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SOCIAL CAPITAL AND LABOR MARKET NETWORKS

Brian J. Asquith
Judith K. Hellerstein
Mark J. Kutzbach
David Neumark

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ABSTRACT

We explore the links between social capital and labor market networks at the neighborhood level. We harness rich data taken from multiple sources, including matched employer-employee data with which we measure the strength of labor market networks, data on behavior such as voting patterns that have previously been tied to social capital, and new data – not previously used in the study of social capital – on the number and location of non-profits at the neighborhood level. We use a machine learning algorithm to identify potential social capital measures that best predict neighborhood-level variation in labor market networks. We find evidence suggesting that smaller and less centralized schools, and schools with fewer poor students, foster social capital that builds labor market networks, as does a larger Republican vote share. The presence of establishments in a number of non-profit oriented industries are identified as predictive of strong labor market networks, likely because they either provide public goods or facilitate social contacts. These industries include, for example, churches and other religious institutions, schools, country clubs, and amateur or recreational sports teams or clubs.

Brian J. Asquith
NBER
1050 Massachusetts Ave.
Cambridge, MA 02138
basquith86@gmail.com

Judith K. Hellerstein
Department of Economics
Tydings Hall
University of Maryland
College Park, MD 20742
and NBER
hellerst@econ.umd.edu

Mark J. Kutzbach
Center for Financial Research
Federal Deposit Insurance Corporation
550 17th Street NW, MB-2127
Washington, DC 20429
mkutzbach@fdic.gov

David Neumark
Department of Economics
University of California at Irvine
3151 Social Science Plaza
Irvine, CA 92697
and NBER
dneumark@uci.edu

I. Introduction

The Oxford English dictionary defines social capital as "The networks of relationships among people who live and work in a particular society, enabling that society to function effectively."[1] In this paper, we explore the links between measures of social capital and a particular type of network among people; specifically, we use machine learning methods to examine whether higher social capital in a neighborhood is associated with stronger labor market networks among neighbors. We harness the richness of data taken from multiple sources, including matched employer-employee data with which we measure the strength of labor market networks, data on behavior such as voting patterns that have previously been tied to social capital, and new data – not previously used in the study of social capital – on the number and location of non-profit sector establishments at the neighborhood level.

We are motivated in this paper by the large body of empirical research documenting the importance of informal contacts in the labor market. The origins of this research are usually traced to Granovetter (1974). He interviewed people in Newton, Massachusetts about how they found their jobs, finding that about half of workers (among technical, professional, and managerial workers) found their jobs through a social contact. However, many also found jobs through a work contact, emphasizing that friends and relatives are not the only potential source of information about jobs or referrals to jobs. Later survey evidence summarized in Ioannides and Datcher Loury (2004) establishes some reliance on friends and relatives to find jobs; in particular, they report that 15.5 percent of the unemployed and 8.5 percent of the employed contact friends and relatives as part of their job search. Our work derives more specifically from recent empirical research showing that networks based on residential communities or neighborhoods improve labor market outcomes for residents, including higher wages, longer tenure, and faster re-employment for displaced workers (Hellerstein et al., 2014, and Hellerstein et al. 2016).[2]

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[1] See https://en.oxforddictionaries.com/definition/social_capital (viewed August 23, 2017).

[2] Using confidential Long-Form 2000 Census data (in Boston), Bayer et al. (2008) show that two individuals who live on the same Census block are about one-third more likely to work on the same block than are two individuals who live in the same block group but not on the same block. (The latter may be alike, but are less likely to be networked.) Taking this further, Hellerstein et al. (2011) and Hellerstein et al. (2014) show that neighbors are more likely to work at the same *business establishment*, consistent with the hypothesis that labor market networks mitigate information imperfections in the labor market.

All of this work documenting the importance of neighborhood-based labor market networks to labor market outcomes of its residents raises a fundamental question: Does variation in the amount of social capital across neighborhoods lead to some neighborhoods being more networked in ways that increase the flow of labor market information and good job market matches among its residents? In this paper, we explore the answer to this question by investigating the relationship between a new, neighborhood-based version of the labor market network measure we first developed in Hellerstein et al. (2011) and neighborhood characteristics that are often viewed as related to concepts of social capital. These social capital measures have been hypothesized to increase connections among neighbors and should also foster labor market networks as we measure them.

Guided to a large extent by previous literature, we construct neighborhood-level measures of social capital of various kinds that we fit broadly into four categories. The first set of measures we construct reflect the demographic homogeneity of neighborhoods. These measures are motivated by findings in Alesina and La Ferrara (2002), suggesting that trust of others both in the community and more generally in society is viewed as an important component of social capital and is partly a function of community characteristics that are shared among residents (Lochner et al., 1999).

Second, we use information on the size and characteristics of local school districts to construct a set of variables reflecting the extent parental involvement in schools. We hypothesize that greater parental involvement in schools generates social capital, as parents are invested in schools and interacting with each other's children and with other neighborhood residents. We believe that this involvement will be higher in smaller schools that are more community based (Cotton, 1996; Gardner et al., 2000), in schools with higher-income parents (Guryan et al., 2008), and in schools with smaller student-teacher ratios.

Third, we include voting behavior measures that include voter turnout, prevailing political opinion, and ideological homogeneity. Voter turnout is associated with high civic participation (Guiso et al., 2004), another important component of social capital (Lochner et al., 1999). Other studies have shown that liberals' and conservatives' political priorities arising from differences in moral perspectives (Haidt, 2007) lead to trusting different institutions (Putnam, 1994, and Dugan, 2015). For example, Putnam (1994) suggests that conservatives may be more supportive of local, potentially more private associations that build 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.[3] Because these institutions may differ in the extent to which they build neighborhood social capital that augments labor market networks, we include the Democratic two-party vote share. We also control for ideological homogeneity by way of the maximum of the two-party vote share, because homogeneity has been shown in other contexts to foster social capital (Alesina and La Ferrera, 2002), and in this case, would indicate that others in your community share your beliefs.

Finally, the major focus of our paper to build on past work suggesting that civic institutions (e.g., Coleman, 1988; Putnam, 2000), religious organizations (e.g., Putnam, 2000), and other non-profits (Rupasingha et al., 2006) contribute importantly to social capital. To explore the role of these non-profits as facilitators of social capital that strengthen labor market networks, we make novel use of a new data source in the study of social capital. We use data on the universe of establishments, from the National Establishment Time Series (NETS), to measure the number and composition of non-profits by Census tract, and we explore – using machine learning methods – which ones are associated with evidence of stronger labor market networks.

The goal of our analysis is to explore the relationships between these measures of social capital and the measure of the importance of neighborhood-based labor market networks developed in Hellerstein et al. (2011). This network measure is explained below, but its core idea is to quantify the extent to which neighbors are clustered at the same employers, controlling for the geographic proximity of peoples' workplaces to where they live. We construct this measure using data from the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau, which provides highly comprehensive wage and salary employment data. This employer-employee matched data links persons to residences and, if they are employed in a job covered by Unemployment Insurance, to the locations of establishments for

[3] Think, for example, of different perspectives on local control of school and even school funding (see, e.g., Meyer et al., 1987).

their employer.

Theoretical models of labor market networks assume that there is imperfect information that hinders the search behavior of unemployed workers and/or firms, and that information flows through networks. These models generally fall into one of two categories that describe the information imperfections and how they are mitigated by networks. First, in models such as Calvó-Armengol and Jackson (2007) and Ioannides and Soetevent (2006), unemployed workers do not have full information about job vacancies, and job searchers can learn about job vacancies either directly from employers or indirectly via employed individuals among their network contacts. Second, in Montgomery (1991), the information imperfection is on the employer side, and firms learn about a potential worker's ability if the firm employs individuals from the potential worker's network. In both of these frameworks, the existence of the network increases the job-finding probabilities of unemployed job searchers.[4] The measure of clustering we use is consistent with network connections between neighbors arising from either of these two models.

Our analysis is cross-sectional, based on a network measure we have constructed for one year (2010) and social capital measures that correspond as closely as possible to that year based on data availability. In this paper, we do not pretend to explore what drives the variation in our social capital measures. While we are not particularly concerned with reverse causation, it is possible that there are other characteristics of neighborhoods associated with our social capital measures that also influence the extent to which neighbors are networked in the labor market. We do try to use a comprehensive set of potential measures of neighborhood-level social capital to explain variation in our network measure, as well as some obvious control variables that will likely help explain our network measure. Nonetheless, given that social capital is multi-dimensional, and given that there are many other neighborhood characteristics that could potentially help explain variation in our network measure, our evidence should be viewed primarily as descriptive work that can strengthen existing hypotheses and potentially generate new ones about the links between social capital and labor market networks. In this way, our research is similar in approach to Chetty

[4] Jackson (2008, Chapter 10) provides a transparent discussion and comparison of these models.

et al. (2014), which, in part, examines how factors varying across geographies correlate with upward mobility. More closely related – although focused crime rather than labor market outcomes – is Sharkey et al. (2017), who study the relationship between crime and local non-profits that focus on reducing violence.[5]

We generate a large set of possible social capital measures based on prior research. Given the exploratory nature of this paper, and the multiplicity of possible social capital measures, we use a machine learning algorithm to identify important potential social capital measures that best predict the variation in our labor market network measure. We view the use of machine learning as a key component of this research. There are many potential variables that could explain variation in the strength of labor market networks and also can be interpreted as capturing social capital. We want to let the data tell us which variables to include. The machine learning helps us avoid having to choose, ex ante, which of these variables are likely to reflect social capital, or, worse, to search for significant predictors that can be most easily interpreted, ex post, as reflecting social capital. In addition, the machine learning algorithm we use (LASSO) imposes sparsity on the candidate social capital measures, which, given that we have a large vector of such candidate measures, helps in providing interpretable estimates by focusing on the most important predictors.

II. The Observed Network Isolation Index

The first important task is to define our measure of the neighborhood labor market network. In Hellerstein et al. (2011), we developed a worker-level measure of a labor market network that captures the extent to which employees of a business establishment come disproportionately from people who live in the same neighborhood (defined as a Census tract). This measure is important because the models of labor market networks we reference above predict that that if neighbors are networked together they will cluster at the same establishments.

[5] Sharkey et al. use a different and narrower data source on non-profits, from the National Center for Charitable Statistics, which includes organizations that have registered for tax-exempt status with the IRS. We explored using this same data source, but decided not to because the tax-exempt unit is often a central location, meaning we could not identify local establishments of an organization. Moreover, we were interested in very local measures of establishments – at the tract level – whereas Sharkey et al. use city-level measures. Finally, establishments in the non-profit sector that are not themselves non-profits can play a role in enhancing social capital.

We use Census tracts as our residential neighborhood definition because Census tracts define the boundaries that are traditionally used to measure residential segregation (Iceland and Weinberg, 2002), and because Census tracts are defined to ensure that the tracts are "as homogeneous as possible with respect to population characteristics, economic status, and living conditions" (U.S. Census Bureau, n.d. (a)). This is a reasonable definition of a neighborhood in which co-residents are likely to interact, more so because most Census tracts are relatively small, facilitating contact at schools, churches, community organizations, etc. – a point we return to below. To help ensure that neighborhoods are compact enough to facilitate interaction among residents, we restrict the Census tracts in our analysis to "urban" tracts, which are defined based on population density, and may fall in both central cities and suburbs.[6] Limiting our analysis to urban tracts focuses our analysis on areas where workers live closer together and sort across a large set of employers, so any effects of social capital should be more apparent with this sample both due to a high capacity of social interaction and potentially more evidence of clustering in establishments in our measure of labor market networks.

