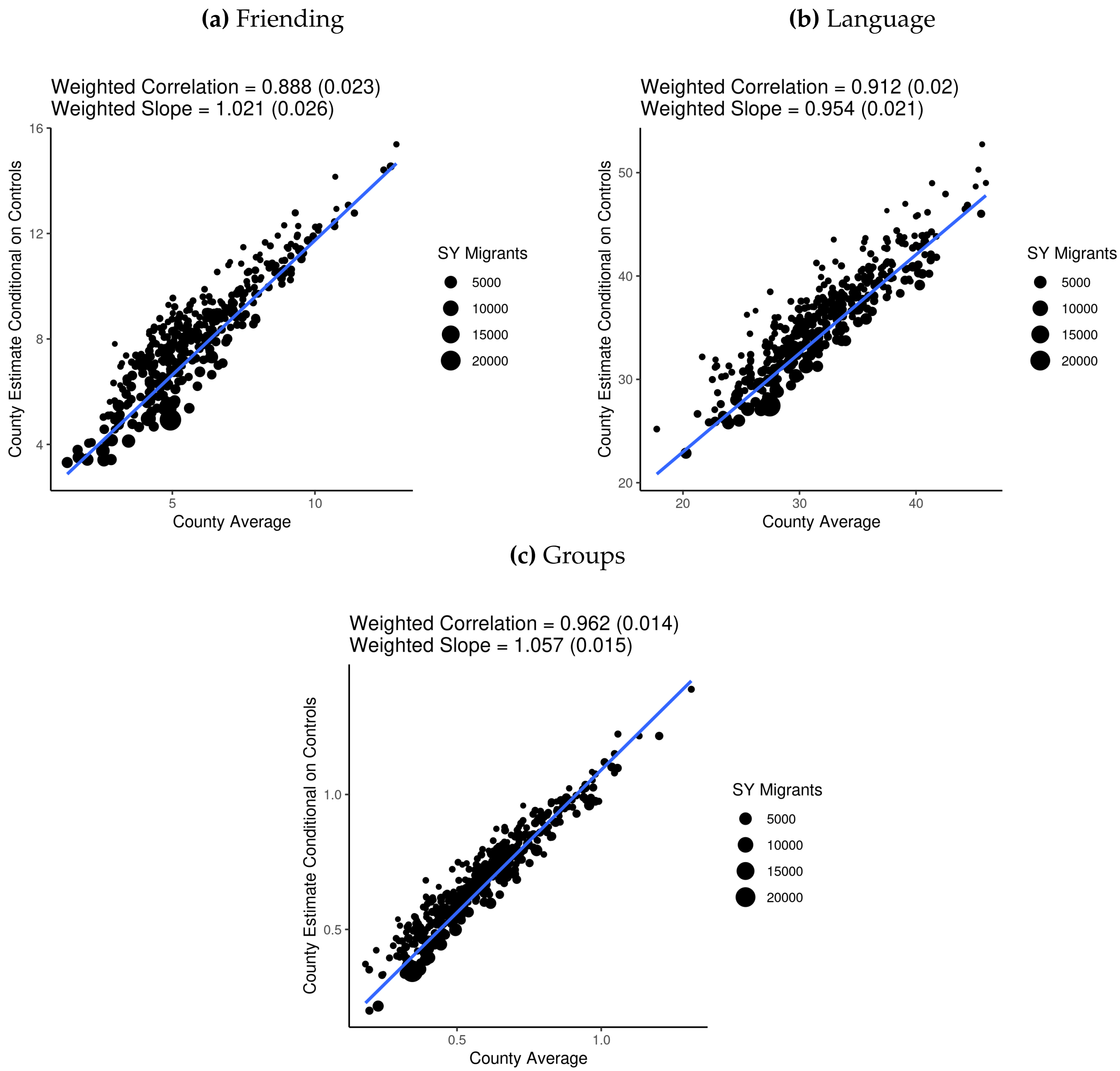

**Note:** Figures show binned scatter plots of individual Syrian migrants' number of local German native friends on the x-axis, against their share of content produced in German in panels (a) and (b), and the number of local native groups they are in panels (c) and (d). Appendix 3 provides more details on each measure. The measures in panels (b) and (d) are first residualized on the individual-level controls used in column 3 of Table A11. Lines are fit from quadratic regressions.

**Figure A6:** Integration Over Time For 2015-16 Cohort — Additional Measures



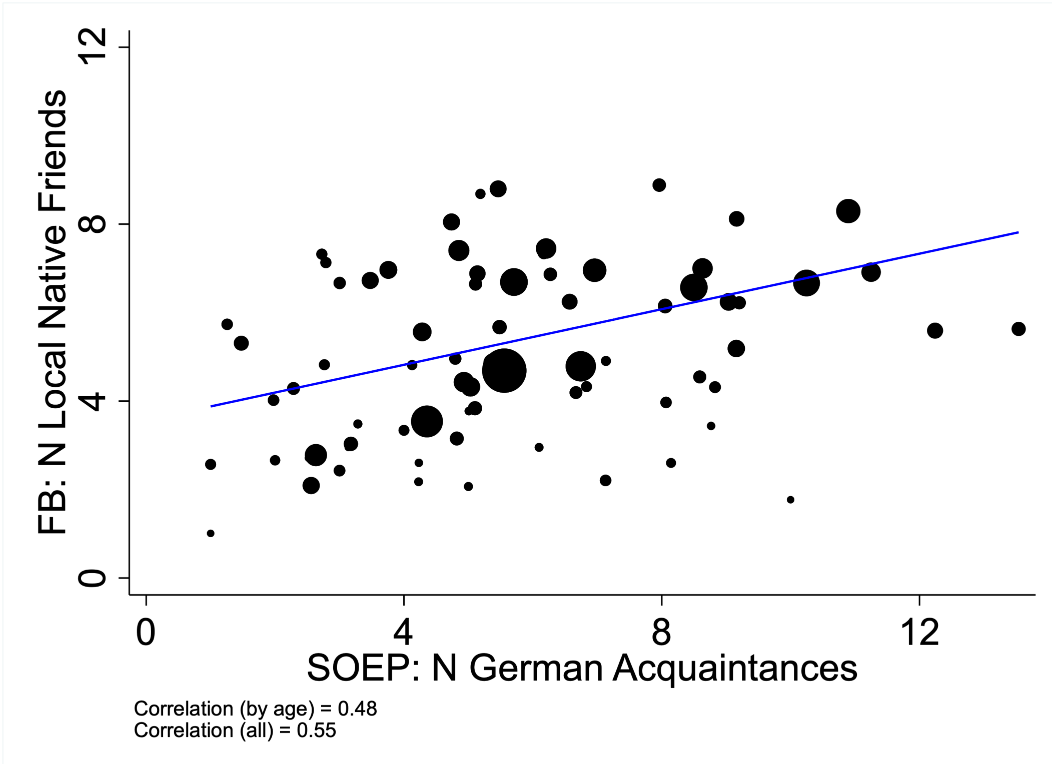

**Note:** Figures show the average values, by quarter, of integration measures for users in the Syrian migrant sample with an observed arrival in 2015 or 2016. The measures are share of friends native (left column) and the share of content consumed in German (right column). Appendix 3 provides more details on each measure. The top row shows overall trends. In the bottom row each observation's shape and color represents a gender-by-age group.

**Figure A7:** Regional Estimates With and Without Controls



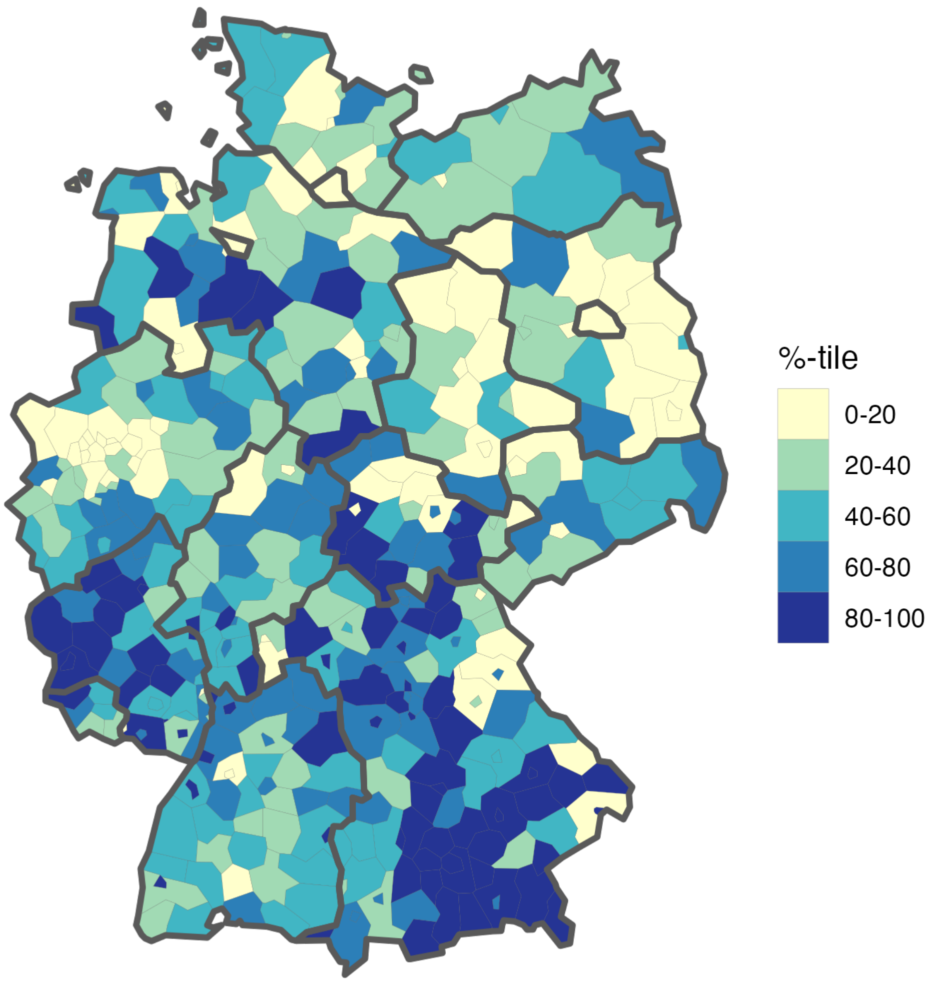

**Note:** Figures show the relationship between county averages of integration outcomes among Syrian migrants vs county-level fixed effect estimates constructed from versions of equation 1. The outcomes are a user's number of local German native friends in panel (a), whether the user produces content in German in panel (b), and the number of local native groups a user is in in panel (c). Appendix 3 provides more details on each measures. The controls in the fixed effect regressions are those used in column 3 of Table A11.

**Figure A8:** Comparing Regional Estimates of Integration - Facebook vs. SOEP



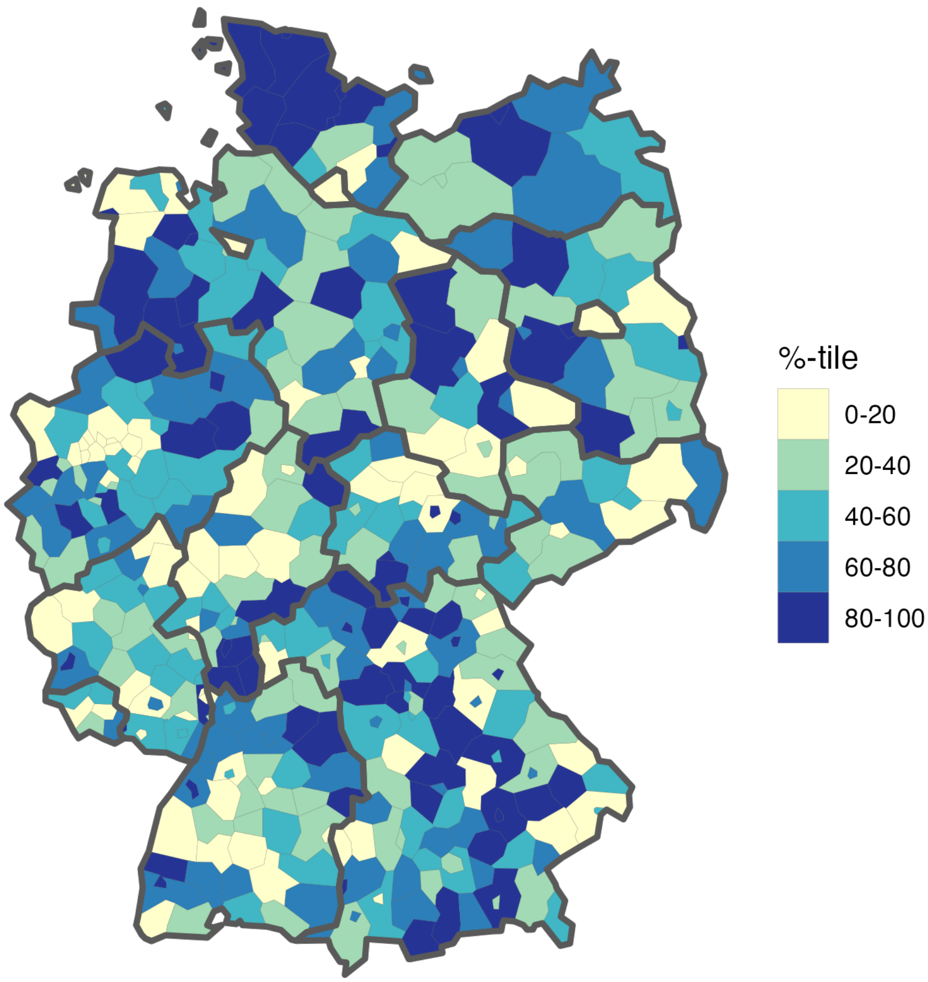

**Note:** Figure compares estimates of social integration based on our Facebook sample with the average number of acquaintances made by recent Syrian migrants in Germany in the SOEP data. The SOEP question is "How many German people have you met since your arrival in Germany with whom you have regular contact?". Each observation in the Figure is a state-by-age-group combination. The size of each dot corresponds to the number of Syrian migrants in the Facebook data. At the bottom of the figure, we report two correlations. The first is a correlation at the state by age-group level, i.e., the same level of aggregation as shown in the plot. The second is a correlation estimated at the state-level, i.e., we further aggregate observations to the state-level and then correlate the two data sources. Both correlations are weighted by the number of Syrian migrants in our Facebook sample.

**Figure A9:** Regional Estimates of Integration - German Language Usage



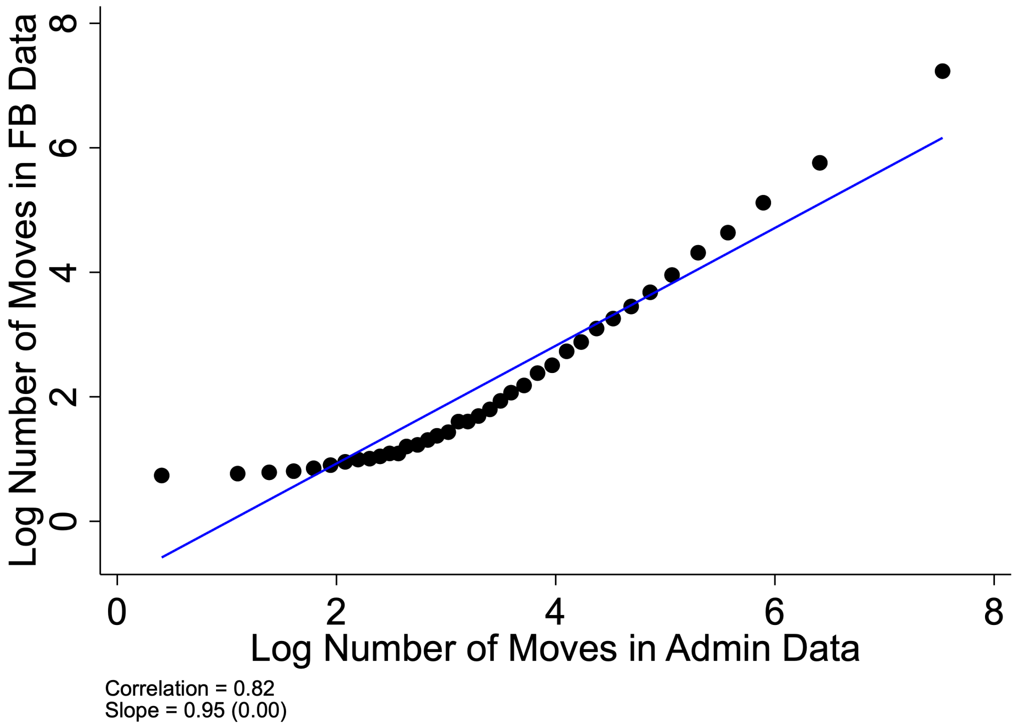

**Note:** Figure shows county-level estimates of Syrian migrant integration based on the share that produce content in the German language (residualized on regional patterns of Facebook usage). Darker areas indicate the highest integration counties.

**Figure A10:** Regional Estimates of Integration - Local Native Group Joining



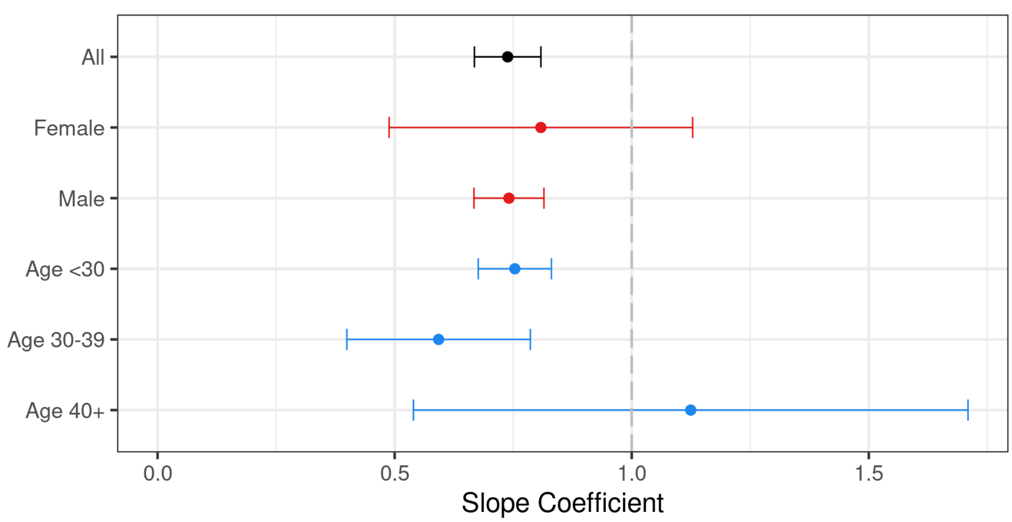

**Note:** Figure shows county-level estimates of Syrian migrant integration based on the average number of native local groups joined (residualized on regional patterns of Facebook usage. This includes the average number of total groups natives in the region have joined, allowing us to account for variation driven by differential usage of the groups feature in general). Colors correspond to measure ventiles. Darker areas indicate the highest integration counties.

**Figure A11:** Comparing Movers in Facebook and Administrative Data




**Note:** Figure compares the number of moves between counties made by all individuals (i.e., including natives, migrants, and others) between the ages of 18-64 in 2016 and 2017 in Facebook and administrative data. We obtained the administrative data from the German Statistical Office. Each observation in this analysis is a county-to-county combination. The Figure is a binned scatter plot with 40 equally sized bins. The Figure is weighted by the the total number of individuals living in origin and destination county.

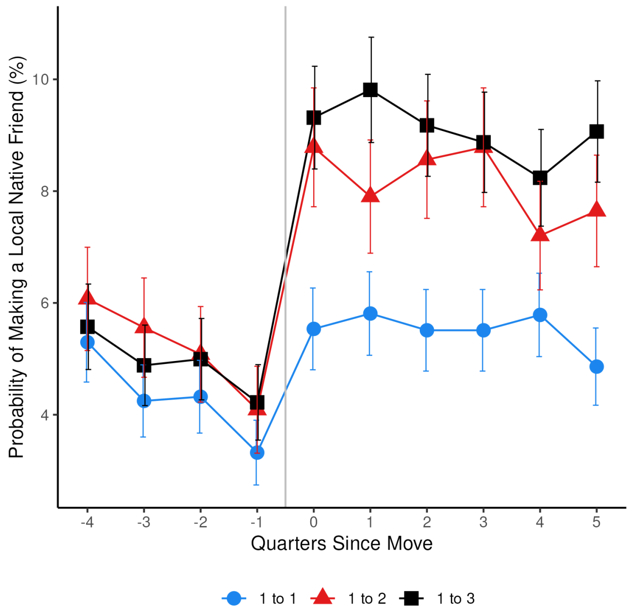
**Figure A12:** Syrian Migrant Movers - Slope by Demographics



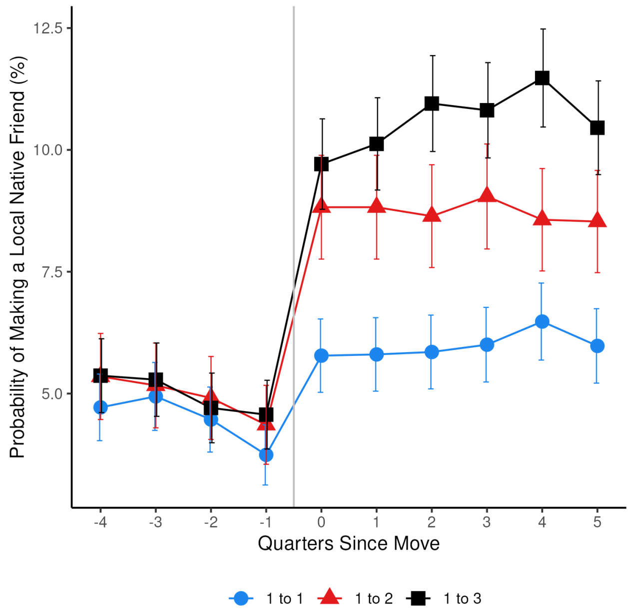

**Note:** Figure shows slopes corresponding to versions of Figure A19 over certain sub-samples. The coefficient in black corresponds to the slope using the full sample of Syrian migrant movers; the coefficients in red use samples of only one gender; and the coefficients in blue use samples of only one age group. Bars display 95% confidence intervals. The sample sizes used to generate each coefficient are (from top to bottom) 32,853, 6,144, 26,709, 20,796, 8,623, and 3,434.

