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Social Capital Determinants and Labor Market Networks

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Social capital, networks, and determinants of social capital

- O.E.D. definition of social capital:
  - "The networks of relationships among people who live and work in a particular society, enabling that society to function effectively"
  - A network is not social capital unless it leads to productive social outcomes
- We study a measure of local labor market networks we have developed in past work
  - Local labor market networks, as we measure them, are productive (e.g., better job matches)
- We study what predicts/is associated with our measure of local labor market networks

Terminology of "social capital"

- Structural social capital: association links and activities, whether in formal organizations or informal associations
  - Contrasts with behavioral (or cognitive) social capital: perceptions of support, reciprocity, trust, etc.
- Our network measure *is* a measure of social capital – informal associational links, *and* productive
- We view the measures we relate to network strength as potential *determinants of* social capital – i.e., the productive outcomes
  - Semantic issue (?): but guards against us calling "everything" that could connect people "social capital," without knowing whether those connections are productive
  - E.g., "ethnic homogeneity" per se isn't social capital, but it can produce social capital

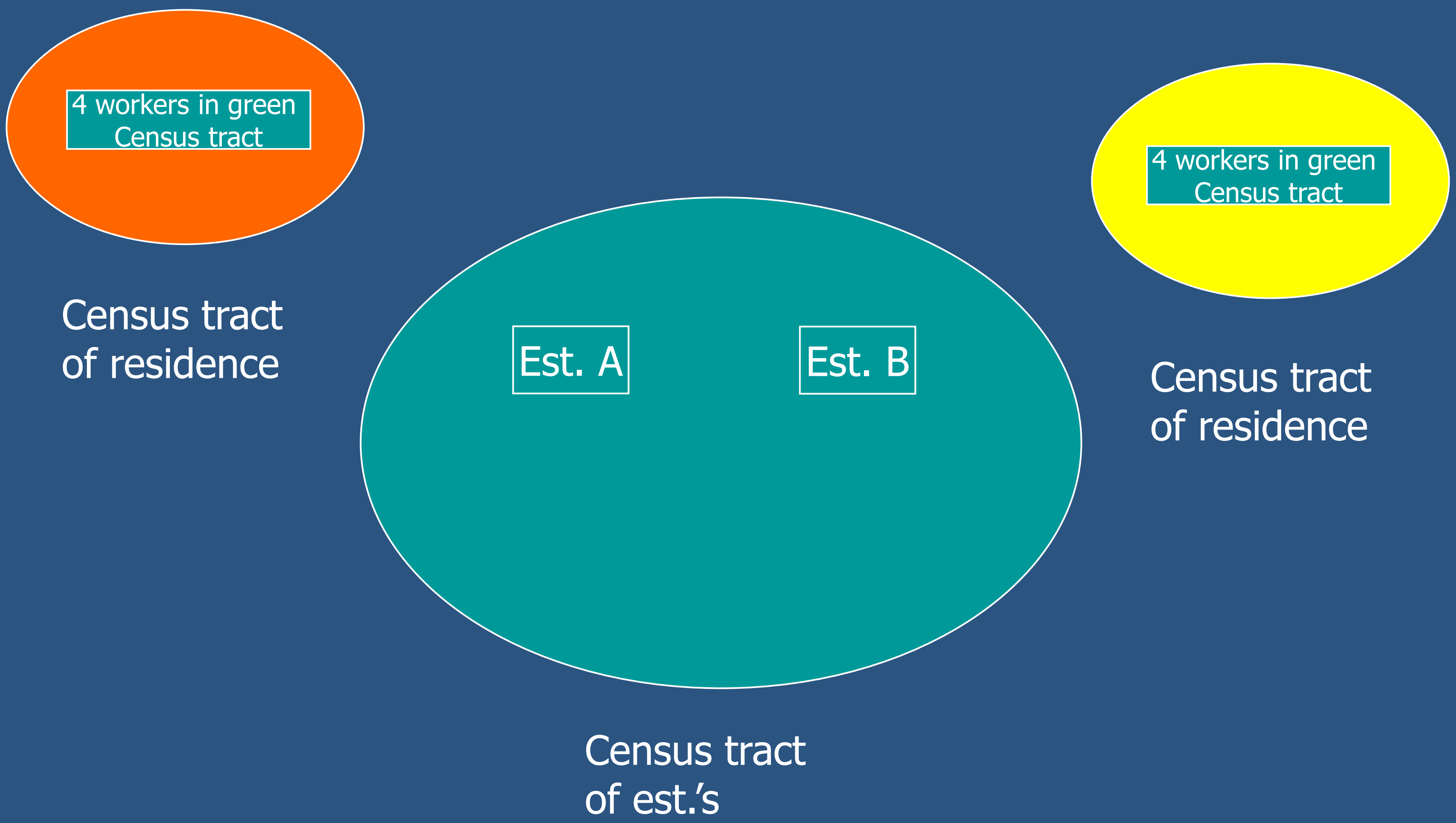
Research question

- Our question: Are hypothesized determinants of social capital associated with stronger labor market networks?
  - Measure of labor market networks developed and “validated” in our past work, which we interpret as social capital
  - Past/new measures of determinants of social capital with rich data from many sources
  - Machine learning to examine whether/which neighborhood social capital determinants are associated with stronger labor market networks