To construct our worker-level network measure, we compute for each worker, in the establishment where they work, the percentage of his or her co-workers who live in the same Census tract. For worker i in tract c this observed network isolation is:

$$(1) \qquad NI_{ic} = \frac{\sum_{j \neq i} I_C(i,j) \cdot I_E(i,j)}{\sum_{j \neq i} I_E(i,j)},$$

where $I_C(i, j)$ is an indicator for whether co-worker j of worker i also lives in the same Census tract as i, and $I_E(i, j)$ is an indicator for whether i and j work in the same establishment. The sums in the numerator and denominator are taken over all workers other than the worker i who work in worker i's establishment. Their ratio is the share of co-workers with whom each worker is co-resident.

In this research we then operationalize a measure of network isolation at the neighborhood level by averaging NI_{ic} over individuals who live in the same Census tract. This community-based network index is

[6] For more detail, see Section V below.

a natural metric because it is derived from the individual network measure we have developed and tested previously. We construct the observed community-based network index in two different (but closely related) ways. The first version of the index builds up from the observed network index NI_{ic} for all employed neighbors in a residential Census tract at that time.[7] Then, at the community level, the community network index is the average of the network indexes of each of the neighbors:

$$(2) \qquad NI_c^W = \left[\frac{1}{W_c} \sum_{i=1}^{W_c} NI_{ic} \right] \times 100,$$

where W_c is the number of employed neighbors (i.e., workers) in the neighborhood.

The second version of our community-based network index is constructed over all residents of a Census tract who are of working-age, whether or not they are employed. We denote this measure as NI_c^P, where the P signifies that this measure is calculated over people, not workers. It is measured as:

$$(3) \qquad NI_c^P = \left[\frac{1}{P_c} \sum_{i=1}^{P_c} NI_{ic} \right] \times 100,$$

where P_c is the number of working-age neighbors (i.e., people) in the neighborhood. Because we define NI_{ic} = 0 for persons who are not employed, NI_c^P will always be smaller than NI_c^W, more so when the employment rate in the tract is lower (as NI_c^P then includes more zeros).

The strength of any relationships between social capital measures and labor market networking may differ across the two measures. If social capital primarily influences employment outcomes for those who would be employed in any case, by increasing the number of workers who share an employer, then we might expect stronger relationships between social capital and NI_c^W. But an effect of social capital on employment itself could strengthen the estimated relationships with NI_c^P, if the additional employed people tend to work with their neighbors. That said, NI_c^W may be a preferable measure regardless, because it is more likely to be independent of local economic conditions that may be correlated with our social capital measures (in particular, those that are counts of establishments in the non-profit sector) – a correlation that could create spurious evidence of a relationship between social capital and NI_c^P.

[7] We define workers at single-employee firms (who have no co-workers) as having an NI_{ic} of zero.

For this project, we draw data from multiple sources, some public and some restricted-access. The dataset for measuring NI_c^W and NI_c^P, our neighborhood network measures, is the Census Bureau's LEHD Infrastructure Files, which combine state-provided data on earnings records for jobs linked with employer account information (Abowd, 2009). The LEHD jobs frame consists of Unemployment Insurance covered employment, which is the same domain as the Quarterly Census of Employment and Wages and inclusive of the vast majority of wage and salary jobs (Stevens, 2007). The Person History File, a component of the Infrastructure Files, provides quarterly earnings of a person at an employer within a state, as well as observed or imputed assignments to establishments at an employer. The Employer Characteristics File gives establishment location, size, and industry. Information on characteristics of individuals in the LEHD, including age, comes from the Individual Characteristics File (ICF), which is compiled at the Census Bureau from Decennial Censuses and from federal administrative data sources.[8] We also use longitudinal information on where individuals have lived (whether they are employed or not) that comes from a confidential dataset called the Composite Person Record (CPR). The CPR, also derived from administrative data, reports an annual place of residence for individuals. It is this unique combination of administrative records on residential address and workplace information for individuals that enables us to calculate our network measures NI_c^W and NI_c^P.

Given that our research here is cross-sectional in nature, we use information for only the year 2010 to construct the network measures, as that year corresponds most closely to the rest of our data. (Some of the other aggregate Census data is used to construct social capital measures or potential controls, as discussed below.) We extract home and workplace information for workers at 110 million primary jobs held at a snapshot in time, April 1 in 2010, where a primary job is defined as the highest earning among the jobs of a worker on that day. Because we only observe employment on a quarterly basis, we define a job as held on April 1 if we observe the worker to work with a given employer in both the first and second

[8] The Social Security Administration's Numident file provides sex, date of birth, place of birth, citizenship, and race. The 2000 Census short and long forms provide age, sex, race, ethnicity, education, and national origin. The ICF combines these sources, where observed, and imputes values for the rest. The ICF can be linked to the LEHD earnings records using personal identifying information.

quarters of the year, based on the inference that jobs held with the same employer in both quarters are most likely also active on April 1. This follows the definition used in LEHD public-use data products of instantaneous counts of jobs.[9,10] We use draws from an imputation model that assigns establishments to workers in the case of employers with multiple units within a state, where such assignments are uncertain.[11] While the uncertainty represented by this imputation would tend to reduce our estimates of network isolation at the neighborhood level, our previous research using LEHD has found that the relative differences in networking across groups are not affected by using the imputation.[12] Following the methods described above and using home and workplace information for each job, we calculate NI_{ic} for each worker, and then average these by the Census-tract residence count of the same set of workers to compute NI_c^W, and by the Census-tract count of all persons age 19 to 64 in administrative records to compute NI_c^P. The latter calculation includes both those observed to be employed on April 1, as well as those with no employment or no job that spanned the first and second quarter.

III. Social Capital Measures and Potential Controls

Because we use a Census tract-level measure of neighborhood labor-market connectedness, we also need to construct measures of social capital that vary by Census tract in order to learn about the relationship between labor market networks and neighborhood social capital. We take two distinct approaches to how we incorporate these measures into our analysis. First, for conventional tract-level variables that reflect the homogeneity of communities as well as general demographic characteristics and commuting patterns, we

[9] We use the Person History Enhanced Across SEIN and Non-SEIN Transitions (PHEASANT) process to consolidate state level Person History Files. The PHEASANT takes successor/predecessor transitions of employers into account when calculating a worker's job spell duration and earnings at an employer.
[10] Our definition of employment omits those who were not employed by the same employer over the two quarters, even if they worked in both; these individuals may have had job-to-job transitions or periods of non-employment.
[11] Most states do not require employers to assign workers to a particular establishment. For workers at multi-unit employers (about 44 percent of all jobs), or jobs where the reporting firm has multiple establishments in the same state, we make use of the imputation model developed by the LEHD program to allocate establishments to workers (Abowd, 2009). For the set of active establishments during a worker's tenure, the model attempts to replicate the size distribution of establishments and the observed distribution of commute distances. Although the model makes ten imputation draws for each job, which are equally weighted for the production of small area statistics in public-use data, we use only the first such draw.
[12] Hellerstein et al. (2014) find that observed network isolation tends to be lower for samples including multi-unit employers, likely due to noise from the imputation, though variation in observed *NI* across subsets of the data has similar patterns in both single- and multi-unit samples. For example, in Hellerstein et al. (2014), whites have almost double the observed *NI* as blacks in both single-unit jobs and all-jobs samples.

take a traditional approach of consistently including them in all empirical specifications by “forcing” the machine learning algorithm to incorporate them. We take this approach for these conventional variables because they are clearly understood not just as potentially increasing social capital but also as important proxies for socioeconomic characteristics that can affect employment.

Second, and distinctly, for measures of social capital whose importance is less well-understood and which continue to be the subject of scholarly research as to whether they play a meaningful role in social capital, we take a data-driven approach to determining their importance in increasing labor market network connectedness. By using machine learning to do this, we can incorporate a high-dimensional vector of covariates into our empirical models without over-fitting the data and, alternatively, avoid pre-specifying a narrower set of social capital measures.

The measures of social capital that we use come almost exclusively from non-LEHD data sources that we have merged at the Census tract level with our LEHD data. The first of these additional data are the 5-year estimates from the 2008-2012 American Community Survey (ACS).

We extract from the ACS a vector of Census tract economic and demographic characteristics that are known to be related to labor market outcomes and to socioeconomic characteristics of communities more generally, and we force these variables to always be included in the models in our LASSO estimations. The demographic characteristics include: the share of tract residents in poverty; the share of tract-residents who live in owner-occupied housing; the share of tract residents who are Hispanic; the share black non-Hispanic; the share Asian non-Hispanic; the share non-U.S. born; the share currently married; and the share in various education categories (less than high school; share with high school degree or some college; and share with at least a bachelor’s degree).[13]

There are three reasons to include these demographic variables in the analysis – the first two highlighting their role as control variables, and the third as social capital measures. First, for our network measure NI_c^P, individuals who are not employed contribute a value of zero to the tract average. Their non-

[13] While the 2008-2012 ACS is reported in 2010 Census tract geography, statistics for four urbanized 2010 Census tracts were not reported by the ACS and are dropped from our sample.

employment is partially predicted by demographic variables (such as educational attainment), and so including these demographic variables helps control for important features of labor market success. Second, even for the network measure NI_c^W that excludes the non-employed, previous research (e.g. Hellerstein et al., 2011 and Hellerstein et al., 2014) clearly demonstrates variation among the employed in the importance of neighborhood networks across race, ethnicity, and education groups, because, for example, labor markets (and hence neighborhood-based networks) are more local for less-skilled labor, and because of a greater reliance of immigrants on network connections. The third reason to include these controls is that there is evidence that demographic characteristics are key to producing social capital and social trust (Alesina and La Ferrera, 2002; Rupasingha, 2006; and Putnam, 2007). The home ownership rate may be thought of as a measure of social stability and also as an indicator of lower residential density, which has been found to be associated with greater interaction between neighbors (Brueckner and Largey, 2008).

