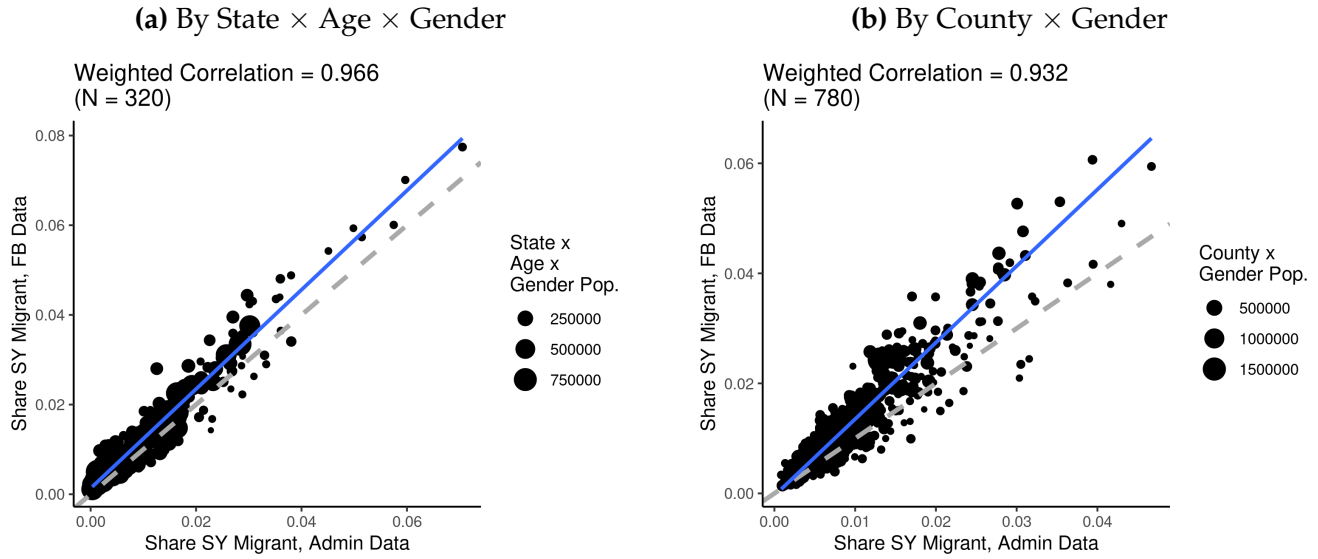


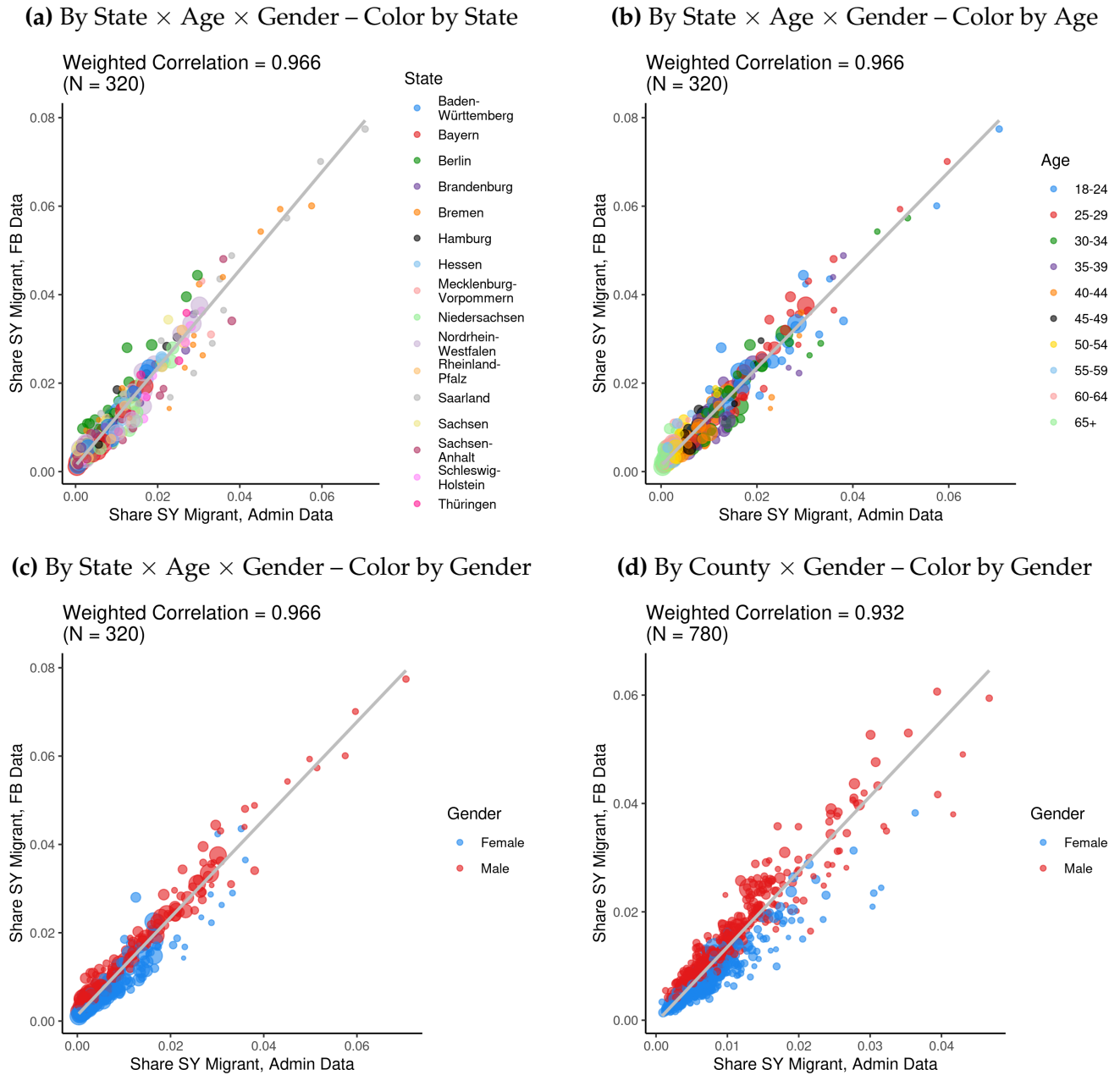
# 1 Additional Figures and Tables

Figure A1: Syrian Migrant Sample vs. Admin Data



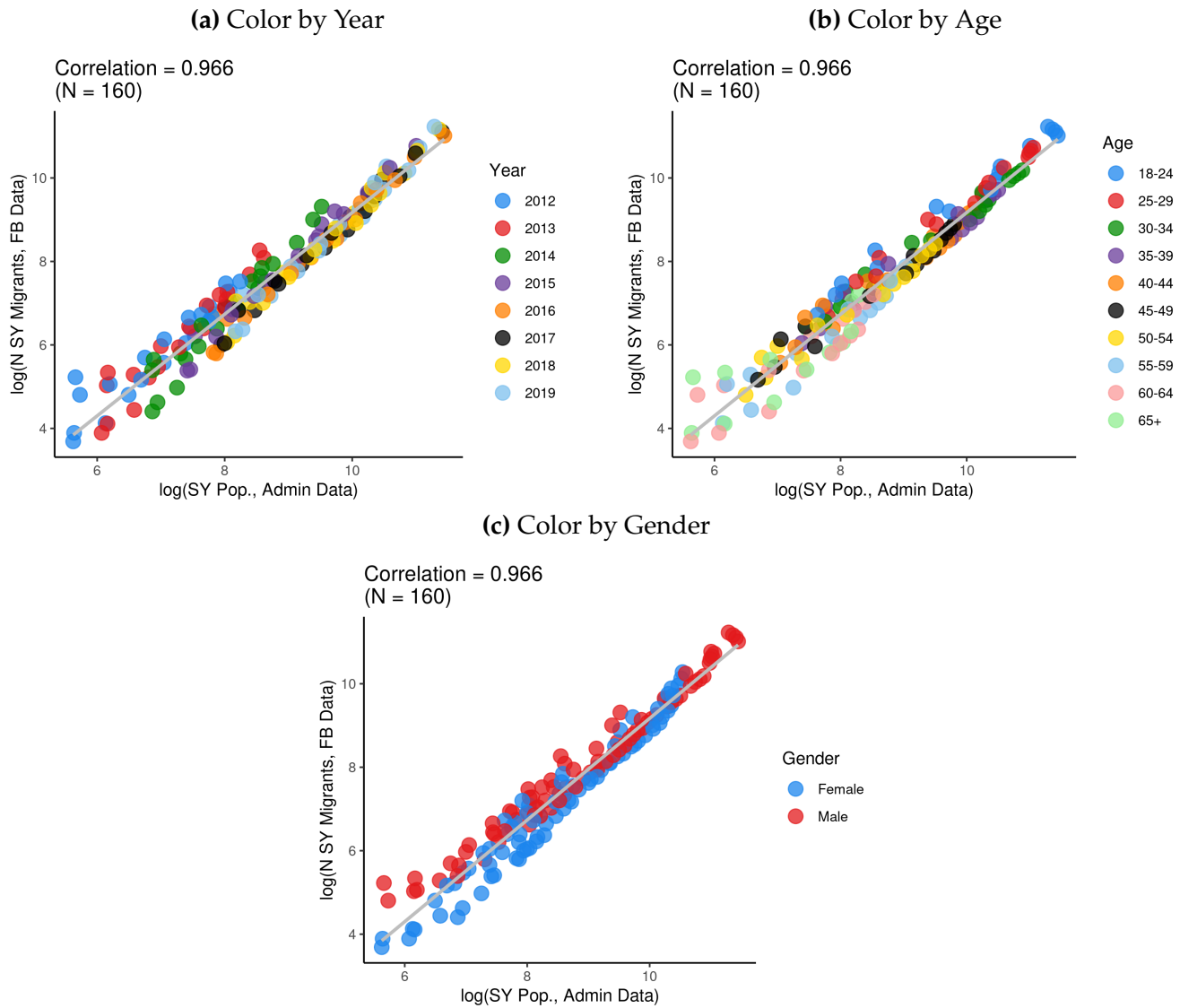
**Note:** Figures show the shares of the primary sample of Facebook users that are also in the Syrian migrant sample (on the y-axis), against shares of the population that are Syrian from administrative data (on the x-axis). The size of each dot is proportional to the true population it represents. The 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, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 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**