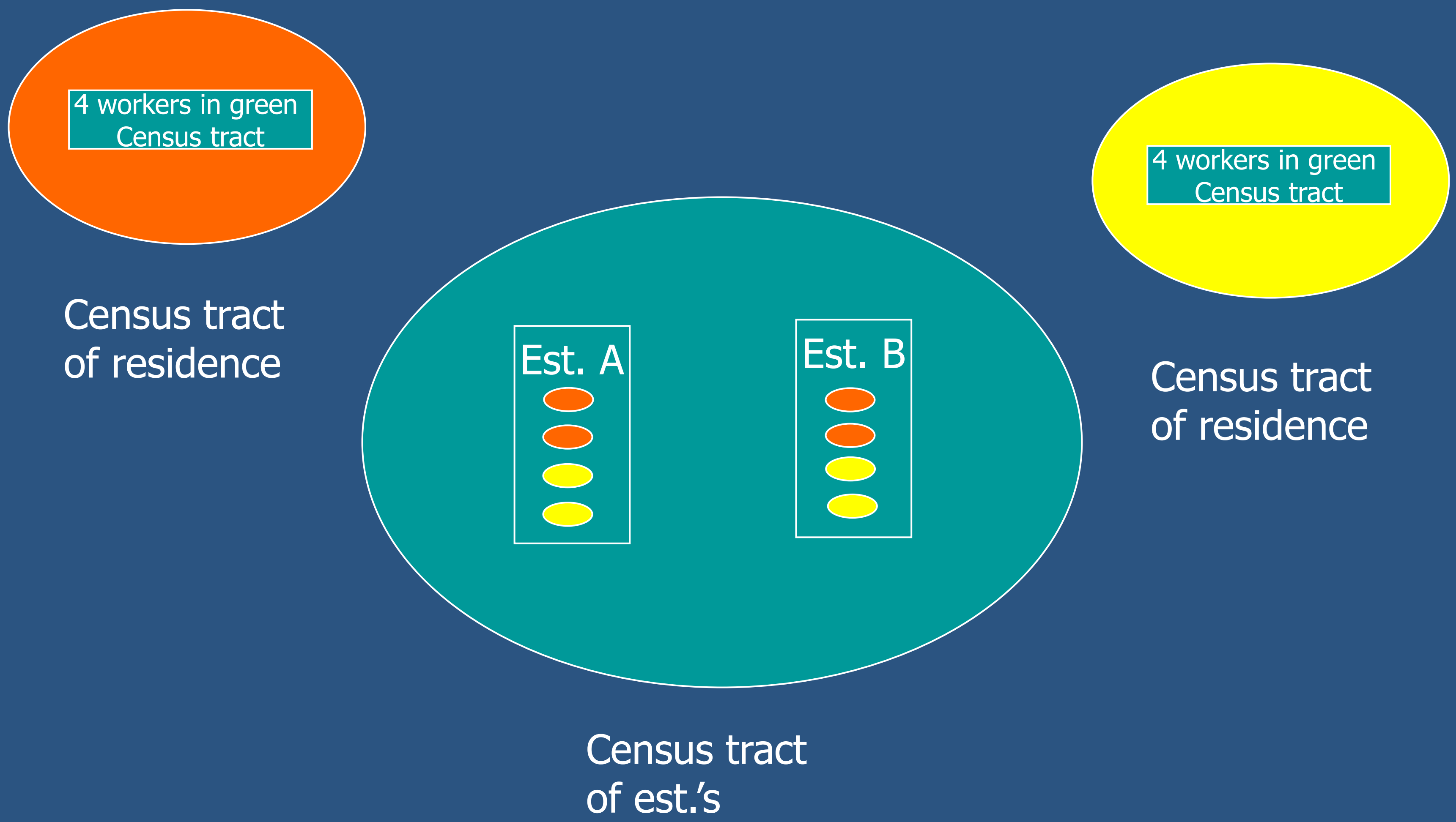
Methods/analysis

- Analysis is cross-sectional, between network measures and social capital determinants
  - Not so concerned about reverse causation, but about omitted variables that drive both
    - We have comprehensive data and controls, but that doesn't rule out other common influences on both
- Why machine learning?