We also extract and use two commuting-related variables from the ACS, aggregated to Census tract-level rates. First, we construct a measure of the fraction of employed local residents whose commutes to work are less than 10 minutes, treating this as a measure of local job access. If there are many nearby jobs, employment rates are likely to be higher (Ihlanfeldt, 2006; Zenou, 2008), and neighborhood residents may work together not because of networks but simply because of job access. The second variable we construct is the fraction of the employed who commute to work by driving alone. Lone commutes suggest that neighbors are not working at similar locations (or at the same establishment), which can reflect the geographic dispersion of employment opportunities for residents of a given Census tract or a lack of transit options. Note, though, that this could also potentially be a measure of social capital, as residents commuting together (by carpool or public transit) may share job information.[14]

We then construct a second set of Census tract-level measures to capture various dimensions of local schools, which we view as potentially related to social capital. These measures enable us to ask

[14] Zenou (2013) argues that spatial distances can create social distances, where workers who engage in long commutes forfeit the opportunity to expand their social network because of driving time's opportunity costs. If so-called "weak ties" – ties outside of immediate family and friends – can improve job matching, then it stands to reason that driving alone can also be forfeited opportunity to expand one's social ties.

whether neighborhood social capital that is school-based also translates into more networked labor market networks. We first overlay a 2010 map of U.S. Census Bureau school district boundaries onto a map of Census tracts.[15] We then assign to each Census tract characteristics of the school district in which it falls, obtaining school-level characteristics from the Department of Education's Common Core of Data. School districts often cover multiple Census tracts, in which case all Census tracts in the district are assigned the same school-level variables. When school district boundaries bisect a Census tract, the tract is assigned school-level variables that reflect a weighted average of the characteristics of the school districts it serves, with the weight being the fraction of land area in the Census tract covered by the district.

The school district variables we construct are: the average student-teacher ratio; the share of students in the schools on free or reduced-price lunch; the number of different districts to which students in the Census tract are assigned; and the average number of Census tracts served by the school districts in a tract (which in the case of one district covering the entire tract is simply the number of tracts that district serves). Higher student-teacher ratios and the number of students in the school on free/reduced-price lunch may reflect school districts where parents do not have resources to invest in social capital via the local schools. Our measure of the number of different districts to which students in living in a tract are assigned could be viewed in one of two ways. It could be negatively related to the extent to which schools are strongly community based, if when a tract is divided into many districts, the residents of the tract are less likely to interact with each other at their children's school. On the other hand, it could be an indicator of small school districts in which parents interact more, thus fostering social capital at more local levels. Our related measure – of the number of tracts served by the school – is meant to capture how large the school district or districts in the tract are. We view this measure as unambiguously measuring the size of school districts, which we expect to be negatively related to social capital (paralleling the second interpretation of the number of districts variable).

A third set of covariates we construct to use in predicting NI_c^W and NI_c^P reflects voting patterns at

[15] We use school district boundaries. In states with non-unified school districts, these may be elementary school boundaries. While elementary school boundaries might be more relevant with regard to parent interaction (and hence social capital), data on elementary district boundaries were much sparser.

the Census tract level. We view these measures as motivated directly by the social capital literature cited earlier. We generated a dataset of 2008 presidential voting results by 2010 Census tracts using the Harvard Election Data Archive (HEDA, Ansolabehere et al., 2014). HEDA's publicly available files allow us to match precinct-level voting results to Census Voting Districts (VTDs), and a Census Bureau crosswalk between VTDs and Census geography at the Census block level allows us to overlay VTDs onto Census tracts. We construct three Census tract-level variables from the HEDA data: the fraction of the voting age population in the Census tract that voted in the 2008 presidential election; the fraction that voted for the Democratic candidate in 2008 (among those voting for either the Republican or Democratic candidates); and the fraction of votes cast for the candidate of the party winning the majority of votes in the tract. Note that we do not principally interpret these voting-derived variables as reflecting outcomes associated with the policies supported by one group or another. Rather, we view them as descriptors of a neighborhood's population and social behavior. To this end, we also note that Census tracts do not necessarily conform to local or Congressional electoral boundaries, and that we include state fixed effects in some specifications, which would sweep out the influence of any related influence from governance at the state level.

Finally, we use data from the 2013 NETS to construct Census tract level measures of counts of establishments in the non-profit sector (which can include government institutions) such as libraries, churches, civic associations, and community centers, which might facilitate the social capital that builds labor market networks. The NETS is a database that contains address information, employment information, and NAICS industry codes for essentially the universe of establishments in the United States (for more information, see Neumark et al., 2007). To align with the other data we use, we use observations on establishments as of 2010.

As described in Neumark et al. (2007), the NETS is constructed, by Walls & Associates, from Dun & Bradstreet (D&B) data.[16] The NETS is based on D&B's Data Universal Numbering System (DUNS) Marketing Information (DMI) file for each year. The primary purpose of D&B's data collection effort is to

[16] For more details, see http://exceptionalgrowth.org/downloads/NETSDatabaseDescription2013.pdf (viewed November 30, 2017), and the appendix of Neumark et al. (2011).

provide information on businesses to the business community, by constructing a set of "predictive indicators" (e.g., the D&B rating and Paydex scores), and for marketing purposes. The DMI file for each year is constructed from an ongoing effort to capture each business establishment in the United States in each year, including nonprofits and the public sector. The NETS is a longitudinal file that links DMI files, although we do not exploit the longitudinal dimension in this paper.

The DMI files underlying the NETS are based on a multi-layered process incorporating many data sources, in which D&B uses a massive data collection effort to try to identify and assemble information on all business establishments. This includes over 100 million telephone calls from four calling centers each year, as we as information from legal and court filings, newspapers and electronic news services, public utilities, all Secretaries of State, government registries and licensing data, payment and collections information, company filings, and the U.S. postal service. One highly desirable feature of the NETS database is that it covers essentially all establishments. This reflects the fact that it is designed to capture the universe rather than a sample of establishments.

Unlike the LEHD, the NETS potentially has complete coverage of non-profit establishments, which makes it a better data source for capturing this type of social capital. Non-profits with no employment would not appear in LEHD, and even some employers, such as religious schools in some states, are exempt from Unemployment Insurance law and not appear in the LEHD (Stevens, 2007).[17] Furthermore, because the NETS contains information for a range of establishment classes, it can in principle teach us whether for-profit organizations such as athletic clubs and restaurants are also associated with higher levels of neighborhood labor market networks.

Non-profits serve many different community functions such as providing public goods (e.g., neighborhood watch associations) or by facilitating social interaction (athletic clubs), or both (Kiwanis clubs). The LASSO estimation's results can, in principle, help establish whether labor market networks are

[17] In Illinois, for example, the state code (820 ILCS 405/211.3, ch. 48, par. 321.3 says: "For the purpose of Section 211.2, the term "employment" shall not include services performed—A. In the employ of (1) a church or convention or association of churches, or (2) an organization or school which is not an institution of higher education, which is operated primarily for religious purposes and which is operated, supervised, controlled or principally supported by a church or convention or association of churches."

correlated with public goods provision ("better" neighborhoods yield stronger networks) or easier social interaction (more meeting opportunities yield stronger networks), although in practice it is not straightforward to classify establishments in the non-profit sector as playing one role or the other.

While the NETS captures all types of business establishments, we draw on past research and theory on social capital that focuses on the non-profit sector. The NETS includes an indicator for legal status that identifies non-profits. However, this field is missing in about one-half of cases. Hence, rather than flagging specific establishments as non-profits, we instead flag all NAICS 6-digit industries in which at least 10 percent of establishments with this field non-missing are coded as non-profits, and we use all the establishments in these industries in order to classify where non-profits – and potential social capital – are located. Note that our definition is quite broad, in that we use a (rather low) threshold of 10 percent of establishments in the detailed industry in defining an industry as being "non-profit," and we use counts of all establishments in the industry as a measure of the intensity of activity in the industry. We use this rather expansive view of where non-profits – and potentially for-profits that engage in the same activities – can generate social capital as a starting point. We then deploy LASSO to let the data implicitly tell us whether and where our criterion for defining the non-profit sector is too broad in the sense of not fostering social capital that leads to stronger labor market networks.

The NETS in many cases has either the establishment's exact geo-coordinates or the Census block group or tract where it is located. We use Geographic Information System (GIS) software to map establishments in the NETS to Census tracts. In each Census tract, we construct counts of establishments in each of the 6-digit NAICS categories we have identified as an industry with high non-profit concentration.

It is important to emphasize that our social capital measures are local measures. As such, our results should be interpreted as reflecting the effects of local social capital on the strength of neighborhood labor market networks. There could be social capital created by non-profits at a less local level that facilitate sharing of information about jobs, such as government-run websites for either private or public jobs.[18] And some of the businesses or institutions in the non-profit sector that we study may play this role at

[18] See, for example, https://www.usajobs.gov/ (viewed December 4, 2017).

a more aggregate level than the Census tract.

IV. Machine Learning: LASSO

In order to examine the relationship between our social capital measures and our local labor market network measure, we utilize a machine learning algorithm known as LASSO, and specifically the LASSO procedure developed in Belloni et al. (2012).[19]

LASSO is not the only machine learning algorithm that we could use to select social capital measures, but we think it will yield a better-fitted model to the data than its two main alternatives, ridge regressions and pretesting. As detailed in Abadie and Kasy (2017), ridge regressions fit models best when most regressors are expected to have non-zero coefficients, while pretesting fits best when most potential coefficients are expected to be set to zero (called high sparsity). LASSO fits best in intermediate cases where there is a high degree of sparsity, but where one wants to avoid an overly aggressive assumption on the number of coefficients being set to zero. LASSO is also appropriate in cases like ours where the literature is somewhat ambiguous on the breadth of institutions that might instigate some network-based social capital: there are good reasons to think that a significant set will have no impact, but there are many possible variables (in our case, social capital measures) for which we are estimating coefficients (Abadie and Kasy, 2017).

The key to understanding LASSO starts by examining the objective function when seeking to estimate a vector of parameters β (Belloni et al., 2014):

$$\hat{\beta} = \underset{b}{\operatorname{argmin}} \sum_{c=1}^{n} (y_c - \Sigma_{l=1}^{p} x_{cl} b_l)^2 + \lambda \sum_{l-1}^{p} |b_l| \gamma_l. \quad (4)$$

Note that the first term on the right-hand side of the equation is the usual Ordinary Least Squares (OLS) objective function – minimizing the sum of squared errors when given a linear equation relating a dependent variable y to a vector of observable variables x (tract level observations are denoted by c, and regressors by l).[20] When researchers do not have strong priors as to which observable characteristics belong

[19] Also see Belloni et al. (2014) and particularly Belloni et al. (2016) for an extension to clustered covariance structures.
[20] For concreteness, in our context, y_c is the network measure (NI_c^W or NI_c^P) at the Census tract level c, and x_{cl} is the vector of potential contributors to a high observed level of network connectedness.

in the vector x, and especially when the set of possible x's is large (and perhaps even larger than the sample size) – so that there is a risk of "over-fitting" – LASSO serves as a covariate reduction technique where the data guide the researchers as to the set of observable characteristics among those in x that best belong in the regression. As such, the second term on the right-hand side is a penalty function, where the γ_l's are penalty loadings applied to each covariate x_l and λ is a general penalty factor; the penalty factors are selected by the LASSO algorithm. The LASSO estimation procedure identifies the set of parameters that best predict the data under the assumption that all other coefficients of the other possible regressors should be set to zero; that is, the LASSO-reported coefficients are artificially shrunken, with some going to zero, to keep the number of predictors small. The final step (post-LASSO estimation procedure) is to then estimate an OLS regression using only the restricted set of covariates as regressors, which "restores" the proper coefficient values on the selected regressors.

