# The Social Integration of International Migrants: Evidence from the Networks of Syrians in Germany

Michael Bailey (Facebook) Drew Johnston (Harvard) Martin Koenen (Harvard) Theresa Kuchler (NYU Stern, CEPR, NBER) Dominic Russel (Harvard) Johannes Stroebel (NYU Stern, CEPR, NBER)

### **Background / Motivation**

- Over 70 million people alive today have been forcibly displaced from their home country
- Big question: how can host countries help migrants integrate into their new communities?
  - Some prior work on job market integration
  - Little study of *social* integration



• We answer five questions:

- We answer five questions:
  - 1. How can we measure migrants' social integration?

- We answer five questions:
  - 1. How can we measure migrants' social integration?
  - 2. How much does integration vary across space?

- We answer five questions:
  - 1. How can we measure migrants' social integration?
  - 2. How much does integration vary across space?
  - 3. What makes a place good at integrating migrants?

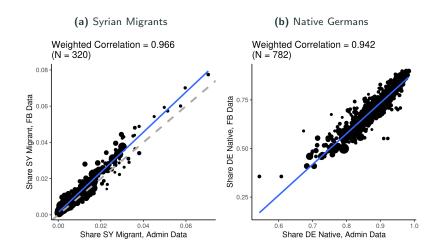
- We answer five questions:
  - 1. How can we measure migrants' social integration?
  - 2. How much does integration vary across space?
  - 3. What makes a place good at integrating migrants?
  - 4. Can regional policies influence integration?

- We answer five questions:
  - 1. How can we measure migrants' social integration?
  - 2. How much does integration vary across space?
  - 3. What makes a place good at integrating migrants?
  - 4. Can regional policies influence integration?
  - 5. Does exposure to migrants affect natives' attitudes?

- We focus on Syrian refugees in Germany
  - $\bullet~{\approx}900k$  migrants, largest refugee population in Europe
  - Almost all arrived after Syrian Civil War
- Work with de-identified data from Facebook

- Active Facebook users aged 18+ in Germany
- We split into Syrians/Natives/Others using:
  - 1. Past and present location signals
  - 2. Self reported hometown/high school
  - 3. Language usage
- Sample size = 350k Syrians, 18m Germans

#### Sample Construction (2)



• Each dot is a gender x age bucket x region bucket

#### 1. Friendships to nearby German natives

- 1. Friendships to nearby German natives
- 2. German language usage

- 1. Friendships to nearby German natives
- 2. German language usage
- 3. Local groups with native Germans
  - Local soccer clubs, volunteering groups, etc

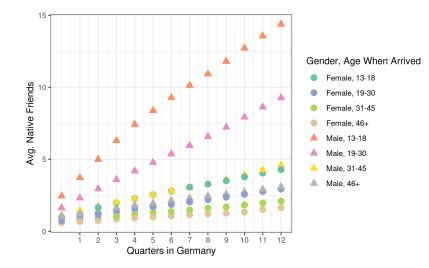
## Sample Summary (1)

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

	Mean	SD	P10	P25	P50	P75	P90	P99
Age	32.90	10.26	22	25	31	38	48	66
Female (0/100)	32.07	46.68	0	0	0	100	100	100
DE College (0/100)	7.92	27.00	0	0	0	0	0	100
N Friends	347.89	385.84	62	117	226	423	751	2431
N Groups	104.55	137.09	8	22	56	129	256	831
Qs Since 1st on FB in DE	20.30	8.04	7	15	23	25	28	36
N Local Native Friends	5.03	12.24	0	0	1	4	13	87
N Local Syrian Friends	14.99	17.43	1	4	9	20	36	103
Produces DE Content (0/100)	30.40	46.00	0	0	0	100	100	100
N Local Native Groups	0.55	1.41	0	0	0	0	2	9

- Syrian migrant sample is (correctly) young, male
- Relatively low levels of integration
  - Highly correlated within individuals
  - Matches SOEP survey (regular contact with 6 Germans on average)

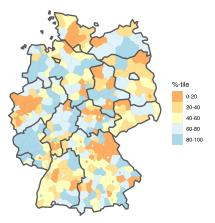
### Sample Summary (2)