**Figure A13:** Change in Syrian Migrants' Friending of Local Natives Around a Move—Split by Friendship Initiator

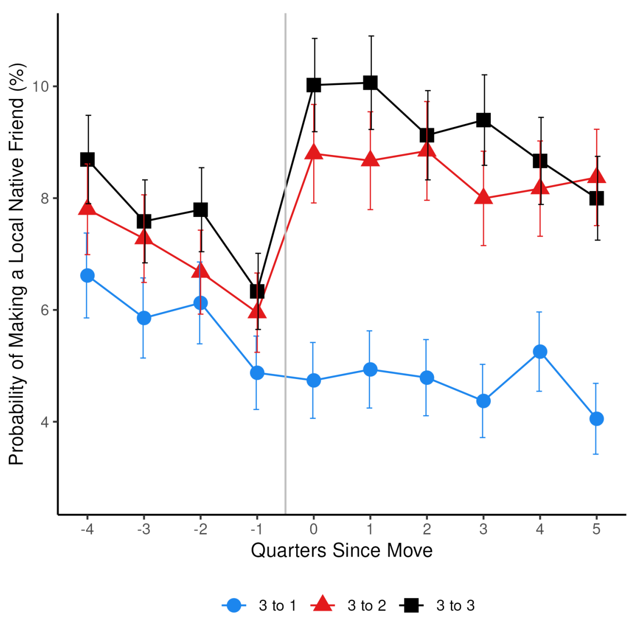
**(a)** Moving From Bottom Integration Tercile (Only Friendships Initiated by Syrian Migrants)



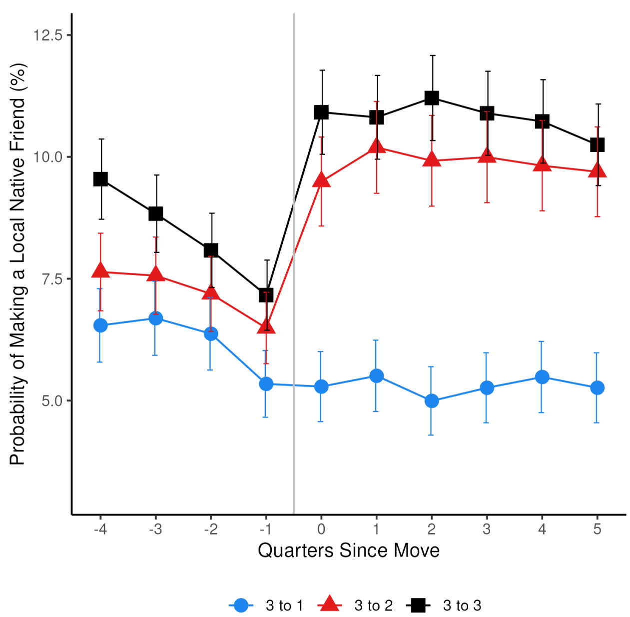

**(b)** Moving From Bottom Integration Tercile (Only Friendships Initiated by Native Germans)




**(c)** Moving From Top Integration Tercile (Only Friendships Initiated by Syrian Migrants)



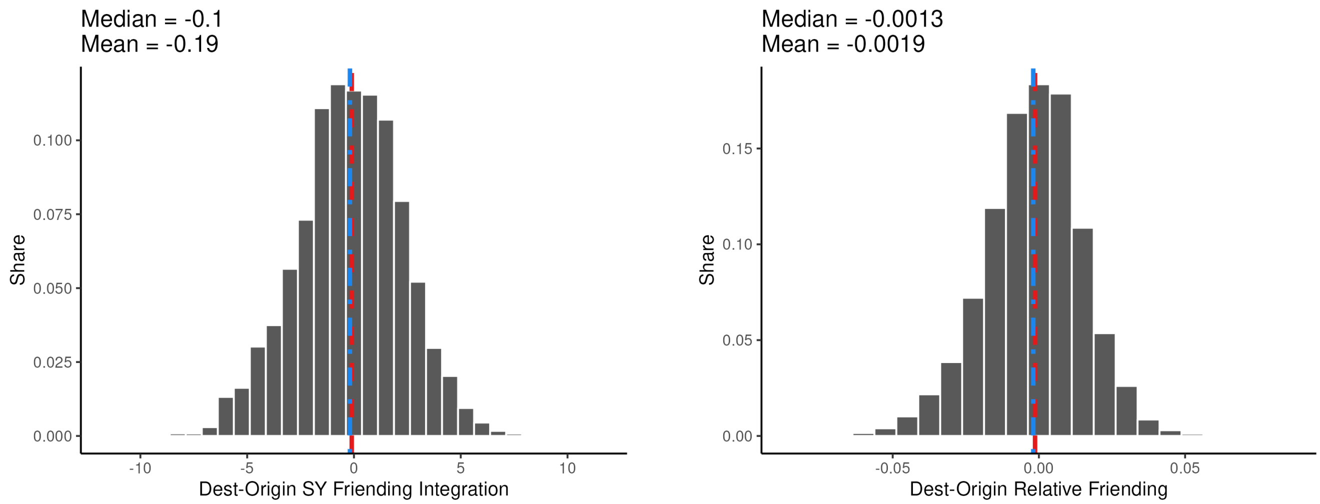

**(d)** Moving From Top Integration Tercile (Only Friendships Initiated by Native Germans)




**Note:** This figure reproduces the analyses presented in Figure 3. Panels (a) and (b) disaggregate the results of panel (a) of Figure 3, splitting the friendships formed into two groups according to whether it was the Syrian migrant or the local German native who sent the friendship request on Facebook. Panels (c) and (d) repeat the same exercise for panel (b) of Figure 3.

**Figure A14:** Distribution of Syrian Migrant Moves

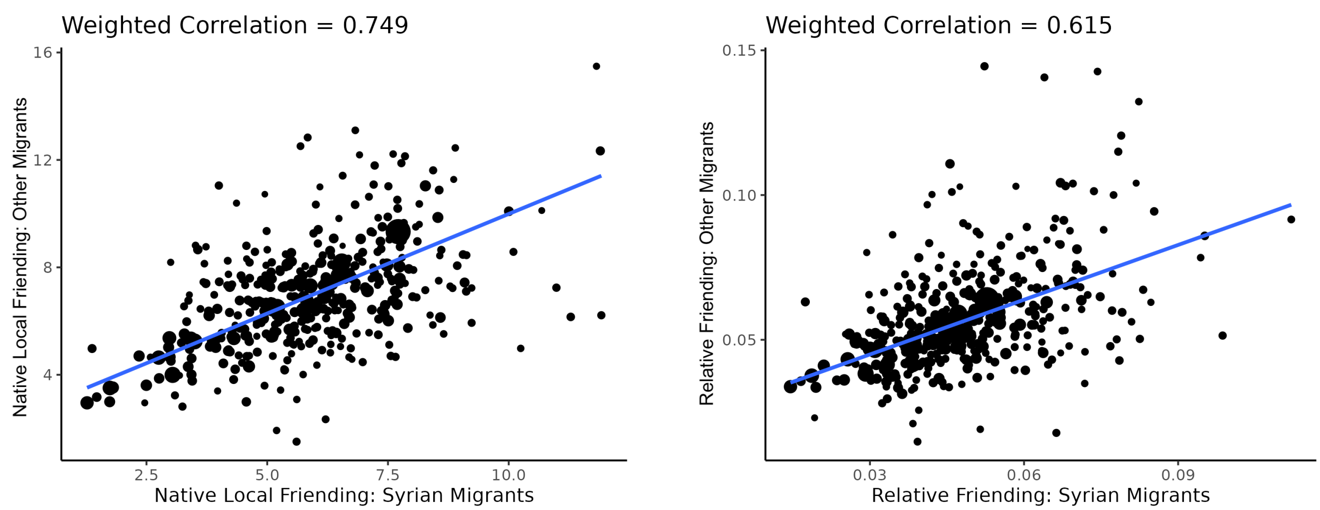
**(a)** Distribution of Δ Friending Integration **(b)** Distribution of Δ Relative Friending




**Note:** Figures show, for Syrian migrant movers, the distribution of destination minus origin regional friending-based measures of Syrian migration integration. Panel (a) shows the distribution of the measure in Figure 2. Panel (b) shows the distribution of relative friending in Figure 4. The red and blue lines show the median and mean, respectively.

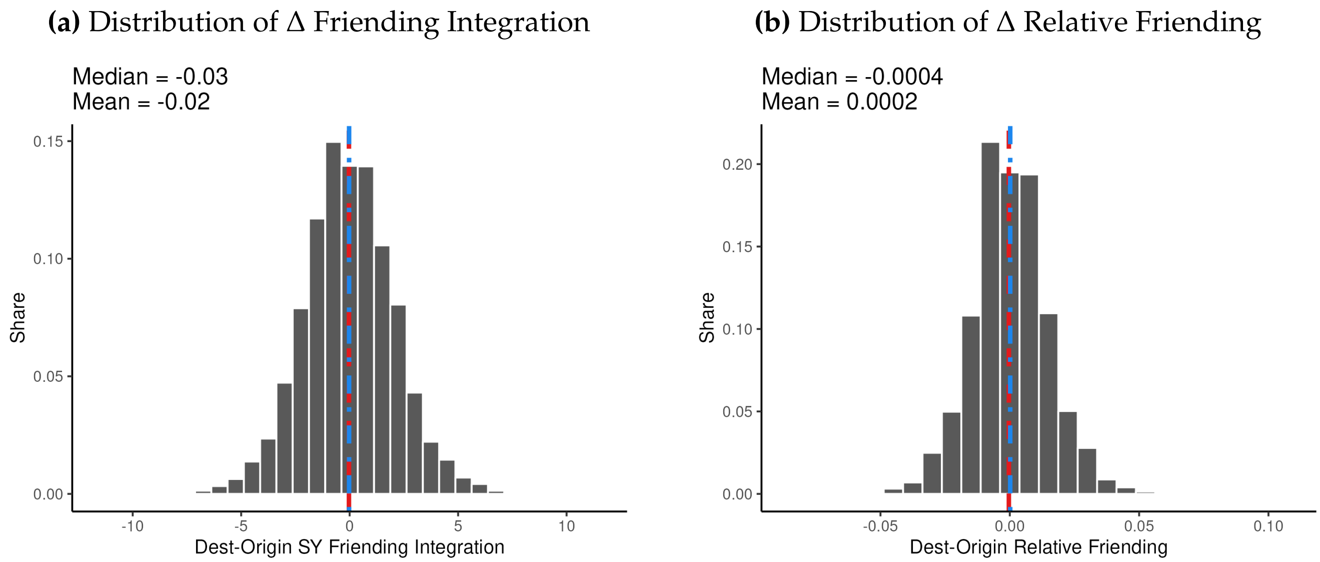
**Figure A15:** Social Integration Across Counties: Syrian Migrants vs Other Migrants

**(a)** Friending Integration **(b)** Relative Friending



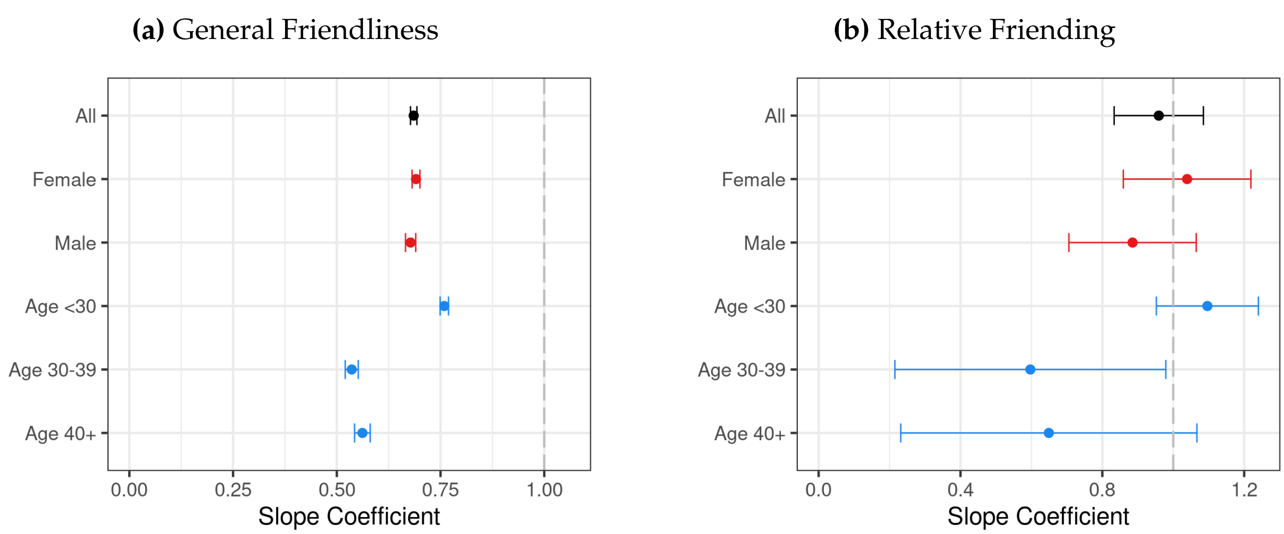

**Note:** Figure compares estimates of friending integration (panel a) and relative friending (panel b) across counties. Measures on the x-axis are calculated for Syrian migrants. Measures on the y-axis are calculated for users from one of the five countries with the most asylum applicants in Germany in 2020 other than Syria: Turkey, Afghanistan, Iraq, Nigeria, and Iran.

**Figure A16:** Distribution of German Native Moves



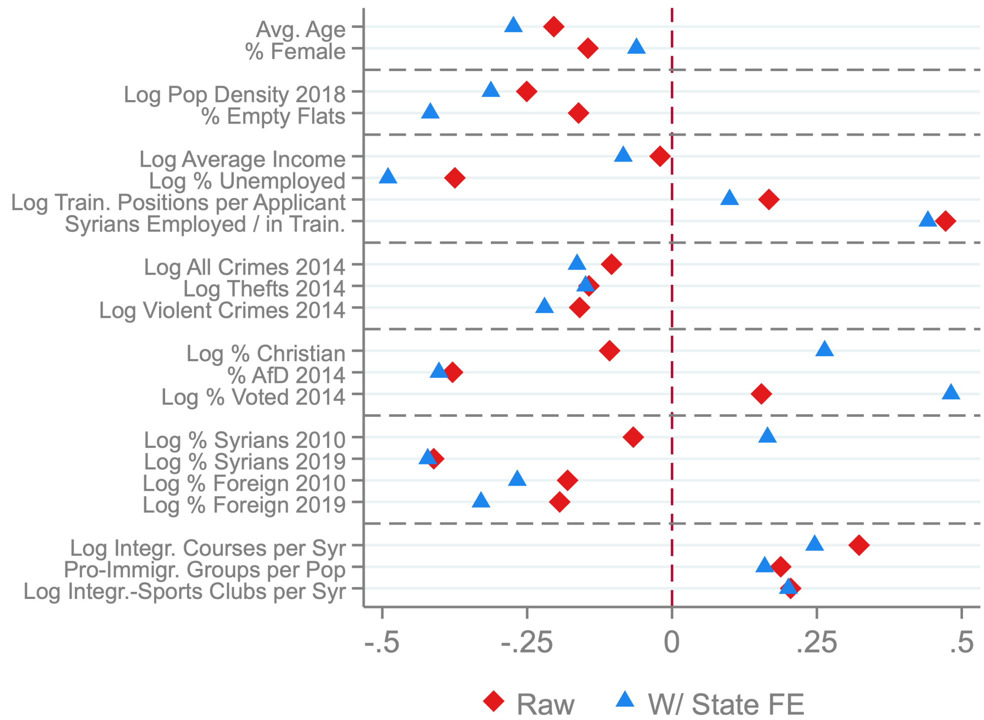

**Note:** Figures show, for German native movers, the distribution of destination minus origin regional friending-based measures of Syrian migration integration. Panel (a) shows the distribution of the measure in Figure 2. Panel (b) shows the distribution of relative friending in Figure 4. The red and blue lines show the median and mean, respectively.

**Figure A17:** Δ Native Mover Behaviors vs. Matched Non-Movers - Slope By Demographics




**Note:** Figures show slopes corresponding to versions of the respective panels in Figure 6. The coefficients in black are the slopes using the full sample of German native movers; the coefficients in red use samples of only one gender; and the coefficients in blue use samples of only one age group. Bars display 95% confidence intervals.

**Figure A18:** County-Level Univariate Correlations with Friending Integration - Long Version




**Note:** Figure presents correlations between our county-level measure of social integration and various other regional measures. Social integration is based on Syrian migrants number of native local friends (Figure 2). Correlations are weighted by the size of the Syrian migrant sample in each county. Red diamonds depict raw, univariate correlations and blue triangles depict correlations after controlling for state fixed effects. For more information on each measure, see Appendix Table A16.

**Table A1:** Syrian Migrant and German Native Sample Summaries - Additional Measures

***Panel (a): Syrian Migrant Sample***

| | Mean | SD | P10 | P25 | P50 | P75 | P90 | P99 |
|---|---|---|---|---|---|---|---|---|
| N Native Friends | 9.09 | 20.54 | 0 | 0 | 2 | 8 | 24 | 151 |
| N Top 50 Native Friends | 1.02 | 2.46 | 0 | 0 | 0 | 1 | 3 | 16 |
| % of Friends Native | 3.04 | 6.19 | 0.00 | 0.00 | 0.80 | 2.99 | 8.19 | 40.25 |
| N Local Other Refugee Country Friends | 2.04 | 3.63 | 0 | 0 | 1 | 2 | 6 | 21 |
| N Local Recent Other Refugee Country Friends | 1.04 | 1.87 | 0 | 0 | 0 | 1 | 3 | 10 |
| % Content Produced in DE | 3.39 | 9.89 | 0.00 | 0.00 | 0.00 | 2.31 | 8.48 | 70.00 |
| % Content Consumed in DE | 3.48 | 8.64 | 0.00 | 0.00 | 0.00 | 2.91 | 9.09 | 60.00 |
| Consumes DE Content (0/100) | 41.81 | 49.32 | 0 | 0 | 0 | 100 | 100 | 100 |
| Account in DE | 14.90 | 35.61 | 0 | 0 | 0 | 0 | 100 | 100 |
| % Groups Local Native | 0.88 | 3.55 | 0.00 | 0.00 | 0.00 | 0.00 | 2.22 | 15.38 |
| Avg. % Native in DE Groups | 31.09 | 30.21 | 0.15 | 0.52 | 25.06 | 56.44 | 77.84 | 92.91 |

***Panel (b): German Native Sample***

| | Mean | SD | P10 | P25 | P50 | P75 | P90 | P99 |
|---|---|---|---|---|---|---|---|---|
| N Native Friends | 204.73 | 189.58 | 40 | 74 | 148 | 269 | 443 | 1151 |
| N Top 50 Native Friends | 36.87 | 8.76 | 25 | 33 | 39 | 43 | 46 | 49 |
| % of Friends Native | 82.09 | 14.70 | 63.75 | 77.84 | 86.67 | 91.61 | 94.52 | 98.16 |
| N Local Other Refugee Country Friends | 1.12 | 2.58 | 0 | 0 | 0 | 1 | 3 | 17 |
| N Local Recent Other Refugee Country Friends | 0.05 | 0.22 | 0 | 0 | 0 | 0 | 0 | 1 |
| % Content Produced in DE | 94.49 | 9.70 | 81.19 | 92.90 | 100.00 | 100.00 | 100.00 | 100.00 |
| % Content Consumed in DE | 88.60 | 16.55 | 65.84 | 84.06 | 95.90 | 100.00 | 100.00 | 100.00 |
| Consumes DE Content (0/100) | 97.69 | 15.02 | 100 | 100 | 100 | 100 | 100 | 100 |
| Account in DE | 98.61 | 11.69 | 100 | 100 | 100 | 100 | 100 | 100 |
| % Groups Local Native | 22.07 | 22.34 | 0.00 | 4.55 | 16.67 | 33.33 | 50.00 | 100.00 |
| Avg. % Native in DE Groups | 90.42 | 5.88 | 83.52 | 88.16 | 91.70 | 94.15 | 95.95 | 100.00 |

**Note:** Table presents summary statistics describing users in our Facebook samples. Panel (a) shows users in the Syrian migrant sample. Panel (b) shows users in the German native sample. Each measure is winsorized at the 99% level. Section 1.1 describes sample construction. Appendix 3 provides more information on how individual-level outcomes are defined.

**Table A2:** Correlation Between Integration Outcomes, Individual Level

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) N Local Native Friends | 1.00 | | | | | | | | | | | | | | |
| (2) N Native Friends | 0.64 | 1.00 | | | | | | | | | | | | | |
| (3) N Top 50 Native Friends | 0.61 | 0.54 | 1.00 | | | | | | | | | | | | |
| (4) % of Friends Native | 0.69 | 0.61 | 0.88 | 1.00 | | | | | | | | | | | |
| (5) N Local SY Friends | 0.29 | 0.14 | 0.01 | 0.02 | 1.00 | | | | | | | | | | |
| (6) N Local Other Refugee Country Friends | 0.47 | 0.30 | 0.19 | 0.23 | 0.54 | 1.00 | | | | | | | | | |
| (7) N Local Recent Other Refugee Country Friends | 0.28 | 0.15 | 0.06 | 0.07 | 0.53 | 0.85 | 1.00 | | | | | | | | |
| (8) % Content Produced in DE | 0.45 | 0.40 | 0.65 | 0.67 | -0.02 | 0.17 | 0.03 | 1.00 | | | | | | | |
| (9) % Content Consumed in DE | 0.46 | 0.40 | 0.67 | 0.68 | -0.01 | 0.18 | 0.05 | 0.80 | 1.00 | | | | | | |
| (10) Produces DE Content | 0.24 | 0.19 | 0.27 | 0.31 | 0.04 | 0.11 | 0.03 | 0.33 | 0.33 | 1.00 | | | | | |
| (11) Consumes DE Content | 0.37 | 0.25 | 0.37 | 0.40 | 0.09 | 0.19 | 0.12 | 0.52 | 0.45 | 0.27 | 1.00 | | | | |
| (12) Account in DE | 0.32 | 0.21 | 0.32 | 0.34 | 0.11 | 0.19 | 0.13 | 0.34 | 0.47 | 0.25 | 0.57 | 1.00 | | | |
| (13) N Local Native Groups | 0.29 | 0.25 | 0.25 | 0.27 | 0.12 | 0.14 | 0.09 | 0.23 | 0.25 | 0.14 | 0.26 | 0.24 | 1.00 | | |
| (14) % Groups Local Native | 0.33 | 0.26 | 0.37 | 0.40 | 0.03 | 0.13 | 0.05 | 0.36 | 0.37 | 0.19 | 0.27 | 0.24 | 0.61 | 1.00 | |
| (15) Avg. % Native in DE Groups | 0.32 | 0.23 | 0.32 | 0.36 | 0.01 | 0.14 | 0.08 | 0.33 | 0.35 | 0.26 | 0.38 | 0.36 | 0.43 | 0.47 | 1.00 |

**Note:** Table presents correlations at the user level across outcome measures for the Syrian migrant sample. Each measure is winsorized at the 99% level. Appendix 3 provides more information on how outcomes are defined.