  - Multiplicity of potential social capital measures that could help explain network variation
  - Wanted to avoid:
    - Ex ante selection (unclear anyway)
    - Searching for significant predictors easiest to rationalize ex post as social capital measures

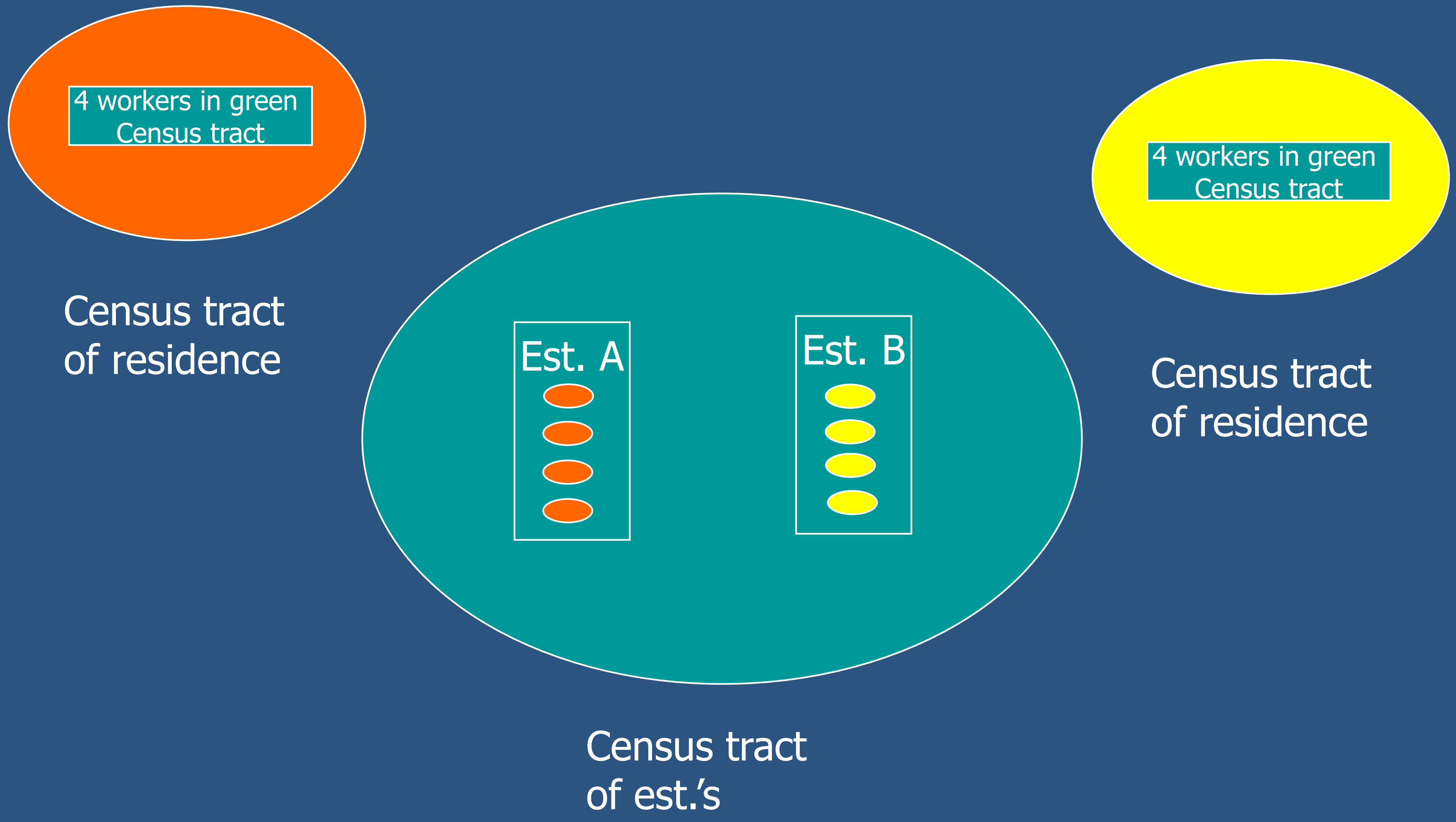
Schematic of measurement of networks (HMN, 2011)