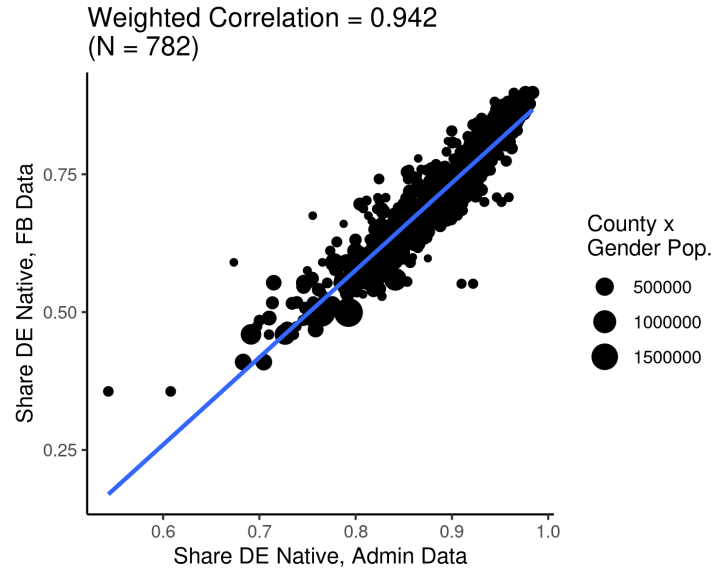
**Note:** Figures show the shares of the primary sample of Facebook users that are also in the Syrian migrant sample (on the y-axis), against shares of the population that are Syrian from administrative data (on the x-axis). The size of each dot is proportional to the size of the population it represents. 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, 55-59, 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**



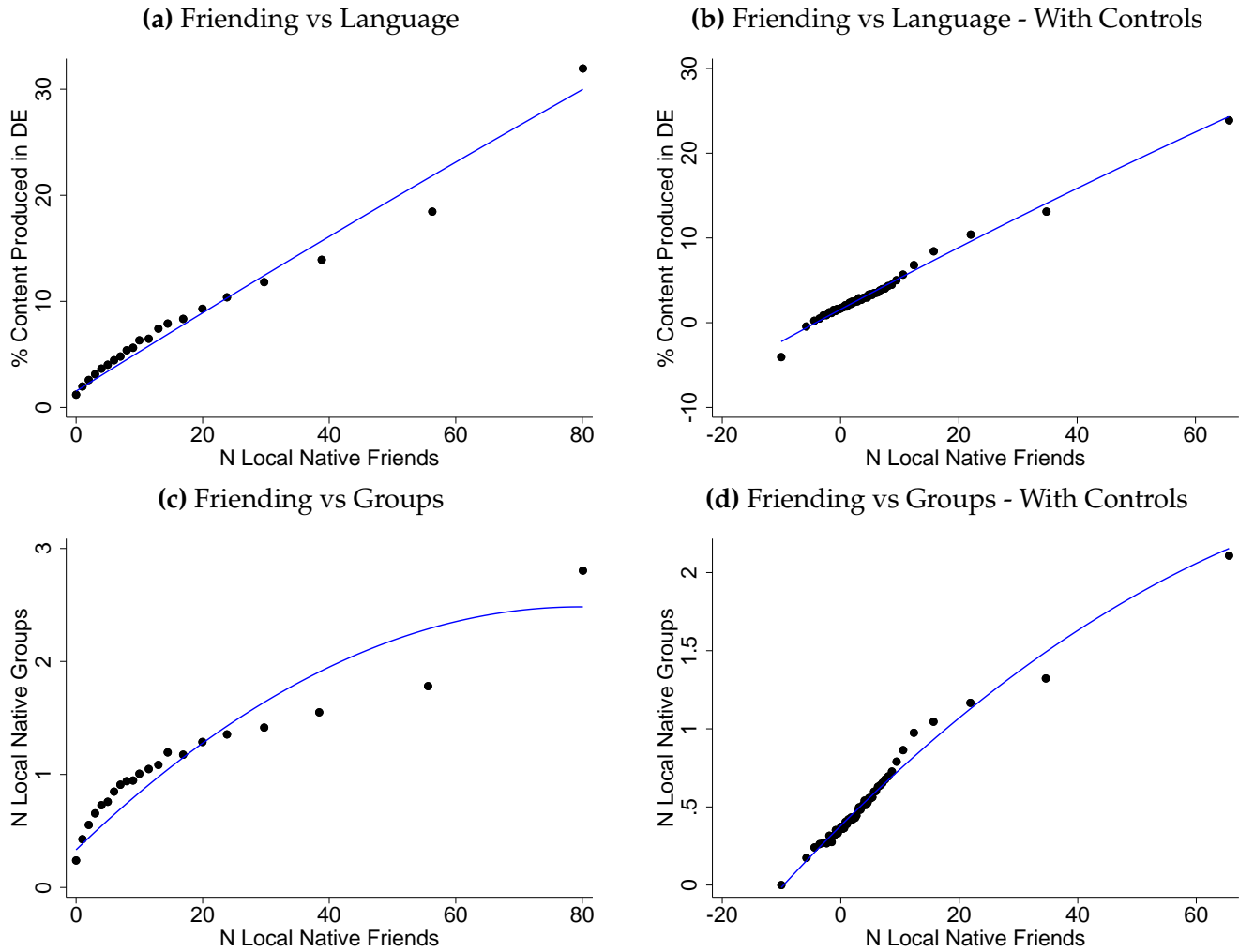
**Note:** Figure shows the number of users in our Syrian migrant sample using Facebook in Germany by the end of each year from 2012 to 2019 (on the y-axis), against analogous measures of Syrian migrant population from German administrative data (on the x-axis). Each observation is an age by gender by 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**



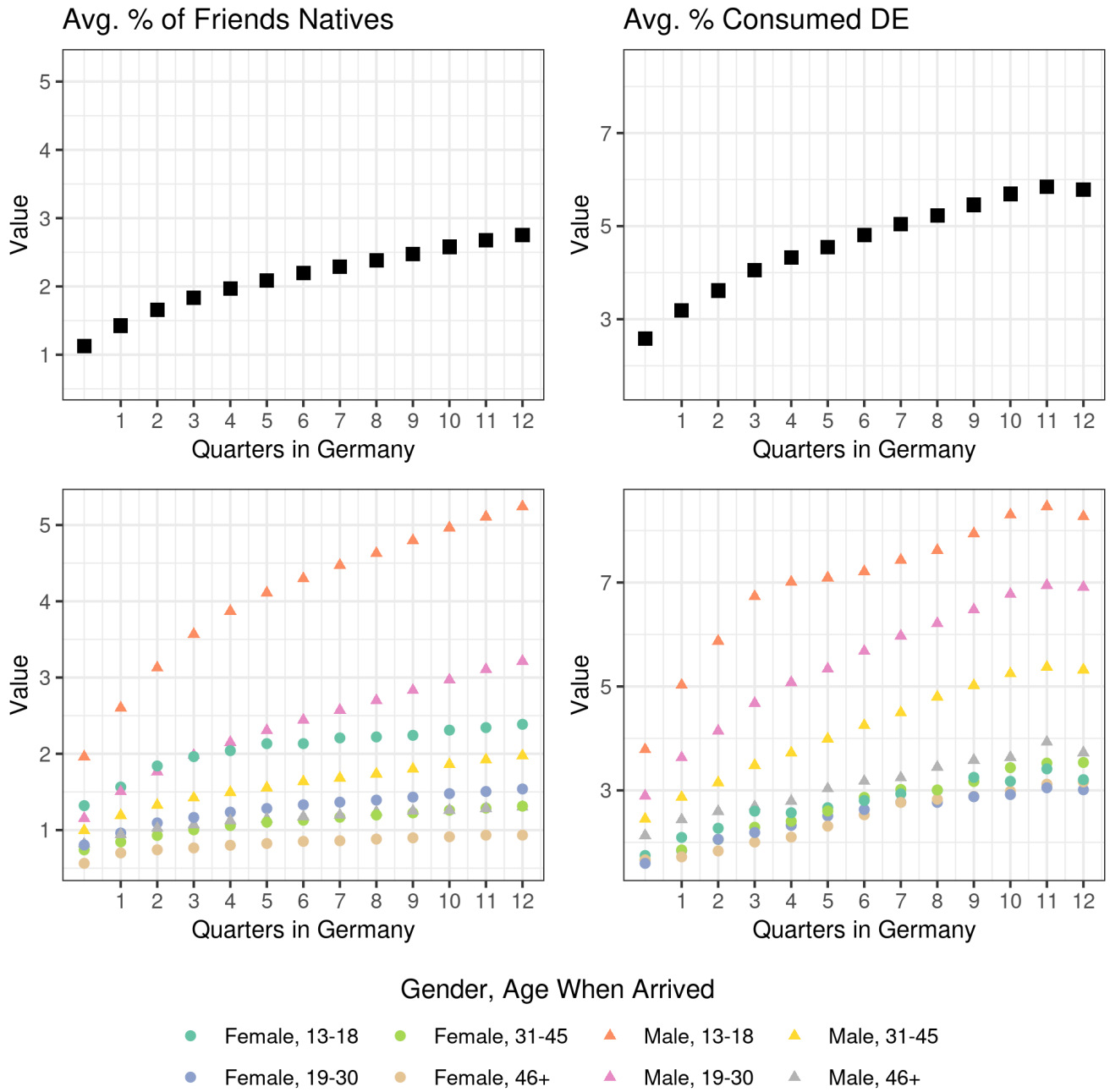
**Note:** Figure shows the shares of the primary sample of Facebook users that are also in the German native sample (on the y-axis), against shares of the population that are native from administrative data (on the x-axis). Each observation is a county by gender group. The size of each dot is proportional 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.