• Male, younger migrants better integrated

- Large data allow us to measure *county-level* integration
- Use average integration outcomes of SY migrants
  - Will focus on friendships to local German natives
- Ensure we capture real-world patterns by residualizing on (small) spatial differences in FB usage among natives
  - No differences in migrant usage

#### **Regional Estimates of Integration - N Local Native Friends**



- Top decile has 2x as many friends as bottom (3.9 vs 7.9)
- High reliability in split-sample
- Matches SOEP survey data on migrant friendships

- Three possible drivers:
  - 1. Differences in migrant observables
  - 2. Differences in migrant un-observables
  - 3. Effects of place
- Able to rule out possibility 1 directly
  - No large differences in observables across places
- We will separate possibilities 2 and 3 by looking at the (few) migrants who move between counties

• Consider a migrant who moves from a "low integration" place to a "high integration" place. If...

- Consider a migrant who moves from a "low integration" place to a "high integration" place. If...
  - ...place differences are from **migrant characteristics**, movers' behavior *WILL NOT* change to stayer levels

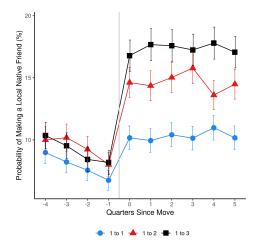
- Consider a migrant who moves from a "low integration" place to a "high integration" place. If...
  - ...place differences are from **migrant characteristics**, movers' behavior *WILL NOT* change to stayer levels
  - ...place differences are from **place effects**, movers' behavior *WILL* change to stayer level

- Consider a migrant who moves from a "low integration" place to a "high integration" place. If...
  - ...place differences are from **migrant characteristics**, movers' behavior *WILL NOT* change to stayer levels
  - ...place differences are from place effects, movers' behavior WILL change to stayer level
- Intuition follows number of recent movers papers [Card et al., 2013, Finkelstein et al., 2016, Finkelstein et al., 2019, Chetty and Hendren, 2018]

- Sample: Migrants who move to a non-neighboring county
- Outcome: Do they make a local native friend in a quarter?
- First: Group counties by integration outcome terciles
- Then: Study migrants moving from one tercile to another
  → Can measure changes in integration around moves
  → Do people who move to a "better" area integrate
  more?

#### Measuring the Effects of Place Using Movers (3)





• Suggestive evidence for place-based effects

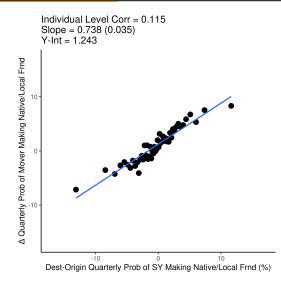
- Now: Model migrants' integration as sum of individual unobservables and place-based effects
  - These place-based effects can vary with observables
- When a migrant moves only place-based effect changes
- Movers then let us estimate the share of variation driven by place-based effects

#### Measuring the Effects of Place Using Movers (5)

$$y_{i,t}^{\Delta} = \alpha_0 + \alpha_1 x_{i,t}^{\Delta} + \xi_t + \epsilon_{i,t}$$

- $y_{i,t}^{\Delta}$  = change in friending after moving
  - $\rightarrow$  The change in a Syrian's probability of making a local native friend in each of the 4 quarters after vs before moving
- $x_{i,t}^{\Delta}$  = change in friending if user *i* adapted perfectly
  - $\rightarrow\,$  The difference in average friending between Syrians in the origin and destination who match the mover on demographics
- $\xi_t =$ Quarter of move fixed effect
- $\alpha_1$  identifies share of variation due to place effects

#### Measuring the Effects of Place Using Movers (6)



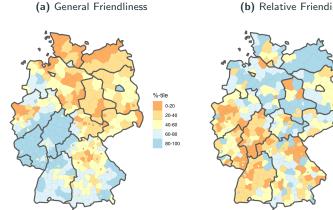
• Suggests 74% of variation is due to place-based effects

- Takeaway: Local environments have strong effects on migrants' integration
- Our estimates are probably a lower bound
  - We can't capture any place-based effects a person can bring with them (language, education, etc)



- General Friendliness: How many friends do natives have?
- **Relative Friendliness**: Do natives befriend Syrians in proportion to their local population share?
- Both components are strongly correlated with economic outcomes among Syrians
  - However, this distinction is important for policy