**Table A3:** Correlation Between Integration Outcomes, Individual Level - With Controls

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) N Local Native Friends | 1.00 | | | | | | | | | | | | | | |
| (2) N Native Friends | 0.61 | 1.00 | | | | | | | | | | | | | |
| (3) N Top 50 Native Friends | 0.60 | 0.54 | 1.00 | | | | | | | | | | | | |
| (4) % of Friends Native | 0.69 | 0.62 | 0.86 | 1.00 | | | | | | | | | | | |
| (5) N Local SY Friends | 0.20 | 0.07 | 0.02 | 0.03 | 1.00 | | | | | | | | | | |
| (6) N Local Other Refugee Country Friends | 0.39 | 0.24 | 0.17 | 0.20 | 0.46 | 1.00 | | | | | | | | | |
| (7) N Local Recent Other Refugee Country Friends | 0.20 | 0.09 | 0.05 | 0.06 | 0.45 | 0.83 | 1.00 | | | | | | | | |
| (8) % Content Produced in DE | 0.43 | 0.38 | 0.61 | 0.63 | -0.01 | 0.15 | 0.03 | 1.00 | | | | | | | |
| (9) % Content Consumed in DE | 0.44 | 0.39 | 0.63 | 0.63 | 0.00 | 0.16 | 0.04 | 0.77 | 1.00 | | | | | | |
| (10) Produces DE Content | 0.19 | 0.15 | 0.21 | 0.24 | 0.02 | 0.06 | -0.00 | 0.27 | 0.27 | 1.00 | | | | | |
| (11) Consumes DE Content | 0.31 | 0.21 | 0.32 | 0.33 | 0.02 | 0.12 | 0.05 | 0.48 | 0.40 | 0.21 | 1.00 | | | | |
| (12) Account in DE | 0.25 | 0.17 | 0.26 | 0.27 | 0.04 | 0.12 | 0.07 | 0.28 | 0.42 | 0.19 | 0.51 | 1.00 | | | |
| (13) N Local Native Groups | 0.25 | 0.22 | 0.24 | 0.26 | 0.03 | 0.08 | 0.03 | 0.23 | 0.25 | 0.13 | 0.22 | 0.18 | 1.00 | | |
| (14) % Groups Local Native | 0.28 | 0.23 | 0.33 | 0.36 | 0.02 | 0.09 | 0.02 | 0.31 | 0.32 | 0.14 | 0.22 | 0.18 | 0.63 | 1.00 | |
| (15) Avg. % Native in DE Groups | 0.23 | 0.17 | 0.26 | 0.29 | -0.04 | 0.05 | -0.00 | 0.27 | 0.29 | 0.19 | 0.30 | 0.27 | 0.43 | 0.42 | 1.00 |

**Note:** Table presents correlations at the user level across outcome measures for the Syrian migrant sample. Each measure is first winsorized at the 99% level. Appendix 3 provides more information on how outcomes are defined. Before constructing the correlations, each measure is residualized on the individual-level controls used in column 3 of Table A11.

**Table A4:** Syrian Migrant Integration by Demographics - Language and Groups

| | Produces Content in German (0/100) | | | | N Local Native Groups | | | |
|---|---|---|---|---|---|---|---|---|
| Age 25 - 34 | -2.407*** | -2.241*** | -2.275*** | -3.312*** | 0.167*** | 0.171*** | 0.136*** | 0.140*** |
| | (0.204) | (0.203) | (0.203) | (0.596) | (0.006) | (0.006) | (0.006) | (0.019) |
| Age 35 - 44 | -7.133*** | -7.161*** | -6.875*** | -6.615*** | -0.002*** | -0.007*** | 0.039* | 0.072** |
| | (0.238) | (0.237) | (0.237) | (0.733) | (0.007) | (0.007) | (0.007) | (0.023) |
| Age 45 - 54 | -13.651*** | -13.798*** | -12.553*** | -16.243*** | -0.184*** | -0.189*** | -0.064*** | -0.070*** |
| | (0.306) | (0.305) | (0.307) | (0.854) | (0.010) | (0.010) | (0.009) | (0.027) |
| Age 55+ | -18.045*** | -18.134*** | -16.451*** | -24.395*** | -0.298*** | -0.300*** | -0.088*** | -0.228*** |
| | (0.382) | (0.380) | (0.384) | (1.116) | (0.012) | (0.012) | (0.012) | (0.035) |
| Female | -15.767*** | -15.560*** | -16.725*** | -18.765*** | -0.202*** | -0.200*** | -0.372*** | -0.447*** |
| | (0.164) | (0.164) | (0.173) | (0.418) | (0.005) | (0.005) | (0.005) | (0.013) |
| Household Member in DE 1+ Year Prior | -2.420*** | -2.298*** | -2.113*** | | -0.057*** | -0.058*** | -0.060*** | |
| | (0.384) | (0.383) | (0.382) | | (0.012) | (0.012) | (0.012) | |
| Non-Household Family in DE 1+ Year Prior | 3.418*** | 3.451*** | 4.045*** | | 0.023*** | 0.025*** | 0.030*** | |
| | (0.347) | (0.345) | (0.345) | | (0.011) | (0.011) | (0.010) | |
| Quarters Since DE FEs | X | X | X | X | X | X | X | X |
| Prev Quarters in NUTS3 FEs | X | X | X | X | X | X | X | X |
| Personal Usage Controls | X | X | X | X | X | X | X | X |
| County FEs | | X | X | X | | X | X | X |
| Log (1 + Total Outside Germany Friends) | | | X | X | | | X | X |
| Log (1 + Total Other Groups) | | | X | X | | | X | X |
| Log (1 + Total Content Produced Past Year) | | | X | X | | | X | X |
| Household FE | | | | X | | | | X |
| N | 349,072 | 349,072 | 349,072 | 84,216 | 349,072 | 349,072 | 349,072 | 84,216 |
| R-Squared | 0.098 | 0.108 | 0.113 | 0.590 | 0.059 | 0.076 | 0.133 | 0.606 |
| Sample Mean | 30.401 | 30.401 | 30.401 | 27.215 | 0.545 | 0.545 | 0.545 | 0.574 |

**Note:** Table shows results from regressing various measures on language- and groups-based measures of integration. Each observation in every column is a user in the Syrian migrant Facebook sample. Columns 1 and 5 include controls for age and gender, as well as fixed effects for the number of quarters on Facebook in their current county and the number of quarters since arrival in Germany. For the latter fixed effect, we use a single dummy value for those for which we do not observe arrival, but obtain nearly identical results if we instead drop these users. We also include dummies for whether the user has another Syrian migrant household member or non-household family member in Germany more than year prior to their arrival. For all users not in the “observe arrival timing” sample, these two dummies are set to 0. Columns 2 and 6 add county fixed effects. Columns 3 and 7 add controls for each user’s total number of friends outside Germany, total number of non-local/native groups joined, and total amount of content produced in the last year. Columns 4 and 8 add a household fixed effect, limiting to households for which we observe more than one Syrian migrant. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

**Table A5:** Syrian Migrant Integration by Demographics - Other Measures

| | N Native Friends | N Top 50 Native Friends | % of Friends Native | % Content Produced in DE | % Content Consumed in DE | Account in DE | % Groups Local Native | Avg. % Native in DE Groups |
|---|---|---|---|---|---|---|---|---|
| Age 25 - 34 | -0.894*** | 0.004*** | -0.467*** | 0.076** | 0.078*** | -2.683*** | 0.197*** | -0.136*** |
| | (0.184) | (0.014) | (0.032) | (0.044) | (0.038) | (0.160) | (0.010) | (0.160) |
| Age 35 - 44 | -4.728*** | -0.263*** | -1.446*** | -0.694*** | -0.749*** | -7.099*** | 0.043 | -4.347*** |
| | (0.216) | (0.016) | (0.038) | (0.051) | (0.044) | (0.187) | (0.012) | (0.187) |
| Age 45 - 54 | -6.928*** | -0.454*** | -1.927*** | -1.245*** | -1.298*** | -7.676*** | -0.164*** | -6.940*** |
| | (0.279) | (0.021) | (0.049) | (0.066) | (0.057) | (0.241) | (0.015) | (0.254) |
| Age 55+ | -8.157*** | -0.421*** | -1.862*** | -1.221*** | -1.327*** | -6.151*** | -0.350*** | -7.334*** |
| | (0.349) | (0.026) | (0.061) | (0.083) | (0.072) | (0.302) | (0.019) | (0.360) |
| Female | -7.188*** | -0.787*** | -2.334*** | -2.339*** | -2.154*** | -5.377*** | -0.485*** | -11.601*** |
| | (0.157) | (0.012) | (0.027) | (0.037) | (0.032) | (0.136) | (0.009) | (0.137) |
| Household Member in DE 1+ Year Prior | -0.610 | -0.030 | 0.013 | 0.146 | -0.057 | 0.182 | -0.014 | -0.875*** |
| | (0.347) | (0.026) | (0.061) | (0.082) | (0.071) | (0.300) | (0.019) | (0.295) |
| Non-Household Family in DE 1+ Year Prior | 0.667*** | 0.075*** | 0.360*** | 0.535*** | 0.404*** | 3.659*** | 0.098*** | 2.649*** |
| | (0.314) | (0.023) | (0.055) | (0.074) | (0.064) | (0.271) | (0.017) | (0.257) |
| Quarters Since DE FEs | X | X | X | X | X | X | X | X |
| Prev Quarters in County FEs | X | X | X | X | X | X | X | X |
| Personal Usage Controls | X | X | X | X | X | X | X | X |
| County FEs | X | X | X | X | X | X | X | X |
| Log (1 + Total Outside Germany Friends) | X | X | X | X | X | X | X | X |
| Log (1 + Total Other Groups) | X | X | X | X | X | X | X | X |
| Log (1 + Total Content Produced Past Year) | X | X | X | X | X | X | X | X |
| N | 349,072 | 349,072 | 349,072 | 345,814 | 346,367 | 349,072 | 345,162 | 237,563 |
| R-Squared | 0.064 | 0.111 | 0.163 | 0.121 | 0.125 | 0.083 | 0.077 | 0.171 |
| Sample Mean | 10.592 | 1.101 | 3.221 | 3.388 | 3.474 | 14.896 | 0.754 | 31.091 |

**Note:** Table shows results from regressing various measures on outcomes for Syrian migrants in the Facebook sample. All columns include controls for age, gender, time spent on Facebook, number of friends outside Germany, total number of non-local/native groups joined, and total amount of content produced in the last year. They include fixed effects for county, the number of quarters since arrival in Germany (with a single dummy for those for which we do not observe arrival) and the number of quarters on Facebook in their current county. They also include dummies for whether the user has another Syrian migrant household member or non-household family member in Germany more than year prior to their arrival. Column 8 limits to migrants who are members of at least one group of majority users in Germany. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

**Table A6:** Signal Correlation Between Outcomes, Regional Level

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| ***Panel A: Baseline Integration Measures*** | | | | | | | |
| (1) SY Migrants - N Local Native Friends | X | | | | | | |
| (2) SY Migrants - Produced Content in DE | 0.65 | X | | | | | |
| (3) SY Migrants - N Local Native Groups | 0.27 | 0.55 | X | | | | |
| (4) SY Migrants - N Local SY Friends | -0.04 | -0.55 | -0.42 | X | | | |
| ***Panel B: Decomposition of Integration Measures*** | | | | | | | |
| (5) General Friendliness | 0.64 | 0.31 | -0.04 | 0.11 | X | | |
| (6) Relative Friending | 0.77 | 0.56 | 0.43 | -0.16 | -0.05 | X | |
| ***Panel C: Labor Market Integration Measure*** | | | | | | | |
| (7) Share Syrians in Employment or Training | 0.46 | 0.63 | 0.14 | -0.36 | 0.29 | 0.34 | X |

**Note:** Table presents signal-adjusted correlations between county-level estimates. The outcomes in panel (a) are the regional averages of Syrian migrants after residualizing on local German natives' Facebook usage, as described in Section 2. The outcomes in panel (b) are the regional decomposition measures described in Section 3.1. Row 5 is general friendliness, generated as a regional average of German natives after residualizing on local German natives' Facebook usage. Row 6 is relative friending, generated as the quotient from dividing the measure in row 1 by the measure in row 5. The outcome in panel C is an external county-level measure of the share of all Syrians that are employed or in training programs as described in Section 4.2. Correlations are weighted by the number of Syrian migrant users in each county. Our methodology for adjusting correlations to remove sampling error is described in Appendix 5.

**Table A7:** Syrian Migrant Mover and Comparable Non-Mover Sample Summaries

| | **All** | | **To Below Median Place** | | **To Above Median Place** | |
|---|---|---|---|---|---|---|
| | **Movers** | **Matched** | **Movers** | **Matched** | **Movers** | **Matched** |
| % Female | 18.70 | 18.70 | 19.54 | 19.54 | 17.95 | 17.95 |
| Avg Age | 27.97 | 27.49 | 27.98 | 27.51 | 27.97 | 27.47 |
| Avg Qs in DE | 6.47 | 6.42 | 6.54 | 6.50 | 6.40 | 6.36 |
| Avg Friends Made (total in year) | 44.72 | 43.97 | 44.78 | 44.07 | 44.66 | 43.87 |
| % of Qs Produ in DE | 45.77 | 45.01 | 44.31 | 44.01 | 47.09 | 45.90 |
| % of Qs Makes Native Local Friend | 11.80 | 17.18 | 10.51 | 16.72 | 12.96 | 17.60 |

**Note:** Table presents summary statistics describing the movers underlying Figure A19 and their matched non-movers in their origin. Movers are matched to non-movers on county, time, age group (18-29, 30-39, 40+), gender, and the year we first observed the user on Facebook in Germany. To be in the final sample, a mover must be matched to five or more non-movers in both the origin and destination. Measures are constructed using the movers' information in the year prior to the move and their matched users in the origin location and time. Matched non-mover summaries are generated by first constructing measures within each mover's set of matched movers, then averaging across these measures. "Avg Friends Made" is constructed from summing quarterly measures that are winsorized at the 99% level across all migrant user-by-quarter observations. "% of Qs Makes Native Local Friend" is residualized by local natives' Facebook usage.

**Table A8:** Δ Migrant Mover Friending Integration vs. Matched Non-Movers: Robustness

| | Change Quarterly Prob of Making Native Local Friend | | | |
|---|---|---|---|---|
| Dest-Origin Quarterly Prob of SY Making Native Local Friend | 0.738*** (0.036) | | 0.758*** (0.051) | 0.724*** (0.053) |
| Origin Quarterly Prob of SY Making Native Local Friend | | -0.712*** (0.037) | | |
| Dest Quarterly Prob of SY Making Native Local Friend | | 0.773*** (0.037) | | |
| Quarter FEs | X | X | X | X |
| Origin County FEs | | | X | |
| Dest County FEs | | | | X |
| N | 32,853 | 32,853 | 32,849 | 32,845 |
| Sample Mean | 0.934 | 0.934 | 0.933 | 0.938 |

**Note:** Table shows results from regressions exploring the change in friending of Syrian migrants to German natives, before and after a move within Germany. Column 1 corresponds to the relationship depicted in Figure A19. Column 2 regresses each component of the difference in the right-hand side measure in column 1 separately on the outcome. Columns 3 and 4 repeat column 1 with origin and destination fixed effects, respectively. We correct for sampling error in the right-hand side measures by randomly splitting the individual-level non-mover data into two halves and instrumenting for one set of averages with the other. See Appendix 5 for more information this procedure. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

**Table A9:** Native Mover and Comparable Non-Mover Sample Summaries

***Panel A: Yearly General Friendliness Sample***

| | All | | To Below Median Place | | To Above Median Place | |
|---|---|---|---|---|---|---|
| | Movers | Matched | Movers | Matched | Movers | Matched |
| % Female | 51.95 | 51.95 | 51.74 | 51.74 | 52.07 | 52.07 |
| Avg Age | 33.70 | 33.34 | 34.21 | 33.87 | 33.39 | 33.03 |
| Avg Friends Made (total in year) | 21.22 | 20.11 | 19.71 | 19.68 | 22.12 | 20.36 |
| Yearly General Friendliness | 5.33 | 9.74 | 4.81 | 9.49 | 5.63 | 9.89 |

***Panel B: Yearly Relative Friending Sample***

| | All | | To Below Median Place | | To Above Median Place | |
|---|---|---|---|---|---|---|
| | Movers | Matched | Movers | Matched | Movers | Matched |
| % Female | 52.75 | 52.75 | 52.48 | 52.48 | 52.90 | 52.90 |
| Avg Age | 31.90 | 31.86 | 32.35 | 32.35 | 31.65 | 31.58 |
| Avg Friends Made (total in year) | 28.19 | 20.70 | 26.41 | 20.20 | 29.21 | 20.99 |
| Yearly Relative Friending | 0.20 | 0.23 | 0.17 | 0.22 | 0.21 | 0.23 |

**Note:** Table presents summary statistics describing the users underlying Figure 6. Panels (a) and (b) show summaries for movers and matched non-movers in panels (a) and (b) of Figure 6, respectively. Measures are constructed using movers' information in the year prior to the move and their matched users in the origin location and time. Matched non-mover summaries are generated by first constructing measures within each mover's set of matched movers, then averaging across these measures. "Avg Friends Made" is constructed from summing quarterly measures winsorized at the 99% level across all native user-by-quarter observations. The final outcome in each panel is residualized by local natives' Facebook usage.

**Table A10:** Change in Native Mover SY Migrant Friending vs Matched Non-Movers

| | Change in Mover Yearly General Friendliness | | | | Change in Mover Yearly Relative Friending | | | |
|---|---|---|---|---|---|---|---|---|
| Dest-Origin Yearly General Friendliness | 0.685*** | | 0.711*** | 0.602*** | | | | |
| | (0.004) | | (0.005) | (0.005) | | | | |
| Origin Yearly General Friendliness | | -0.636*** | | | | | | |
| | | (0.005) | | | | | | |
| Dest Yearly General Friendliness | | 0.739*** | | | | | | |
| | | (0.005) | | | | | | |
| Dest-Origin Yearly Relative Friending | | | | | 0.959*** | | 0.926*** | 0.988*** |
| | | | | | (0.064) | | (0.094) | (0.086) |
| Origin Yearly Relative Friending | | | | | | -0.988*** | | |
| | | | | | | (0.071) | | |
| Dest Yearly Relative Friending | | | | | | 0.926*** | | |
| | | | | | | (0.071) | | |
| Quarter FEs | X | X | X | X | X | X | X | X |
| Origin County FEs | | | X | | | | X | |
| Dest County FEs | | | | X | | | | X |
| N | 1,771,041 | 1,771,041 | 1,771,041 | 1,771,041 | 1,096,874 | 1,096,874 | 1,096,874 | 1,096,874 |
| Sample Mean | 3.160 | 3.160 | 3.160 | 3.160 | 0.005 | 0.005 | 0.005 | 0.005 |

**Note:** Table shows results from regressions exploring the change in friending of natives, before and after a move within Germany. Columns 1 and 5 correspond to the relationships depicted in panels (a) and (b) of Figure 6. Columns 2 and 6 regress each component of the difference in the right-hand side measure in columns 1 and 5 separately on the outcome. Columns 3 and 7 repeat columns 1 and 5 with origin fixed effects; columns 4 and 8 repeat columns 1 and 5 with destination fixed effects. We correct for sampling error in the right-hand side measures by randomly splitting the individual-level non-mover data into two halves and instrumenting for one set of averages with the other. See Appendix 5 for more information this procedure. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

## 2 Construction of "Native German" Sample

For many of our analyses we use a sample of Facebook users, which we refer to as "German natives", that meet *both* criteria 1 and 2 described below (as well as the primary sample inclusion criteria described in Section 1.1). Our methodology is not intended to proxy for citizenship status or ethnicity; rather it generates a sample of users who generally use the German language and—according to self-reported profile information and home region predictions—appear to have lived in Germany for a substantial amount of time. This will include, for example, individuals of Syrian descent who report a German hometown and primarily use the German language on Facebook. For more details, see footnote 3.

- **Criteria 1:** The user meets *one* of the following
  - The user produces $\geq$ 75% of their content in German
  - The user produces $\geq$ 50% of their content in German, AND lists a German hometown or high school on their profile
- **Criteria 2:** The user meets *all* of the following
  - Does not list a hometown in a "top migration country"
  - Does not list a high school in a "top migration country..
  - Did not first have a predicted home region in a "top migration country

The top migration countries are the 15 countries outside of the European Union and within Eastern Europe, the Middle East, or Africa with the most foreign nationals in Germany.

# 3 Individual-Level Outcomes

We consider three dimensions of social integration of Syrian migrants: friendship, language, and participation within local groups. Within each dimension, we construct a number of measures, though we focus on a primary measure within each dimension, which is noted in **bold**.

1. Friendship Measures
   (a) ***N Local Native Friends:* The number of friends a user has in the same county or a bordering county that are in the German native sample.**
   (b) *N Native Friends:* The number of friends a user has in the German native sample.
   (c) *N Top 50 Native Friends:* The number of a user's closest 50 friends that are in the German native sample.
   (d) *% of Friends Native:* The percent a user's total friends that are in the German native sample.
2. Language Measures
   (a) *% Content Produced in DE*: The share of content a user produces (e.g., in posts, comments) that is in German. "Half-life" of 30 days (i.e., a post 30 days ago is weighted as half a post today).
   (b) *% Content Consumed in DE*: The share of the content a user engages with by using the "react" and "comment" features that is in German. 1 comment = 7 reactions. "Half-life" of 30 days.
   (c) ***Produces Any DE Content* : An indicator for "% Content Produced in DE" is >1%.**
   (d) *Consumes Any DE Content*: An indicator for "% Content Consumed in DE" is >1%.
   (e) *Account in DE*: Whether a user selected German as their language in their account settings.
3. Local Group Participation Measures
   (a) ***N Local Native Groups*: The number of groups a user is in that have 5 - 5,000 users; $\geq$ 90% of users in Germany and $\geq$ 75% of users in one NUTS2 region; and $\geq$ 50% of users in the German native sample.**
   (b) *% Groups Local Native*: The share of groups a user is in that match the criteria in "N Local Native Groups."
   (c) *Avg. % Native in DE Groups*: Among groups a user is in which have > 90% of users in Germany, the average share of users that are German natives.

We also observe the following additional measures at the individual level:

- *N Local Syrian Friends*: The number of friends a user has in the same county or a bordering county that are in the Syrian migrant sample
- *N Local Other Refugee Country Friends*: The number of friends a user has in the same or bordering county that are migrants (determined by hometown, high school, or past usage) from one of the five countries with the most asylum applicants in Germany in 2020 other than Syria: Turkey, Afghanistan, Iraq, Nigeria, and Iran.

- *N Local Recent Other Refugee Country Friends*: The number of friends a user has matching the "N Local Other Refugee Country Friends" criteria with observed arrival in Germany 2015 or later. As described in Section 1.1, users with an "observed arrival timing" are those who first used Facebook outside of Germany.