For any given covariate x_l, its γ_l can be set to zero so that the covariate is forced to always be included in the OLS regression (i.e., a non-zero coefficient on the given x_l is not penalized). In our context, as we explained above, because we know that some demographic characteristics of neighborhoods are strongly and consistently related to labor market outcomes of residents, we force certain demographic covariates to be included in all our post-LASSO regressions. In addition, we also force the entire vector of state fixed effects to be included in some specifications. Belloni et al. (2012) and Belloni et al. (2016) develop a modified LASSO procedure that we use because it has some attractive properties, including that it accommodates clustered standard errors which is important in our context.

The candidate x variables that we have collected and categorized into four categories as described above are: demographic and commuting variables; school-district variables; voting pattern variables; and non-profit penetration in the Census tract. As explained above, because most of the demographic and commuting variables are at least partially accounting for economic conditions in the Census tract that lead to better labor market outcomes as embedded in our network measure, for these we set the penalty loadings (the γ's) on these variables to be zero so that they appear in all of our post-LASSO OLS regressions.

We have two other control variables that we alternate between forcing to appear in the model in some specifications and excluding in others. We do this because, on the one hand, they may be mechanically related to our network measure, while on the other hand they may capture a dimension of social capital. One is what we call a “transport isolation index” (see Hellerstein et al., 2014). This is intended to control for differences in transportation infrastructure that can generate variation in our network measures even when there is no actual sharing of the type that underlies network models. For example, transportation infrastructure in an area (like a highway or subway line) might lead to many people from one tract of residence working in a common tract, which can lead some of them to work in the same establishment simply for this reason. To control for observed network isolation that is the result of commuting tendencies rather than interpersonal connections, we construct transport isolation measures corresponding to each networking measure, which we label TI_c^W and TI_c^P. We compute these on a per worker and per person basis from TI_{ic}, (as with NI_{ic} in Equation 1), which gives the share of total workers in an employment tract who reside in the same tract as that worker – i.e., who have the same origin and destination tracts in their commute. In this way, the transport isolation indices are constructed in an identical manner as the network measures, following Equations 2 and 3, except that we use the workplace Census tract rather than the establishment. But while the transport index may be higher in some Census tracts because of the availability of local transportation infrastructure, it may alternatively be high in those tracts because of social capital in a neighborhood that leads neighbors to work in the same neighborhoods. If it is the latter, the transportation index, like the network isolation index itself, is an outcome, and including it in the estimation could “over-control” for the determinants of our network measure.

The second control that we either include or exclude is the simple count of all NETS establishments operating in the neighborhood Census tract, regardless of industry classification. The number of establishments in a Census tract can be correlated with the network index mechanically because it can lead to clusters of neighbors working together due to geographical proximity, and thus may be an important control to force in the regression. Alternatively, the number of these establishments actually may be a measure of social capital, if, for example, local zoning laws lead to land being allocated to a large number of small establishments, versus restricting the local area to residential use or a few, large employers.

For the other three sets of variables – school-district variables, voting pattern variables, and non-profit penetration in the Census tract – we allow the LASSO procedure to pick the variables that remain, and then we estimate their coefficients by OLS. Both the variable selection and the ensuing estimated coefficients tell us whether and which of these social capital proxies are related to neighborhood labor market networks. The rationale for this strategy is that these variables are among the set of potential measures of social capital we explore and would otherwise not be included in a model to explain variation in the strength of labor market networks. We want to let the data tell us which variables should be included as explanatory variables (while avoiding over-fitting), and we want to give the reader a less restrictive view of the data than if we made ex ante decisions about which variables and types of non-profits reflect social capital. A machine-learning approach to the social capital measures also avoids the risk of mining the data to find a reasonably small set of predictors that can be most easily interpreted, ex post, as reflecting social capital.

The fact that the results of the LASSO procedure do not necessarily yield causal evidence does not trouble us. There simply is a scarcity of wide-scale demographic evidence that ties labor market network strength to local organizations and characteristics that are typically associated with social capital. That said, it is important to note that one cannot draw policy conclusions from these associations, such as whether, for example, increasing the presence of non-profit sector establishments would boost labor market networks.

V. Results

Table 1 reports descriptive statistics for all of our variables with the exception of the tabulations of establishments in the non-profit sector in the NETS. Our sample of approximately 34,000 Census tracts is determined by our urban area restriction as well as limitations due to data availability.[21] Our network

[21] Starting with the U.S. total of 73,057 Census tracts, we first limit to the 44,127 that are classified as fully urban and in a state where LEHD jobs data was available in 2010 (we exclude 1,267 tracts in Massachusetts and the District of Columbia). We also exclude the small number of tracts that do not have at least 100 residents with LEHD earnings. Linking to the voting and schooling data further limits the sample to (approximately) 34,000, with the voting data being more restrictive. Census tracts have a target population of 4,000 residents, with the 25th, 50th, and 75th percentiles of our tracts, by population, having 2,886, 3,966, and 5,190 persons, respectively. Given this similar sizing

measures are calculated over 48.3 million workers whose highest earning job is at one of 3.3 million unique employers located at one of 4 million unique establishments. The mean of the observed network isolation index NI_c is about 1.6 when we calculate it using only workers (which we denote NI_c^W);[22] it falls to about 1.0 when we include the non-employed in the calculation (which we denote NI_c^P), who by definition have NI_{ic} = 0. As in Hellerstein et al. (2014), the average transport isolation measures – 0.59 for workers and 0.37 for the population – are significantly lower than observed network isolation, which is consistent with labor markets being more networked than what might be anticipated from location factors alone.[23]

In interpreting the means of the demographic and education variables, recall that these are computed over tracts, and are for urban tracts only. Thus, these means are not representative of the entire U.S. population. In the last panel, the schooling and voting variables reveal that most tracts include only one school district (the mean is about 1.33). The high Democratic vote share is a reflection of the selection on urban tracts. The high majority vote share (0.68) points to considerable homogeneity in voting.

Table 2 reports information from the NETS on all 6-digit NAICS industries with at least 10 percent of establishments coded as non-profits, drawn from the universe of establishments with non-missing legal status. The entries are rank-ordered from the highest percentage to the lowest. This percentage begins at above 50, and is high for industries including charities, humane societies, hospitals and clinics, athlete associations, rehab facilities, etc. We can imagine that some of these are more likely to be associated with higher social capital that might be tied to labor market networks (e.g., churches, places of worship, etc., NAICS code 813110, and civic associations, NAICS code 813410), others might be tied to social capital

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and the nature of our evaluation, we do not weight our estimates by population, so each Census tract serves as an observation.

[22] This is lower, by a factor of about three, than in Hellerstein et al. (2014). The differences arise due to the restriction to urban tracts in this paper, and the inclusion of multi-unit establishments. In that paper and in Hellerstein et al. (2011) we present a scaled version of this network measure (averaged across all workers) that subtracts out the clustering of neighbors in establishments that can occur randomly, and computes this difference relative to the maximum clustering that can occur. This adjustment is less important in the present paper, where we are more interested in explaining variation in the network measure than in asking "how important" networks are.

[23] Moreover, the 1.6 figure for NI_c^W (for example) should not be interpreted relative to 100 percent, but relative to the maximum amount of clustering that could occur; this is much lower, because given the size distribution of firms, all neighbors typically could not work at the same establishment as any given reference person. (See Hellerstein et al., 2011.)

but play little role in labor market networks (e.g., activity centers for disabled persons, NAICS code 624120), and others might be weakly connected to social capital in the first place (e.g., apartment and condominium management, NAICS code 531311). However, rather than try to prespecify in advance which industries are likely to facilitate the kind of social capital that builds labor market networks, we use our machine-learning approach to identify these industries (as well as to select among the other potential social capital variables we constructed).[24]

As preliminary evidence, Table 3 reports results of regressions for the two versions of our network measure – NI_c^W and NI_c^P – including the demographic controls, the other controls, and the social capital measures (e.g., the school district and voting variables) based on prior research. We use simple OLS in this table and not LASSO, and we just include this very small set of social capital measures. The specifications vary with respect to whether the tract-level isolation index and establishment counts are included, and whether or not we include state fixed effects, and for each version of the dependent variable we first report results with the social capital measures excluded.

The estimated coefficients on the demographic variables are a bit hard to interpret, since the variables can be quite strongly related. For example, both the share of tract residents living in poverty and the fraction black are each strongly positively correlated with our observed network isolation index and with each other, but the estimated coefficients on these variables in Table 3, while both generally statistically significant, are often opposite in sign. The estimate of a higher network measure where the share of immigrants (non-natives) is higher is consistent with past findings on immigrants, language, and the importance of networks (e.g., Hellerstein et al., 2011). The education results sometimes indicate that the observed network measure is highest where the share with low education is highest, consistent with less-educated workers participating in more local labor markets. The positive effect of the share with a bachelor's degree (or higher) in some specifications (relative to high school graduates or those with some college – the omitted group), suggests that the more highly-educated also have good network connections –

[24] To facilitate cross-referencing this table to the LASSO results reported below on which industries are retained, in Table 2 we highlight the NAICS codes for the retained industries (as well the words used to provide a short description of the industry in the remainder of the paper).

perhaps more so because of access to social capital than the local nature of their labor market.

With regard to the commuting variables, tracts with shorter commutes appear to be more networked. However, this likely is due to some extent to a higher density of jobs nearby, which is consistent with the finding that the estimated effect of the short-commute variable declines by about three-quarters when the transport isolation index is included (in columns (3), (4), (7), and (8)). Commuting by driving alone is associated with lower values of NI_c^W and NI_c^P.[25]

We also find that our network measure is higher when residential mobility is lower (based on a higher share that did not move in the last year). There is also evidence – in the specifications including the tract-level isolation index and the establishment counts – that NI_c^W and NI_c^P are also higher when the share of housing that is owner occupied is higher. Both results may simply reflect the fact that residential mobility and home ownership rates are measures of socioeconomic characteristics of neighborhoods. But it is worth noting that both results also are consistent with more sharing of labor market information between neighbors when neighbors are more likely to know each other – whether somewhat mechanically because they are simple likely to have been at the same address longer, and perhaps also because homeowners interact with neighbors in a variety of ways that renters do not.

The bottom rows of the table report results for the schooling- and voting-related social capital measures. The estimated signs of the effects of the schooling variables are consistent with our expectations. Census tracts with more school districts (which may be a proxy for smaller school districts) appear more networked. Similarly, tracts with smaller school districts– which serve fewer tracts – are also more networked, and tracts where school districts report smaller average class sizes – which may have to do more with school size – are more networked. With regard to the voting variables, it appears that more homogeneous voting and voter turnout are strongly positively correlated with $NI_c^W$and NI_c^P, while tracts with a larger Democratic vote share seem to have less-extensive labor market networks.[26]

[25] Whether one drives to work alone can also be interpreted as a reflection of network connections among neighbors, raising the possibility that including this variable subsumes other network effects. However, all of our estimated relationships with network-related measures were changed only negligibly by excluding this variable.

[26] Recall the earlier discussion of the local nature of our social capital measures. It may be that a higher Democratic vote share is associated with support for institutions that provide social capital at a more aggregate level.

In Tables 4 and 5 we turn to the LASSO estimates. These are the specifications into which we introduce the counts of non-profit establishments by industry, and allow the data-driven machine learning algorithm to determine which of the overall sets of social capital variables belong in the regression. In each table we report estimates from four specifications; excluding and including (via forcing) the tract-level isolation index, and excluding and including (via forcing) the state fixed effects. We always include the demographic controls, and we use the LASSO procedure to choose among the school district and voting social capital measures, and the non-profit sector social capital measures.