#### General and Relative Friendliness (2)



(b) Relative Friending

%-tile

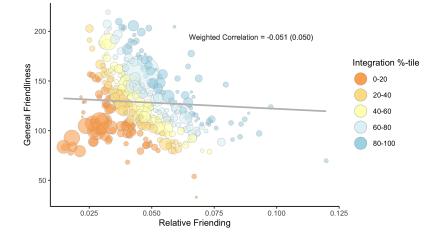
0-20

20-40

40-60

60-80 80-100

#### General and Relative Friendliness (3)

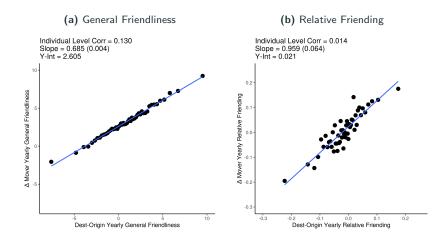


- Why do general/relative friendliness differ across places?
  - Could be characteristics of natives (e.g. preferences)
  - Could be institutions
- Unlike the migrant case, there is no initial random assignment across places
- Size of place-based effects is important for policy

Correlates of Native Behavior

$$y_{i,t}^{\Delta} = \alpha_0 + \frac{\alpha_1}{\alpha_1} x_{i,t}^{\Delta} + \xi_t + \epsilon_{i,t}$$

- This design is similar to the design we used for migrants
- $y_{i,t}^{\Delta}$  = change in the native's behavior post-move
  - $\rightarrow\,$  The change in the native's level of general/relative friending in the year following their move, relative to the year before
- $x_{i,t}^{\Delta}$  = change in behavior if the native adapted perfectly
  - $\rightarrow\,$  Difference in general/relative friending between observably identical natives in the destination and origin
- $\alpha_1$  identifies share of variation due to place effects

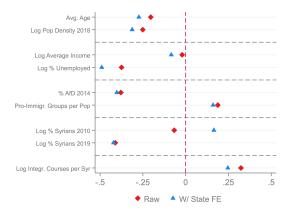


• Large slopes  $\rightarrow$  large role for place-based factors

- Something about places seems to determine integration.
- But what is it?
  - Civic programs?
  - Geography?
  - Government policies?

# Why Do Places Differ? (2)

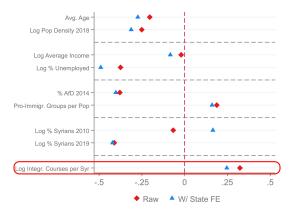
County-Level Univariate Correlations with Friending Integration



- Correlations give some sense, but are they are causal?
- Do these affect general friendliness or relative friendliness?

# Why Do Places Differ? (2)

County-Level Univariate Correlations with Friending Integration



- Correlations give some sense, but are they are causal?
- Do these affect general friendliness or relative friendliness?

- Integration courses are the most common policy
- Can teach language skills, culture, civics
- Teachers in the courses need experience teaching German as a second language
  - Relatively few have these qualifications
- Areas varied in the availability of potential teachers in 2015-2016
  - $\rightarrow$  Instrument for course availability using unemployed specialized teachers

# Causal Effects of Regional Policy (2)

#### Integration Courses and Teacher Unemployment Rates

	Log Integration Courses per Syrian 2015-19					
Log Unemp. General Schools Teachers 2014 per Syrian	0.088 (0.05)					
Log Unemp. Vocat. School Teachers 2014 per Syrian		0.084 (0.05)				
Log Unemp. Driving and Sports Teachers 2014 per Syrian			0.052 (0.06)			
Log Unemp. Other School Teachers 2014 per Syrian				0.229*** (0.05)		
Control Covariates	x	x	x	x		
Control Log General Unemployment Rate	x	х	x	х		
F-statistic	2.37	3.67	0.94	20.97		
N	390	367	388	390		
R-Squared	0.349	0.354	0.347	0.379		

- Unemployment among German as a second language teachers predicts integration course completion
- Strong F-stat given county-level regression