Schematic —”even” (random?) allocation



Schematic —segregation by residential location => networks



Observed network isolation

- Network isolation for worker *i* in tract *c*

$$NI_{ic} = \frac{\sum_{j \neq i} I_C(i,j) \cdot I_E(i,j)}{\sum_{j \neq i} I_E(i,j)}$$

- $I_C(i, j)$ = indicator for whether co-worker *j* of worker *i* also lives in the same residential neighborhood as *i*
- $I_E(i, j)$ = indicator for whether *i* and *j* work in the same establishment
- Sums taken over all workers except *i*
- Measures share of co-workers with whom worker *i* is co-resident

Adjustments needed

- Some clustering of neighbors in establishments occurs randomly, in particular because people tend to work near where they live
  - In HMN, we measure this directly, and adjust
    - Measure clustering relative to “random clustering,” which we compute by distributing workers in a Census tract randomly to establishments in that Census tract
  - Here we control for it in regression
- Condition on skill, which we do in earlier work by doing the random clustering conditional on skill

Other research establishes productivity of networks

- HKN (2014): robust finding that workers hired into jobs with greater network connections to co-residents have lower turnover (LEHD 2004-2007)
  - True in highly-saturated models: e.g., worker characteristics, controls for "network" of neighbors at nearby employers, employer-year fixed effects, etc.
  - Much evidence points to higher wages also, but less robust
- HKN (2019): labor market networks coupled with connections to hiring at neighbors' employers speed re-employment after mass layoffs, and at better jobs

Network measures in this paper: effective network isolation indexes

- Network isolation index constructed by averaging NI_{ic} over individuals in same tract, one computed over workers, and one over people

$$NI_C^W = \left[\frac{1}{W_C} \sum_{i=1}^{W_C} NI_{ic} \right] \times 100$$

$$NI_C^P = \left[\frac{1}{P_C} \sum_{i=1}^{P_C} NI_{ic} \right] \times 100$$

  - Possible advantage of NI_C^P: picks up effects on employment
  - Possible disadvantage is more sensitivity to local labor market conditions
- We also construct tract-level analogues as controls – “transport isolation indexes”
  - Clustering of neighbors by tract (not establishment), to pick up transportation infrastructure that could create illusion of clustering by establishment (parallels correction for random clustering in HMN, 2011)

Data for measuring neighborhood labor market networks

- LEHD: workers (and neighbors) aged 18-64
- 2010 data, to correspond to other data we use
- Home and workplace information for 110 million jobs at beginning of 2nd quarter (to match LEHD public-use products), and linked to other information on workers, past residences, etc.
- About 34,000 (urban) tracts

Descriptive statistics: network measures (and related controls)

Variable	Description	Mean	Std. dev.
NI_c^W	Observed tract average network isolation index, per worker	1.609	1.113
TI_c^W	Observed tract average transport isolation index, per worker	0.588	0.612
NI_c^P	Observed tract average network isolation index, per resident	1.013	0.710
TI_c^P	Observed tract average transport isolation index, per resident	0.373	0.393

- Magnitudes
  - NI_C^W = 1.609: on average, 1.6% of co-workers live in same tract
    - Maximum is much less than 100%, because of sizes of firms where tract residents live
  - TI_C^W = 0.588: on average, 0.6% of those who work in same *tract* live in same tract
  - Implication: clustering of neighbors by establishment is a good deal higher than what is predicted by location factors alone

Are determinants of social capital in a neighborhood associated w/ stronger labor market networks?