The results using NI_c^W, the measure that is constructed using only workers, are reported in Table 4. The first two columns exclude the state fixed effects, and present each variant of the specification including or excluding the transport isolation index and establishment count. The last two columns force the addition of the state fixed effects. We always set the penalty loadings on the demographic controls, on the transportation index and overall establishment count (when included), and on the state fixed effects (when included) to zero, so that these variables remain in the regression because of their potential importance in determining the clustering of neighbors into establishments for economic and social reasons that have nothing to do with social capital. Standard errors are always calculated with clustering at the county level.

One interesting result is that the estimated effects of the demographic and commuting controls are largely unchanged relative to Table 3. With regard to the schooling and voting social capital variables, the post-LASSO results retain the Democratic vote share in all specifications. The number of districts, the average tracts served by the district, and the student/teacher ratio variables are retained only in some specifications (and different ones), depending on the inclusion of the establishment count and transport index controls, and the state fixed effects. However, the signs are the same as in Table 3, always indicating that neighborhoods with smaller districts and schools are more networked. The share free/reduced-price lunch, majority vote share, and voter turnout variables are dropped in all cases.

The last set of results – which appear on the second page of the table – pertain to the counts of non-profit establishments in 91 industries with a large share of such establishments.[27] Including the fixed state effects has little impact on which industries are picked out by the LASSO procedure. But whether or not the tract-level isolation index and the establishment counts are included has somewhat more impact. Among the industries in which the count of non-profit sector establishments is often retained and the estimated coefficient is positive and statistically significant, many seem like natural or even stereotypical types of establishments that would foster social capital in one of a number of ways. This list includes the following: hobby clubs, civic associations, Scouts, PTAs, etc. (NAICS code 813410);[28] churches, mosques, etc. (NAICS code 813110); fire and rescue services, including volunteer fire departments (NAICS code 922160); schools (NAICS code 611110); country clubs and golf courses (NAICS code 713910); and amateur and recreational sports teams and numerous other types of sports-related clubs (NAICS code 713990). Note that only some of these are retained irrespective of whether the tract-level isolation index and establishment counts are included.

These types of non-profits picked out by the LASSO procedure seem to be those likely to encourage contacts between neighbors. For example, country clubs may generate contacts between those who work in related jobs and share social contacts, given that there may be significant socioeconomic homogeneity. And in the case of schools, the contacts seem likely to be between parents with children, paralleling, to some extent, evidence suggesting that labor market network connections between neighbors are stronger among neighbors with school-age children of similar ages (Bayer et al., 2008, Table 7).

There are other non-profit establishments that are retained with significant positive coefficients and which could also foster social capital, although perhaps less directly with regard to communication among neighbors. These include: police departments (NAICS code 922120); ambulance and rescue services (NAICS code 621910); city and mayors' office (NAICS code 921110); and nursing homes (NAICS code 623110).[29] Finally, there are, to be sure, some findings that seem harder to interpret as reflecting social

[27] The order of the industries is the same as in Table 2, ranked from the largest to smaller percentage of non-profits.
[28] One has to exercise caution in characterizing these industries, as Table 2 indicates a much longer list of establishment types for each NAICS code we use.
[29] For many of these public goods (e.g., police, mayors' offices, cemeteries), the establishment count may reflect

capital, such as the positive effect of cemeteries (NAICS code 812220), and the negative effect of professional associations ((NAICS code 813920).

In total, in our view, the non-profit sectors that appear most consistently across our LASSO specifications have estimated coefficients that are positive, as we conjectured. This list includes (using shortened descriptions): churches, fire and rescue services, schools, police departments, ambulance or rescue services, country clubs, mayors' offices, nursing homes, and amateur or recreational sports teams or clubs.[30] Overall, then, we regard the industries selected by the LASSO procedure in explaining variation in the worker-based network measure (NI_c^W) as broadly supportive of the idea that non-profits that foster interaction between residents facilitate the development of social capital that helps create labor market connections among neighbors.

The magnitudes of the estimated relationships between some of our social capital measures are non-trivial. For example, in column (3), the estimated coefficient on amateur/recreational sports teams and clubs (NAICS code 713990) is 0.039. In Appendix Table A1, we show the standard deviations of the non-profit sector counts; for this industry, the standard deviation is 0.98. Thus, a one standard deviation change would increase NI_c^W by about the same 0.039, and given a mean of NI_c^W of 1.609, the implied effect is about 2.4 percent. The magnitude is a shade smaller similar for churches, mosques, etc., and much larger for country clubs. With regard to the other social capital variables, a 10 percentage point lower Democratic vote share is associated with about a 0.1 (or about a 6 percent) increase in the network measure, perhaps consistent with more general reliance on local institutions in less Democratic areas.

We note that this list is not merely composed of the industries that are most intensively non-profit or the largest industries with a non-profit component. Such a finding might have been consistent with non-profits simply being a byproduct of social largesse, which might be related to our networking measure, or

decentralization, with Census tracts in smaller municipalities or those where service provision is more disaggregated being more likely to have their own facilities. In that case, local presence of these public goods facilities may be as much a reflection of strong community ties as an indication of a higher service level of public goods. We readily acknowledge, however, that this is a potential ex post rationalization of these particular findings.

[30] Note that we also show a handful of industries (e.g.., NAICS code 611630) with no estimates; we do this because this industry is selected when we look at NI_c^P, in Table 5 (discussed below). There are no such industries that appear in Table 5 but not in Table 4.

an indication that only the largest and most widespread types of non-profits have a discernable statistical relationship with our networking measure. Of the fifteen industries with the highest non-profit reporting share (see Table 2), including community chests (NAICS code 813219), homeowners' associations (NAICS code 813990), advocacy organizations (NAICS code 813319), and charitable foundations (NAICS code 813211), none are retained in Table 4, and only one (advocacy organizations) is retained in Table 5, as described below. Some widespread industries not retained include academies, colleges, and professional schools (NAICS code 611310) and labor unions (NAICS code 813930).

Table 5 reports results of the same analyses as in Table 4, but uses the network measure that includes the non-employed, NI_c^P. The coefficients on the demographic and commuting controls generally are qualitatively similar across the tables, although the magnitudes sometimes change. As was discussed in Section II, NI_c^P, which includes zeros, is always smaller and, correspondingly, the estimates in Table 5 tend to be lower in magnitude. That the relative magnitudes across coefficients may change is unsurprising since these variables are characteristics that help describe the economic health of the Census tracts and therefore are likely to directly affect employment. Specifications including the transport isolation measures, which are also sensitive to employment, should help to control for employment-related effects on our networking measure.

With regard to the "prior" social capital measures, in Table 5 the LASSO procedure selects the same "prior" social capital measures, in almost the exact same specifications, as in Table 4, with quite similar magnitudes. In particular, it selects the Democratic vote share in every specification, with coefficient estimates of similar (negative) magnitude. It also selects the number of school districts in both specifications with state fixed effects, and sometimes also selects the measure of school districts served and the student/teacher ratio (both with negative effects).

Finally, the industries selected in Table 5 are very similar to those in Table 5, although again the estimated magnitudes sometimes vary and are typically a bit smaller in Table 5. Like for the worker-based network measure, a number of the robust findings across specifications in Table 5 are for industries that seem natural to interpret as positive social capital effects, including: churches, fire and rescue services, schools, police departments, ambulance or rescue services, country clubs, mayors' offices, and amateur or recreational sports teams or clubs. Again, there are some industries selected that may also reflect social capital, although perhaps not in as clear a manner; and there are some results that are unexpected (similar to those in Table 4, so we do not note them again). Overall, like we did for the worker-based network measure (NI_c^W), we regard the industries selected by the LASSO procedure in explaining variation in the population-based network measure (NI_c^P) as broadly supportive of the idea that neighborhoods that have high concentrations of non-profits successfully foster interaction between residents and facilitate the development of social capital that helps create labor market connections among neighbors.

VI. Conclusions

Our goal in this paper is to conduct some exploratory empirical analyses to identify characteristics of neighborhoods (Census tracts) that may facilitate the development of social capital that can explain variation, across neighborhoods, in the extent of labor market networking among neighbors. We draw on prior literature, mainly on social capital, to construct neighborhood-level measures of social capital of various kinds, focused primarily on characteristics of schools and school districts, and of voting behavior. In addition, we measure the prevalence in neighborhoods of businesses/institutions concentrated in the non-profit sector that are likely to increase social capital and network ties. We use machine-learning methods to let the data tell us which of these measures help predict neighborhood variation in a measure of neighborhood-based labor markets that we have used in past research, which both captures potential network connections among neighbors, and is associated with better job market matches and labor market outcomes.

With regard to schooling and voting, our analysis suggests that schools that are likely smaller and in less centralized school districts foster social capital that builds labor market networks, as does a larger Republican vote share, which we interpret as a population characteristic. Among industries with a reasonable share of non-profits, a number are identified as predictive of strong labor market networks, and these industries do, in fact, seem to us to likely play this role via either public goods provision or facilitating social contacts. These industries include: churches and other religious institutions, fire and rescue services, schools, police departments, ambulance or rescue services, country clubs, mayors' offices, nursing homes, and amateur or recreational sports teams or clubs. For many of these, it seems plausible to think that people working or looking for work may develop relationships that lead to sharing of labor market information among neighbors and among employers. Overall, we regard the industries selected by the LASSO procedure as broadly supportive of the idea that establishments in the non-profit sector that foster interaction between residents facilitate the development of social capital that helps create labor market connections among neighbors.