#### Table 1: IV Estimates - Measures of Integration and Integration Courses

	Integration	General Friendliness	Relative Friending	Language	Employ. / Training
Log Integration Courses per Syrian	1.698***	0.204	1.389***	0.193***	0.891***
	(0.33)	(0.21)	(0.25)	(0.07)	(0.15)
Control Covariates	x	x	x	x	x
Control Log General Unemployment Rate	x	x	x	x	x
N	390	390	390	390	384

- Integration courses tend to improve language acquisition, employment outcomes, and relative friending
- No large impact on general friendliness
- $\bullet$  We tend to find IV estimates > OLS estimates
  - Marginal courses tend to be in low-integration areas
  - Women more likely to forgo courses if supply limited

- We've seen that:
  - Migrants in different regions vary in their integration
  - Migrant characteristics do not explain these differences
  - Characteristics of place matter more than characteristics of its residents
- But what explains heterogeneity within a place?
  - Previous contact may shape attitudes for natives
  - ...But not clear how wide-reaching these effects are.

- School entry cutoffs cause quasi-random variation in contact
- Students born before or after the cutoff are placed into cohorts with different demographics
- Around the cutoff there is quasi-random variation in an individual's social network
- We consider neighboring cohorts in a school, where one year has a Syrian and one does not

$$Y_i = \alpha_1 Syrian In Cohort_s + \xi_{t,L} + \gamma_s + \epsilon_{i,t}.$$

Here, Y<sub>i</sub> is a social outcome, SyrianInCohort<sub>s</sub> is an indicator if an individual has a Syrian in their class, ξ<sub>t,L</sub> is a county-by-year FE, and γ<sub>s</sub> is a school FE.

	Syrian Friends			Friends Classmates)	Syrian Friends (Excluding Syrian Classmates and their Friends)		
Syrian in Cohort	0.020***	0.020***	0.005***	0.005***	0.005***	0.005***	
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	
Syrian in Cohort x Standardized Cohort Size		-0.007*** (0.001)		-0.003*** (0.001)		-0.003*** (0.001)	
School FE	х	х	х	Х	х	х	
Birth Year x County FE	Х	х	х	Х	х	х	
N	115,625	115,625	115,625	115,625	115,625	115,625	
Mean in Control Cohort	0.054	0.054	0.029	0.029	0.027	0.027	

• Germans exposed to a Syrian make more Syrian friends

- Even friends in totally different settings
- Points to a shift in attitudes
- Effect is larger in smaller cohorts

## Summary

1. We present the most systematic measurements of the social integration of Syrians in Germany

- 1. We present the most systematic measurements of the social integration of Syrians in Germany
- 2. Integration levels are generally quite low, but with a lot of variation across people and places

- 1. We present the most systematic measurements of the social integration of Syrians in Germany
- 2. Integration levels are generally quite low, but with a lot of variation across people and places
- 3. These differences seem to be largely driven by the characteristics of the place, not the people living there

- 1. We present the most systematic measurements of the social integration of Syrians in Germany
- 2. Integration levels are generally quite low, but with a lot of variation across people and places
- 3. These differences seem to be largely driven by the characteristics of the place, not the people living there
- 4. These local institutions can also be changed with policy, such as integration courses

- 1. We present the most systematic measurements of the social integration of Syrians in Germany
- 2. Integration levels are generally quite low, but with a lot of variation across people and places
- 3. These differences seem to be largely driven by the characteristics of the place, not the people living there
- 4. These local institutions can also be changed with policy, such as integration courses
- 5. Contact between Syrians and native Germans can improve integration in the long run

## References

Card, D., Heining, J., and Kline, P. (2013).

Workplace heterogeneity and the rise of west german wage inequality.

The Quarterly journal of economics, 128(3):967–1015.

Chetty, R. and Hendren, N. (2018).

The impacts of neighborhoods on intergenerational mobility ii: County-level estimates.

The Quarterly Journal of Economics, 133(3):1163–1228.

Finkelstein, A., Gentzkow, M., and Williams, H. (2016). Sources of geographic variation in health care: Evidence from patient migration.

The Quarterly Journal of Economics, 131(4):1681–1726.

Finkelstein, A., Gentzkow, M., and Williams, H. L. (2019). **Place-based drivers of mortality: Evidence from migration.** Technical report, National Bureau of Economic Research.