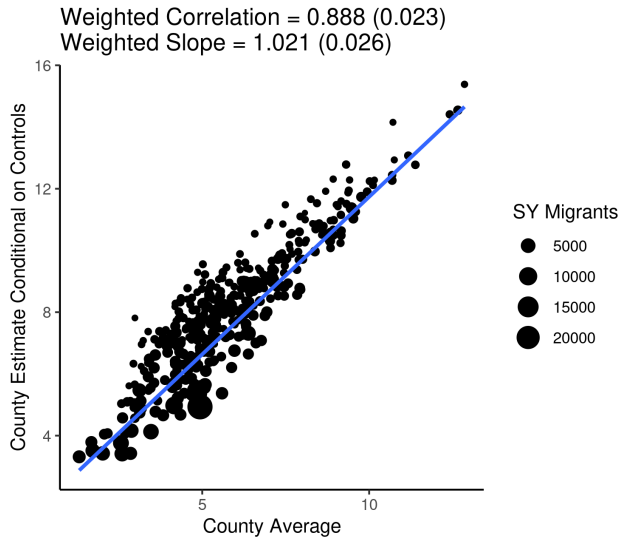
**Figure A6: Integration Over Time For 2015-16 Cohort — Additional Measures**



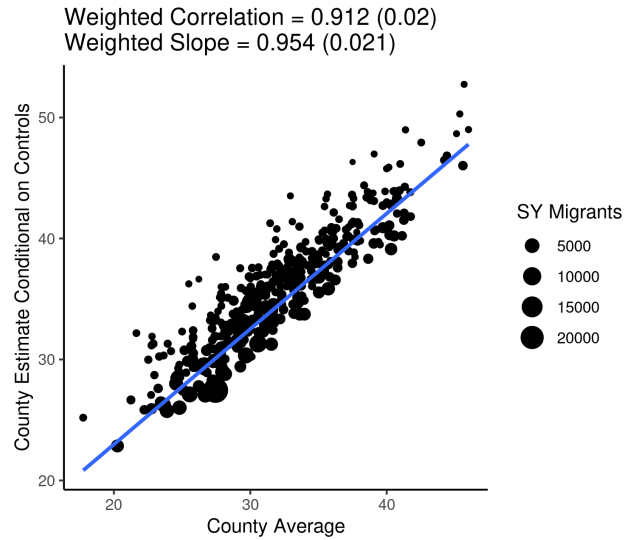
**Note:** Figures show the average values, by quarter, of integration measures for users in the Syrian migrant sample with an observed arrival in 2015 or 2016. The measures are share of friends native (left column) and the share of content consumed in German (right column). Appendix 3 provides more details 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**

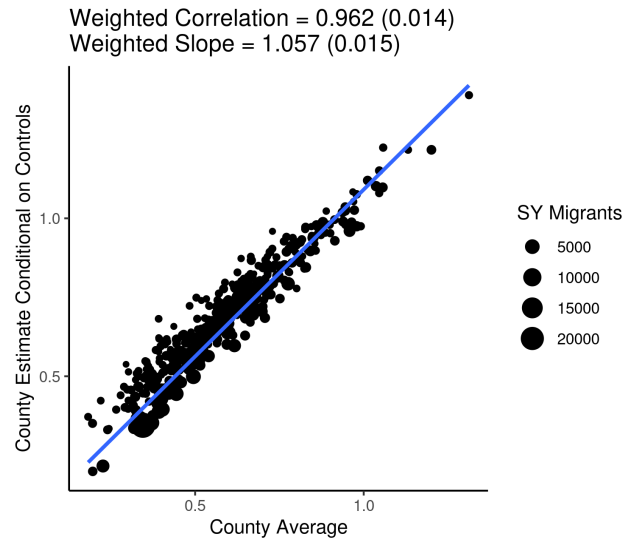
**(a) Friending**



**(b) Language**

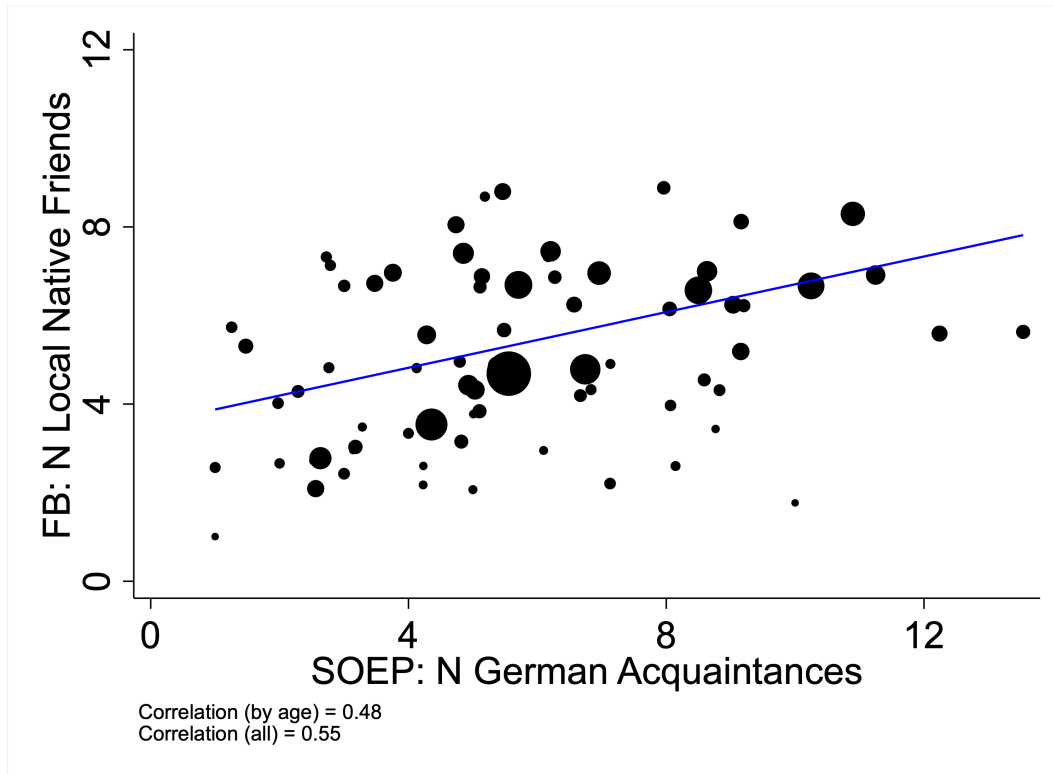


**(c) Groups**



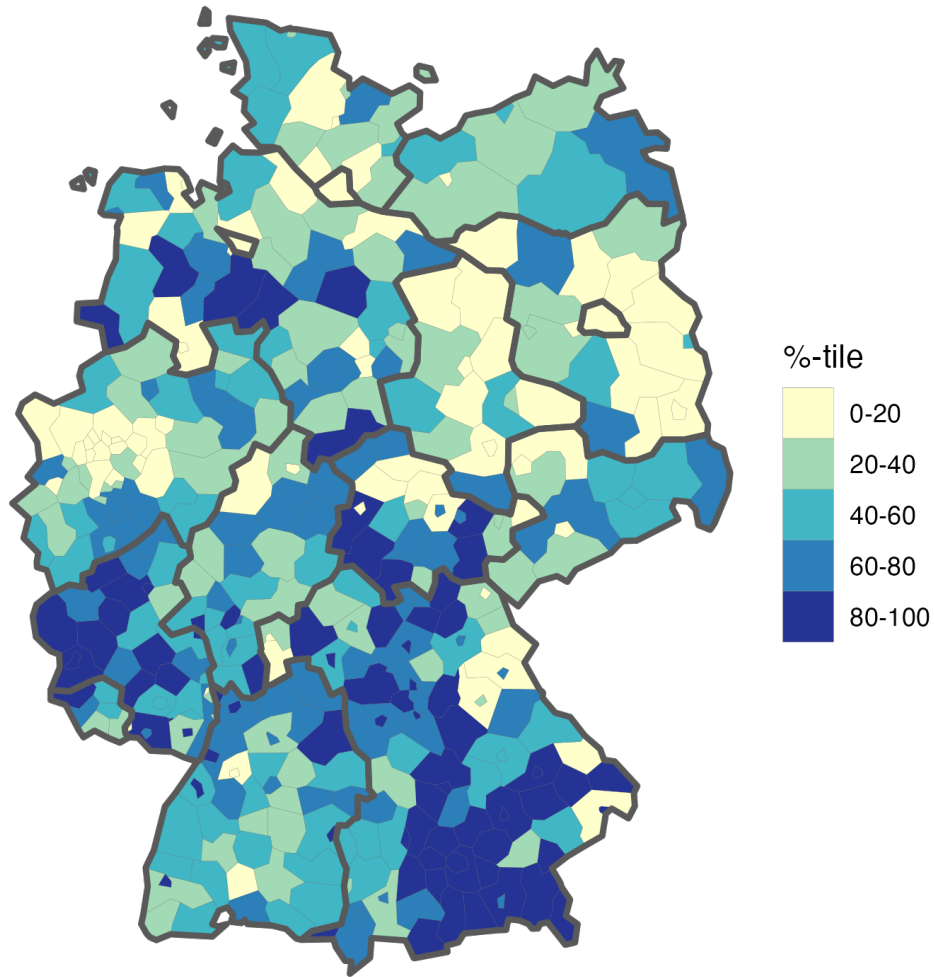
**Note:** Figures show the relationship between county averages of integration outcomes among Syrian migrants vs county-level fixed effect estimates constructed from versions of equation 1. The outcomes are a user's number of local German native friends in panel (a), whether the user produces content 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



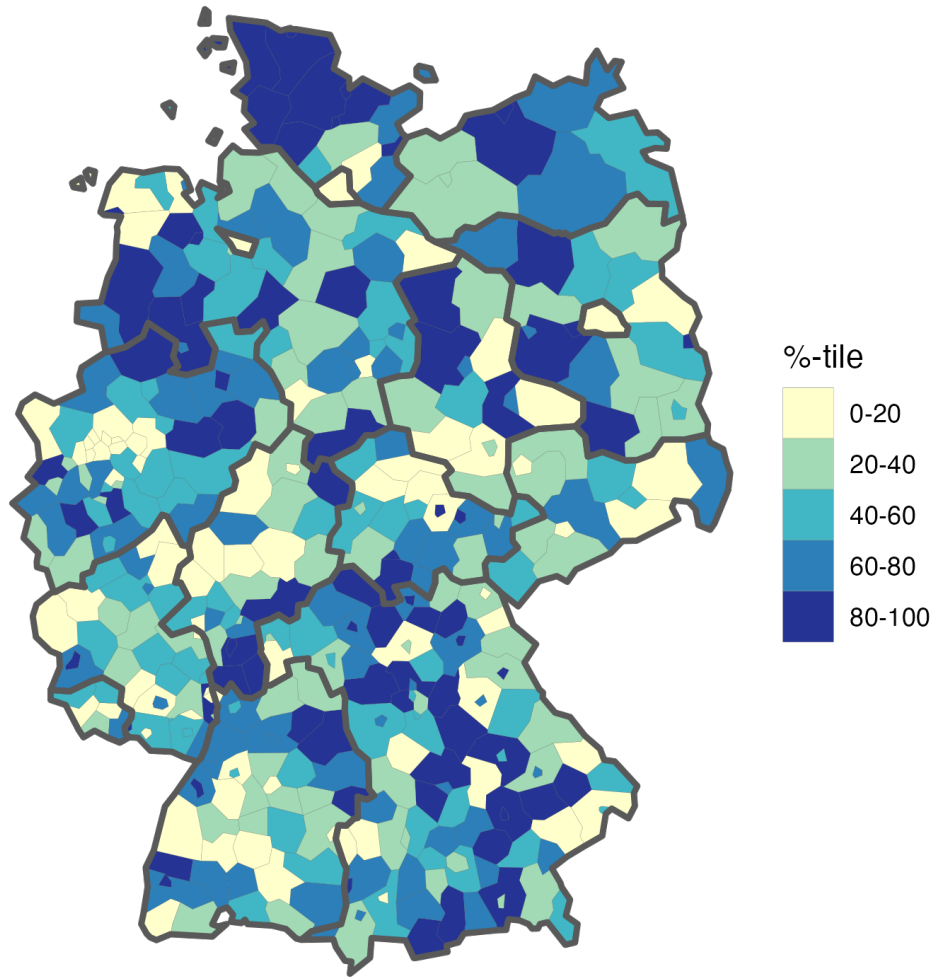
**Note:** Figure compares estimates of social integration based on our Facebook sample with the average number of acquaintances made by recent Syrian migrants in Germany in the SOEP data. The SOEP question is "How many German people have you met since your arrival in Germany with whom you have regular 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**