- Social capital determinants guided by previous literature
  - Demographic features/homogeneity of neighborhoods associated with trust of others and society more generally (e.g., Alesina and La Ferrara, 2002)
  - Schools: smaller, higher-income parents, and small classes, which may be associated with higher parental involvement in schools, interaction with neighbors, etc. (e.g., Gardner et al., 2000)
  - Voting
    - Turnout (civic participation, e.g., Guiso et al., 2004)
    - Conservative/liberal views: trust in different institutions (e.g., Putnam, 1994)
    - Homogeneity
  - New measures of civic institutions, religious organizations, and other non-profits (Coleman, 1988; Putnam, 2000; Rupasingha et al., 2006)

Social capital determinants from Census (examples)

- Census measures/controls
  - Share owner-occupied housing; residential mobility
  - Job access measure (ACS): share commuting < 10 minutes
  - Share who commute alone (ACS)
    - Could reflect social capital or geography of jobs
  - Demographic and other homogeneity: HHI for racial/ethnic shares; and Gini coefficient for income

School-related social capital determinants

- From 2010 school district boundaries (U.S. Census Bureau School Boundary Map), Census tract maps, and data from Dept. of Education's "Common Core"
  - Average student/teacher ratio (predicted negative effect)
  - Share on FRPL (predicted negative effect)
  - Number of districts to which students in tract assigned
    - Could reduce networking because tracts fragmented, or could increase it by reflecting small schools with more parental involvement
  - First two could also reflect other factors associated with SES, but especially for NI_C^W, which "conditions" on working, not clear why this would be correlated with network strength

Voting measures

- 2008 presidential voting results by 2010 tracts (from Harvard Election Data Archive)
  - Fraction of voting age population that voted (predicted positive effect)
  - Fraction that voted Democratic
    - Prediction? Putnam (1994) suggests that conservatives may be more supportive of local, potentially more private associations that build structural social capital at the local level, whereas liberals might be less supportive out of a concern that current inequalities will be embedded in local social capital.
  - Fraction of votes for candidate of party winning vote in tract (homogeneity, predicted positive effect)

New measures of non-profit *sector* establishments of many types

- 2013 NETS
  - Longitudinal data on universe of establishments in United States, based on Dun & Bradstreet data
  - More complete coverage of non-profits than LEHD
  - Highly-detailed NAICS codes
  - Detailed geographic information (geocoded or Census block or tract)
- Non-profit status not always reported well (50%), and some clear errors at individual level (e.g., specific churches verified from their website coded as for-profit)
  - We use all NAICS 6-digit industries with 10% of non-missing cases coded as non-profits (85 total)
  - We use counts of non-profit establishments, by 6-digit sector (chosen by machine learning)
    - We add overall count of NETS establishments, so we estimate effect of *composition*

Estab's in non-profit sector can produce social capital in different ways

- Public goods/community functions (e.g., neighborhood associations; Neighborhood Watch)
- Social interactions (e.g., athletic clubs)
- Both (Kiwanis culbs)
- Evidence from machine learning algorithm can help establish whether stronger labor market networks are associated with public goods provisions ("estab's" that strengthen neighbhood ties), or social interactions (e.g., country clubs)
  - But not always easy to distinguish

“Non-profit” social capital examples (I)

NAICS12	NAICS Description (6-digit)	Non-Profit Count	Total Estab’s	% Non-Profit
813410	Alumni associations; Alumni clubs; Automobile clubs (except road and travel services); Book discussion clubs; Booster clubs; Boy guiding organizations; Civic associations; Classic car clubs; Computer enthusiasts clubs; Ethnic associations; Farm granges; Fraternal associations or lodges, social or civic; Fraternal lodges; Fraternal organizations; Fraternities (except residential); Garden clubs; Girl guiding organizations; Golden age clubs; Granges; Historical clubs; Membership associations, civic or social; Parent-teachers' associations; Poetry clubs; Public speaking improvement clubs; Retirement associations, social; Scouting organizations; Senior citizens' associations, social; Singing societies; Social clubs; Social organizations, civic and fraternal; Sororities (except residential); Speakers' clubs; Student clubs; Students' associations; Students' unions; University clubs; Veterans' membership organizations; Women's auxiliaries; Women's clubs; Writing clubs; Youth civic clubs; Youth clubs (except recreational only); Youth farming organizations; Youth scouting organizations; Youth social clubs	14839	44974	33.0