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Table 1: Summary Statistics for Census, School, and Voting Variables, Census Tract Level

Variable	Description	Mean	Std. dev.	25th percentile	Median	75th percentile
NI_c^W	Observed tract average network isolation index, per worker	1.609	1.113	0.88	1.35	2.03
TI_c^W	Observed tract average transport isolation index, per worker	0.588	0.612	0.24	0.40	0.70
NI_c^P	Observed tract average network isolation index, per resident	1.013	0.710	0.53	0.84	1.29
TI_c^P	Observed tract average transport isolation index, per resident	0.373	0.393	0.14	0.25	0.45
Number of NETS establishments	Count	214.5	209.4	101	165	265
Poor	Proportion	0.170	0.140	0.06	0.13	0.25
Hispanic	Proportion	0.200	0.238	0.03	0.10	0.27
Black, non-Hispanic	Proportion	0.174	0.253	0.02	0.06	0.20
Asian, non-Hispanic	Proportion	0.066	0.104	0.01	0.03	0.08
Other race, non-Hispanic	Proportion	0.030	0.035	0.01	0.02	0.04
Non-native	Proportion	0.159	0.141	0.05	0.11	0.23
Currently married	Proportion	0.468	0.135	0.38	0.48	0.56
Education < high school	Proportion	0.155	0.126	0.06	0.12	0.22
Education ≥ Bachelor's degree	Proportion	0.282	0.192	0.12	0.24	0.41
Commute < 10 minutes	Proportion	0.120	0.076	0.07	0.10	0.16
Commute by driving alone	Proportion	0.744	0.135	0.69	0.78	0.84
Did not move in last year	Proportion	0.820	0.101	0.77	0.84	0.89
Share of housing owner-occupied	Proportion	0.587	0.237	0.42	0.61	0.78
Number of districts	Count of number of districts	1.329	0.785	1.00	1.00	1.00
Average number of tracts in school district(s)	Count of number of tracts	1.366	2.510	0.21	0.49	1.20
Student/teacher ratio	Ratio	16.880	3.425	14.51	16.11	19.28
Free/reduced-price lunch share	Proportion	0.497	0.230	0.31	0.52	0.70
Majority vote share	Proportion, maximum of Democratic or Republican vote share	0.681	0.136	0.57	0.65	0.77
Democratic vote share	Proportion, Democratic share of Democratic and Republican votes	0.635	0.182	0.50	0.62	0.77
Voter turnout	Proportion voting Democratic and Republican as share of voting age population	0.528	0.214	0.37	0.52	0.67

Note: There are approximately 34,000 Census tract observations. The network measures are calculated using the LEHD Infrastructure Files for jobs held in 2010 at the beginning of the second quarter. For details on the residence-based network isolation measures, see Equations 2 and 3 in Section II. For details on the residence-based transport isolation measures, see Section IV. Establishment counts are totaled by Census tract from the National Establishment Time Series. Census tract demographic characteristics are constructed from the 2008-2012 ACS 5-year file. Measures of school districts and voting are derived from the Department of Education's Common Core of Data and the Harvard Election Data Archive (HEDA), respectively.

Table 2: NETS Tabulations of 6-Digit NAICS Industries with ≥ 10 Percent of Establishments Non-Profit