## 4 Syrian Migrant Integration by Demographics

We explore the heterogeneity in integration outcomes by demographics formally using the the following multivariate regression model:

$$Y_{i,j} = \alpha_0 + \alpha_1 Z_i + \psi_{j(i)} + \epsilon_i. \tag{1}$$

For the results in columns 1-4 of Table A11, $Y_{i,j}$ is the number of native local friends of individual $i$ has. All specifications include various controls $Z_i$ for the amount of time users spend on Facebook, ensuring that differences in observed integration outcomes are not driven by variation in the intensity of Facebook usage. We also include fixed effects for the user's number of quarters since arrival in Germany and the number of quarters living in their current county.

In column 1, $Z_i$ also includes dummies for age, gender, and whether the user has another Syrian migrant household member or non-household family member who was in Germany more than a year prior to their arrival.[1] Consistent with the univariate patterns in Figure 1, we find that younger and male Syrians befriend disproportionately many local German natives. All else equal, a female Syrian migrant has 3.7 fewer local native friends than a male does. Similarly, a Syrian migrant aged 55 or older has 4.6 fewer native local friends than a comparable individual under the age of 25. Column 1 also shows that, while migrants with a family member who arrived earlier in Germany *outside* of the household have more local native friends, individuals with an earlier arriving Syrian migrant *inside* their household have fewer local native friends. This result adds to prior findings that connections to other migrants support integration in some settings and hinder it in others (e.g., Lazear, 1999; Edin, Fredriksson and Åslund, 2003; Cutler, Glaeser and Vigdor, 2008; Damm, 2009; Beaman, 2012; Martén, Hainmueller and Hangartner, 2019). In our context, the results suggest that somewhat-distant familial connections might provide support and guidance to help the social integration of newly arriving migrants, whereas the presence of close household connections might reduce the need to form connections with local natives.

Column 2 adds fixed effects for the Syrian migrants' current county of residence, $\psi_{j(i)}$, to the regression. The $R^2$ increases by 21% from 0.132 to 0.160, consistent with the presence of important regional differences in the social integration of Syrian migrants. The coefficients on the demographic characteristics in $Z_i$ are largely unaffected by the addition of county fixed effects, suggesting there is a little selection based on these characteristics into more or less integrated places.

Column 3 adds controls for each user's total number of friends outside Germany, total number of groups joined, and total amount of recent content produced. These controls absorb additional variation in individuals' Facebook usage patterns beyond those in column 1, but could also remove variation in the true sociability of individuals that might influence their ability and desire to socially integrate with natives. While most coefficients remain largely unchanged, the gender coefficient falls somewhat in absolute terms, from -3.6 to -3.2. A possible interpretation is that Syrian migrant men generally have larger social networks, but, even conditional on overall network size, also make more German friends.

In column 4 of Table A11 we add household fixed effects while dropping individuals without additional household members from the sample. Even within the same household, and conditional on

[1]Family and household information is determined through self-reports and model-based imputations. Similar data are used in Bailey et al. (2022) and Chetty et al. (2022*a*,*b*).

**Table A11:** Syrian Migrant Integration by Demographics - Friending to Natives

| | Facebook Sample N Local Native Friends | | | | SOEP Sample N German Acquaintances | |
|---|---|---|---|---|---|---|
| Age 25 - 34 | -1.012*** | -0.894*** | -0.873*** | -1.148*** | -0.839* | -1.089** |
| | (0.053) | (0.052) | (0.052) | (0.129) | (0.47) | (0.47) |
| Age 35 - 44 | -2.963*** | -3.019*** | -2.941*** | -2.375*** | -1.116* | -1.070* |
| | (0.062) | (0.061) | (0.061) | (0.158) | (0.58) | (0.58) |
| Age 45 - 54 | -4.012*** | -4.102*** | -4.147*** | -4.765*** | -2.362*** | -2.238*** |
| | (0.080) | (0.079) | (0.079) | (0.184) | (0.78) | (0.77) |
| Age 55+ | -4.548*** | -4.531*** | -4.586*** | -7.226*** | -3.378*** | -3.594*** |
| | (0.100) | (0.098) | (0.099) | (0.241) | (1.24) | (1.23) |
| Female | -3.676*** | -3.610*** | -3.225*** | -3.267*** | -1.421*** | -1.512*** |
| | (0.043) | (0.042) | (0.045) | (0.090) | (0.47) | (0.48) |
| Household Member in DE 1+ Year Prior | -0.377*** | -0.290** | -0.352*** | | | |
| | (0.100) | (0.099) | (0.099) | | | |
| Non-Household Family in DE 1+ Year Prior | 0.524*** | 0.621*** | 0.421*** | | | |
| | (0.091) | (0.089) | (0.089) | | | |
| Quarters Since DE FEs | X | X | X | X | X | X |
| Prev Quarters in NUTS3 FEs | X | X | X | X | | |
| Personal Usage Controls | X | X | X | X | | |
| County / State FEs | | X | X | X | | X |
| Log (1 + Total Outside Germany Friends) | | | X | X | | |
| Log (1 + Total Other Groups) | | | X | X | | |
| Log (1 + Total Content Produced Past Year) | | | X | X | | |
| Household FE | | | | X | | |
| N | 349,072 | 349,072 | 349,072 | 84,216 | 1,095 | 1,095 |
| R-Squared | 0.132 | 0.160 | 0.165 | 0.658 | 0.048 | 0.093 |
| Sample Mean | 5.029 | 5.029 | 5.029 | 4.195 | 6.232 | 6.232 |

**Note:** Table explores variation in migrants' social integration. Each observation in columns 1-4 is a user in the Syrian migrant Facebook sample. Column 1 includes (i) controls for age and gender; (ii) fixed effects for the number of quarters on Facebook in their current county and the number of quarters since arrival in Germany (we use a single dummy value for those for which we do not observe arrival, but obtain nearly identical results if we instead drop these users); (iii) dummies for whether the user has another Syrian migrant household member or non-household family member in Germany prior to their arrival. (For all users not in the "observe arrival timing" sample, these two dummies are set to 0); and (iv) the following measures of the Facebook usage intensity: linear controls for log(0.5 + minutes on FB in the last 28 days), log(91 - days on Facebook out of the last 90), log(1081 - days on Facebook out of the last 1080). Column 2 adds county fixed effects. Column 3 adds controls for each user's total number of friends outside Germany, total number of non-local/native groups joined, and total amount of content produced in the last year. Column 4 adds a household fixed effect, limiting to households for which we observe more than one Syrian migrant. Columns 5 and 6 use data from the Socio-Economic Panel in 2016. The dependent variable in these columns is the number of new acquaintances made in Germany (see footnote 8). Each observation is a recent migrant from Syria living in Germany as of the date of the survey. Both columns 5 and 6 include controls for the number of quarters in Germany. Column 6 also controls for state fixed-effects. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

general Facebook usage patterns, younger and male Syrian migrants are better socially integrated.

Appendix Table A4 presents results analogous to column 1-4 of Table A11 for our key language- and group-based measures of social integration, and Table A5 presents results analogous to column 3 of Table A11 for a number of other outcomes. Across all measures, we find highly consistent relationships between age, gender, and family connections and the social integration of Syrian migrants.

One concern with this analysis may be that, despite our strict controls for Facebook usage and the consistency of our results across outcome, the observed differences in integration outcomes across demographic groups may still be driven by patterns of Facebook usage, rather than reflecting true demographic variation in social integration. To address this concern, we also look at related outcomes in the Socio-Economic Panel data, namely the number of native acquaintances made in Germany among a sample of recent Syrian migrants. In 2016, the SOEP administered a survey specifically targeted at recent migrants to Germany. We focus on the 1,095 Syrian migrants in the data that are 18+ years old.

Columns 5 and 6 show that the patterns of friending across demographics in the SOEP data mirror those we observe in the Facebook data in columns 1-4. Female and older migrants have fewer local acquaintances than male and younger migrants, respectively, on average. This holds with state fixed effects in column 6. Indeed, even the coefficient estimates using the Facebook and SOEP data are generally quite similar. We interpret this as reassuring as it shows that the patterns of social integration we identify in the Facebook data align closely with available survey evidence. The Facebook data, however, is much larger and more detailed, allowing us to more precisely explore the spatial variation in integration and to better understand the determinants of this variation.

## 5 Assessing the Reliability of Regional Estimates

A potential concern with our regional estimates of integration outcomes is that the differences we observe might be due to sampling error, instead of capturing actual differences in the parameters of interest. In this appendix we explore this concern and describe the methods used to address it.[2]

To assess the degree to which our variation is driven by sampling error, we seek an estimate of:

$$r = \frac{Var(\delta_j)}{Var(\delta_j) + Var(\epsilon_j)} \tag{2}$$

Here $\delta_j$ is the true (un-observable) parameter for county $j$, $Var(\delta_j)$ is the variance of that parameter across all counties, and $Var(\epsilon_j)$ is the variance due to sampling error (noise) when we measure our estimate $Var(\hat{\delta}_j)$, such that $Var(\hat{\delta}_j) = Var(\delta_j) + Var(\epsilon_j)$. Our outcome of interest is the reliability, $r$.

We estimate $r$ in two ways: (i) a "split sample" estimate generated by randomly splitting the individual-level data in half (within counties) and comparing the resulting estimates; and (ii) a "standard error-based" estimate generated by comparing the magnitudes of the standard error squared of each estimate with the variance of the estimates across counties.

Formally, our "split sample" estimates are given by:

$$\hat{r} = Corr(\hat{\delta}_j^1, \hat{\delta}_j^2) \cdot \frac{\sqrt{Var(\hat{\delta}_j^1)Var(\hat{\delta}_j^2)}}{Var(\hat{\delta}_j)} \tag{3}$$

Where $\hat{\delta}_j$ is the county-level estimate of $\delta$ in county $j$, the average of individual-level measures across users in the county; $Var(\hat{\delta}_j^1)$ and $Var(\hat{\delta}_j^2)$ are the population-weighted variances of these measures in the first and second split samples; $Var(\hat{\delta}_j)$ is the population-weighted variance in the full sample; and $Corr(\hat{\delta}_j^1, \hat{\delta}_j^2)$ is the population-weighted correlation.

Our "standard error-based" estimates are given by:

$$\hat{r} = \frac{Var(\hat{\delta}_j) - E[s^2_{\hat{\delta}_j}]}{Var(\hat{\delta}_j)} \tag{4}$$

Where $s_{\hat{\delta}_j}$ is the standard error of the county level average $\hat{\delta}_j$ for county $j$.

The first two columns of Appendix Table A12 show that the reliability of each of our regional averages is around 0.9 or above regardless of the method used. This suggests that 90% or more of the variance in a given regional measure reflects true latent differences rather than sampling error.

As noted in Section 2, there are moderate differences in the Facebook usage of natives across space (largely at the intensive margin) which could affect the raw regional averages we measure. To account for this, our estimates in Figure 2 and Appendix Figures A9 and A10 are constructed after residualizing by differences in natives' Facebook usage. Column 3 of Appendix Table A12 shows split-sample reliability estimates using $\hat{\delta}_j^1$ and $\hat{\delta}_j^2$ that have been residualized in this same manner. The reliability estimates are largely unchanged, suggesting they are not driven by regional differences in usage.

[2]The methods described in this appendix are similar to procedures used in Chetty and Hendren (2018*b*), Chetty et al. (2022*a*), and Chetty et al. (2022*b*).

**Table A12:** Reliability of County-Level Measures, Syrian Migrant Sample

| | Reliability | | |
|---|---|---|---|
| | Split-Sample | SE-Based | Split-Sample, Usage Control |
| N Local Native Friends | 0.962 | 0.961 | 0.938 |
| Produced Any DE Content | 0.909 | 0.901 | 0.883 |
| N Local Native Groups | 0.948 | 0.946 | 0.934 |
| N Local Syrian Friends | 0.989 | 0.989 | 0.989 |

**Note:** Table shows the reliability of county-level measures. In columns 1 and 2 the measures are averages across Syrian migrant users. In column 3 these measures are residualized on extensive and intensive measures of local natives' Facebook usage, as described in Section 2. Reliability is defined by equation 2. The split sample reliability estimates are generated using equation 3. The standard error-based reliability estimates are generated using equation 4.

In Section 3.1, we construct regional measures of *general friendliness* using the German native sample. The sample size for these measures is very large and, accordingly, the reliability estimates using both methods is greater than 0.995. Therefore, essentially all of the sampling error present in our measures of *relative friending* (generated by dividing the Syrian migrant integration outcomes by general friendliness) is driven by the Syrian migrant integration outcomes.

In Table 4 we correlate regional measures against each other across counties. In these cases, the correlations between the estimates may understate the true correlations between parameters because of noise introduced by the sampling error. To recover estimates of the correlation between the true parameters we calculate:

$$\hat{Corr}(\psi_j, \mu_j) = Corr(\hat{\psi}_j, \hat{\mu}_j)\sqrt{\frac{1}{\hat{r}_\psi}}\sqrt{\frac{1}{\hat{r}_\mu}}. \tag{5}$$

Where $Corr(\hat{\psi}_j, \hat{\mu}_j)$ is the correlation between estimates $\hat{\psi}_j$ and $\hat{\mu}_j$ (of parameters $\psi_j$ and $\mu_j$) across all counties $j$, and $\hat{r}_\psi$ are $\hat{r}_\mu$ are their reliability estimates from equation 4. We present these "signal correlations" in Appendix Table A6.

In Section 2.1 and 3.2, we use certain regional (and region-by-demographics) measures as right-hand side variables in our movers specifications. The sampling error in these estimates will attenuate their regression coefficients. To see this, take the simple regression $Y = \beta \cdot X + \omega$ where we observe $\hat{X}$, an estimate of $X$ with independent sampling error $\epsilon$. Then when estimating $Y = \hat{\beta} \cdot \hat{X} + \nu$ we have:

$$\begin{aligned}\hat{\beta} &= \frac{Cov(Y, \hat{X})}{Var(\hat{X})} \\ &= \frac{Cov(Y, X+\epsilon)}{Var(X+\epsilon)} \\ &= \frac{Cov(Y, X)}{Var(X) + Var(\epsilon)} < \frac{Cov(Y, X)}{Var(X)} = \beta.\end{aligned} \tag{6}$$

To account for this, in our movers analyses we first randomly split the individual-level data used to construct the relevant right-hand side measures in two halves. We then instrument for the value constructed by one half with the other. To see the intuition behind this procedure, let $\hat{X}_1$ and $\hat{X}_2$ be the split sample estimates. Then the first stage of a two-stage least squares estimate is given by $\hat{X}_1 = \phi_1 \cdot \hat{X}_2 + \nu_1$, where $\phi_1 = \hat{r} = \frac{Var(X)}{Var(X)+Var(\epsilon_2)}$. The reduced form is given by $Y = \phi_2 \cdot \hat{X}_2 + \nu_2$, where $\phi_2 = \frac{Cov(Y,X)}{Var(X)+Var(\epsilon_2)}$. Then the resulting estimate is:

$$\hat{\beta} = \frac{\phi_2}{\phi_1} = \phi_2 \cdot \frac{1}{\hat{r}} \approx \frac{Cov(Y,X)}{Var(X)} = \beta. \tag{7}$$

## 6 Königsteiner Schlüssel and the Assignment of Refugees to Place

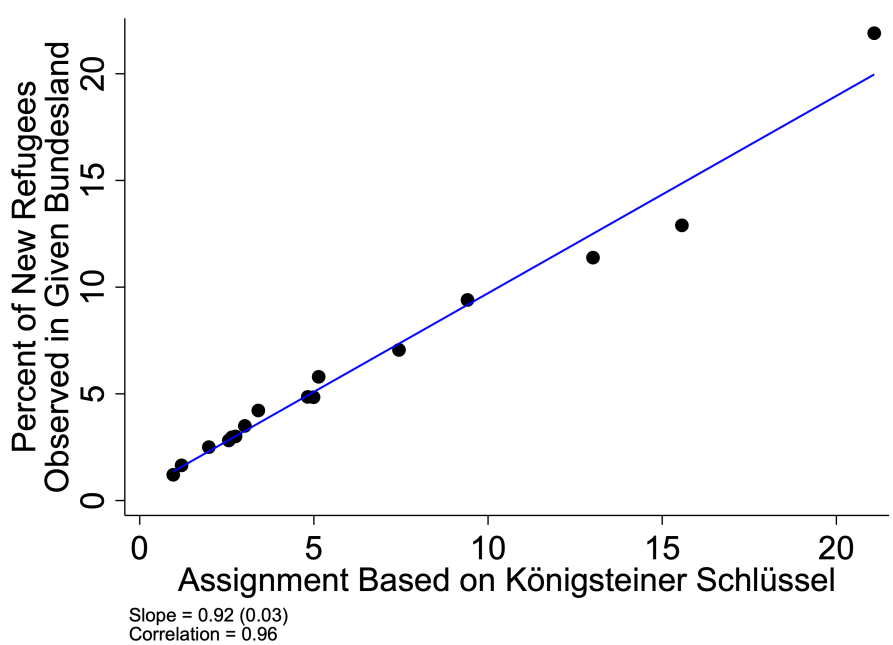
In this section, we attempt to compare the official refugee allocation rule—the so-called Königsteiner Schlüssel—to observed administrative data on refugee assignment.

The Königsteiner Key is an allocation rule which was designed in the 1940s to assign refugees to the sixteen different German states. It takes as input a state's population and tax income and weights these two factors with 1/3 and 2/3, respectively (Deutscher Bundestag, 2020). The key is updated annually, but given the slow-moving nature of its inputs, it is stable over time.

To infer to what extent the key has been abided to during the time period of interest for our study, we compare the 2019 assignment key (for data availability reasons) to the percentage of the total number of refugees that live in a given state and have been in Germany for less than 1 year, for each year from 2015 to 2019. The latter measure is intended to approximate for new-arrivals in the absence of direct data on this and the data for this approximate measure is obtained from the German Statistical Office.

Figure A13 shows the result of our comparison. The correlation of 0.96 and a slope of 0.92 indicates that the observed assignment lines up very closely with the official assignment rule. We find this reassuring, as it suggests that despite the large influx of migrants during these year, refugee assignment largely followed the official assignment key. While we believe this is strong suggestive evidence that, to adhere to this rule, assignment to places was somewhat random, it remains possible that the composition of migrants by place is non-random.

**Table A13:** Comparison Königsteiner Key and Assignment of Refugees to Place




**Note:** Figure compares assignment of recent refugees to place with the official assignment key, i.e. the Königsteiner Schlüssel from 2019. The Königsteiner Schlüssel is compromised of a state's total population and a state's tax income where the former is weighted with one third and the latter is weighted two thirds. Assignment of recent refugees is approximated by the percentage of the total number of refugees that live in a given state and have been in Germany for less than 1 year, for each year from 2015 to 2019. The data comes from the German Statistical Office.

# 7 Identifying Place Based Effects with Movers

To quantify the contribution of place-based effects to the spatial variation in migrants' integration outcomes, we propose a simple model in which the rate of friendships between migrants and a local natives is determined by the sum of place-based effects—which we allow to vary across time and with observable migrant characteristics—and other *unobservable* individual-level factors of the individuals involved. Since only place-based factors change around a move, this model allows us to estimate the share of regional variation in the social integration of migrants that can be attributed to place-based effects. We describe here the friending model and identifying assumptions in the context of the migrant mover design from Section 2.1. These features carry over to the native mover design in Section 3.2.

**Friending model.** We consider the following basic model of friending between migrants and locals which is similar to Finkelstein, Gentzkow and Williams (2016). We let each individual's friending outcome be the sum of their county's effect ($\text{PlaceEffect}^{(p)}$) and their personal individual effect ($\text{IndivEffect}_i$). Let $\text{AvgIndivEffect}^{(p)}$ be the average of IndivEffects for individuals in county $p$. Then the difference between the average outcomes, $x$, in two regions, (2) and (1), is the sum of differences between the place-based effect and the average of individual-effects.

$$x^{(2)} - x^{(1)} = (\text{PlaceEffect}^{(2)} - \text{PlaceEffect}^{(1)}) + (\text{AvgIndivEffect}^{(2)} - \text{AvgIndivEffect}^{(1)}). \tag{8}$$

We want to know the share of $x^{(2)} - x^{(1)}$ that is due to place-based effects, formally:

$$\frac{\text{PlaceEffect}^{(2)} - \text{PlaceEffect}^{(1)}}{(\text{PlaceEffect}^{(2)} - \text{PlaceEffect}^{(1)}) + (\text{AvgIndivEffect}^{(2)} - \text{AvgIndivEffect}^{(1)})}. \tag{9}$$

We cannot observe any of these parameters directly. At the individual level, however, we know that when a mover moves from (1) to (2), only the place-based factors should change. Her individual level effects are constant, so any change in friending outcomes must be driven by place based effects. So for mover $i$ who moves from (1) to (2) at time $t$:

$$y^{\Delta}_{i,t} = (\text{PlaceEffect}^{(2)} - \text{PlaceEffect}^{(1)}). \tag{10}$$

Where $y^{\Delta}_{i,t}$ is the change in outcome before and after the move for mover $i$. Then $\alpha$, below, is equivalent to equation 9, our outcome of interest.

$$y^{\Delta}_{i,t} = \alpha \cdot (x^{(2)} - x^{(1)}). \tag{11}$$

In addition to this baseline logic, we allow for separate place effects across certain observable demographics such as age and gender, as well as time since moving to Germany. The *AvgIndivEffect* is then the average of the remaining unobservable individual effects. When estimating $\alpha$ we remove the variation in $y^{\Delta}_{i,t}$ explained by overall time trends (e.g., if throughout Germany Syrian migrants make more native friends over time) by adding quarter of move fixed effects, $\xi_t$.