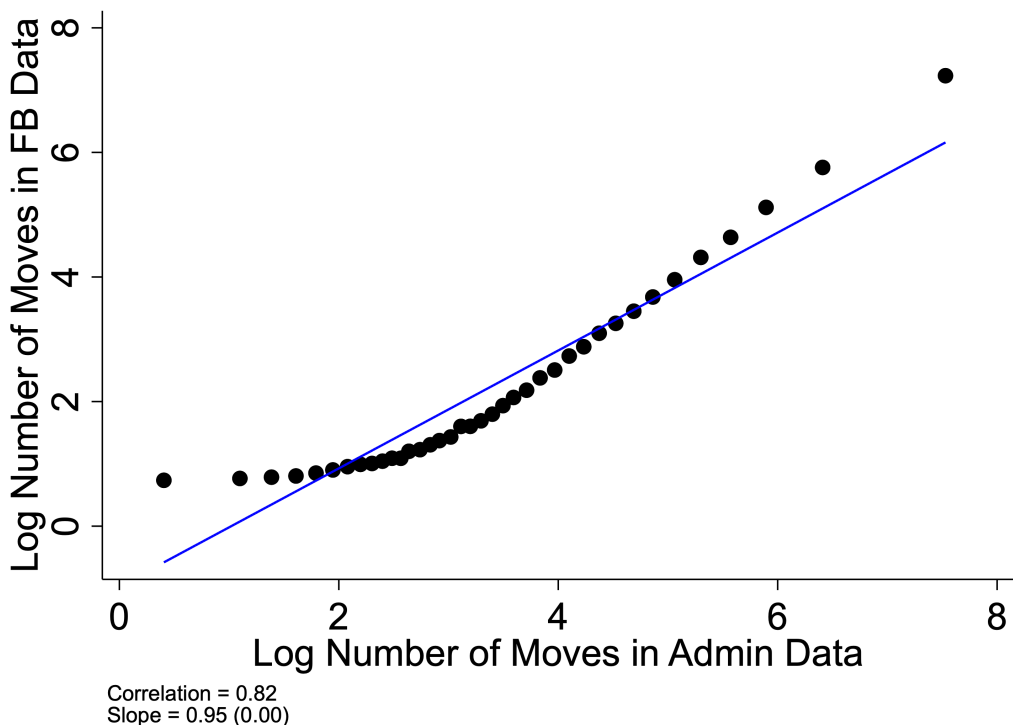
**Note:** Figure shows county-level estimates of Syrian migrant integration based on the share that produce content in the German language (residualized on regional patterns of Facebook usage). Darker areas indicate the highest integration counties.

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



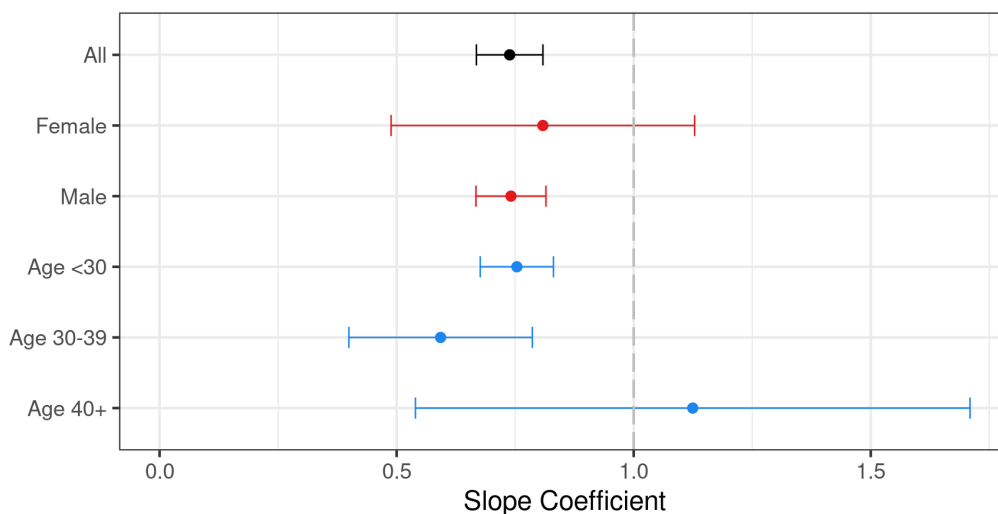
**Note:** Figure shows county-level estimates of Syrian migrant integration based on the average number of native local groups joined (residualized on regional patterns of Facebook usage. This includes the average number of total groups natives in the region have joined, allowing us to account for variation 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.

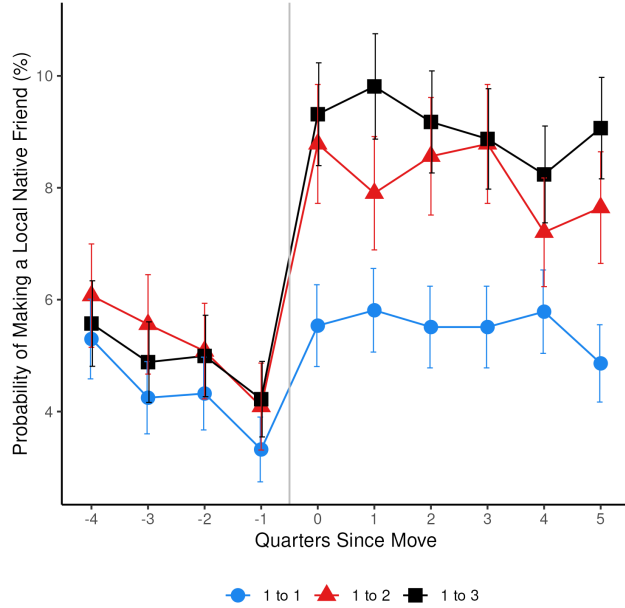
**Figure A12: Syrian Migrant Movers - Slope by Demographics**



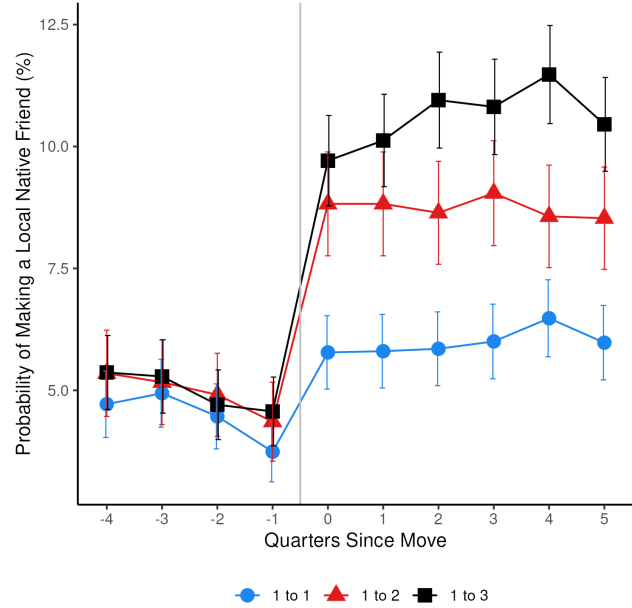
**Note:** Figure shows slopes corresponding to versions of Figure A19 over certain sub-samples. The coefficient in black corresponds to the slope using the full sample of Syrian migrant movers; the coefficients in red use samples of only one gender; and the coefficients in blue use samples of only one 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**

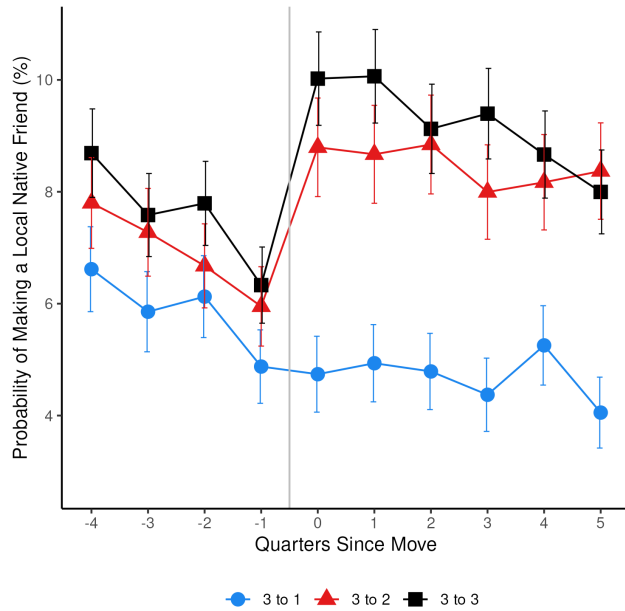
**(a) Moving From Bottom Integration Tercile (Only Friendships Initiated by Syrian Migrants)**



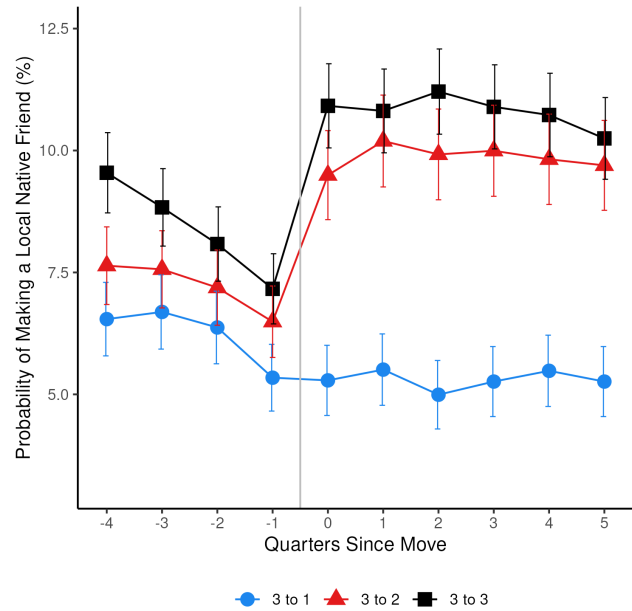
**(b) Moving From Bottom Integration Tercile (Only Friendships Initiated by Native Germans)**