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
813219	Community chests; Federated charities; United fund councils; United funds for colleges	1812	3277	55.3%
711120	Ballet companies; Ballet productions, live theatrical; Classical dance companies; Contemporary dance companies; Dance companies; Dance productions, live theatrical; Dance theaters; Dance troupes; Folk dance companies; Interpretive dance companies; Jazz dance companies; Modern dance companies; Tap dance companies; Theater companies, dance; Theaters, dance; Theatrical dance productions, live	76	155	49.0%
813312	Animal rights organizations; Animal welfare associations or leagues; Conservation advocacy organizations; Environmental advocacy organizations; Humane societies; Natural resource preservation organizations; Wildlife preservation organizations	1642	3672	44.7%
813990	Athletic associations, regulatory; Athletic leagues (i.e., regulating bodies); Condominium corporations; Condominium owners' associations; Cooperative owners' associations; Homeowners' associations; Homeowners' associations, condominium; Property owners' associations; Sports governing bodies; Sports leagues (i.e., regulating bodies); Tenants' associations (except advocacy)	7886	17947	43.9%
621410	Abortion clinics; Birth control clinics; Childbirth preparation classes; Counseling services, family planning; Family planning centers; Family planning counseling services; Fertility clinics; Pregnancy counseling centers; Reproductive health services centers	619	1420	43.6%
623220	Alcoholism rehabilitation facilities (except licensed hospitals), residential; Convalescent homes or hospitals for psychiatric patients; Drug addiction rehabilitation facilities (except licensed hospitals), residential; Halfway houses for patients with mental health illnesses; Halfway houses, substance abuse (e.g., alcoholism, drug addiction); Homes for emotionally disturbed adults or children; Homes, psychiatric convalescent; Hospitals, psychiatric convalescent; Mental health facilities, residential; Mental health halfway houses; Psychiatric convalescent homes or hospitals; Residential group homes for the emotionally disturbed; Substance abuse (i.e., alcoholism, drug addiction) halfway houses; Substance abuse facilities, residential	534	1227	43.5%
624230	Disaster relief services; Emergency relief services; Emergency shelters for victims of domestic or international disasters or conflicts; Immigrant resettlement services; Refugee settlement services; Relief services, disaster; Relief services, emergency; Shelters for victims of domestic or international disasters or conflicts, emergency	582	1403	41.5%
813319	Accident prevention associations; Antipoverty advocacy organizations; Aviation advocacy organizations; Community action **advocacy organizations**; Drug abuse prevention advocacy organizations; Drunk driving prevention advocacy organizations; Firearms advocacy organizations; Gun control organizations; Neighborhood development advocacy organizations; Peace advocacy organizations; Public safety advocacy organizations; Social change advocacy organizations; Social service advocacy organizations; Substance abuse prevention advocacy organizations; Taxpayers' advocacy organizations; Temperance organizations; Tenants' advocacy associations; Tenants' associations, advocacy; World peace and understanding advocacy organizations	6837	16606	41.2%
624110	Adoption agencies; Adoption services, child; Aid to families with dependent children (AFDC); Child guidance agencies; Child welfare services; Community centers (except recreational only), youth; Foster care placement agencies; Foster home placement services; Self-help organizations, youth; Teen outreach services; Youth centers (except recreational only); Youth guidance organizations; Youth self-help organizations	2913	7115	40.9%
622110	Children's hospitals, general; General medical and surgical hospitals; Hospitals, general medical and surgical; Hospitals, general pediatric; Osteopathic hospitals	3986	9913	40.2%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
711110	Broadway theaters; Burlesque companies; Comedy troupes; Community theaters; Dinner theaters; Improvisational theaters; Mime theaters; Musical theater companies or groups; Musical theater productions, live; Opera companies; Puppet theaters; Repertory companies, theatrical; Road companies, theatrical; Stock companies, theatrical; Summer theaters; Theater companies (except dance); Theater companies (except dance), amateur; Theaters, dinner; Theaters, live theatrical production (except dance); Theaters, musical; Theatrical repertory companies; Theatrical road companies; Theatrical stock companies; Vaudeville companies	1004	2500	40.1%
813910	Agricultural organizations (except youth farming organizations, farm granges); Animal breeders' associations; Bankers' associations; Better business bureaus; Boards of trade; Business associations; Chambers of commerce; Construction associations; Contractors' associations; Distributors' associations; Farmers' associations; Farmers' unions; Growers' associations; Hospital associations; Industrial associations; Insurers' associations; Junior chambers of commerce; Manufacturers' associations; Merchants' associations; Mining associations; Producers' associations; Public utility associations; Real estate boards; Restaurant associations; Retailers' associations; Service industries associations; Shipping companies' associations; Trade associations; Warehousing associations; Wholesalers' associations	9376	23707	39.5%
712120	Archeological sites (i.e., public display); Battlefields; Heritage villages; Historical forts; Historical ships; Historical sites; Pioneer villages	555	1422	39.0%
813211	Charitable trusts, awarding grants; Community foundations; Corporate foundations, awarding grants; Educational trusts, awarding grants; Grantmaking foundations; Philanthropic trusts, awarding grants; Scholarship trusts (i.e., grantmaking, charitable trust foundations); Trusts, charitable, awarding grants; Trusts, educational, awarding grants; Trusts, religious, awarding grants	4761	12624	37.7%
624210	Community meals, social services; Food banks; Meal delivery programs; Mobile soup kitchens; Soup kitchens	183	499	36.7%
624120	Activity centers for disabled persons, the elderly, and persons diagnosed with intellectual and developmental disabilities; Centers, senior citizens'; Community centers (except recreational only), adult; Companion services for disabled persons, the elderly, and persons diagnosed with intellectual and developmental disabilities; Day care centers for disabled persons, the elderly, and persons diagnosed with intellectual and developmental disabilities; Day care centers, adult; Disability support groups; Home care of elderly, non-medical; Homemaker's service for elderly or disabled persons, non-medical; Self-help organizations for disabled persons, the elderly, and persons diagnosed with intellectual and developmental disabilities; Senior citizens activity centers; Senior citizens centers	5305	14778	35.9%
6241	Individual and family services	11679	33005	35.4%
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%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
611310	Academies, college or university; Academies, military service (college); Business colleges or schools offering baccalaureate or graduate degrees; Colleges (except junior colleges); Colleges, universities, and professional schools; Conservatories of music (colleges or universities); Dental schools; Hospital management schools offering baccalaureate or graduate degrees; Hospitality management schools offering baccalaureate or graduate degrees; Law schools; Medical schools; Military academies, college level; Military service academies (college); Parochial schools, college level; Private colleges (except community or junior college); Professional schools (e.g., business administration, dental, law, medical); Schools, correspondence, college level; Schools, medical; Schools, professional (colleges or universities); Seminaries, theological, offering baccalaureate or graduate degrees; Theological seminaries offering baccalaureate or graduate degrees; Universities	5666	17482	32.4%
813920	Accountants' associations; Architects' associations; Bar associations; Consultants' associations; Dentists' associations; Dietitians' associations; Educators' associations; Engineers' associations; Health professionals' associations; Hospital administrators' associations; Learned societies; Medical associations; Nurses' associations; Occupational therapists' associations; Optometrists' associations; Peer review boards; Personnel management associations; Pharmacists' associations; **Professional associations**; Professional membership associations; Professional standards review boards; Psychologists' associations; Scientific associations; Social workers' associations; Standards review committees, professional	3946	12231	32.2%
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%
621420	Alcoholism treatment centers and clinics (except hospitals), outpatient; Detoxification centers and clinics (except hospitals), outpatient; Drug addiction treatment centers and clinics (except hospitals), outpatient; Mental health centers and clinics (except hospitals), outpatient; Outpatient mental health centers and clinics (except hospitals); Outpatient treatment centers and clinics (except hospitals) for substance abuse (i.e., alcoholism, drug addiction); Outpatient treatment centers and clinics for alcoholism; Outpatient treatment centers and clinics for drug addiction; Psychiatric centers and clinics (except hospitals), outpatient; Substance abuse treatment centers and clinics (except hospitals), outpatient	1926	6128	31.4%
623210	Group homes, intellectual and developmental disability; Homes with or without health care, intellectual and developmental disability; Hospitals, intellectual and developmental disability; Intellectual and developmental disability facilities (e.g., homes, hospitals, intermediate care facilities), residential; Intellectual and developmental disability homes; Intellectual and developmental disability hospitals; Intellectual and developmental disability intermediate care facilities; Intermediate care facilities, intellectual and developmental disability	568	1817	31.3%
611210	Academies, junior college; Colleges, community; Colleges, junior; Community colleges; Community colleges offering a wide variety of academic and technical training; Junior colleges; Junior colleges offering a wide variety of academic and technical training; Schools, junior college; Schools, junior college vocational	838	2691	31.1%
624310	Habilitation job counseling and training, vocational; Job counseling, vocational rehabilitation or habilitation; Job training, vocational rehabilitation or habilitation; Rehabilitation job counseling and training, vocational; Sheltered workshops (i.e., work experience centers); Vocational habilitation job counseling; Vocational habilitation job training facilities (except schools); Vocational rehabilitation agencies; Vocational rehabilitation job counseling; Vocational rehabilitation job training facilities (except schools); Vocational rehabilitation or habilitation services (e.g., job counseling, job training, work experience); Work experience centers (i.e., sheltered workshops); Workshops for persons with disabilities	2919	9586	30.5%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
712130	Animal exhibits, live; Animal safari parks; Aquariums; Arboreta; Arboretums; Aviaries; Botanical gardens; Conservatories, botanical; Gardens, zoological or botanical; Menageries; Parks, wild animal; Petting zoos; Reptile exhibits, live; Wild animal parks; Zoological gardens; Zoos	243	811	30.0%
525920	Bankruptcy estates; Personal estates (i.e., managing assets); Personal investment trusts; Personal trusts; Private estates (i.e., administering on behalf of beneficiaries); Testamentary trusts; Trusts, estates, and agency accounts	230	814	28.3%
311313	Beet pulp, dried, manufacturing; Beet sugar refining; Brown beet sugar refining; Brown sugar made from beet sugar; Confectioner's beet sugar manufacturing; Granulated beet sugar manufacturing; Liquid beet syrup manufacturing; Liquid sugar made from beet sugar; Molasses made from sugar beets; Raw beet sugar manufacturing; Sugar, confectionery, made from sugar beets; Sugar, granulated, made from sugar beets; Sugar, invert, made from sugar beets; Sugar, liquid, made from sugar beets; Syrup made from sugar beets	14	51	27.5%
621991	Blood banks; Blood donor stations; Eye banks; Organ banks, body; Organ donor centers, body; Placenta banks; Plasmapheresis centers; Sperm banks, human	427	1570	27.2%
925120	Community development agencies, government; County development agencies; Land redevelopment agencies, government; Redevelopment land agencies, government; Regional planning and development program administration; Urban planning commissions, government; Zoning boards and commissions	501	1852	27.1%
712110	Art galleries (except retail); Art museums; Community museums; Contemporary art museums; Decorative art museums; Fine arts museums; Galleries, art (except retail); Halls of fame; Herbariums; Historical museums; Human history museums; Interactive museums; Marine museums; Military museums; Mobile museums; Multidisciplinary museums; Museums; Natural history museums; Natural science museums; Observatories (except research institutions); Planetariums; Science and technology museums; Sports halls of fame; Traveling museum exhibits; War museums; Wax museums	3207	12009	26.7%
624190	Alcoholism and drug addiction self-help organizations; Alcoholism counseling (except medical treatment), nonresidential; Alcoholism self-help organizations; Community action service agencies; Counseling services; Crisis intervention centers; Drug addiction self-help organizations; Exoffender rehabilitation agencies; Exoffender self-help organizations; Family social service agencies; Family welfare services; Hotline centers; Individual and family social services, multi-purpose; Marriage counseling services (except by offices of mental health practitioners); Mediation, social service, family, agencies; Multiservice centers, neighborhood; Offender self-help organizations; Parenting support services; Parole offices, privately operated; Probation offices, privately operated; Rape crisis centers; Referral services for personal and social problems; Rehabilitation agencies for offenders; Self-help organizations (except for disabled persons, the elderly, persons diagnosed with intellectual and developmental disabilities); Social service agencies, family; Social service centers, multipurpose; Suicide crisis centers; Support group services; Telephone counseling services; Travelers' aid centers; Welfare service centers, multi-program	8478	32377	26.2%
561591	Convention and visitors bureaus; Convention bureaus; Tourism bureaus; Tourist information bureaus; Visitors bureaus	211	808	26.1%
922160	Ambulance and fire service combined; **Fire and rescue service**; Fire departments (e.g., government, volunteer (except private)); Fire marshals' offices; Fire prevention offices, government; **Firefighting** (except forest), government and **volunteer** (except private); Firefighting services (except forest and private)	4715	18083	26.1%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
611110	Academies, elementary or secondary; Boarding schools, elementary or secondary; **Elementary and secondary schools**; Elementary schools; Finishing schools, secondary; Handicapped, schools for, elementary or secondary; High schools; High schools offering both academic and technical courses; High schools offering both academic and vocational courses; **Junior high schools**; Kindergartens; Middle schools; Military academies, elementary or secondary; Montessori schools, elementary or secondary; Parochial schools, elementary or secondary; Preparatory schools, elementary or secondary; Primary schools; Private schools, elementary or secondary; School boards, elementary and secondary; School districts, elementary or secondary; Schools for the handicapped, elementary or secondary; Schools for the intellectually and developmentally disabled (except preschool, job training, vocational rehabilitation); Schools for the physically disabled, elementary or secondary; Schools, elementary; Schools, secondary; Secondary schools offering both academic and technical courses; Seminaries, below university grade	30846	119478	25.8%
623990	**Boot camps** for delinquent youth; Boys' and girls' residential facilities (e.g., homes, ranches, villages); Camps, boot or disciplinary (except correctional), for delinquent youth; Child group foster homes; Children's villages; Delinquent youth halfway group homes; Disabled group homes without nursing care; Disciplinary camps for delinquent youth; **Group foster homes** for children; Group homes for the disabled without nursing care; Group homes for the hearing impaired; Group homes for the visually impaired; Halfway group homes for delinquents and ex-offenders; Homes for children with health care incidental; Homes for unwed mothers; Juvenile halfway group homes; Orphanages	2621	10163	25.8%
622210	Alcoholism rehabilitation hospitals; Children's hospitals, psychiatric or substance abuse; Detoxification hospitals; Drug addiction rehabilitation hospitals; Hospitals for alcoholics; Hospitals, addiction; Hospitals, mental (except intellectual and developmental disability); Hospitals, psychiatric (except convalescent); Hospitals, psychiatric pediatric; Hospitals, substance abuse; Mental (except intellectual and developmental disability) hospitals; Mental health hospitals; Psychiatric hospitals (except convalescent); Rehabilitation hospitals, alcoholism and drug addiction	794	3191	24.9%
925110	Building standards agencies, government; Housing authorities, nonoperating; Housing programs, planning and development, government	1268	5119	24.8%
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%
926130	Communications commissions; Communications licensing commissions and agencies; Energy development and conservation programs, government; Federal Communications Commission (FCC); Irrigation districts, nonoperating; Licensing and inspecting of utilities; Mosquito eradication districts; Nuclear energy inspection and regulation offices; Public service (except transportation) commissions, nonoperating; Public utility (except transportation) commissions, nonoperating; Regulation of utilities; Sanitation districts, nonoperating; Solar energy regulation; Wind generated electrical power regulation	275	1167	23.6%
522130	Corporate credit unions; Credit unions; Federal credit unions; State credit unions; Unions, credit	2962	12821	23.1%
621910	Air ambulance services; **Ambulance services**, air or ground; Emergency medical transportation services, air or ground; Rescue services, air; **Rescue services**, medical	1197	5342	22.4%
922120	Alcohol, tobacco, and firearms control; Criminal investigation offices, government; DEA (Drug Enforcement Administration); Drug enforcement agencies and offices; Federal Bureau of Investigation (FBI); Federal police services; Highway patrols, police; **Housing police**, government; Marshals' offices; **Park police**; Police academies; Police and fire departments, combined; **Police departments** (except American Indian or Alaska Native); Sheriffs' offices (except court functions only); State police; Transit police	3125	14154	22.1%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