“Non-profit” social capital examples (II)

NAICS12	NAICS Description (6-digit)	Non-Profit Count	Total Estab’s	% Non-Profit
813110	Bible societies; Churches; Convents (except schools); Missions, religious organization; Monasteries (except schools); Mosques, religious; Places of worship; Religious organizations; Retreat houses, religious; Shrines, religious; Synagogues; Temples, religious	73178	228934	32.0%
813930	Employees’ associations for improvement of wages and working conditions; Federation of workers, labor organizations; Federations of labor; Industrial labor unions; Labor federations; Labor unions (except apprenticeship programs); Trade unions (except apprenticeship programs); Trade unions, local; Unions (except apprenticeship programs), labor	2892	11966	24.2%
713910	Country clubs; Golf and country clubs; Golf courses (except miniature, pitch-n-putt)	2682	12361	21.7%

Machine learning to select social capital "predictors" of networks

- Estimation from objective function (Belloni et al., 2014):

$$\hat{\beta} = \underset{b}{\arg\min} \sum_{c=1}^{n} (y_c - \sum_{l=1}^{p} x_{cl} b_l)^2 + \lambda \sum_{l=1}^{p} | b_l | \gamma_l$$

  - Used when researchers don't have strong priors on which variables matter, many possible predictors (even more than sample size), and there is risk of "over-fitting"
  - "Shrinks" coefficients, with some going to zero, to keep number of predictors small
  - First term is OLS objective function
  - Second term is penalty function
    - λ overall, and γ_l applied to each covariate
    - Values chosen by LASSO algorithm to choose best predictors, based on cross-validation, which can be thought of incorporating the accuracy of out of sample prediction into the estimation
  - Followed by OLS on selected variables (SE's clustered by county)

OLS and LASSO results (examples/highlights): commuting and neighborhood variables (full controls and state FE's)

	NI_c^W		NI_c^P	
	OLS	LASSO	OLS	LASSO
Variables	(1)	(2)	(3)	(4)
Commute < 10 minutes	0.788***	0.768†	0.435***	0.388†
	(0.076)	(0.056)	(0.042)	(0.033)
Commute by driving alone	-0.443***	-0.474†	-0.150***	-0.192†
	(0.066)	(0.037)	(0.036)	(0.022)
Share did not move	0.321***	0.305†	0.208***	0.229†
in last year	(0.066)	(0.052)	(0.039)	(0.030)
Share housing	0.318***	0.324†	0.201***	0.199†
owner-occupied	(0.040)	(0.027)	(0.023)	(0.016)
Population (1,000s)/	-0.012***	-0.012†	-0.007***	-0.006†
sq. mile	(0.003)	(0.001)	(0.001)	(0.0004)
Gini coefficient of	1.78***	1.67†	1.01***	0.954†
household income	(0.083)	(0.065)	(0.048)	(0.039)
Race/ethnicity Herfindahl-	0.235***	0.248†	0.191	0.188†
Hirschmann index	(0.043)	(0.033)	(0.026)	(0.021)
Observed tract average	1.280***	1.27†	1.26***	1.25†
transport isolation index, per worker	(0.017)	(0.007)	(0.012)	(0.006)
Count of NETS estab's (100s)	0.051***	0.062†	0.030***	0.042†
	(0.005)	(0.003)	(0.003)	(0.002)

- Driving alone: less networked
- Less residential mobility: more networked
- Racially/ethnically homogeneous: more networked

OLS and LASSO results: prior social capital variables (full controls and state FE's)