**Taking model to the data.** We bring this model to the data by comparing the rate at which movers make friends in the year before and after their move to the difference in the average friending rates of otherwise similar non-movers in each location.[3] Focusing on migrant movers (rather than on native movers as in section 3.2), for each user $i$ moving in quarter $t$, the outcome of interest is the change in the quarterly probability of making at least one local German friend, $y^{\Delta}_{i,t}$, defined as:

$$y^{\Delta}_{i,t} = 0.25 \left[ \sum_{\tau=t}^{t+3} Y_{i,\tau} - \sum_{\tau=t-4}^{t-1} Y_{i,\tau} \right]. \tag{12}$$

Here, $Y_{i,t}$ is an indicator for whether Syrian migrant $i$ makes at least one local German friend in quarter $t$. Similar to before, we residualize each side of the difference on regional measures of natives' Facebook usage. To compare $y^{\Delta}_{i,t}$ to differences in the average integration rates of observably similar non-movers in each place, we construct sets of users who match each mover on the important determinants of social integration in Section 1.4: gender, age group, and time spent in Germany. Formally, for user $i$ moving in quarter $t$, we let $O(i,t)$ and $D(i,t)$ be the sets of similar non-movers in the origin at time $t-4$ and in the destination at time $t$, respectively. We then define the differences in their average outcomes, $x^{\Delta}_{i,t}$, as:

$$x^{\Delta}_{i,t} = 0.25 \left[ \frac{1}{|D(i,t)|} \sum_{j \in D(i,t)} \sum_{\tau=t}^{t+3} Y_{j,\tau} - \frac{1}{|O(i,t)|} \sum_{j \in O(i,t)} \sum_{\tau=t-4}^{t-1} Y_{j,\tau} \right]. \tag{13}$$

The set cardinalities $|O(i,t)|$ and $|D(i,t)|$ are the number of non-movers in the matched comparison groups for each mover. Intuitively, $x^{\Delta}_{i,t}$ is the difference in the average quarterly probability of a non-mover migrant making a native local friend between the destination location in the year after the move and the origin location in the year before the move. Time-specific measures allow for changes in the differences between regions over time. Again, we residualize each side of the difference on regional measures of natives' Facebook usage. We then estimate:

$$y^{\Delta}_{i,t} = \alpha_0 + \alpha_1 x^{\Delta}_{i,t} + \xi_t + \epsilon_{i,t}, \tag{14}$$

where slope $\alpha_1$ is our outcome of interest. An estimate of $\alpha_1$ close to 1 would suggest that, within the first year of moving, migrant movers' friending behavior fully adjusts to the level of local non-movers' friending behavior. An $\alpha_1$ close to 0 would suggest that migrants do not adjust their friending rates systematically toward the level of local non-movers. Because migrant observables do not differ significantly across space, under the relatively weak identification assumptions discussed below, $\alpha_1$ estimates the share of the observed differences in the social integration of migrants across locations that are due to causal place-based effects rather than unobservable individual characteristics. The quarter of move fixed effect, $\xi_T$, remove variation in overall time trends in the rates of befriending local natives.

One challenge with our estimation is that we only observe a sample estimate of each mover's $x^{\Delta}_{i,t}$, denoted by $\hat{x}^{\Delta}_{i,t}$. Measurement error in the true differences in friending probabilities of non-movers across locations would thus lead to attenuation bias in $\alpha_1$. To account for this sampling error, when

[3] In this analysis we limit to movers who were in their origin and destination counties for four or more consecutive quarters each, less stringent than the prior analysis which required six quarters in the destination. In addition, we only include observations for which there are at least five "matched" non-movers in both the origin and destination.

estimating equation 14, we randomly split the individual-level data of the friending behavior of non-movers used to construct $\hat{x}^{\Delta}_{i,t}$ into two sub-samples and instrument for the value constructed in one sub-sample with the value constructed in the other sub-sample (see Appendix 5 for details).

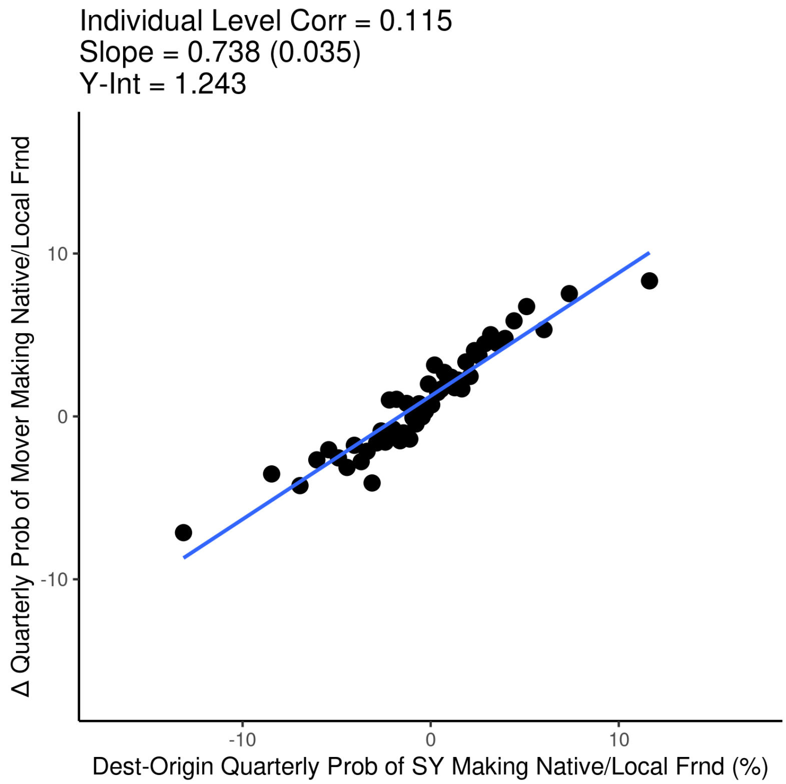
**Identification Assumptions.** Our interpretation of $\alpha_1$ relies on the identifying assumption that place-based effects are additive and additively separable from any unobservable individual-level factors. This additivity allows us to aggregate the level of within-migrant differences across migrants to identify $\alpha$. It implies, for example, that a move from place A to place B should have the same effect as a move from place B to place A. This is supported by Figure 3, as well as the results in Figure A19 and Table A8. Additive separability also implies that migrants' friending rates between locations will vary by the same *absolute amount* across unobservables. (The model does, however, allow for non-additive relationships between our key observables—gender, age, and time in Germany—and migrants' friending rates). Our identification also relies on there being no systematic shocks to unobservable factors that coincide exactly with the move quarter and affect native friending differentially by origin and destination.

These identifying assumptions are relatively weak and allow for movers to differ from non-movers on observable and unobservable characteristics, and for these differences to correlate with origin and destination characteristics. For example, our model allows for "better integrating migrants" to be more likely to move to "better places." Intuitively, this is because our estimates come from *within-migrant* differences in integration over time, and "better" integrating migrants will make more friends both before and after the move. This differs from designs used in papers such as Chetty and Hendren (2018*a*) and Chetty and Hendren (2018*b*). These papers, which rely on cross-sectional outcomes, use within-family designs to rule out selection effects. Our data allow us to measure the outcome in the panel context (as in Finkelstein, Gentzkow and Williams, 2016), mitigating these concerns.

Our research design allows the level of movers' pre-move friending within an origin county to correlate with destination friending levels due to differences in individual characteristics. Movers' native friending around a move can also differ from the trends of non-movers. This could occur if, as suggested by Figure 3, all movers make fewer local connections in anticipation of a move or more connections immediately after a move. Each of these would increase $\alpha_0$, but leave $\alpha_1$ unaffected. Our model would be affected if these downward trends in movers' propensity to make friends before relocating differed systematically by the integration levels in the movers' destinations.[4] Figure 3 provides evidence that such differential trends do not exist. As an additional test, in Figure A13, we decompose our results from Figure 3 into friendships initiated by the mover and those initiated by the Germans in their destination. We find that, following a move, both migrant-initiated and *native-initiated friendships* change in the predicted direction. This provides more evidence that our results are not driven by changes in migrant friending preferences around the time of the move that correlate with the characteristics of the destination.

[4]Put differently, our model allows for migrants' individual characteristics to change around a move so long as they do not differ systematically by destination location. For example, our estimates of $\alpha_1$ would be biased upward if movers to better places became differentially less sociable before a move.

**Figure A19:** $\Delta$ Syrian Migrant Mover Friending Integration vs. Matched Non-Movers




**Note:** Figure shows a binned scatter plot describing the change in the friending of Syrian migrants to German natives before and after a move within Germany. The population is Syrian migrant users who moved between two non-neighboring counties and were in the first and second county for 4+ consecutive quarters each. The y-axis displays $y^{\Delta}_{i,t}$, movers' change in the quarterly probability of making a native local friend the year before to after the move. The x-axis displays $\hat{x}^{\Delta}_{i,t}$, the difference in average outcomes for comparable non-movers at the same time. We match each mover to a set of non-movers who lived in the origin location a year before the move and to a set who lived in the destination location at the move. In addition we also match movers to non-movers of the same gender and age bucket (18-29, 30-39, 40+), and whom we first observed on Facebook in Germany in the same year. We include observations for which there is at least 5 non-movers in both the origin and destination match group. We control for quarter of move fixed effects. We correct for sampling error in the x-axis measures by randomly splitting the individual-level non-mover data into two halves and instrumenting for one set of averages with the other. See Appendix 5 for more information this procedure. Standard errors are shown in parentheses. Appendix Table A8 presents formal regression results on the relationships in this figure.

**Results for Migrant Movers.** Figure A19 displays a binned scatter plot of $y^{\Delta}_{i,t}$ against $x^{\Delta}_{i,t}$, with the slope corresponding to $\alpha_1$ in equation 14.[5] The relationship is symmetric around zero and linear, consistent with additive effects of place. The fact that the scatter plot is horizontally centered around zero also suggests that, conditional on demographics, migrants do not systematically move to places with higher or lower levels of integration. The slope estimate is 0.738: nearly three quarters of the observed regional variation in Syrian migrants' friendship formation with local natives is directly attributable to place-based effects that occur within the first year of after their move, rather than individual characteristics. In Appendix Figure A12 we plot the slope estimates separately for samples of users that are male, female, younger than 30 years old, 30 to 39 years old, and over 40 years old. For each group, the estimates are similar, suggesting our results are not driven by any particular demographic group of Syrian migrants.

[5]Appendix Table A7 summarizes the sample of movers and the corresponding matched sample of otherwise similar non-movers in the origin location.

While this section focuses on measures of social integration based on migrants' friending patterns, Appendix 8 explores our language-based measure of integration. Whereas our prior analysis could use panel data on quarterly friending rates, our language outcome—whether the user produces content in German—is only observable at high quality in the cross section. We thus study how a mover's language use *today* is shaped by the set of places they have lived, following similar analyses in Chetty and Hendren (2018*a*) and Finkelstein, Gentzkow and Williams (2021). Our results suggest that place-based effects drive much of the cross-sectional variation in Syrian migrants' German language usage.

The prior results have documented that when Syrian migrants move between German counties, their social integration patterns quickly adjust from those of their origin towards those of their destination county. Our results thus show that most of the observed regional differences in social integration are explained by the effect of places—either due to institutional factors associated with the location, or due to local native characteristics—rather than by the characteristics of the migrants. In this context, it is important to note that a mover design will not even capture the full extent to which individual integration is shaped by place-based effects. For example, Syrian migrants who learn the German language in high-integration places (possibly in local integration courses) might then use these skills to make German friends more quickly after moving to a low-integration place. This effect might be considered "place-based" in the sense that it is shaped by features of the mover's origin location, but will not be captured by our estimates. To the extent that such additional long-term place-based effects are important, our estimates of $\alpha_1$ will even *understate* the extent to which places truly shape migration outcomes.

## 8 Cross-Sectional Analysis of Movers and German Language Usage

We assess the degree to which selection drives our regional estimates of German language integration using a cross-sectional movers design. This follows similar designs in Chetty and Hendren (2018*a*) and Finkelstein, Gentzkow and Williams (2021), and differs from the design used in Sections 2.1 and 3.2 which utilize panel data on movers' friending. In particular, we model German language usage as a linear combination of the outcomes of non-movers in each of the mover's locations. Then, using the same mover criteria as in Figure A19, we estimate:

$$y_i = \alpha_0 + \alpha_1 \sum_p q(i,p) * x_{p,d(i)} + \kappa_{d(i)} + \epsilon_i \tag{15}$$

Here, $y_i$ is an indicator for whether individual $i$ produces German content on Facebook and $q(i,p)$ is the share of their quarters in Germany spent in place $p$. The notation $d(i)$ represents a set of demographics used to match movers to similarly situated non-movers. $x_{p,d}$ is the share of users in place $p$ and demographic group $d$ that produces German content, and $\kappa_{d(i)}$ are demographic group fixed effects, which remove variation driven by the demographic matching from our slope estimates. In our strictest specifications, we also add fixed effects for users' first and current county in Germany.

**Table A14:** Syrian Migrant Mover Language Integration vs Weighted Average of Places

| | Produces Content in German (0/100) | | | | |
|---|---|---|---|---|---|
| Predicted Prob. Of Using German (Weighted Avg. of Places Lived) | 0.863*** | 0.857*** | 0.863*** | 0.813*** | 0.816*** |
| | (0.037) | (0.043) | (0.058) | (0.042) | (0.058) |
| FEs | Cohort | Cohort | Cohort | Cohort X Curr. Cnty. | Cohort X Curr. Cnty. X First Cnty. |
| Sample | | < 75% in Max County | < 60% in Max County | | |
| N | 23,249 | 18,233 | 10,172 | 23,069 | 14,474 |
| Sample Mean | 38.075 | 37.959 | 38.252 | 38.099 | 36.977 |

**Note:** Table shows results for comparisons between the German language usage of Syrian migrants who moved between counties and their predicted language usage based on the outcomes of non-movers in the places they lived. For each location, movers are matched non-movers by age, gender, and the first year they used Facebook in Germany (cohort). Column 1 shows our baseline specification from equation 15, which includes cohort fixed effects. Column 2 limits to only users who spent < 75% of their quarters in Germany in one county. Column 3 limits to those who spent < 60%. Column 4 repeats column 1 with cohort-by-current county fixed effects; column 5 repeats column 1 with cohort-by-current county-by-first county in Germany fixed effects. We correct for sampling error in the right-hand side measures by randomly splitting the individual-level non-mover data into two halves and instrumenting for one set of averages with the other. See Appendix 5 for more information this procedure. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

In contrast to equation 14, our unit of observation is a mover, not a move, and we use movers' location for every quarter they have been in Germany. As in our panel analyses, we cannot observe $x_{p,c(i)}$, but instead account for sampling error by constructing estimates $\hat{x}_{p,c(i)}$ from random halves of the data and instrumenting for one with the other. We also again relax the assumption of fully additive-seperability between individual-level factors and place-based effects by matching movers to similarly situated non-movers on gender, age group, and year of arrival in Germany. This allows for non-additive interactions with these demographics. We enforce that each mover must have 20 matched non-movers.[6]

Table A14 presents results from our analysis. In column 1, an estimate of $\alpha_1$ close to 1 would suggest that a Syrian migrant's likelihood of using German on Facebook is close to the averages of migrants in each location they have lived, weighted by the amount of time they lived in each location. The resulting slope estimate of 0.86 shows that this is the case. While this evidence is consistent with places having an *effect* on migrants' German language integration, it does not rule out alternative explanations. For example, it is possible that our sample includes many users who have spent a long time in a single location, and that the right hand side weighted averages are often dominated by a single region. If this were the case, our estimates could be largely driven by movers behaving similarly to local non-movers in general, rather than by place-based effects in particular. Columns 2 and 3 provide evidence that this story does not drive our overall results, as our estimates of $\alpha_1$ remain similar when limiting our sample to users who spent <75% or <60% of their time in Germany in one county, respectively.

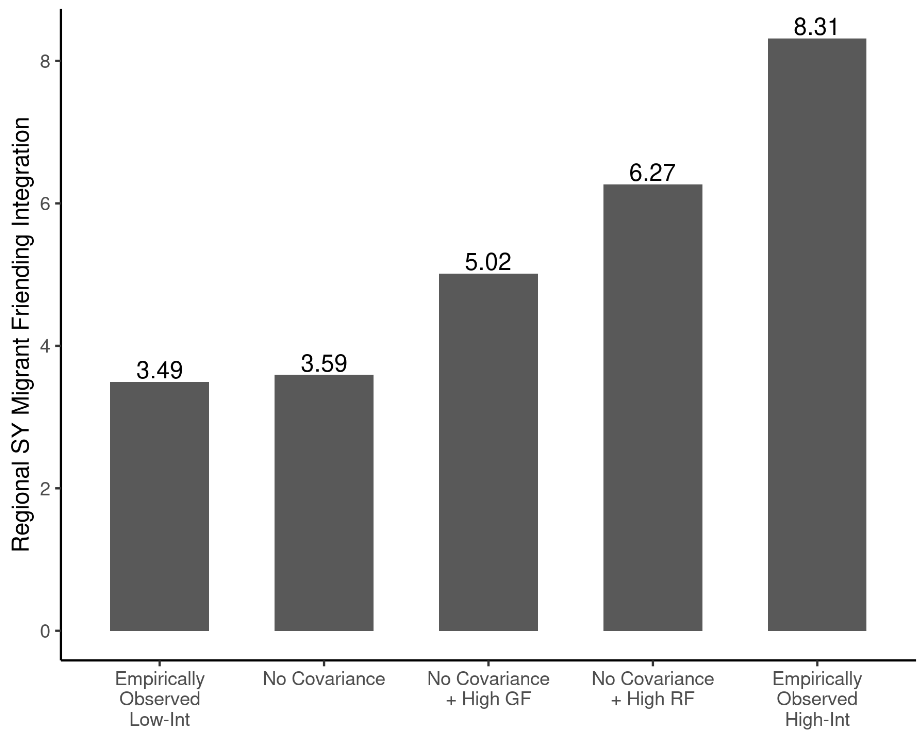
In column 4 we take another approach to testing whether our results are indicative of causal effects of place. In particular, we control for each user's current county, thereby identifying our slope estimates from variation in the user's origin counties. The slope estimate decrease slightly, but remains around 0.81. This suggests that much of the variation in language outcomes amongst movers across regions today is determined by where they *originally* lived in Germany, providing evidence against selection effects. In the final column, we control for both first county and final county fixed effects. Our identitication, therefore, comes from the amount of *time* users' spend in each particular place. The slope estimates remains at 0.82, providing more evidence that a migrant's probability of using the German language scales linearly in proportion to the time they spend in high- and low-integration places.

[6]This threshold is higher than the five user minimum in Section 2.1. Our sample in this analysis, however, will remain larger because we (mechanically) do not enforce temporal matching.

## 9 Decomposition of High- vs Low-Integration Regional Differences

In Figure A20, we conduct counterfactual exercises to explore the degree to which each of our two components explain the differences between counties with high- and low-friending integration. This follows a similar exercise in Chetty et al. (2022*b*). The first and fifth bars show the average integration of migrants in top and bottom quintile counties, respectively. Syrian migrants in top quintile counties make 8.31 native local friends on average, versus 3.49 in bottom quintile counties. In the second bar we multiply the bottom quintile averages of general friendliness and relative friending, thereby removing any within-quintile covariance. Doing so somewhat increases the value from the first bar, consistent with the small negative correlation between the two components in Table 4. The third and fourth bars replace the bottom-quintile averages of general friendliness and relative friending with the corresponding top-quintile averages, respectively. We view this as a counterfactual in which we hold one of the two integration components of low-integration regions fixed and adjust the other to the levels of high-integration regions. We interpret the difference between the second and fourth bars (2.68), compared to the second and third bars (1.43), as relative friending explaining about 1.9x as much of the difference between high and low-integration places as general friendliness.

**Figure A20:** Decomposition of Difference Between High- and Low-Integration Regions




**Note:** Figure shows how much of the difference between high and low friending integration counties is driven by general friendliness versus relative friending. The first and fifth bars show the average friending integration of Syrian migrants in top and bottom quintile counties, respectively. The second bar replaces each county observation from the first bar with the bottom quintile averages of general friendliness and relative friending. The third and fourth bars replace the bottom-quintile averages of general friendliness and relative friending with the corresponding top-quintile averages, respectively.

# 10 Individual-level Correlates of Natives Behavior Towards Migrants

This appendix explores the relationship between observable native characteristics and behaviors toward Syrian migrants. In particular we focus on their (i) friending of local Syrian migrants; (ii) general friendliness; (iii) relative friending; and (iv) joining of pro-immigration organizations on Facebook.

**Table A15:** Natives - Measures of Friending

| | N Local SY Friends | | General Friendliness | | Relative Friending | | In Pro Imm. Group (0/100) | |
|---|---|---|---|---|---|---|---|---|
| Age 25 - 34 | -0.073*** | -0.073*** | -19.097*** | -14.407*** | -0.059*** | -0.061*** | 0.359*** | 0.146*** |
| | (0.000) | (0.000) | (0.098) | (0.092) | (0.001) | (0.001) | (0.018) | (0.018) |
| Age 35 - 44 | -0.116*** | -0.114*** | -55.586*** | -52.328*** | -0.081*** | -0.080*** | 0.951*** | 0.858*** |
| | (0.000) | (0.000) | (0.103) | (0.097) | (0.001) | (0.001) | (0.018) | (0.018) |
| Age 45 - 54 | -0.132*** | -0.131*** | -62.533*** | -62.415*** | -0.098*** | -0.095*** | 1.116*** | 1.152*** |
| | (0.000) | (0.000) | (0.108) | (0.102) | (0.001) | (0.001) | (0.019) | (0.019) |
| Age 55+ | -0.139*** | -0.141*** | -82.666*** | -84.728*** | -0.098*** | -0.095*** | 2.105*** | 2.157*** |
| | (0.000) | (0.000) | (0.108) | (0.102) | (0.001) | (0.001) | (0.020) | (0.020) |
| Female | -0.015*** | -0.015*** | -19.519*** | -18.725*** | -0.008*** | -0.009*** | 0.882*** | 0.843*** |
| | (0.000) | (0.000) | (0.056) | (0.053) | (0.001) | (0.001) | (0.010) | (0.010) |
| Has College | 0.006*** | 0.006*** | 4.131*** | 7.619*** | -0.000 | -0.002*** | 1.931*** | 1.788*** |
| | (0.000) | (0.000) | (0.060) | (0.056) | (0.001) | (0.001) | (0.011) | (0.011) |
| Prev Quarters in NUTS3 FEs | X | X | X | X | X | X | X | X |
| Personal Usage Controls | X | X | X | X | X | X | X | X |
| County FEs | | X | | X | | X | | X |
| N | 17,768,822 | 17,768,822 | 17,768,822 | 17,768,822 | 17,515,164 | 17,515,164 | 17,768,141 | 17,768,141 |
| R-Squared | 0.020 | 0.031 | 0.170 | 0.263 | 0.001 | 0.002 | 0.035 | 0.042 |
| Sample Mean | 0.086 | 0.086 | 122.510 | 122.510 | 0.074 | 0.074 | 4.835 | 4.835 |

**Note:** Table shows results from regressing various outcomes on the demographics of users in the German native Facebook sample. The outcome is their number of local friends in the Syrian migrant sample in columns 1 and 2; their number of local friends in the German native sample in columns 3 and 4; their relative friending to Syrians and Germans defined by equation 2 in columns 5 and 6; and the number of groups registered with *ProAsyl* they are in in columns 7 and 8. Columns 1, 3, 5, and 7 include controls for age, gender, and whether they list a college on Facebook, as well as fixed effects the number of quarters on Facebook in their current county. They also include linear controls for log(0.5 + minutes on FB in the last 28 days), log(91 - days on Facebook out of the last 90), log(1081 - days on Facebook out of the last 1080). Columns 2, 4, 6, and 8 add county fixed effects. In columns 7 and 8 the personal usage controls also include fixed effects for each number of Facebook groups a user is in. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Equation 1 is our multivariate regression of interest. Each observation is a German native user. In all specifications we include controls for the amount of time each user spends on Facebook and for the number of quarters they have been on Facebook in their current county. In certain specifications we also include county fixed effects. $Y_i$ represents measures of the four outcomes listed above. Friending of local Syrian migrants is measured by the user's number of local Syrian migrant friends. Individual-level general friendliness is measured by the user's number of local native friends. We construct individual-level relative friending by replacing each term in the numerator of equation 2—$NLocalFriends_c^{DE\rightarrow SY}$ and $NLocalFriends_c^{DE\rightarrow DE}$—with its individual-level analog.[7] We identify pro-immigration Facebook pages and groups using a combination of string, url, and manual matching. Our outcome measure is

[7] A user must have at least one local native friend for this individual-level measure. The county-level average of this measure will equal the county-level measure in equation 2 if each observation in the former is weighted by the user's number of local native friends.

whether a user "likes" one of these page or is in one of these groups. In total, we identify 8,171 groups and pages, and measure 2.1 million user-page or user-group connections.