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

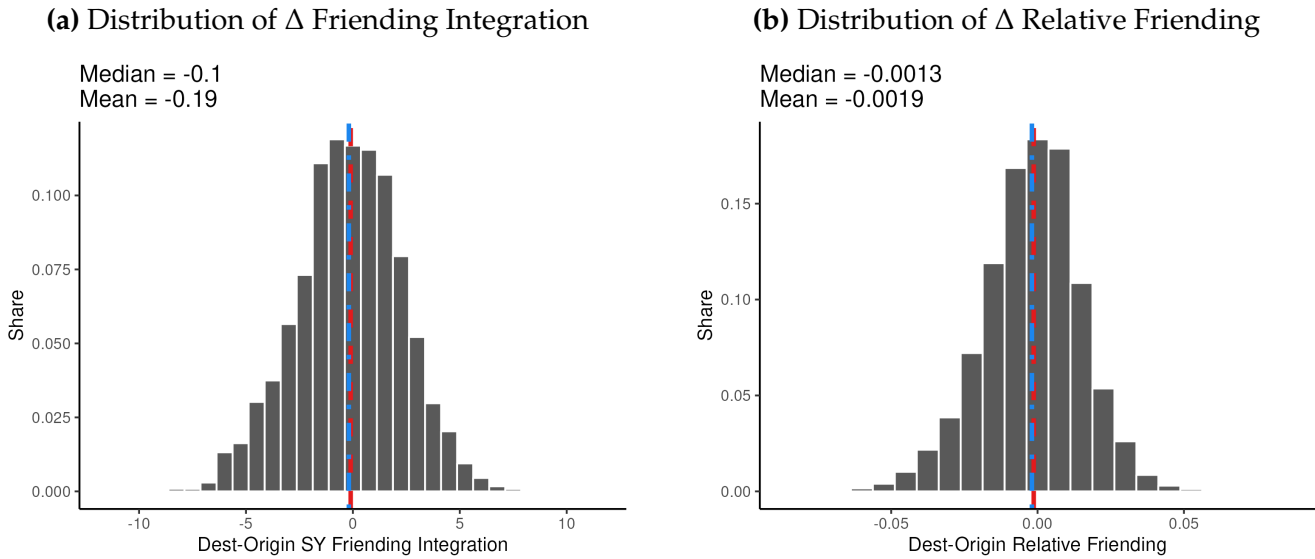


**(d) Moving From Top Integration Tercile (Only Friendships Initiated by Native Germans)**



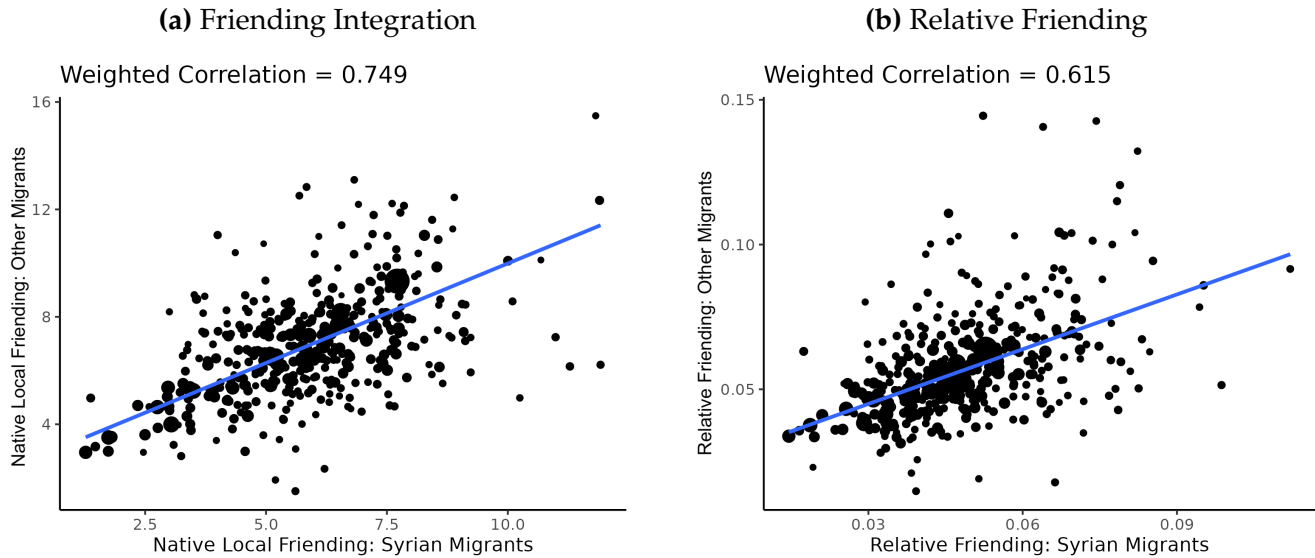
**Note:** This figure reproduces the analyses presented in Figure 3. Panels (a) and (b) disaggregate the results of panel (a) of Figure 3, splitting the friendships formed into two groups according to whether it was the Syrian migrant or the local German native who sent the friendship request on Facebook.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

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



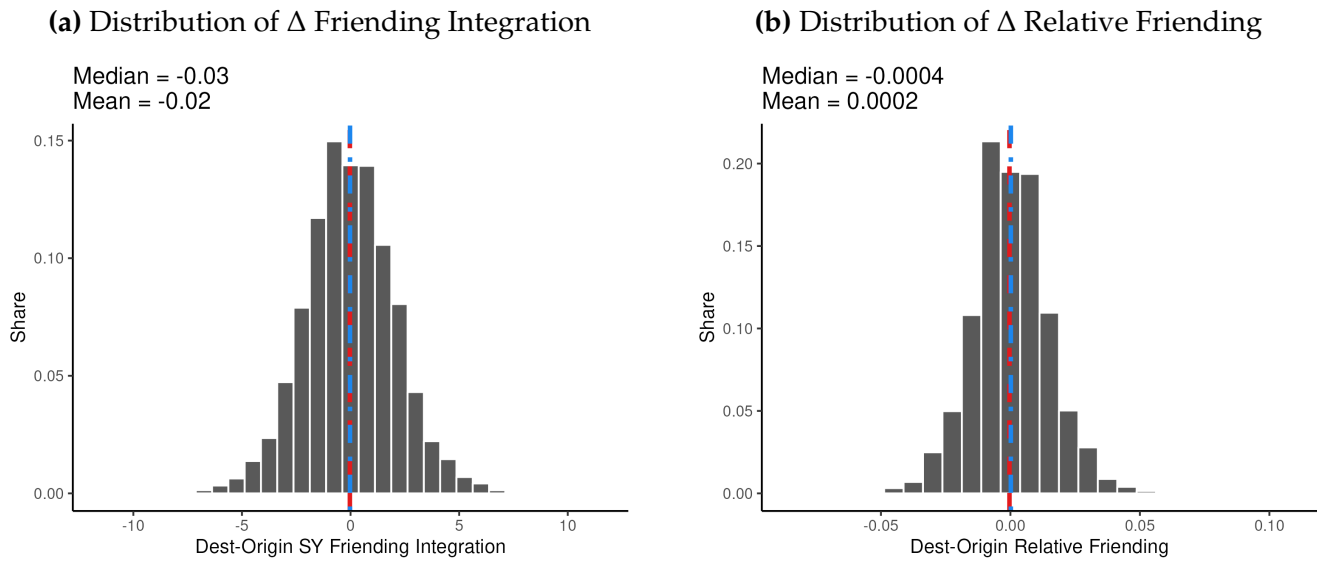
**Note:** Figures show, for Syrian migrant movers, the distribution of destination minus origin regional friending-based measures of Syrian migration integration. Panel (a) shows the distribution of the measure in Figure 2. Panel (b) shows the distribution of relative friending in Figure 4. The red and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

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



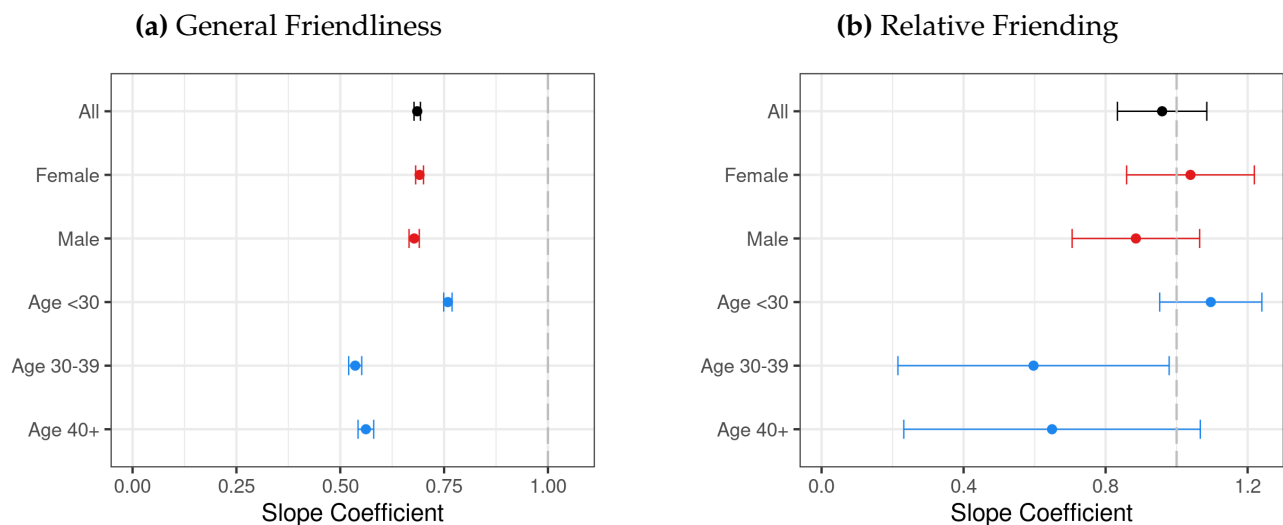
**Note:** Figure compares estimates of friending integration (panel a) and relative friending (panel b) across counties. Measures on the x-axis are calculated for Syrian migrants. Measures on the y-axis are calculated for users from one of the five countries with the most asylum applicants in Germany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