	NI_c^W		NI_c^P	
	OLS	LASSO with full controls + state FEs	OLS	LASSO with full controls + state FEs
Variables	(1)	(2)	(3)	(4)
Number of districts	0.048^{***}	$0.046^{\dagger}$	0.029^{***}	$0.028^{\dagger}$
	(0.007)	(0.005)	(0.005)	(0.003)
Average number of tracts	-0.002	-0.003	-0.0005	
in school district(s)	(0.002)	(0.002)	(0.001)	
Student/teacher ratio	0.0004		-0.002	
	(0.002)		(0.002)	
Free/reduced-price	-0.034		-0.073^{***}	$-0.060^{\dagger}$
lunch share	(0.025)		(0.015)	(0.012)
Majority vote share	0.116^{*}		0.061^{*}	
	(0.060)		(0.034)	
Democratic vote share	-0.819^{***}	$-0.746^{\dagger}$	-0.575^{***}	$-0.453^{\dagger}$
	(0.055)	(0.037)	(0.031)	(0.019)
Voter turnout	0.0005	$0.046^{\dagger}$	0.013	$0.028^{\dagger}$
	(0.021)	(0.005)	(0.013)	(0.003)

- Signs of significant estimates mostly consistent with expectations (retained variables highlighted)
  - More districts: more networked (suggests smaller districts plays role)
  - Higher turnout: more networked
  - Higher Democratic vote share: less networked

LASSO results: non-profit social capital variables (consistent positive effects on network measures) – out of 90 NAICS codes in non-profit sector

NAICS	Examples
525120	Union health and welfare funds
611110	Elementary and secondary schools; Junior high schools
621910	Ambulance services, air or ground; Rescue services, medical
622310	Children's hospitals, specialty
711130	Chamber musical groups
713910	Country clubs; Golf courses (except miniature, pitch-n-putt)
721214	Children's camps
813110	Churches; Mosques; Synagogues
813211	Charitable trusts; Community foundations
813410	Civic associations; Fraternal organizations; Fraternities (except residential); Parent-teachers' associations; Scouting organizations
813930	Labor unions
921110	Advisory commissions; City and town managers' offices; Mayor's offices
922120	Housing police; Park police; Police departments
922160	Fire and rescue service; Firefighting, government and volunteer
Industries are included in this table if all of the estimated LASSO coefficients across different specifications were positive, and at least three (out of six) were statistically significant at the 5-percent level.	

Results for non-profits (I)

- Many seem like natural or even stereotypical types of estab's that would foster social capital
  - Hobby clubs, civic associations, Scouts, PTAs, etc. (NAICS code 813410)
  - Churches, mosques, etc. (813110)
  - Fire and rescue services, including volunteer fire departments (922160)
  - Schools (611110)
  - Country clubs and golf courses (713910)
- Likely to encourage contacts between neighbors, and perhaps also those who work in similar types of jobs (country clubs, churches, schools may be segregated by SES)

Results for non-profits (II)

- Others may foster social capital, but perhaps not via contacts among neighbors
  - Police departments (NAICS code 922120)
  - City and mayors' office (NAICS code 921110); could reflect decentralization
  - Hospitals (NAICS code 622310)
- Not really any with positive effects that don't seem to fit one of these interpretations
- Some negative effects (same criteria) are hard to interpret (e.g., social science research and development services (NAICS code 541720); apprenticeship training programs (NAICS code 611513); homeowners' associations (NAICS code 813990))
  - But wouldn't have expected positive effects, arguably, and estimated effects much smaller

Magnitudes are sizable, comparable to traditional social capital determinants

- Examples – non-profit sector:
  - NAICS 813410 (hobby clubs, scouts, PTAs): 1 SD increase in non-profit sector count increases NI_c^W by 2.4%
  - NAICS 813110 (churches, mosques, synagogues): 1 SD increase in non-profit sector count increases NI_c^W by 6.7%
  - NAICS 813410 (country clubs and golf courses): 1 SD change in non-profit sector count increases NI_c^W by 2.9%
  - Comparable or larger than for many of the “traditional” variables in the social capital literature (especially aggregating across multiple NAICS codes)

Conclusions

- We find surprisingly (?) consistent evidence that social capital measures are positively associated with measures of the strength of labor market networks at the Census tract level
- True for variables tied to past work/writing on social capital
  - Smaller, more decentralized, less poor schools
  - Higher Republican votes share
- True for our new measures of non-profit-sector estab's, which we view as measuring density of institutions that facilitate social capital, such as
  - Churches and religious institutions
  - Schools
  - Police departments
  - Country clubs
  - Labor unions
  - For many, evidence consistent with non-profits that facilitate social capital in the form of labor market network connections among neighbors