Table A15 presents results. Columns 1 and 2 show that younger natives and male natives are more likely to befriend migrants than older and female natives, respectively. Columns 3 and 4 show that these patterns are driven in part by general friendliness: a native being younger, male, or college educated is associated with having a larger network of local native friends. Columns 5 and 6 show that our individual-level measure of relative friending is also higher for younger and male German natives, while it is somewhat lower for college educated Germans compared to college educated Germans. Because Syrian migrants in Germany are more likely to be young and male than the average German native (see Table 1), one possible explanation for this finding is that homophily plays a strong role in shaping which natives befriend Syrian migrants. For example, younger German natives might be more likely to connect with younger Syrian migrants because younger people in general are more likely to connect, rather than because of particular behaviors toward migrants.

Columns 7 and 8 show that older, female, and college-educated natives are more likely than others to join pro-immigration groups on Facebook, conditional on Facebook usage. (For these analyses we include fixed effects for each number of total Facebook groups as user is in, holding constant a user's overall propensity to join Facebook groups. Our results remain qualitatively unchanged without this control). These are *opposite* the relationships presented for relative friending in columns 5 and 6, suggesting that is not necessarily those who are most supportive of pro-immigration groups that are most likely to disproportionately befriend Syrian migrants. This is again consistent with a story in which homophily, above specific attitudes or behaviors toward migrants, contribute to the demographic differences we observe in prior columns.

## 11 High School Matching Procedure

We assign users to high schools using a three-step process. On Facebook, users can provide the high school that they attended in their profile. Some of these high schools (such as "Hogwarts" and "the School of Hard Knocks") are obviously incorrect, so we begin by filtering out such schools. We are left with a list of plausible high school names, which we then need to disambiguate, since many high schools share the same name. For this, we use a listing of high schools from the websites of German state governments (see DatenSchule Project.) For each user in our sample, we are able to observe the counties in which they lived during high school age. We use this information and their self-reported high school name to match them to a high school in the administrative data. To do this, we make use of a fuzzy string matching algorithm, applied to the list of high schools that are in the regions in which they lived between the ages of 13 and 18.[8] Using this methodology, we are able to match 1.2 million of the 2.2 million users to high schools from the administrative data.

In the second step, we consider the users who report a high school that we are unable to find in the administrative data. In some cases, simple misspellings or inconsistencies in the school's name prevent a match from being formed between the two data sets. In other cases, these discrepancies are due to variations in states' criteria for including schools in the lists provided on their websites (e.g., states differ in their inclusion of vocational high schools in the lists we use). For this reason, we create a listing of school names that are reported by 50 or more users in a single county, but which are not included in the administrative data. We allow users to be assigned to these well-attested schools as we would any other. We call these schools the "non-canonical schools", and include them in all regressions, though our results are robust to excluding them. This process adds another 81 thousand users to our sample. For users who attend a school which we cannot find in the administrative data, and which appears in the self-reported data fewer than 50 times in the same county, we discard their self-reported school.

Finally, for users without a validated self-reported high school, we attempt to impute the school they attended using information on their social network. Intuitively, this approach takes advantage of the fact that most users will attend the same school as their friends who live in the same area and are the same age. To do this, we find the modal high school among a user's friends in the county they live in (as well as counties bordering it) and who are no more than 3 years different in age from the user. If this modal high school is attended by at least 10 friends, and there are at least 5 times as many friends attending this high school as the next most common school, we assign the user to this high school. We repeat this process 10 times, adding 137 thousand more users to our sample.[9]

We are able to assign 63% of native users to high schools using this methodology. In the cohorts we use for our regression, the median cohort has 31 students, with an inter-quartile range of 15 to 52 students. The match rate is lower (24%) for Syrian migrant students, since they have relatively few local friends and are less likely to list a high school on their profile. Any mistakes we make in assigning Syrians to high schools are likely to bias our analyses away from finding an effect of exposure.

[8]If we are unable to find a high school that matches in one of the regions that they lived in, we consider the regions that neighbor the regions the user lived in.

[9]To get a sense for the predictive power of the above imputation methodology, we can examine how accurate it is in determining the high school attended by users who self-report the school they attended. The imputation method is able to assign a school to 25% of such users, agreeing with the self-reported school in more than 90% of cases.

## 12 Validating General Friendliness Against External Surveys

In this appendix, we assess the degree to which regional differences in general friendliness—given by the number of Facebook friendships that German natives have with other local German natives—reflects true variation in sociability versus just variation in regional Facebook usage patterns. As discussed in the paper, regional variation in observed Facebook usage patterns of German natives are small. For example, there is not much variation in the share of the German population that is on Facebook, or the time spent on Facebook by those that are active. Nevertheless, one might be concerned that our measures of general friendliness are predominantly picking up variation in social norms, for example related to how well I must know a person before sending them a Facebook friend request. To assess this concern, we benchmark our measures of general friendliness to related measures of sociability observed in two external surveys, the European Social Survey and the European Values Survey.

**European Social Survey (ESS).** We analyze how often people meet socially and take part in social activities using two questions from the European Social Survey (European Research Infrastructure Consortium, 2020, 2021). The first question captures the frequency of social meetings: "How often do you meet socially with friends, relatives, or work colleagues?" Respondents could answer: never (0), less than once a month (1), once a month (2), several times a month (3), once a week (4), several times a week (5), or every day (6). The second question captures participation in social activities: "Compared to Other People Your Age, How Often Do You Take Part in Social Activities?" Respondents could answer: much less than most (1), less than most (2), about the same (3), more than most (4), or much more than most (5). In our analysis, we pool responses from rounds 8 and 9 of the ESS, conducted between 2016 and 2017 as well as between 2018 and 2019, respectively. Figure A21 plots state-level measures of general friendliness against average survey responses (the ESS does not provide respondent locations at a more disaggregated level). Panel (a) shows a strong positive correlation between general friendliness and the average frequency of social meetings. Panel (b) shows a positive correlation between general friendliness and the frequency of participating in social activities.

**European Value Survey (EVS).** The European Values Survey (EVS, 2022*a*,*b*) attempts to measure how trusting people are of one another in a region. Respondents were asked, "Could you tell me whether you trust people you meet for the first time completely, somewhat, not very much, or not at all?" We study responses from wave five of the EVS, conducted in Germany between 2017 and 2018. We measure average trust at both the NUTS2 and NUTS3-level. Panels (c) and (d) show a positive correlation between what percentage of people generally trust strangers—measured as the percentage who responded "Trust Completely" or "Trust Somewhat."—and general friending. These surveys provide reasonable evidence that friending activity on Facebook reflects true friending behavior.

**Figure A21:** General Friendliness Measured on Facebook Validated Against Survey Responses


**(a)** Frequency of Social Meetings

**(b)** Frequency of Participation in Social Activities

**(c)** Percentage who Trust Strangers (NUTS2)

**(d)** Percentage who Trust Strangers (NUTS3)

**Note:** Figure shows constructed measures of general friendliness benchmarked against survey data from the European Social Survey (ESS) and the European Values Survey (EVS). All panels show general friendliness on the x-axis. Panel (a) plots the average coded response to "How often do you meet socially with friends, relatives, or work colleagues?" Responses are coded as follows: never (0), less than once a month (1), once a month (2), several times a month (3), once a week (4), several times a week (5), or every day (6). Panel (b) plots the average coded response to "How often do you take part in social activities?" Responses are coded as follows: much less than most (1), less than most (2), about the same (3), more than most (4), or much more than most (5). Panel (c) plots the percentage of people who "trust somewhat" or "trust completely" people they meet for the first time by NUTS2 region. Panel (d) plots the percentage of people who "trust somewhat" or "trust completely" people they meet for the first time by NUTS3 region (counties). All panels size points by population. Lines of best fit are weighted by population.

## 13 Data Description of County-Level Covariates

Table A16: Data Description of County-Level Covariates

| Variable | Description | Data Source |
|---|---|---|
| Average Age | Average age of populaton, 2014 | German Statistical Office: Series 12411-0018 |
| % Female Age | Share of population that is female, 2014 | German Statistical Office: Series 12411-0018 |
| Pop. Density 2018 | Population density, 2018. | Thünen-Landatlas: Bevölkerungsdichte |
| % Empty Flats | Share of flats that are vacant, 2011 | Thünen-Landatlas: Wohnungsleerstand |
| Average Income | Average income, 2018 | Statistische Ämter des Bundes und der Länder (Federal and state statistical offices: Einkommen (Kreise)) |
| % Unemployed | Unemployment rate, 2014 | Bundesagentur für Arbeit (Federal Employment Agency): Beschäftigte nach Staatsangehörigkeiten |
| Train. Positions per Applicant | Number of training positions (Lehrstellen) per applicant (Auszubildender) | Bundesagentur für Arbeit (Federal Employment Agency): Bewerber und Berufsausbildungsstellen: Analysedaten |
| Syrians Employed / in Train. | Number of Syrians employed or in training divided by Syrian population | Bundesagentur für Arbeit (Federal Employment Agency): Beschäftigte nach Staatsangehörigkeiten in combination with German Statistical Office: Series 12521-0041 |
| All Crimes 2014 | Reported crimes (total) per population, 2014 | Polizeiliche Kriminalstatistik (Police Crime Statistics) 2014 in combination with German Statistical Office: Series 12411-0018 |
| Thefts 2014 | Theft crimes per population, 2014 | Polizeiliche Kriminalstatistik (Police Crime Statistics) |

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Table A16: Data Description of County-Level Covariates (Continued)

| Variable | Description | Data Source |
|---|---|---|
| Violent crimes 2014 | Violent crimes per population, 2014 | Polizeiliche Kriminalstatistik (Police Crime Statistics) |
| % Christian | Number of Christians per population, 2011 | Zensus Datenbank (Census Results) |
| % AfD 2014 | Vote share Alternative für Deutschland (AfD), European elections, 2014, demeaned by state | Der Bundeswahlleiter (Federal Returning Officer): Europawahl 2014 |
| % Voted 2014 | Log turnout, European elections, 2014 | Der Bundeswahlleiter (Federal Returning Officer): Europawahl 2014 |
| % Syrians 2010 | Number of Syrians divided by population, 2010 | German Statistical Office: Series 12521-0041 and 12411-0018 |
| % Syrians 2019 | Number of Syrians divided by population, 2019 | German Statistical Office: Series 12521-0041 and 12411-0018 |
| % Foreign 2010 | Number of foreigners divided by population, 2010 | German Statistical Office: Series 12521-0041 and 12411-0018 |
| % Foreign 2019 | Number of foreigners divided by population, 2019 | German Statistical Office: Series 12521-0041 and 12411-0018 |
| Integr. Courses per Syrian | Number of integration courses completed 2015-2019 per Syrian | Federal Office for Migration and Refugees: Integrationskursgeschäftsstatistik in combination with German Statistical Office: Series 12521-0041 |
| Pro-Immigr. Groups per Population | Number of groups affiliated with ProAsyl activist group per Population | ProAsyl (not publicly available, data received directly from organisation) |
| Integr. Sports Clubs per Syrian | Number of sports clubs that are part of Integration through Sport initiative per Syrian | German Olympic Sports Confederation |
| Unemp. General Schools Teachers per Pop. 2014 | Number of unemployed general school teachers divided by population, 2014 | Bundesagentur für Arbeit (Federal Employment Agency) (not publicly available, data acquired directly from organisation) |

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Table A16: Data Description of County-Level Covariates (Continued)

| Variable | Description | Data Source |
|---|---|---|
| Unemp. Higher Ed. School Teachers per Pop. 2014 | Number of unemployed university and research institute teachers divided by population, 2014 | Bundesagentur für Arbeit (Federal Employment Agency) (not publicly available, data acquired directly from organisation) |
| Unemp. Driving and Sports Teachers per Pop. 2014 | Number of driving and sports teachers divided by population, 2014 | Bundesagentur für Arbeit (Federal Employment Agency) (not publicly available, data acquired directly from organisation) |
| Unemp. Other School Teachers per Pop. 2014 | Number of teachers in other education centers divided by population, 2014 | Bundesagentur für Arbeit (Federal Employment Agency) (not publicly available, data acquired directly from organisation) |

# 14 Survey Screenshots

**Figure A22:** Survey Intro

**(a)** English

**Hello, we'd like to hear from you!**

We are conducting research on the effects of social networks. This survey will take 2 minutes or less to complete. Some of these questions may be personal in nature and you can choose to skip any question that you'd prefer not to answer or exit the survey at any time. Your responses, together with information we have about you and how you use Meta Products, may be used for purposes such as to personalize and improve our Products, support research and innovation for social good, and for other purposes described in our Data Policy. The results of this research may be published in an academic journal. In the publication, all results are reported so that individuals cannot be identified. Thank you very much for your participation!

Continue

**(b)** German

**Hallo, wir würden gerne deine Meinung hören!**

Im Rahmen einer wissenschaftlichen Studie führen wir eine Umfrage durch, in der es um die Auswirkungen von sozialen Netzwerken geht. Die Teilnahme dauert höchstens 2 Minuten. Einige der Fragen können sehr persönlich sein. Du kannst sie überspringen, wenn du sie nicht beantworten möchtest, oder die Umfrage jederzeit beenden. Deine Antworten sowie Informationen, die wir über dich und deine Verwendung von Meta-Produkten haben, können unter Umständen dafür genutzt werden, unsere Produkte zu personalisieren und zu verbessern sowie Forschung und Innovationen zum Wohle der Gesellschaft zu unterstützen. Weitere mögliche Verwendungszwecke sind in unserer Datenrichtlinien beschrieben. Forschungsergebnisse die auf dieser Studie beruhen können in einer wissenschaftlichen Fachzeitschrift veröffentlicht werden. Die Ergebnisse werden in der Publikation so angeben, dass einzelne Personen nicht identifiziert werden können. Vielen Dank für deine Teilnahme!

Weiter

**(c)** Arabic

**مرحبًا، يسعدنا معرفة رأيك!**

نحن نجري بحثًا حول تأثيرات شبكات التواصل الاجتماعي. لن يستغرق إكمال هذا الاستبيان سوى دقيقتين أو أقل. قد تكون بعض هذه الأسئلة شخصية بطبيعتها ويمكنك اختيار تخطي أي سؤال تفضّل في أغراض مثل إضفاء طابع شخصي Meta عدم الإجابة عنه أو الخروج من الاستبيان في أي وقت. قد تتم الاستعانة بردودك بالإضافة إلى المعلومات المتوفرة لدينا عنك وعن كيفية استخدامك لمنتجات على منتجاتنا وتحسينها ودعم الأبحاث والابتكار من أجل الأعمال الخيرية الاجتماعية، ولأغراض أخرى ورد وصفها في سياسة البيانات التي نتبعها. وقد يتم نشر نتائج هذا البحث في دورية أكاديمية. وعند النشر، يتم تسجيل جميع النتائج بما لا يسمح بأي فرصة للتعرف على الأفراد. شكرًا جزيلاً على مشاركتك!

متابعة

**Figure A23:** Survey Question: Frequency of Social Interactions

**(a)** English

In the following we are going to ask you several questions about your interactions with the German population. By this, we mean individuals who have lived in Germany most of their lives.

**In general, do you agree or disagree with the following statement: "I have many social interactions with Germans in the city I live in."**

- ○ Strongly agree
- ○ Somewhat agree
- ○ Neither agree nor disagree
- ○ Somewhat disagree
- ○ Strongly disagree

**(b)** German

Im Folgenden stellen wir dir einige Fragen zu deinen Interaktionen mit der deutschen Bevölkerung. Damit meinen wir Personen, die den Großteil ihres Lebens in Deutschland verbracht haben.

**Inwiefern stimmst du der folgenden Aussage zu: „Ich habe in der Stadt, in der ich wohne, viele soziale Interaktionen mit Deutschen."**

- ○ Stimme völlig zu
- ○ Stimme eher zu
- ○ Keine Meinung
- ○ Stimme eher nicht zu
- ○ Stimme überhaupt nicht zu

**(c)** Arabic

سنطرح عليك فيما يلي عدة أسئلة حول تعاملاتك مع الشعب الألماني. ونعني بهذا الأفراد الذين عاشوا في ألمانيا معظم حياتهم.

**"بصفة عامة، هل توافق أم لا توافق على العبارة التالية: "لدي تعاملات اجتماعية كثيرة مع الألمان في المدينة التي أعيش فيها".**

- أوافق بشدة ○
- أوافق نوعًا ما ○
- لست موافقًا ولا غير موافق ○
- لا أوافق نوعًا ما ○
- لا أوافق بشدة ○

**Figure A24:** Survey Question: Types of Interactions

**(a)** English

**Which of the following interactions with Germans have you had in the past year? Please check all that apply.**

- ☐ I have been invited to a German friend's home (for a dinner, a birthday party, etc.)
- ☐ I have invited a German friend to my home (for a dinner, a birthday party, etc.)
- ☐ I have gone to a restaurant, cafe, or bar with German friends
- ☐ I have been greeted on the street by German friends
- ☐ I have played sports with German friends

**(b)** German

**Welche der folgenden Interaktionen mit Deutschen hattest du im letzten Jahr? Bitte wähle alle zutreffenden Antworten aus.**

- ☐ Ein/e deutsche/r Freund/in hat mich zu sich nach Hause eingeladen (zum Abendessen, zu einer Geburtstagsfeier etc.)
- ☐ Ich habe eine/n deutschen Freund/in zu mir nach Hause eingeladen (zum Abendessen, zu einer Geburtstagsfeier etc.)
- ☐ Ich war mit deutschen Freunden in einem Restaurant, Café oder einer Bar
- ☐ Ich wurde auf der Straße von deutschen Freunden gegrüßt
- ☐ Ich habe mich mit deutschen Freunden zum Sport getroffen

**(c)** Arabic

**.أي من التعاملات التالية مع الألمان قمت بها خلال العام الماضي؟ يرجى تحديد كل الإجابات المناسبة**

- ☐ تمت دعوتي لمنزل صديق ألماني (لتناول وجبة طعام أو حضور حفلة عيد ميلاد، وما إلى ذلك)
- ☐ قمت بدعوة صديق ألماني إلى منزلي (لتناول وجبة طعام أو حضور حفلة عيد ميلاد، وما إلى ذلك)
- ☐ ذهبت إلى مطعم أو مقهى أو حانة مع أصدقاء ألمان
- ☐ تم الترحيب بي في الشارع من قبل أصدقاء ألمان
- ☐ مارست الرياضة مع أصدقاء ألمان

**Figure A25:** Survey Question: Effects of Social Integration

**(a)** English

**Do you have German friends or acquaintances that have helped you or a member of your family? If so, please select all the ways in which they have helped.**

- ☐ Finding a job
- ☐ Navigating the healthcare system (finding doctors, scheduling appointments, etc.)
- ☐ Finding an apartment or place to live
- ☐ Completing school work
- ☐ Navigating the bureaucracy (filling out official documents, identifying the right people to speak to, etc.)
- ☐ Finding language or integration courses

**(b)** German

**Hast du deutsche Freunde oder Bekannte, die dir oder einem Mitglied deiner Familie bei etwas geholfen haben? Wenn ja, wähle bitte alle Dinge aus, bei denen dir geholfen wurde.**

- ☐ Bei der Suche nach einem Job
- ☐ Beim Navigieren des Gesundheitssystems (Ärzte finden, Termine vereinbaren etc.)
- ☐ Bei der Suche nach einer Wohnung oder einem Ort zum Wohnen
- ☐ Bei Hausaufgaben (z. B. für die Schule oder Uni)
- ☐ Bei bürokratischen Angelegenheiten (offizielle Dokumente ausfüllen, richtige Ansprechpartner finden etc.)
- ☐ Bei der Suche nach Sprach- oder Integrationskursen

**(c)** Arabic

**هل لديك أصدقاء أو معارف ألمان ساعدوك أو ساعدوا أحد أفراد عائلتك؟ إذا كان الأمر كذلك، يرجى تحديد جميع الطرق التي قدّموا بها المساعدة.**

- ☐ البحث عن وظيفة
- ☐ التنقل ضمن نظام الرعاية الصحية (العثور على الأطباء وجدولة المواعيد، وما إلى ذلك)
- ☐ البحث عن شقة أو مكان للإقامة
- ☐ إكمال عمل مدرسي
- ☐ التعامل مع الإجراءات البيروقراطية (ملء المستندات الرسمية وتحديد الأشخاص المناسبين للتحدث معهم، وما إلى ذلك)
- ☐ البحث عن دورات تدريبية في اللغة أو الاندماج

**Figure A26:** Survey Question: Satisfaction in Germany

**(a)** English

| How satisfied are you with your life in Germany? |
|---|
| ○ Very satisfied |
| ○ Somewhat satisfied |
| ○ Neither satisfied nor dissatisfied |
| ○ Somewhat dissatisfied |
| ○ Very dissatisfied |

**(b)** German

| Wie zufrieden bist du mit deinem Leben in Deutschland? |
|---|
| ○ Sehr zufrieden |
| ○ Eher zufrieden |
| ○ Weder zufrieden noch unzufrieden |
| ○ Eher unzufrieden |
| ○ Sehr unzufrieden |

**(c)** Arabic

| ما مدى رضاك عن حياتك في ألمانيا؟ |
|---|
| راضٍ إلى درجة كبيرة ○ |
| راضٍ نوعًا ما ○ |
| لست راضيًا ولا غير راضٍ ○ |
| غير راضٍ نوعًا ما ○ |
| غير راضٍ إلى درجة كبيرة ○ |

# 15 Regional Measures of Integration and Friending

Table A17:

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 1001 | Flensburg, Stadt | DEF01 | 5.53 | 84.1 | 0.0658 | 32.6 |
| 1002 | Kiel, Landeshauptstadt | DEF02 | 5.86 | 119.3 | 0.0490 | 29.8 |
| 1003 | Lübeck, Hansestadt | DEF03 | 5.05 | 106.2 | 0.0478 | 30.9 |
| 1004 | Neumünster, Stadt | DEF04 | 3.46 | 84.8 | 0.0408 | 31.4 |
| 1051 | Dithmarschen | DEF05 | 6.64 | 100.0 | 0.0665 | 33.5 |
| 1053 | Herzogtum Lauenburg | DEF06 | 5.09 | 100.8 | 0.0504 | 29.1 |
| 1054 | Nordfriesland | DEF07 | 5.28 | 92.9 | 0.0567 | 33.6 |
| 1055 | Ostholstein | DEF08 | 5.44 | 88.0 | 0.0618 | 31.9 |
| 1056 | Pinneberg | DEF09 | 4.24 | 106.4 | 0.0400 | 26.8 |
| 1057 | Plön | DEF0A | 4.62 | 102.0 | 0.0453 | 31.7 |
| 1058 | Rendsburg-Eckernförde | DEF0B | 4.21 | 109.6 | 0.0385 | 27.3 |
| 1059 | Schleswig-Flensburg | DEF0C | 4.87 | 101.4 | 0.0479 | 33.9 |
| 1060 | Segeberg | DEF0D | 4.49 | 105.4 | 0.0427 | 29.8 |
| 1061 | Steinburg | DEF0E | 3.90 | 96.4 | 0.0404 | 27.6 |
| 1062 | Stormarn | DEF0F | 5.39 | 110.3 | 0.0488 | 26.9 |
| 2000 | Hamburg, Freie und Hansestadt | DE600 | 6.69 | 146.9 | 0.0456 | 30.3 |
| 3101 | Braunschweig, Stadt | DE911 | 5.44 | 120.9 | 0.0451 | 33.2 |
| 3102 | Salzgitter, Stadt | DE912 | 2.44 | 94.3 | 0.0259 | 22.2 |
| 3103 | Wolfsburg, Stadt | DE913 | 5.51 | 87.6 | 0.0627 | 29.5 |
| 3151 | Gifhorn | DE914 | 5.06 | 116.7 | 0.0432 | 29.2 |
| 3153 | Goslar | DE916 | 4.31 | 88.3 | 0.0489 | 28.3 |
| 3154 | Helmstedt | DE917 | 5.33 | 89.3 | 0.0594 | 26.7 |
| 3155 | Northeim | DE918 | 6.63 | 113.0 | 0.0588 | 30.6 |
| 3157 | Peine | DE91A | 4.55 | 98.7 | 0.0460 | 30.7 |
| 3158 | Wolfenbüttel | DE91B | 7.78 | 101.9 | 0.0762 | 32.0 |
| 3159 | Göttingen | DE91C | 7.41 | 122.1 | 0.0607 | 38.7 |
| 3241 | Region Hannover | DE929 | 5.78 | 126.3 | 0.0457 | 29.7 |
| 3251 | Diepholz | DE922 | 7.27 | 121.0 | 0.0602 | 36.0 |
| 3252 | Hameln-Pyrmont | DE923 | 6.16 | 104.9 | 0.0589 | 30.7 |
| 3254 | Hildesheim | DE925 | 6.77 | 113.3 | 0.0596 | 36.1 |
| 3255 | Holzminden | DE926 | 6.51 | 100.5 | 0.0648 | 28.3 |
| 3256 | Nienburg (Weser) | DE927 | 11.65 | 124.9 | 0.0931 | 43.1 |
| 3257 | Schaumburg | DE928 | 5.45 | 109.0 | 0.0502 | 31.2 |
| 3351 | Celle | DE931 | 9.27 | 97.9 | 0.0949 | 43.7 |
| 3352 | Cuxhaven | DE932 | 5.37 | 100.9 | 0.0533 | 33.6 |
| 3353 | Harburg | DE933 | 6.03 | 114.1 | 0.0528 | 32.0 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 3354 | Lüchow-Dannenberg | DE934 | 9.30 | 112.1 | 0.0834 | 32.0 |
| 3355 | Lüneburg | DE935 | 5.79 | 110.4 | 0.0524 | 29.3 |
| 3356 | Osterholz | DE936 | 4.48 | 118.4 | 0.0380 | 25.4 |
| 3357 | Rotenburg (Wümme) | DE937 | 6.10 | 121.9 | 0.0500 | 32.6 |
| 3358 | Heidekreis | DE938 | 7.48 | 101.5 | 0.0737 | 32.9 |
| 3359 | Stade | DE939 | 4.68 | 129.3 | 0.0361 | 27.9 |
| 3360 | Uelzen | DE93A | 6.26 | 102.2 | 0.0612 | 28.0 |
| 3361 | Verden | DE93B | 6.95 | 118.6 | 0.0585 | 29.7 |
| 3401 | Delmenhorst, Stadt | DE941 | 4.16 | 97.2 | 0.0428 | 26.3 |
| 3402 | Emden, Stadt | DE942 | 8.94 | 117.9 | 0.0759 | 31.2 |
| 3403 | Oldenburg (Oldenburg), Stadt | DE943 | 6.79 | 121.5 | 0.0559 | 31.3 |
| 3404 | Osnabrück, Stadt | DE944 | 5.98 | 134.0 | 0.0444 | 27.0 |
| 3405 | Wilhelmshaven, Stadt | DE945 | 3.54 | 79.4 | 0.0446 | 26.8 |
| 3451 | Ammerland | DE946 | 8.54 | 134.1 | 0.0639 | 31.3 |
| 3452 | Aurich | DE947 | 6.57 | 124.1 | 0.0533 | 31.9 |
| 3453 | Cloppenburg | DE948 | 11.56 | 172.7 | 0.0669 | 44.3 |
| 3454 | Emsland | DE949 | 7.24 | 153.6 | 0.0471 | 33.4 |
| 3455 | Friesland | DE94A | 5.57 | 91.9 | 0.0607 | 29.5 |
| 3456 | Grafschaft Bentheim | DE94B | 8.00 | 138.6 | 0.0576 | 34.7 |
| 3457 | Leer | DE94C | 4.61 | 125.6 | 0.0367 | 24.9 |
| 3458 | Oldenburg | DE94D | 6.74 | 110.5 | 0.0611 | 34.7 |
| 3459 | Osnabrück | DE94E | 6.67 | 141.0 | 0.0471 | 33.0 |
| 3460 | Vechta | DE94F | 6.03 | 156.2 | 0.0387 | 34.6 |
| 3461 | Wesermarsch | DE94G | 6.09 | 107.0 | 0.0569 | 21.4 |
| 3462 | Wittmund | DE94H | 6.76 | 116.7 | 0.0580 | 32.6 |
| 4011 | Bremen, Stadt | DE501 | 5.23 | 122.2 | 0.0428 | 27.1 |
| 4012 | Bremerhaven, Stadt | DE502 | 4.08 | 93.2 | 0.0439 | 25.0 |
| 5111 | Düsseldorf, Stadt | DEA11 | 4.33 | 116.9 | 0.0370 | 30.5 |
| 5112 | Duisburg, Stadt | DEA12 | 1.87 | 97.7 | 0.0192 | 23.3 |
| 5113 | Essen, Stadt | DEA13 | 2.99 | 109.0 | 0.0275 | 24.6 |
| 5114 | Krefeld, Stadt | DEA14 | 3.41 | 102.1 | 0.0334 | 29.1 |
| 5116 | Mönchengladbach, Stadt | DEA15 | 2.92 | 103.9 | 0.0281 | 26.1 |
| 5117 | Mülheim an der Ruhr, Stadt | DEA16 | 2.71 | 100.5 | 0.0270 | 24.9 |
| 5119 | Oberhausen, Stadt | DEA17 | 1.75 | 91.7 | 0.0190 | 25.5 |
| 5120 | Remscheid, Stadt | DEA18 | 2.91 | 105.1 | 0.0277 | 30.7 |
| 5122 | Solingen, Klingenstadt | DEA19 | 3.11 | 96.8 | 0.0321 | 28.3 |
| 5124 | Wuppertal, Stadt | DEA1A | 2.84 | 112.2 | 0.0254 | 22.6 |
| 5154 | Kleve | DEA1B | 4.67 | 102.2 | 0.0456 | 28.5 |
| 5158 | Mettmann | DEA1C | 3.88 | 109.7 | 0.0353 | 28.0 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 5162 | Rhein-Kreis Neuss | DEA1D | 4.12 | 126.4 | 0.0326 | 31.0 |
| 5166 | Viersen | DEA1E | 5.93 | 103.5 | 0.0572 | 34.5 |
| 5170 | Wesel | DEA1F | 2.99 | 106.4 | 0.0281 | 25.7 |
| 5314 | Bonn, Stadt | DEA22 | 7.24 | 134.3 | 0.0541 | 34.9 |
| 5315 | Köln, Stadt | DEA23 | 6.68 | 152.9 | 0.0437 | 34.1 |
| 5316 | Leverkusen, Stadt | DEA24 | 3.60 | 103.8 | 0.0347 | 31.0 |
| 5334 | Städteregion Aachen | DEA2D | 5.20 | 138.2 | 0.0378 | 33.7 |
| 5358 | Düren | DEA26 | 4.11 | 132.9 | 0.0309 | 32.6 |
| 5362 | Rhein-Erft-Kreis | DEA27 | 4.29 | 119.1 | 0.0359 | 33.2 |
| 5366 | Euskirchen | DEA28 | 7.26 | 158.5 | 0.0457 | 33.6 |
| 5370 | Heinsberg | DEA29 | 4.54 | 117.3 | 0.0388 | 32.2 |
| 5374 | Oberbergischer Kreis | DEA2A | 7.39 | 157.8 | 0.0469 | 35.5 |
| 5378 | Rheinisch-Bergischer Kreis | DEA2B | 5.83 | 131.9 | 0.0444 | 35.4 |
| 5382 | Rhein-Sieg-Kreis | DEA2C | 6.50 | 153.2 | 0.0424 | 34.9 |
| 5512 | Bottrop, Stadt | DEA31 | 1.52 | 93.2 | 0.0163 | 25.7 |
| 5513 | Gelsenkirchen, Stadt | DEA32 | 1.27 | 89.8 | 0.0141 | 18.5 |
| 5515 | Münster, Stadt | DEA33 | 8.78 | 164.3 | 0.0536 | 32.7 |
| 5554 | Borken | DEA34 | 6.66 | 149.8 | 0.0444 | 31.2 |
| 5558 | Coesfeld | DEA35 | 5.13 | 142.6 | 0.0360 | 25.9 |
| 5562 | Recklinghausen | DEA36 | 3.06 | 113.0 | 0.0271 | 24.5 |
| 5566 | Steinfurt | DEA37 | 6.42 | 150.3 | 0.0427 | 28.1 |
| 5570 | Warendorf | DEA38 | 5.40 | 135.0 | 0.0400 | 30.9 |
| 5711 | Bielefeld, Stadt | DEA41 | 6.73 | 140.6 | 0.0482 | 33.8 |
| 5754 | Gütersloh | DEA42 | 8.84 | 139.9 | 0.0630 | 36.5 |
| 5758 | Herford | DEA43 | 6.46 | 125.6 | 0.0513 | 31.1 |
| 5762 | Höxter | DEA44 | 6.70 | 135.8 | 0.0493 | 32.4 |
| 5766 | Lippe | DEA45 | 5.95 | 129.0 | 0.0463 | 30.4 |
| 5770 | Minden-Lübbecke | DEA46 | 6.87 | 134.6 | 0.0510 | 31.0 |
| 5774 | Paderborn | DEA47 | 7.90 | 156.7 | 0.0505 | 32.7 |
| 5911 | Bochum, Stadt | DEA51 | 3.47 | 118.5 | 0.0293 | 23.3 |
| 5913 | Dortmund, Stadt | DEA52 | 3.52 | 116.8 | 0.0301 | 25.1 |
| 5914 | Hagen, Stadt der FernUniversität | DEA53 | 2.50 | 103.5 | 0.0241 | 24.3 |
| 5915 | Hamm, Stadt | DEA54 | 3.43 | 106.0 | 0.0324 | 25.7 |
| 5916 | Herne, Stadt | DEA55 | 1.79 | 89.2 | 0.0200 | 22.0 |
| 5954 | Ennepe-Ruhr-Kreis | DEA56 | 3.84 | 109.0 | 0.0352 | 29.3 |
| 5958 | Hochsauerlandkreis | DEA57 | 8.18 | 170.0 | 0.0480 | 31.2 |
| 5962 | Märkischer Kreis | DEA58 | 4.37 | 134.8 | 0.0325 | 26.3 |
| 5966 | Olpe | DEA59 | 7.60 | 221.9 | 0.0344 | 31.8 |
| 5970 | Siegen-Wittgenstein | DEA5A | 6.23 | 187.3 | 0.0333 | 32.2 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 5974 | Soest | DEA5B | 6.69 | 140.8 | 0.0476 | 29.7 |
| 5978 | Unna | DEA5C | 3.26 | 109.6 | 0.0297 | 25.5 |
| 6411 | Darmstadt, Wissenschaftsstadt | DE711 | 5.15 | 139.7 | 0.0369 | 35.8 |
| 6412 | Frankfurt am Main, Stadt | DE712 | 7.53 | 147.7 | 0.0509 | 36.6 |
| 6413 | Offenbach am Main, Stadt | DE713 | 4.96 | 138.9 | 0.0357 | 32.2 |
| 6414 | Wiesbaden, Landeshauptstadt | DE714 | 7.91 | 141.2 | 0.0560 | 40.8 |
| 6431 | Bergstraße | DE715 | 4.89 | 151.0 | 0.0324 | 35.7 |
| 6432 | Darmstadt-Dieburg | DE716 | 3.73 | 143.3 | 0.0260 | 32.3 |
| 6433 | Groß-Gerau | DE717 | 4.35 | 140.0 | 0.0311 | 31.4 |
| 6434 | Hochtaunuskreis | DE718 | 5.98 | 140.6 | 0.0425 | 34.8 |
| 6435 | Main-Kinzig-Kreis | DE719 | 5.11 | 162.2 | 0.0314 | 31.6 |
| 6436 | Main-Taunus-Kreis | DE71A | 5.42 | 124.6 | 0.0434 | 34.7 |
| 6437 | Odenwaldkreis | DE71B | 5.57 | 170.6 | 0.0326 | 45.7 |
| 6438 | Offenbach | DE71C | 4.48 | 138.8 | 0.0324 | 32.0 |
| 6439 | Rheingau-Taunus-Kreis | DE71D | 5.00 | 142.9 | 0.0351 | 36.0 |
| 6440 | Wetteraukreis | DE71E | 8.22 | 163.3 | 0.0505 | 36.3 |
| 6531 | Gießen | DE721 | 7.62 | 177.2 | 0.0430 | 34.8 |
| 6532 | Lahn-Dill-Kreis | DE722 | 4.62 | 195.6 | 0.0235 | 27.4 |
| 6533 | Limburg-Weilburg | DE723 | 7.39 | 179.3 | 0.0411 | 32.6 |
| 6534 | Marburg-Biedenkopf | DE724 | 7.17 | 193.7 | 0.0370 | 35.7 |
| 6535 | Vogelsbergkreis | DE725 | 6.51 | 194.2 | 0.0335 | 36.2 |
| 6611 | Kassel, documenta-Stadt | DE731 | 5.46 | 134.4 | 0.0406 | 27.9 |
| 6631 | Fulda | DE732 | 7.66 | 203.5 | 0.0375 | 32.1 |
| 6632 | Hersfeld-Rotenburg | DE733 | 8.04 | 164.2 | 0.0489 | 35.0 |
| 6633 | Kassel | DE734 | 4.39 | 153.9 | 0.0286 | 32.2 |
| 6634 | Schwalm-Eder-Kreis | DE735 | 7.86 | 157.9 | 0.0497 | 32.4 |
| 6635 | Waldeck-Frankenberg | DE736 | 6.59 | 178.0 | 0.0370 | 30.2 |
| 6636 | Werra-Meißner-Kreis | DE737 | 8.47 | 143.9 | 0.0587 | 33.0 |
| 7111 | Koblenz, kreisfreie Stadt | DEB11 | 7.43 | 158.8 | 0.0468 | 36.3 |
| 7131 | Ahrweiler | DEB12 | 7.98 | 163.9 | 0.0487 | 37.7 |
| 7132 | Altenkirchen (Westerwald) | DEB13 | 6.03 | 190.0 | 0.0318 | 32.4 |
| 7133 | Bad Kreuznach | DEB14 | 7.39 | 176.4 | 0.0417 | 40.0 |
| 7134 | Birkenfeld | DEB15 | 7.99 | 185.8 | 0.0430 | 35.0 |
| 7135 | Cochem-Zell | DEB1C | 8.60 | 182.6 | 0.0472 | 41.7 |
| 7137 | Mayen-Koblenz | DEB17 | 9.11 | 192.2 | 0.0473 | 39.5 |
| 7138 | Neuwied | DEB18 | 6.80 | 162.8 | 0.0417 | 35.2 |
| 7140 | Rhein-Hunsrück-Kreis | DEB1D | 7.36 | 177.7 | 0.0415 | 31.4 |
| 7141 | Rhein-Lahn-Kreis | DEB1A | 6.93 | 174.9 | 0.0394 | 32.1 |
| 7143 | Westerwaldkreis | DEB1B | 7.50 | 198.1 | 0.0379 | 30.4 |