# Appendix

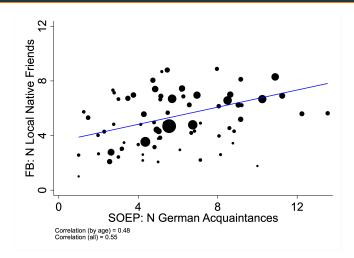
## Appendix - Multivariate Sample Summary

	Facebook Sample N Local Native Friends					
Age 25 - 34	-1.012*** (0.053)	-0.894*** (0.052)	-0.873*** (0.052)	-1.148*** (0.129)		
Age 35 - 44	-2.963*** (0.062)	-3.019*** (0.061)	-2.941*** (0.061)	-2.375*** (0.158)		
Age 45 - 54	-4.012*** (0.080)	-4.102*** (0.079)	-4.147*** (0.079)	-4.765*** (0.184)		
Age 55+	-4.548*** (0.100)	-4.531*** (0.098)	-4.586*** (0.099)	-7.226*** (0.241)		
Female Household Member in DE 1+ Year Prior Non-Household Family in DE 1+ Year Prior	-3.676*** (0.043)	-3.610*** (0.042)	-3.225*** (0.045)	-3.267*** (0.090)		
	-0.377*** (0.100)	-0.290** (0.099)	-0.352*** (0.099)			
	0.524*** (0.091)	0.621*** (0.089)	0.421*** (0.089)			
Quarters Since DE FEs	х	х	х	х		
rev Quarters in NUTS3 FEs	х	х	х	х		
ersonal Usage Controls	х	x	х	X		
County / State FEs		х	х	x		
.og (1 + Total Outside Germany Friends)			x	x		
.og (1 + Total Other Groups) .og (1 + Total Content Produced Past Year)			x	x		
log (1 + Total Content Produced Past Year) lousehold FE			x	x		
N	349,072	349,072	349,072	84,216		
R-Squared	0.132	0.160	0.165	0.658		
Sample Mean	5.029	5.029	5.029	4.195		

Age 25 - 34 Age 35 - 44 Age 45 - 54 Age 55+ Female Has College Prev Quarters in NUTS3 FEs Personal Usage Controls County FEs	N Local SY Friends		General Friendliness		Relative Friending		In Pro Imm. Group (0/100						
	-0.073*** (0.000) -0.116*** (0.000) -0.132*** (0.000) -0.139*** (0.000) -0.015*** (0.000) 0.006***	-0.073*** (0.000) -0.114*** (0.000) -0.131*** (0.000) -0.141*** (0.000) -0.015*** (0.000) 0.006*** (0.000) X	-19.097*** (0.098) -55.586*** (0.103) -62.533*** (0.108) -82.666*** (0.108) -19.519*** (0.056) 4.131*** (0.060) X	-14.407*** (0.092) -52.328*** (0.097) -62.415*** (0.102) -84.728*** (0.102) -18.725*** (0.023) 7.619*** (0.056) X	(0.092)    (0.001)      52.328***    -0.081***      (0.097)    (0.001)      -62.415***    -0.098***      (0.102)    (0.001)      -84.728***    -0.098***      (0.02)    (0.001)      -18.725***    -0.008***      (0.053)    (0.001)      7.619***    -0.000      (0.056)    (0.001)	-0.061*** (0.001) -0.080*** (0.001) -0.095*** (0.001) -0.095*** (0.001) -0.009*** (0.001) -0.002*** (0.001) X X X X	0.359*** (0.018) 0.951*** (0.018) 1.116*** (0.019) 2.105*** (0.020) 0.882*** (0.010) 1.931*** (0.011) X X	0.146*** (0.018)					
								0.858*** (0.018)					
								1.152*** (0.019)					
								2.157*** (0.020) 0.843*** (0.010) 1.788*** (0.011) X X X X					
									х				
									х	x x	х		
	N								17,768,822	17,768,822	17,768,822	17,768,822	17,515,164
	R-Squared Sample Mean	0.020	0.031	0.170 122.510					0.263 122.510	0.001	0.002	0.035 4.835	0.042 4.835

#### Return

## **Regional Estimates of Integration - SOEP Validation**



• Our estimates match state-level survey results