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



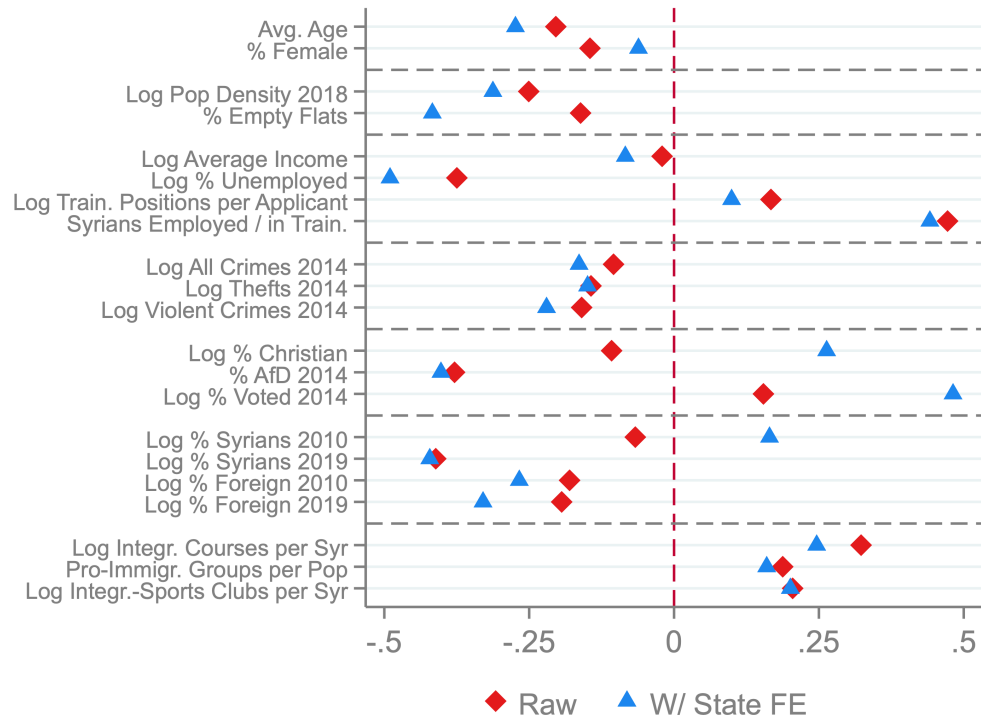
**Note:** Figures show, for German native movers, the distribution of destination minus origin regional friending-based measures of Syrian migration integration. Panel (a) shows the distribution of the measure in Figure 2. Panel (b) shows the distribution of relative friending in Figure 4. The red and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

**Figure A17:  $\Delta$  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*** (0.204)	-2.241*** (0.203)	-2.275*** (0.203)	-3.312*** (0.596)	0.167*** (0.006)	0.171*** (0.006)	0.136*** (0.006)	0.140*** (0.019)
Age 35 - 44	-7.133*** (0.238)	-7.161*** (0.237)	-6.875*** (0.237)	-6.615*** (0.733)	-0.002*** (0.007)	-0.007*** (0.007)	0.039* (0.007)	0.072** (0.023)
Age 45 - 54	-13.651*** (0.306)	-13.798*** (0.305)	-12.553*** (0.307)	-16.243*** (0.854)	-0.184*** (0.010)	-0.189*** (0.010)	-0.064*** (0.009)	-0.070*** (0.027)
Age 55+	-18.045*** (0.382)	-18.134*** (0.380)	-16.451*** (0.384)	-24.395*** (1.116)	-0.298*** (0.012)	-0.300*** (0.012)	-0.088*** (0.012)	-0.228*** (0.035)
Female	-15.767*** (0.164)	-15.560*** (0.164)	-16.725*** (0.173)	-18.765*** (0.418)	-0.202*** (0.005)	-0.200*** (0.005)	-0.372*** (0.005)	-0.447*** (0.013)
Household Member in DE 1+ Year Prior	-2.420*** (0.384)	-2.298*** (0.383)	-2.113*** (0.382)		-0.057*** (0.012)	-0.058*** (0.012)	-0.060*** (0.012)	
Non-Household Family in DE 1+ Year Prior	3.418*** (0.347)	3.451*** (0.345)	4.045*** (0.345)		0.023*** (0.011)	0.025*** (0.011)	0.030*** (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*** (0.184)	0.004*** (0.014)	-0.467*** (0.032)	0.076** (0.044)	0.078*** (0.038)	-2.683*** (0.160)	0.197*** (0.010)	-0.136*** (0.160)
Age 35 - 44	-4.728*** (0.216)	-0.263*** (0.016)	-1.446*** (0.038)	-0.694*** (0.051)	-0.749*** (0.044)	-7.099*** (0.187)	0.043 (0.012)	-4.347*** (0.187)
Age 45 - 54	-6.928*** (0.279)	-0.454*** (0.021)	-1.927*** (0.049)	-1.245*** (0.066)	-1.298*** (0.057)	-7.676*** (0.241)	-0.164*** (0.015)	-6.940*** (0.254)
Age 55+	-8.157*** (0.349)	-0.421*** (0.026)	-1.862*** (0.061)	-1.221*** (0.083)	-1.327*** (0.072)	-6.151*** (0.302)	-0.350*** (0.019)	-7.334*** (0.360)
Female	-7.188*** (0.157)	-0.787*** (0.012)	-2.334*** (0.027)	-2.339*** (0.037)	-2.154*** (0.032)	-5.377*** (0.136)	-0.485*** (0.009)	-11.601*** (0.137)
Household Member in DE 1+ Year Prior	-0.610 (0.347)	-0.030 (0.026)	0.013 (0.061)	0.146 (0.082)	-0.057 (0.071)	0.182 (0.300)	-0.014 (0.019)	-0.875*** (0.295)
Non-Household Family in DE 1+ Year Prior	0.667*** (0.314)	0.075*** (0.023)	0.360*** (0.055)	0.535*** (0.074)	0.404*** (0.064)	3.659*** (0.271)	0.098*** (0.017)	2.649*** (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)
<b>Panel A: Baseline Integration Measures</b>							
(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			
<b>Panel B: Decomposition of Integration Measures</b>							
(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	
<b>Panel C: Labor Market Integration Measure</b>							
(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:  $\Delta$  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*** (0.004)		0.711*** (0.005)	0.602*** (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*** (0.064)	0.926*** (0.094)	0.988*** (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:

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

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.<sup>1</sup> 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., ??????). 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 general Facebook usage patterns, younger and male Syrian migrants are better socially integrated.

<sup>1</sup>Family and household information is determined through self-reports and model-based imputations. Similar data are used in ? and ??.

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

	Facebook Sample				SOEP Sample	
	N Local Native Friends				N German Acquaintances	
Age 25 - 34	-1.012*** (0.053)	-0.894*** (0.052)	-0.873*** (0.052)	-1.148*** (0.129)	-0.839* (0.47)	-1.089** (0.47)
Age 35 - 44	-2.963*** (0.062)	-3.019*** (0.061)	-2.941*** (0.061)	-2.375*** (0.158)	-1.116* (0.58)	-1.070* (0.58)
Age 45 - 54	-4.012*** (0.080)	-4.102*** (0.079)	-4.147*** (0.079)	-4.765*** (0.184)	-2.362*** (0.78)	-2.238*** (0.77)
Age 55+	-4.548*** (0.100)	-4.531*** (0.098)	-4.586*** (0.099)	-7.226*** (0.241)	-3.378*** (1.24)	-3.594*** (1.23)
Female	-3.676*** (0.043)	-3.610*** (0.042)	-3.225*** (0.045)	-3.267*** (0.090)	-1.421*** (0.47)	-1.512*** (0.48)
Household Member in DE 1+ Year Prior	-0.377*** (0.100)	-0.290** (0.099)	-0.352*** (0.099)			
Non-Household Family in DE 1+ Year Prior	0.524*** (0.091)	0.621*** (0.089)	0.421*** (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  $\log(0.5 + \text{minutes on FB in the last 28 days})$ ,  $\log(91 - \text{days on Facebook out of the last 90})$ ,  $\log(1081 - \text{days on Facebook out of the last 1080})$ . 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: \*( $p < 0.10$ ), \*\*( $p < 0.05$ ), \*\*\*( $p < 0.01$ ).

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.<sup>2</sup>

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

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

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:

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

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:

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

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.

In Section 3.1, we construct regional measures of *general friendliness* using the German native sample.

<sup>2</sup>The methods described in this appendix are similar to procedures used in ?, ?, and ?.

**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.

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:

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

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  $\hat{r}_\psi$  and  $\hat{r}_\mu$  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:

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

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  $\phi_1 = \hat{r} = \frac{\text{Var}(X)}{\text{Var}(X) + \text{Var}(\epsilon_2)}$ . The reduced form is given by  $Y = \phi_2 \cdot \hat{X}_2 + \nu_2$ , where  $\phi_2 = \frac{\text{Cov}(Y, X)}{\text{Var}(X) + \text{Var}(\epsilon_2)}$ . Then the resulting estimate is:

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

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

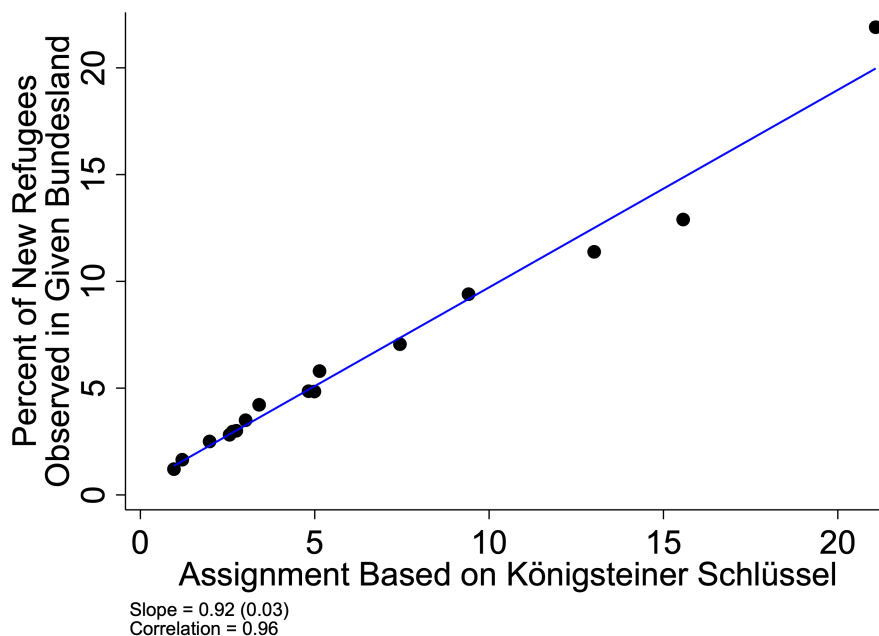
In this section, we attempt to compare the official refugee allocation rule—the so-called Königsteiner Schlüssel—to observed administrative data on refugee assignment.