Continued on next page

Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 7211 | Trier, kreisfreie Stadt | DEB21 | 7.78 | 132.5 | 0.0585 | 39.4 |
| 7231 | Bernkastel-Wittlich | DEB22 | 7.85 | 168.8 | 0.0465 | 35.7 |
| 7232 | Eifelkreis Bitburg-Prüm | DEB23 | 8.68 | 184.6 | 0.0472 | 35.5 |
| 7233 | Vulkaneifel | DEB24 | 12.78 | 192.9 | 0.0661 | 36.8 |
| 7235 | Trier-Saarburg | DEB25 | 9.33 | 173.1 | 0.0539 | 45.1 |
| 7311 | Frankenthal (Pfalz), kreisfreie Stadt | DEB31 | 3.55 | 107.3 | 0.0331 | 31.8 |
| 7312 | Kaiserslautern, kreisfreie Stadt | DEB32 | 4.13 | 121.3 | 0.0340 | 32.2 |
| 7313 | Landau in der Pfalz, kreisfreie Stadt | DEB33 | 6.25 | 144.2 | 0.0434 | 34.9 |
| 7314 | Ludwigshafen am Rhein, kreisfreie Stadt | DEB34 | 3.67 | 117.6 | 0.0312 | 30.9 |
| 7315 | Mainz, kreisfreie Stadt | DEB35 | 6.79 | 148.5 | 0.0458 | 39.9 |
| 7316 | Neustadt an der Weinstraße, kreisfreie Stadt | DEB36 | 5.96 | 137.3 | 0.0435 | 33.0 |
| 7317 | Pirmasens, kreisfreie Stadt | DEB37 | 6.06 | 152.1 | 0.0397 | 34.1 |
| 7318 | Speyer, kreisfreie Stadt | DEB38 | 6.72 | 124.9 | 0.0539 | 34.3 |
| 7319 | Worms, kreisfreie Stadt | DEB39 | 4.66 | 136.4 | 0.0343 | 32.6 |
| 7320 | Zweibrücken, kreisfreie Stadt | DEB3A | 4.98 | 134.4 | 0.0371 | 31.8 |
| 7331 | Alzey-Worms | DEB3B | 5.57 | 155.4 | 0.0357 | 30.5 |
| 7332 | Bad Dürkheim | DEB3C | 4.65 | 139.1 | 0.0334 | 36.4 |
| 7333 | Donnersbergkreis | DEB3D | 7.58 | 145.2 | 0.0520 | 36.0 |
| 7334 | Germersheim | DEB3E | 4.48 | 154.0 | 0.0290 | 30.1 |
| 7335 | Kaiserslautern | DEB3F | 5.59 | 165.0 | 0.0338 | 35.6 |
| 7336 | Kusel | DEB3G | 7.52 | 172.3 | 0.0437 | 32.4 |
| 7337 | Südliche Weinstraße | DEB3H | 6.12 | 177.0 | 0.0345 | 40.0 |
| 7338 | Rhein-Pfalz-Kreis | DEB3I | 4.22 | 154.0 | 0.0274 | 34.1 |
| 7339 | Mainz-Bingen | DEB3J | 5.76 | 168.2 | 0.0343 | 33.9 |
| 7340 | Südwestpfalz | DEB3K | 8.29 | 192.1 | 0.0431 | 43.5 |
| 8111 | Stuttgart, Stadtkreis | DE111 | 6.73 | 153.6 | 0.0438 | 33.3 |
| 8115 | Böblingen | DE112 | 5.02 | 132.1 | 0.0379 | 32.8 |
| 8116 | Esslingen | DE113 | 5.07 | 137.0 | 0.0369 | 32.0 |
| 8117 | Göppingen | DE114 | 5.21 | 130.1 | 0.0400 | 35.1 |
| 8118 | Ludwigsburg | DE115 | 5.10 | 128.4 | 0.0397 | 31.3 |
| 8119 | Rems-Murr-Kreis | DE116 | 5.04 | 141.7 | 0.0355 | 29.5 |
| 8121 | Heilbronn, Stadtkreis | DE117 | 5.55 | 127.5 | 0.0435 | 35.3 |
| 8125 | Heilbronn | DE118 | 4.72 | 151.5 | 0.0312 | 31.6 |
| 8126 | Hohenlohekreis | DE119 | 7.71 | 157.5 | 0.0493 | 35.5 |
| 8127 | Schwäbisch Hall | DE11A | 11.51 | 149.7 | 0.0771 | 36.7 |
| 8128 | Main-Tauber-Kreis | DE11B | 9.20 | 150.6 | 0.0611 | 35.7 |
| 8135 | Heidenheim | DE11C | 4.80 | 119.3 | 0.0404 | 35.9 |
| 8136 | Ostalbkreis | DE11D | 6.17 | 153.9 | 0.0401 | 29.1 |
| 8211 | Baden-Baden, Stadtkreis | DE121 | 8.55 | 132.6 | 0.0644 | 34.6 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 8212 | Karlsruhe, Stadtkreis | DE122 | 6.42 | 147.8 | 0.0433 | 40.6 |
| 8215 | Karlsruhe | DE123 | 5.86 | 157.4 | 0.0371 | 33.1 |
| 8216 | Rastatt | DE124 | 5.57 | 151.8 | 0.0366 | 36.1 |
| 8221 | Heidelberg, Stadtkreis | DE125 | 7.67 | 145.1 | 0.0529 | 40.9 |
| 8222 | Mannheim, Stadtkreis | DE126 | 6.12 | 139.8 | 0.0438 | 37.7 |
| 8225 | Neckar-Odenwald-Kreis | DE127 | 6.45 | 167.2 | 0.0384 | 34.6 |
| 8226 | Rhein-Neckar-Kreis | DE128 | 6.17 | 157.2 | 0.0391 | 36.2 |
| 8231 | Pforzheim, Stadtkreis | DE129 | 4.31 | 126.8 | 0.0341 | 31.4 |
| 8235 | Calw | DE12A | 5.52 | 133.6 | 0.0413 | 34.1 |
| 8236 | Enzkreis | DE12B | 4.22 | 146.1 | 0.0288 | 32.7 |
| 8237 | Freudenstadt | DE12C | 5.38 | 133.8 | 0.0400 | 34.0 |
| 8311 | Freiburg im Breisgau, Stadtkreis | DE131 | 10.30 | 151.4 | 0.0679 | 40.1 |
| 8315 | Breisgau-Hochschwarzwald | DE132 | 6.22 | 150.9 | 0.0410 | 31.4 |
| 8316 | Emmendingen | DE133 | 6.03 | 156.0 | 0.0386 | 32.2 |
| 8317 | Ortenaukreis | DE134 | 5.95 | 159.5 | 0.0372 | 33.3 |
| 8325 | Rottweil | DE135 | 6.04 | 147.8 | 0.0411 | 30.5 |
| 8326 | Schwarzwald-Baar-Kreis | DE136 | 5.25 | 138.9 | 0.0378 | 29.6 |
| 8327 | Tuttlingen | DE137 | 4.91 | 146.6 | 0.0336 | 30.8 |
| 8335 | Konstanz | DE138 | 6.38 | 136.4 | 0.0466 | 34.7 |
| 8336 | Lörrach | DE139 | 4.71 | 128.8 | 0.0365 | 28.2 |
| 8337 | Waldshut | DE13A | 5.44 | 128.6 | 0.0422 | 29.5 |
| 8415 | Reutlingen | DE141 | 5.66 | 143.2 | 0.0396 | 31.1 |
| 8416 | Tübingen | DE142 | 6.87 | 151.6 | 0.0455 | 32.9 |
| 8417 | Zollernalbkreis | DE143 | 5.09 | 141.5 | 0.0360 | 41.6 |
| 8421 | Ulm, Stadtkreis | DE144 | 5.78 | 117.5 | 0.0492 | 37.6 |
| 8425 | Alb-Donau-Kreis | DE145 | 4.78 | 131.6 | 0.0364 | 37.1 |
| 8426 | Biberach | DE146 | 6.91 | 157.5 | 0.0438 | 30.8 |
| 8435 | Bodenseekreis | DE147 | 6.03 | 144.9 | 0.0418 | 29.3 |
| 8436 | Ravensburg | DE148 | 7.49 | 161.4 | 0.0463 | 31.5 |
| 8437 | Sigmaringen | DE149 | 8.18 | 158.7 | 0.0514 | 29.2 |
| 9161 | Ingolstadt | DE211 | 6.06 | 116.9 | 0.0517 | 38.4 |
| 9162 | München, Landeshauptstadt | DE212 | 7.44 | 141.7 | 0.0524 | 37.0 |
| 9163 | Rosenheim | DE213 | 5.05 | 127.9 | 0.0395 | 45.5 |
| 9171 | Altötting | DE214 | 8.16 | 143.7 | 0.0568 | 36.5 |
| 9172 | Berchtesgadener Land | DE215 | 7.24 | 134.8 | 0.0537 | 54.4 |
| 9173 | Bad Tölz-Wolfratshausen | DE216 | 7.11 | 145.7 | 0.0489 | 42.6 |
| 9174 | Dachau | DE217 | 6.04 | 128.7 | 0.0469 | 32.8 |
| 9175 | Ebersberg | DE218 | 3.93 | 103.7 | 0.0380 | 42.0 |
| 9176 | Eichstätt | DE219 | 11.98 | 145.8 | 0.0821 | 44.9 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 9177 | Erding | DE21A | 6.74 | 122.0 | 0.0552 | 43.8 |
| 9178 | Freising | DE21B | 5.30 | 111.6 | 0.0476 | 44.4 |
| 9179 | Fürstenfeldbruck | DE21C | 5.63 | 127.2 | 0.0442 | 42.9 |
| 9180 | Garmisch-Partenkirchen | DE21D | 6.17 | 147.5 | 0.0419 | 48.9 |
| 9181 | Landsberg am Lech | DE21E | 8.70 | 124.8 | 0.0698 | 46.5 |
| 9182 | Miesbach | DE21F | 7.16 | 145.6 | 0.0492 | 40.2 |
| 9183 | Mühldorf a.Inn | DE21G | 6.46 | 156.2 | 0.0414 | 35.4 |
| 9184 | München | DE21H | 7.25 | 139.0 | 0.0521 | 38.8 |
| 9185 | Neuburg-Schrobenhausen | DE21I | 5.35 | 130.2 | 0.0411 | 32.8 |
| 9186 | Pfaffenhofen a.d.Ilm | DE21J | 6.09 | 121.5 | 0.0499 | 39.4 |
| 9187 | Rosenheim | DE21K | 6.99 | 157.5 | 0.0445 | 40.4 |
| 9188 | Starnberg | DE21L | 5.15 | 117.0 | 0.0440 | 41.4 |
| 9189 | Traunstein | DE21M | 7.66 | 163.4 | 0.0467 | 39.9 |
| 9190 | Weilheim-Schongau | DE21N | 6.40 | 136.2 | 0.0466 | 34.2 |
| 9261 | Landshut | DE221 | 8.42 | 123.8 | 0.0684 | 41.8 |
| 9262 | Passau | DE222 | 8.89 | 120.9 | 0.0733 | 41.0 |
| 9263 | Straubing | DE223 | 8.48 | 80.6 | 0.1053 | 41.9 |
| 9271 | Deggendorf | DE224 | 6.30 | 143.8 | 0.0439 | 39.2 |
| 9272 | Freyung-Grafenau | DE225 | 11.09 | 175.8 | 0.0628 | 48.2 |
| 9273 | Kelheim | DE226 | 4.88 | 126.9 | 0.0384 | 33.3 |
| 9274 | Landshut | DE227 | 6.32 | 147.5 | 0.0428 | 38.8 |
| 9275 | Passau | DE228 | 4.19 | 157.8 | 0.0265 | 27.2 |
| 9276 | Regen | DE229 | 6.32 | 169.5 | 0.0374 | 28.8 |
| 9277 | Rottal-Inn | DE22A | 6.16 | 164.9 | 0.0374 | 30.2 |
| 9278 | Straubing-Bogen | DE22B | 5.32 | 148.3 | 0.0358 | 37.7 |
| 9279 | Dingolfing-Landau | DE22C | 4.96 | 142.4 | 0.0347 | 41.3 |
| 9361 | Amberg | DE231 | 5.67 | 92.9 | 0.0612 | 33.7 |
| 9362 | Regensburg | DE232 | 6.40 | 104.3 | 0.0616 | 34.2 |
| 9363 | Weiden i.d.OPf. | DE233 | 3.19 | 84.4 | 0.0378 | 31.8 |
| 9371 | Amberg-Sulzbach | DE234 | 4.09 | 115.8 | 0.0353 | 30.2 |
| 9372 | Cham | DE235 | 8.31 | 170.8 | 0.0488 | 43.4 |
| 9373 | Neumarkt i.d.OPf. | DE236 | 7.25 | 133.6 | 0.0544 | 37.1 |
| 9374 | Neustadt a.d.Waldnaab | DE237 | 4.22 | 135.1 | 0.0311 | 22.5 |
| 9375 | Regensburg | DE238 | 5.39 | 138.7 | 0.0390 | 30.7 |
| 9376 | Schwandorf | DE239 | 7.96 | 125.7 | 0.0632 | 36.1 |
| 9377 | Tirschenreuth | DE23A | 3.00 | 136.0 | 0.0220 | 30.7 |
| 9461 | Bamberg | DE241 | 6.58 | 103.4 | 0.0639 | 37.6 |
| 9462 | Bayreuth | DE242 | 5.19 | 96.1 | 0.0541 | 38.6 |
| 9463 | Coburg | DE243 | 5.76 | 90.6 | 0.0635 | 37.8 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 9464 | Hof | DE244 | 1.40 | 82.9 | 0.0168 | 26.2 |
| 9471 | Bamberg | DE245 | 2.97 | 126.2 | 0.0235 | 32.8 |
| 9472 | Bayreuth | DE246 | 0.50 | 132.2 | 0.0037 | 23.7 |
| 9473 | Coburg | DE247 | 6.25 | 121.0 | 0.0519 | 39.3 |
| 9474 | Forchheim | DE248 | 3.59 | 111.5 | 0.0323 | 29.2 |
| 9475 | Hof | DE249 | 2.75 | 116.8 | 0.0236 | 37.7 |
| 9476 | Kronach | DE24A | 9.77 | 138.8 | 0.0704 | 35.8 |
| 9477 | Kulmbach | DE24B | 8.21 | 107.1 | 0.0767 | 36.4 |
| 9478 | Lichtenfels | DE24C | 3.99 | 128.0 | 0.0311 | 34.9 |
| 9479 | Wunsiedel i.Fichtelgebirge | DE24D | 4.76 | 108.0 | 0.0440 | 35.8 |
| 9561 | Ansbach | DE251 | 5.32 | 93.2 | 0.0571 | 33.4 |
| 9562 | Erlangen | DE252 | 6.81 | 127.5 | 0.0535 | 35.1 |
| 9563 | Fürth | DE253 | 4.33 | 96.8 | 0.0447 | 29.9 |
| 9564 | Nürnberg | DE254 | 5.64 | 117.2 | 0.0481 | 35.4 |
| 9565 | Schwabach | DE255 | 2.58 | 47.8 | 0.0540 | 51.1 |
| 9571 | Ansbach | DE256 | 5.37 | 126.7 | 0.0424 | 39.4 |
| 9572 | Erlangen-Höchstadt | DE257 | 5.10 | 110.6 | 0.0461 | 34.4 |
| 9573 | Fürth | DE258 | 3.19 | 99.4 | 0.0322 | 37.2 |
| 9574 | Nürnberger Land | DE259 | 4.90 | 105.1 | 0.0464 | 35.1 |
| 9575 | Neustadt a.d.Aisch-Bad Windsheim | DE25A | 8.15 | 109.6 | 0.0744 | 41.1 |
| 9576 | Roth | DE25B | 5.39 | 110.9 | 0.0487 | 36.0 |
| 9577 | Weißenburg-Gunzenhausen | DE25C | 4.48 | 128.3 | 0.0348 | 28.5 |
| 9661 | Aschaffenburg | DE261 | 4.63 | 151.3 | 0.0307 | 27.5 |
| 9662 | Schweinfurt | DE262 | 4.30 | 89.8 | 0.0480 | 31.0 |
| 9663 | Würzburg | DE263 | 8.05 | 114.4 | 0.0706 | 41.1 |
| 9671 | Aschaffenburg | DE264 | 4.54 | 176.2 | 0.0258 | 30.6 |
| 9672 | Bad Kissingen | DE265 | 6.40 | 151.9 | 0.0421 | 30.4 |
| 9673 | Rhön-Grabfeld | DE266 | 7.87 | 176.1 | 0.0446 | 34.0 |
| 9674 | Haßberge | DE267 | 8.26 | 122.1 | 0.0677 | 43.3 |
| 9675 | Kitzingen | DE268 | 5.68 | 120.4 | 0.0472 | 31.8 |
| 9676 | Miltenberg | DE269 | 4.67 | 184.7 | 0.0254 | 25.5 |
| 9677 | Main-Spessart | DE26A | 6.93 | 169.8 | 0.0410 | 37.8 |
| 9678 | Schweinfurt | DE26B | 6.20 | 137.8 | 0.0450 | 31.5 |
| 9679 | Würzburg | DE26C | 5.60 | 147.8 | 0.0379 | 29.8 |
| 9761 | Augsburg | DE271 | 6.42 | 133.5 | 0.0480 | 36.9 |
| 9762 | Kaufbeuren | DE272 | 4.42 | 110.3 | 0.0401 | 35.5 |
| 9763 | Kempten (Allgäu) | DE273 | 7.97 | 121.4 | 0.0656 | 34.5 |
| 9764 | Memmingen | DE274 | 6.39 | 102.3 | 0.0625 | 30.9 |
| 9771 | Aichach-Friedberg | DE275 | 6.84 | 145.0 | 0.0473 | 32.3 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 9772 | Augsburg | DE276 | 5.07 | 135.7 | 0.0372 | 31.1 |
| 9773 | Dillingen a.d.Donau | DE277 | 6.26 | 140.4 | 0.0444 | 37.0 |
| 9774 | Günzburg | DE278 | 4.61 | 137.3 | 0.0336 | 36.3 |
| 9775 | Neu-Ulm | DE279 | 4.37 | 112.5 | 0.0389 | 33.8 |
| 9776 | Lindau (Bodensee) | DE27A | 6.92 | 125.4 | 0.0552 | 34.2 |
| 9777 | Ostallgäu | DE27B | 8.06 | 142.5 | 0.0564 | 35.7 |
| 9778 | Unterallgäu | DE27C | 6.81 | 145.5 | 0.0468 | 38.4 |
| 9779 | Donau-Ries | DE27D | 6.05 | 147.9 | 0.0409 | 27.3 |
| 9780 | Oberallgäu | DE27E | 8.07 | 141.6 | 0.0569 | 36.0 |
| 10041 | Regionalverband Saarbrücken | DEC01 | 6.15 | 184.0 | 0.0334 | 27.9 |
| 10042 | Merzig-Wadern | DEC02 | 12.39 | 175.5 | 0.0707 | 39.3 |
| 10043 | Neunkirchen | DEC03 | 6.84 | 196.5 | 0.0347 | 31.3 |
| 10044 | Saarlouis | DEC04 | 8.69 | 196.8 | 0.0444 | 35.9 |
| 10045 | Saarpfalz-Kreis | DEC05 | 6.59 | 187.7 | 0.0354 | 30.8 |
| 10046 | St. Wendel | DEC06 | 9.61 | 197.4 | 0.0486 | 32.6 |
| 11000 | Berlin, Stadt | DE300 | 7.84 | 156.4 | 0.0503 | 27.0 |
| 12051 | Brandenburg an der Havel, Stadt | DE401 | 6.27 | 105.8 | 0.0592 | 27.6 |
| 12052 | Cottbus, Stadt | DE402 | 3.58 | 97.7 | 0.0364 | 24.9 |
| 12053 | Frankfurt (Oder), Stadt | DE403 | 5.74 | 89.6 | 0.0641 | 29.4 |
| 12054 | Potsdam, Stadt | DE404 | 6.71 | 132.1 | 0.0509 | 29.3 |
| 12060 | Barnim | DE405 | 5.79 | 115.1 | 0.0503 | 26.0 |
| 12061 | Dahme-Spreewald | DE406 | 6.16 | 114.3 | 0.0537 | 24.8 |
| 12062 | Elbe-Elster | DE407 | 8.29 | 104.4 | 0.0793 | 32.3 |
| 12063 | Havelland | DE408 | 4.91 | 109.8 | 0.0449 | 26.9 |
| 12064 | Märkisch-Oderland | DE409 | 5.12 | 109.7 | 0.0468 | 24.3 |
| 12065 | Oberhavel | DE40A | 5.41 | 107.5 | 0.0503 | 26.3 |
| 12066 | Oberspreewald-Lausitz | DE40B | 6.68 | 96.5 | 0.0692 | 32.4 |
| 12067 | Oder-Spree | DE40C | 6.29 | 116.5 | 0.0541 | 26.6 |
| 12068 | Ostprignitz-Ruppin | DE40D | 7.94 | 97.0 | 0.0819 | 34.9 |
| 12069 | Potsdam-Mittelmark | DE40E | 5.57 | 113.6 | 0.0491 | 27.6 |
| 12070 | Prignitz | DE40F | 5.96 | 91.9 | 0.0648 | 30.6 |
| 12071 | Spree-Neiße | DE40G | 5.36 | 98.7 | 0.0544 | 28.1 |
| 12072 | Teltow-Fläming | DE40H | 6.31 | 104.6 | 0.0603 | 28.7 |
| 12073 | Uckermark | DE40I | 3.94 | 95.8 | 0.0410 | 30.1 |
| 13003 | Rostock | DE803 | 6.73 | 96.1 | 0.0701 | 29.0 |
| 13004 | Schwerin | DE804 | 5.97 | 100.5 | 0.0595 | 25.7 |
| 13071 | Mecklenburgische Seenplatte | DE80J | 7.55 | 103.8 | 0.0727 | 33.4 |
| 13072 | Landkreis Rostock | DE80K | 6.67 | 97.3 | 0.0683 | 33.2 |
| 13073 | Vorpommern-Rügen | DE80L | 4.99 | 78.6 | 0.0636 | 32.0 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 13074 | Nordwestmecklenburg | DE80M | 4.91 | 90.3 | 0.0546 | 32.1 |
| 13075 | Vorpommern-Greifswald | DE80N | 7.46 | 97.7 | 0.0764 | 30.8 |
| 13076 | Ludwigslust-Parchim | DE80O | 6.26 | 99.8 | 0.0626 | 29.8 |
| 14511 | Chemnitz, Stadt | DED41 | 5.39 | 113.1 | 0.0477 | 30.4 |
| 14521 | Erzgebirgskreis | DED42 | 4.11 | 116.6 | 0.0353 | 24.0 |
| 14522 | Mittelsachsen | DED43 | 5.18 | 108.0 | 0.0480 | 30.5 |
| 14523 | Vogtlandkreis | DED44 | 5.75 | 113.9 | 0.0504 | 32.8 |
| 14524 | Zwickau | DED45 | 6.36 | 106.4 | 0.0599 | 33.1 |
| 14612 | Dresden, Stadt | DED21 | 7.84 | 125.8 | 0.0621 | 29.9 |
| 14625 | Bautzen | DED2C | 7.05 | 116.6 | 0.0605 | 31.7 |
| 14626 | Görlitz | DED2D | 7.06 | 94.2 | 0.0748 | 36.2 |
| 14627 | Meißen | DED2E | 6.92 | 112.3 | 0.0614 | 31.0 |
| 14628 | Sächsische Schweiz-Osterzgebirge | DED2F | 4.94 | 106.0 | 0.0468 | 30.9 |
| 14713 | Leipzig, Stadt | DED51 | 6.21 | 110.6 | 0.0563 | 28.9 |
| 14729 | Leipzig | DED52 | 4.54 | 104.8 | 0.0433 | 23.2 |
| 14730 | Nordsachsen | DED53 | 4.66 | 103.9 | 0.0449 | 27.7 |
| 15001 | Dessau-Roßlau, Stadt | DEE01 | 5.57 | 86.1 | 0.0648 | 30.2 |
| 15002 | Halle (Saale), Stadt | DEE02 | 5.10 | 85.5 | 0.0598 | 28.1 |
| 15003 | Magdeburg, Landeshauptstadt | DEE03 | 5.74 | 105.3 | 0.0545 | 27.1 |
| 15081 | Altmarkkreis Salzwedel | DEE04 | 4.28 | 100.9 | 0.0424 | 34.5 |
| 15082 | Anhalt-Bitterfeld | DEE05 | 5.33 | 84.4 | 0.0630 | 29.5 |
| 15083 | Börde | DEE07 | 5.26 | 102.5 | 0.0512 | 26.3 |
| 15084 | Burgenlandkreis | DEE08 | 7.87 | 101.3 | 0.0774 | 34.8 |
| 15085 | Harz | DEE09 | 9.03 | 98.6 | 0.0914 | 33.6 |
| 15086 | Jerichower Land | DEE06 | 3.72 | 101.8 | 0.0366 | 18.1 |
| 15087 | Mansfeld-Südharz | DEE0A | 7.15 | 98.5 | 0.0726 | 26.7 |
| 15088 | Saalekreis | DEE0B | 3.38 | 90.0 | 0.0375 | 24.5 |
| 15089 | Salzlandkreis | DEE0C | 7.80 | 98.7 | 0.0793 | 28.8 |
| 15090 | Stendal | DEE0D | 7.74 | 107.6 | 0.0721 | 29.8 |
| 15091 | Wittenberg | DEE0E | 6.02 | 96.7 | 0.0622 | 27.8 |
| 16051 | Erfurt, Stadt | DEG01 | 6.44 | 98.3 | 0.0658 | 32.2 |
| 16052 | Gera, Stadt | DEG02 | 4.74 | 78.5 | 0.0605 | 29.6 |
| 16053 | Jena, Stadt | DEG03 | 7.15 | 108.6 | 0.0659 | 35.9 |
| 16054 | Suhl, Stadt | DEG04 | 8.71 | 104.9 | 0.0827 | 46.0 |
| 16055 | Weimar, Stadt | DEG05 | 7.27 | 89.2 | 0.0813 | 37.5 |
| 16056 | Eisenach, Stadt | DEG0N | 4.17 | 79.0 | 0.0528 | 25.5 |
| 16061 | Eichsfeld | DEG06 | 6.78 | 141.9 | 0.0478 | 28.5 |
| 16062 | Nordhausen | DEG07 | 6.50 | 108.5 | 0.0601 | 33.5 |
| 16063 | Wartburgkreis | DEG0P | 10.04 | 140.5 | 0.0717 | 39.5 |

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Table A17: (Continued)

| AGS | Name | NUTS3 | Friending Integration | General Friendliness | Relative Friending | Language Integration |
|---|---|---|---|---|---|---|
| 16064 | Unstrut-Hainich-Kreis | DEG09 | 5.42 | 100.4 | 0.0540 | 30.3 |
| 16065 | Kyffhäuserkreis | DEG0A | 3.57 | 108.1 | 0.0330 | 28.2 |
| 16066 | Schmalkalden-Meiningen | DEG0B | 7.23 | 134.4 | 0.0537 | 36.3 |
| 16067 | Gotha | DEG0C | 5.82 | 108.2 | 0.0537 | 34.3 |
| 16068 | Sömmerda | DEG0D | 3.98 | 107.9 | 0.0369 | 37.5 |
| 16069 | Hildburghausen | DEG0E | 9.14 | 114.5 | 0.0800 | 37.7 |
| 16070 | Ilm-Kreis | DEG0F | 6.39 | 117.2 | 0.0545 | 29.8 |
| 16071 | Weimarer Land | DEG0G | 4.71 | 106.4 | 0.0443 | 32.8 |
| 16072 | Sonneberg | DEG0H | 3.07 | 107.9 | 0.0285 | 27.8 |
| 16073 | Saalfeld-Rudolstadt | DEG0I | 8.19 | 107.0 | 0.0768 | 31.9 |
| 16074 | Saale-Holzland-Kreis | DEG0J | 4.20 | 108.7 | 0.0386 | 31.6 |
| 16075 | Saale-Orla-Kreis | DEG0K | 6.83 | 108.7 | 0.0631 | 30.3 |
| 16076 | Greiz | DEG0L | 8.61 | 110.6 | 0.0778 | 27.9 |
| 16077 | Altenburger Land | DEG0M | 5.93 | 83.0 | 0.0715 | 33.5 |

**Note:** Table shows county-level estimates. Friending integration is the measure mapped in Figure 2. General friendliness is the measure mapped in panel (a) of Figure 4. Relative friending is the measure mapped in panel (b) of Figure 4. Language integration is the share of Syrian migrants on Facebook who produce German content. Because of privacy restrictions, the estimates in this table may differ in small ways from those used to produce results in the paper.

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