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 (?). 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 comprised 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 ?. 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  $\text{IndivEffects}$  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.

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

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

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

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  $t$ :

$$y_{i,t}^{\Delta} = (\text{PlaceEffect}^{(2)} - \text{PlaceEffect}^{(1)}). \quad (10)$$

Where  $y_{i,t}^{\Delta}$  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.

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

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  $y_{i,t}^{\Delta}$  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,  $\zeta_t$ .

**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.<sup>3</sup> 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,  $y_{i,t}^\Delta$ , defined as:

$$y_{i,t}^\Delta = 0.25 \left[ \sum_{\tau=t}^{t+3} Y_{i,\tau} - \sum_{\tau=t-4}^{t-1} Y_{i,\tau} \right]. \quad (12)$$

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  $y_{i,t}^\Delta$  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,  $x_{i,t}^\Delta$ , as:

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

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,  $x_{i,t}^\Delta$  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:

$$y_{i,t}^\Delta = \alpha_0 + \alpha_1 x_{i,t}^\Delta + \zeta_t + \epsilon_{i,t}, \quad (14)$$

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,  $\zeta_T$ , 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  $x_{i,t}^\Delta$ , denoted by  $\hat{x}_{i,t}^\Delta$ . 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

<sup>3</sup>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  $\hat{x}_{i,t}^{\Delta}$  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.

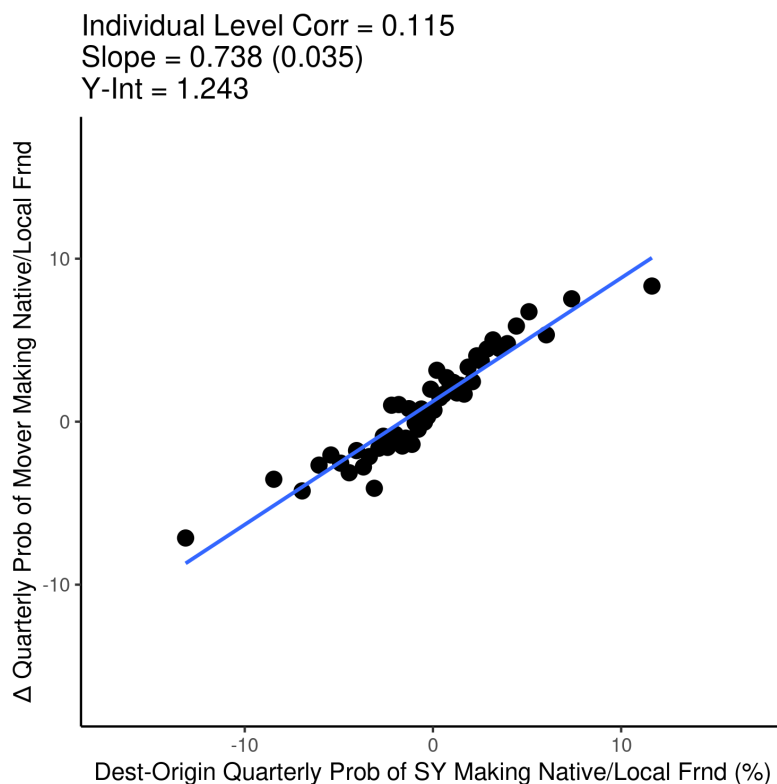
These identifying assumptions are relatively weak and allow for movers to differ from non-movers on observable and unobservable characteristics, and for these differences to correlate with origin and destination characteristics. For example, our model allows for "better integrating migrants" to be more 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 ? and ?. 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 ?), 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.<sup>4</sup> 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.

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<sup>4</sup>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  $y_{i,t}^{\Delta}$ , movers' change in the quarterly probability of making a native local friend the year before to after the move. The x-axis displays  $x_{i,t}^{\Delta}$ , 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  $y_{i,t}^{\Delta}$  against  $x_{i,t}^{\Delta}$ , with the slope corresponding to  $\alpha_1$  in equation 14.<sup>5</sup> 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.

<sup>5</sup>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 ? and ?. 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 ? and ?, 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:

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

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)				
	0.863*** (0.037)	0.857*** (0.043)	0.863*** (0.058)	0.813*** (0.042)	0.816*** (0.058)
Predicted Prob. Of Using German (Weighted Avg. of Places Lived)					
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.<sup>6</sup>

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 identification, 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.

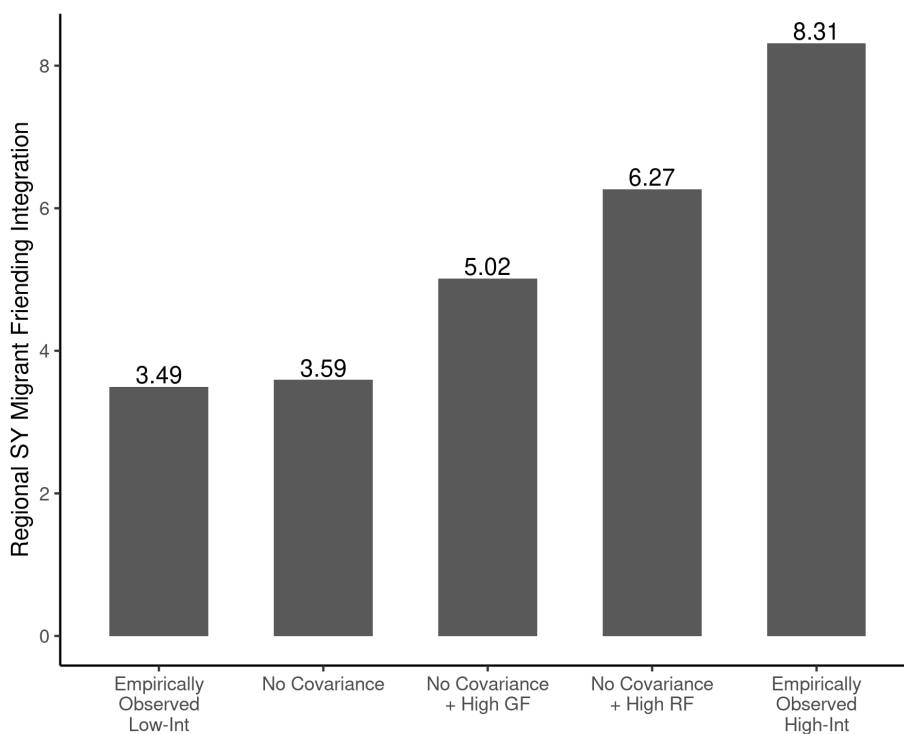
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<sup>6</sup>This threshold is higher than the five user minimum in Section 2.1. Our sample in this analysis, however, will remain larger because we (mechanically) do not enforce temporal matching.

## 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 ?. 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*** (0.000)	-0.073*** (0.000)	-19.097*** (0.098)	-14.407*** (0.092)	-0.059*** (0.001)	-0.061*** (0.001)	0.359*** (0.018)	0.146*** (0.018)
Age 35 - 44	-0.116*** (0.000)	-0.114*** (0.000)	-55.586*** (0.103)	-52.328*** (0.097)	-0.081*** (0.001)	-0.080*** (0.001)	0.951*** (0.018)	0.858*** (0.018)
Age 45 - 54	-0.132*** (0.000)	-0.131*** (0.000)	-62.533*** (0.108)	-62.415*** (0.102)	-0.098*** (0.001)	-0.095*** (0.001)	1.116*** (0.019)	1.152*** (0.019)
Age 55+	-0.139*** (0.000)	-0.141*** (0.000)	-82.666*** (0.108)	-84.728*** (0.102)	-0.098*** (0.001)	-0.095*** (0.001)	2.105*** (0.020)	2.157*** (0.020)
Female	-0.015*** (0.000)	-0.015*** (0.000)	-19.519*** (0.056)	-18.725*** (0.053)	-0.008*** (0.001)	-0.009*** (0.001)	0.882*** (0.010)	0.843*** (0.010)
Has College	0.006*** (0.000)	0.006*** (0.000)	4.131*** (0.060)	7.619*** (0.056)	-0.000 (0.001)	-0.002*** (0.001)	1.931*** (0.011)	1.788*** (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  $\log(0.5 + \text{minutes on FB in the last 28 days})$ ,  $\log(91 - \text{days on Facebook out of the last 90})$ ,  $\log(1081 - \text{days on Facebook out of the last 1080})$ . 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.<sup>7</sup> We identify pro-immigration Facebook pages and groups using a combination of string, url, and manual matching. Our outcome measure is

<sup>7</sup>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.<sup>8</sup> 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.<sup>9</sup>

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.

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<sup>8</sup>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.

<sup>9</sup>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.

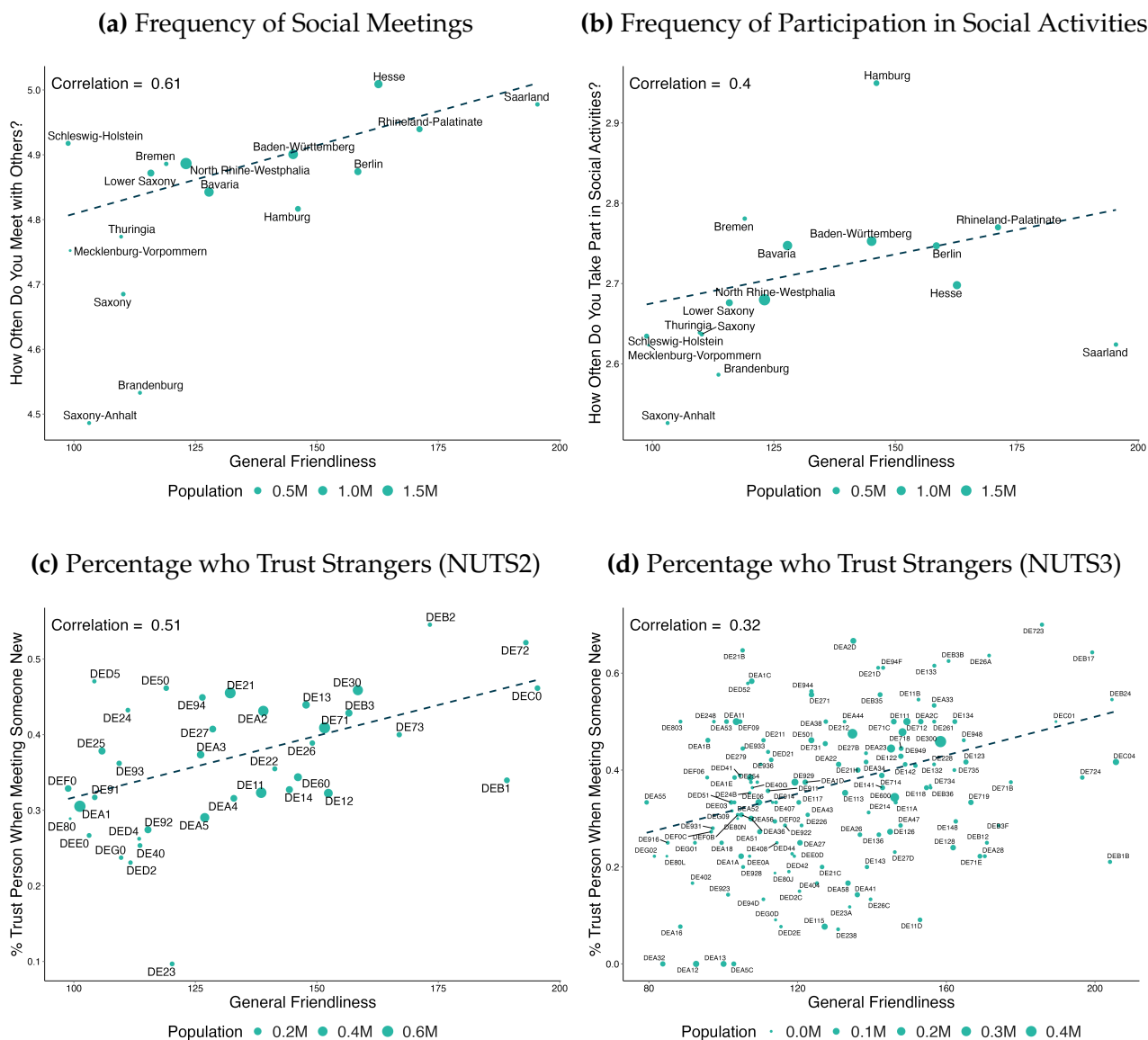
## 12 Validating General Friendliness Against External Surveys

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 (??). 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 (??) 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**



**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	<a href="#">German Statistical Office</a>
% Female Age	Share of population that is female, 2014	<a href="#">German Statistical Office</a>
Pop. Density 2018	Population density, 2018.	<a href="#">Regionalatlas Deutschland</a>
% Empty Flats	Share of flats that are vacant, 2017	<a href="#">Thünen-Landatlas</a>
Average Income	Average income, 2018	<a href="#">Statistische Ämter des Bundes und der Länder (Federal and state statistical offices)</a>
% Unemployed	Unemployment rate, 2014	<a href="#">Bundesagentur für Arbeit (Federal Employment Agency)</a>
Train. Positions per Applicant	Number of training positions (Lehrstellen) per applicant (Auszubildender)	<a href="#">Bundesagentur für Arbeit (Federal Employment Agency)</a>
Syrians Employed / in Train.	Number of Syrians employed or in training divided by Syrian population	<a href="#">Bundesagentur für Arbeit (Federal Employment Agency)</a>
All Crimes 2014	Reported crimes (total) per population, 2014	<a href="#">Polizeiliche Kriminalstatistik (Police Crime Statistics)</a>
Thefts 2014	Theft crimes per population, 2014	<a href="#">Polizeiliche Kriminalstatistik (Police Crime Statistics)</a>
Violent crimes 2014	Violent crimes per population, 2014	<a href="#">Polizeiliche Kriminalstatistik (Police Crime Statistics)</a>
% Christian	Number of Christians per population, 2011	<a href="#">Zensus Datenbank (Census Results)</a>
% AfD 2014	Vote share Alternative für Deutschland (AfD), European elections, 2014, demeaned by state	<a href="#">Der Bundeswahlleiter (Federal Returning Officer)</a>
% Voted 2014	Log turnout, European elections, 2014	<a href="#">Der Bundeswahlleiter (Federal Returning Officer)</a>

Continued on next page

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

Variable	Description	Data Source
% Syrians 2010	Number of Syrians divided by population, 2010	<a href="#">German Statistical Office</a>
% Syrians 2019	Number of Syrians divided by population, 2019	<a href="#">German Statistical Office</a>
% Foreign 2010	Number of foreigners divided by population, 2010	<a href="#">German Statistical Office</a>
% Foreign 2019	Number of foreigners divided by population, 2019	<a href="#">German Statistical Office</a>
Integr. Courses per Syrian	Number of integration courses completed 2015-2019 per Syrian	<a href="#">Federal Office for Migration and Refugees</a>
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	<a href="#">German Olympic Sports Confederation</a>
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 received directly from organisation)
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 received 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 received 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 received 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 angegeben, dass einzelne Personen nicht identifiziert werden können. Vielen Dank für deine Teilnahme!

Weiter

#### (c) Arabic

!مرحباً، يسعدنا معرفة رأيك

نحن نجري بحثاً 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 تقضّل في أغراض مثل إضفاء طابع شخصي Meta عدم الإجابة عنه أو الخروج من الاستبيان في أي وقت. قد تتم الاستعانة بريدوك 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 نتبناها. وقد يتم نشر نتائج هذا البحث في دورية أكاديمية. وعند النشر، يتم تسجيل جميع النتائج بما لا يسمح بأي فرصة للتعرف على الأفراد. شكراً 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."**

<input type="radio"/>	Strongly agree
<input type="radio"/>	Somewhat agree
<input type="radio"/>	Neither agree nor disagree
<input type="radio"/>	Somewhat disagree
<input type="radio"/>	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.“**

<input type="radio"/>	Stimme völlig zu
<input type="radio"/>	Stimme eher zu
<input type="radio"/>	Keine Meinung
<input type="radio"/>	Stimme eher nicht zu
<input type="radio"/>	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: "الذي تعاملات اجتماعية كثيرة مع الألمان في المدينة التي أعيش فيها"**

أوافق بشدة	<input type="radio"/>
أوافق نوعاً ما	<input type="radio"/>
لست موافقاً ولا غير موافق	<input type="radio"/>
لا أوافق نوعاً ما	<input type="radio"/>
لا أوافق بشدة	<input type="radio"/>

## 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.

<input type="checkbox"/>	I have been invited to a German friend's home (for a dinner, a birthday party, etc.)
<input type="checkbox"/>	I have invited a German friend to my home (for a dinner, a birthday party, etc.)
<input type="checkbox"/>	I have gone to a restaurant, cafe, or bar with German friends
<input type="checkbox"/>	I have been greeted on the street by German friends
<input type="checkbox"/>	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.

<input type="checkbox"/>	Ein/e deutsche/r Freund/in hat mich zu sich nach Hause eingeladen (zum Abendessen, zu einer Geburtstagsfeier etc.)
<input type="checkbox"/>	Ich habe eine/n deutschen Freund/in zu mir nach Hause eingeladen (zum Abendessen, zu einer Geburtstagsfeier etc.)
<input type="checkbox"/>	Ich war mit deutschen Freunden in einem Restaurant, Café oder einer Bar
<input type="checkbox"/>	Ich wurde auf der Straße von deutschen Freunden begrüßt
<input type="checkbox"/>	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)	<input type="checkbox"/>
قمت بدعوة صديق ألماني إلى منزلي (لتناول وجبة طعام أو حضور حفلة عيد ميلاد، وما إلى ذلك)	<input type="checkbox"/>
ذهبت إلى مطعم أو مقهى أو حانة مع أصدقاء ألمان	<input type="checkbox"/>
تم الترحيب بي في الشارع من قبل أصدقاء ألمان	<input type="checkbox"/>
مارست الرياضة مع أصدقاء ألمان	<input type="checkbox"/>

## 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.

<input type="checkbox"/>	Finding a job
<input type="checkbox"/>	Navigating the healthcare system (finding doctors, scheduling appointments, etc.)
<input type="checkbox"/>	Finding an apartment or place to live
<input type="checkbox"/>	Completing school work
<input type="checkbox"/>	Navigating the bureaucracy (filling out official documents, identifying the right people to speak to, etc.)
<input type="checkbox"/>	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.

<input type="checkbox"/>	Bei der Suche nach einem Job
<input type="checkbox"/>	Beim Navigieren des Gesundheitssystems (Ärzte finden, Termine vereinbaren etc.)
<input type="checkbox"/>	Bei der Suche nach einer Wohnung oder einem Ort zum Wohnen
<input type="checkbox"/>	Bei Hausaufgaben (z. B. für die Schule oder Uni)
<input type="checkbox"/>	Bei bürokratischen Angelegenheiten (offizielle Dokumente ausfüllen, richtige Ansprechpartner finden etc.)
<input type="checkbox"/>	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	<input type="checkbox"/>
التنقل ضمن نظام الرعاية الصحية (العثور على الأطباء وجدولة المواعيد، وما إلى ذلك)	<input type="checkbox"/>
البحث عن شقة أو مكان للإقامة	<input type="checkbox"/>
إكمال عمل مدرسي	<input type="checkbox"/>
التعامل مع الإجراءات البيروقراطية (ملء المستندات الرسمية وتحديد الأشخاص المناسبين للتحدث معهم، وما إلى ذلك)	<input type="checkbox"/>
البحث عن دورات تدريبية في اللغة أو الاندماج	<input type="checkbox"/>

## Figure A26: Survey Question: Satisfaction in Germany

### (a) English

How satisfied are you with your life in Germany?	
<input type="radio"/>	Very satisfied
<input type="radio"/>	Somewhat satisfied
<input type="radio"/>	Neither satisfied nor dissatisfied
<input type="radio"/>	Somewhat dissatisfied
<input type="radio"/>	Very dissatisfied

### (b) German

Wie zufrieden bist du mit deinem Leben in Deutschland?	
<input type="radio"/>	Sehr zufrieden
<input type="radio"/>	Eher zufrieden
<input type="radio"/>	Weder zufrieden noch unzufrieden
<input type="radio"/>	Eher unzufrieden
<input type="radio"/>	Sehr unzufrieden

### (c) Arabic

ما مدى رضاك عن حياتك في ألمانيا؟	
<input type="radio"/>	راضٍ إلى درجة كبيرة
<input type="radio"/>	راضٍ نوعاً ما
<input type="radio"/>	لست راضياً ولا غير راضٍ
<input type="radio"/>	غير راضٍ نوعاً ما
<input type="radio"/>	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	Holz Minden	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, Klingenstein	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

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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.