623312	Assisted-living facilities without on-site nursing care facilities; Homes for the aged without nursing care; Homes for the elderly without nursing care; Old age homes without nursing care; Old soldiers’ homes without nursing care; Rest homes without nursing care; Retirement homes without nursing care; Senior citizens’ homes without nursing care	706	3266	21.6%
921110	**Advisory commissions**, executive government; **City and town managers’ offices**; County supervisors’ and executives’ offices; Executive offices, federal, state, and local (e.g., governor, mayor, president); Governors’ offices; **Mayor’s offices**; President’s office, United States	6387	29792	21.4%
711320	Agricultural fair managers without facilities; Agricultural fair organizers without facilities; Agricultural fair promoters without facilities; Air show managers without facilities; Air show organizers without facilities; Air show promoters without facilities; Arts event managers without facilities; Arts event organizers without facilities; Arts event promoters without facilities; Arts festival managers without facilities; Arts festival organizers without facilities; Arts festival promoters without facilities; Beauty pageant managers without facilities; Beauty pageant organizers without facilities; Beauty pageant promoters without facilities; Booking agencies, theatrical (except motion picture); Boxing event managers without facilities; Boxing event organizers without facilities; Boxing event promoters without facilities; Concert booking agencies; Concert managers without facilities; Concert organizers without facilities; Concert promoters without facilities; Dance festival managers without facilities; Dance festival organizers without facilities; Dance festival promoters without facilities; Ethnic festival managers without facilities; Ethnic festival organizers without facilities; Ethnic festival promoters without facilities; Fair managers without facilities, agricultural; Fair organizers without facilities, agricultural; Fair promoters without facilities; Fair promoters without facilities, agricultural; Festival managers without facilities; Festival of arts managers without facilities; Festival of arts organizers without facilities; Festival of arts promoters without facilities; Festival organizers without facilities; Festival promoters without facilities; Heritage festival managers without facilities; Heritage festival organizers without facilities; Heritage festival promoters without facilities; Horse show managers without facilities; Horse show organizers without facilities; Horse show promoters without facilities; Managers of agricultural fairs without facilities; Managers of arts events without facilities; Managers of festivals without facilities; Managers of live performing arts productions (e.g., concerts) without facilities; Managers of sports events without facilities; Music festival managers without facilities; Music festival organizers without facilities; Music festival promoters without facilities; Organizers of agricultural fairs without facilities; Organizers of arts events without facilities; Organizers of festivals without facilities; Organizers of live performing arts productions (e.g., concerts) without facilities; Organizers of sports events without facilities; Professional sports promoters without facilities; Promoters of agricultural fairs without facilities; Promoters of arts events without facilities; Promoters of festivals without facilities; Promoters of live performing arts productions (e.g., concerts) without facilities; Promoters of sports events without facilities; Rodeo managers without facilities; Rodeo organizers without facilities; Rodeo promoters without facilities; Sports event managers without facilities; Sports event organizers without facilities; Sports event promoters without facilities; Theater festival managers without facilities; Theater festival organizers without facilities; Theater festival promoters without facilities; Theatrical booking agencies (except motion picture); Theatrical production managers without facilities; Theatrical production organizers without facilities; Theatrical production promoters without facilities; Wrestling event managers without facilities; Wrestling event organizers without facilities; Wrestling event promoters without facilities	1010	4715	21.4%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
221122	Distribution of electric power; Electric power brokers; Electric power distribution systems	361	1727	20.9%
713910	**Country clubs**; Golf and country clubs; **Golf courses** (except miniature, pitch-n-putt)	2772	13310	20.8%
721214	Boys' camps (except day, instructional); Camps (except day, instructional); Children's camps (except day, instructional); Dude ranches; Fishing camps with accommodation facilities; Girls' camps (except day, instructional); Guest ranches with accommodation facilities; Hunting camps with accommodation facilities; Nudist camps with accommodation facilities; Outdoor adventure retreats with accommodation facilities; Recreational camps with accommodation facilities (except campgrounds); Summer camps (except day, instructional); Trail riding camps with accommodation facilities; Vacation camps (except campgrounds, day instructional); Wilderness camps	999	4835	20.7%
519120	Archives; Bookmobiles; Centers for documentation (i.e., archives); Circulating libraries; Film archives; Lending libraries; Libraries (except motion picture stock footage, motion picture commercial distribution); Motion picture film libraries, archives; Music archives; Reference libraries	3470	16800	20.7%
531311	Apartment managers' offices; Condominium managers' offices, residential; Cooperative apartment managers' offices; Managers' offices, residential condominium; Managers' offices, residential real estate; Managing cooperative apartments; Managing residential condominiums; Managing residential real estate; Property managers' offices, residential real estate; Property managing, residential real estate; Real estate property managers' offices, residential; Residential property managing; Residential real estate property managers' offices	663	3239	20.5%
621498	Biofeedback centers and clinics, outpatient; Clinics/centers of health practitioners from more than one industry practicing within the same establishment; Clinics/centers of health practitioners with multi-industry degrees; Community health centers and clinics, outpatient; Infusion therapy centers and clinics, outpatient; Pain therapy centers and clinics, outpatient; Sleep disorder centers and clinics, outpatient	907	4453	20.4%
221310	Canal, irrigation; Filtration plant, water; Impounding reservoirs, irrigation; Irrigation system operation; Water distribution (except irrigation); Water distribution for irrigation; Water filtration plant operation; Water supply systems; Water treatment and distribution; Water treatment plants	1744	8586	20.3%
924110	Enforcement of environmental and pollution control regulations; Environmental protection program administration; NOAA (National Oceanic and Atmospheric Administration); Pollution control program administration; Sanitation engineering agencies, government; Waste management program administration; Water control and quality program administration	1033	5232	19.7%
621491	Group hospitalization plans providing health care services; Health maintenance organization (HMO) medical centers and clinics; HMO (health maintenance organization) medical centers and clinics	252	1325	19.0%
611710	College selection services; Educational consultants; Educational guidance counseling services; **Educational support services**; Educational testing evaluation services; **Educational testing services**; School bus attendant services; Student exchange programs; Test development and evaluation services, educational; Testing services, educational	4544	24088	18.9%
525120	Union health and welfare funds	29	159	18.2%
622310	Cancer hospitals; Children's hospitals, specialty (except psychiatric, substance abuse); Chronic disease hospitals; Extended care hospitals (except mental, substance abuse); Eye, ear, nose, and throat hospitals; Hospitals, specialty (except psychiatric, substance abuse); Leprosy hospitals; Maternity hospitals; Neurological hospitals; Obstetrical hospital; Orthopedic hospitals; Physical rehabilitation hospitals; Rehabilitation hospitals (except alcoholism, drug addiction); Tuberculosis and other respiratory illness hospitals	1004	5632	17.8%
561499	Address bar coding services; Bar code imprinting services; Fundraising campaign organization services on a contract or fee basis; Mail consolidation services; Mail presorting services; Teleconferencing services; Videoconferencing services	796	4497	17.7%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
813940	**Campaign organizations**, political; Constituencies' associations, political party; Local **political organizations**; PACs (Political Action Committees); Political action committees (**PACs**); Political campaign organizations; Political organizations or clubs; Political parties	328	1857	17.7%
721310	Boarding houses; Clubs, residential; Dormitories, off campus; Fraternity houses; Migrant workers' camps; Off campus dormitories; Residence clubs, organizational; Residential clubs; Rooming and boarding houses; Sorority houses; Workers' camps; Workers' dormitories	428	2512	17.0%
812220	Animal cemeteries; **Cemeteries**; Cemetery associations (i.e., operators); Cemetery management services; Columbariums; Crematories (except combined with funeral homes); Mausoleums; **Memorial gardens** (i.e., burial places); Pet cemeteries	981	5876	16.7%
921130	Assessor's offices, tax; Board of Governors, Federal Reserve; Budget agencies, government; Controllers' and comptrollers' offices, government; Customs bureaus; Federal Reserve Board of Governors; Gambling control boards, nonoperating; Internal Revenue Service; Lottery control boards, nonoperating; Property tax assessors' offices; State tax commissions; Taxation departments; Treasurers' offices, government	1026	6165	16.6%
921120	Advisory commissions, legislative; Boards of supervisors, county and local; City and town councils; Congress of the United States; County commissioners; Legislative assemblies; Legislative bodies (e.g., federal, local, and state); Legislative commissions; Study commissions, legislative	829	5369	15.4%
921190	Auditor's offices, government; Civil rights commissions; Civil service commissions; Election boards; General accounting offices, government; General public administration; General services departments, government; Human rights commissions, government; Indian affairs programs, government; Personnel offices, government; Public property management services, government; Purchasing and supply agencies, government; Supply agencies, government	1167	7710	15.1%
221320	Collection, treatment, and disposal of waste through a sewer system; **Sewage disposal** plants; Sewage treatment plants or facilities; Sewer systems; **Waste collection**, treatment, and disposal through a sewer system	292	1938	15.1%
922190	Consumer product safety commissions; Criminal justice statistics centers, government; Disaster preparedness and management offices, government; Emergency planning and management offices, government; Law enforcement statistics centers, government; Public safety bureaus and statistics centers, government; Public safety statistics centers, government	371	2585	14.4%
541720	Archeological research and development services; Behavioral research and development services; Business research and development services; Cognitive research and development services; Demographic research and development services; Economic research and development services; Historic and cultural preservation research and development services; **Humanities research and development services**; Language research and development services; Learning disabilities research and development services; Psychology research and development services; **Social science research and development services**; Sociological research and development services; Sociology research and development services	1183	8242	14.4%
923110	Certification of schools and teachers; County **supervisors of education** (except school boards); Education offices, nonoperating; Education program administration; Education statistics centers, government; State education departments; Teacher certification bureaus; University regents or boards, government	385	2691	14.3%
115111	Cotton ginning; Ginning cotton	103	728	14.0%
623110	**Convalescent homes** or convalescent hospitals (except psychiatric); **Group homes** for the disabled with nursing care; Homes for the aged with nursing care; Homes for the elderly with nursing care; Hospices, inpatient care; **Nursing homes**; Rest homes with nursing care; Retirement homes with nursing care; Skilled nursing facilities	3291	23883	13.8%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
711310	Air show managers with facilities; Air show organizers with facilities; Air show promoters with facilities; Arena operators; Arts event managers with facilities; Arts event organizers with facilities; Arts event promoters with facilities; Arts festival managers with facilities; Arts festival organizers with facilities; Arts festival promoters with facilities; Beauty pageant managers with facilities; Beauty pageant organizers with facilities; Beauty pageant promoters with facilities; Boxing event managers with facilities; Boxing event organizers with facilities; Boxing event promoters with facilities; Concert hall operators; Concert managers with facilities; Concert organizers with facilities; Concert promoters with facilities; Dance festival managers with facilities; Dance festival organizers with facilities; Dance festival promoters with facilities; Ethnic festival promoters with facilities; Fair managers with facilities, agricultural; Fair organizers with facilities, agricultural; Fair promoters with facilities; Fair promoters with facilities, agricultural; Festival managers with facilities; Festival of arts managers with facilities; Festival of arts organizers with facilities; Festival of arts promoters with facilities; Festival organizers with facilities; Festival promoters with facilities; Heritage festival managers with facilities; Heritage festival organizers with facilities; Heritage festival promoters with facilities; Horse show managers with facilities; Horse show organizers with facilities; Horse show promoters with facilities; Live arts center operators; Live theater operators; Managers of agricultural fairs with facilities; Managers of arts events with facilities; Managers of festivals with facilities; Managers of live performing arts productions (e.g., concerts) with facilities; Managers of sports events with facilities; Music festival managers with facilities; Music festival organizers with facilities; Music festival promoters with facilities; Organizers of agricultural fairs with facilities; Organizers of arts events with facilities; Organizers of festivals with facilities; Organizers of live performing arts productions (e.g., concerts) with facilities; Organizers of sports events with facilities; Performing arts center operators; Professional sports promoters with facilities; Promoters of agricultural fairs with facilities; Promoters of arts events with facilities; Promoters of festivals with facilities; Promoters of live performing arts productions (e.g., concerts) with facilities; Promoters of sports events with facilities; Rodeo managers with facilities; Rodeo organizers with facilities; Rodeo promoters with facilities; Sports arena operators; Sports event managers with facilities; Sports event organizers with facilities; Sports event promoters with facilities; Sports stadium operators; Stadium operators; Theater festival managers with facilities; Theater festival organizers with facilities; Theater festival promoters with facilities; Theater operators; Theatrical production managers with facilities; Theatrical production organizers with facilities; Theatrical production promoters with facilities; Wrestling event managers with facilities; Wrestling event organizers with facilities; Wrestling event promoters with facilities	367	2695	13.6%
711211	Baseball clubs, professional or semiprofessional; Baseball teams, professional or semiprofessional; Basketball clubs, professional or semiprofessional; Basketball teams, professional or semiprofessional; Boxing clubs, professional or semiprofessional; Football clubs, professional or semiprofessional; Football teams, professional or semiprofessional; Hockey clubs, professional or semiprofessional; Hockey teams, professional or semiprofessional; Ice hockey clubs, professional or semiprofessional; Jai alai teams, professional or semiprofessional; Major league baseball clubs; Minor league baseball clubs; Professional baseball clubs; Professional football clubs; Professional sports clubs; Roller hockey clubs, professional or semiprofessional; Semiprofessional baseball clubs; Semiprofessional football clubs; Semiprofessional sports clubs; Soccer clubs, professional or semiprofessional; Soccer teams, professional or semiprofessional; Sports clubs, professional or semiprofessional; Sports teams, professional or semiprofessional	269	2009	13.4%
611513	Apprenticeship training programs; Carpenters’ apprenticeship training; Craft union apprenticeship training programs; Electricians’ apprenticeship training; Mechanic’s apprenticeship training; Plumbers’ apprenticeship training; Sheet metal workers’ apprenticeship training; Steam fitters’ apprenticeship training; Trade union apprenticeship training programs; Vocational apprenticeship training	426	3241	13.1%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
114210	Animal trapping, commercial; Fishing preserves; Game preserves, commercial; Game propagation; Game retreats; Hunting preserves	139	1063	13.1%
713990	**Amateur sports teams, recreational**; Amusement device (except gambling) concession operators (i.e., supplying and servicing in others' facilities); Amusement ride concession operators (i.e., supplying and servicing in others' facilities); Archery ranges; **Athletic clubs** (i.e., sports teams) not operating sports facilities, recreational; Aviation clubs, recreational; Ballrooms; Baseball clubs, recreational; Basketball clubs, recreational; Bathing beaches; Beach clubs, recreational; Beaches, bathing; Billiard parlors; Billiard rooms; Boating clubs without marinas; Boccie ball courts; Bowling leagues or teams, recreational; Boxing clubs, recreational; Boys' day camps (except instructional); Bridge clubs, recreational; Camps (except instructional), day; Canoeing, recreational; Carnival ride concession operators (i.e., supplying and servicing in others' facilities); Coin-operated nongambling amusement device concession operators (i.e., supplying and servicing in others' facilities); Concession operators, amusement device (except gambling) and ride; Curling facilities; Dance halls; Discotheques (except those serving alcoholic beverages); Driving ranges, golf; Fireworks display services; Fishing clubs, recreational; Fishing guide services; Fishing piers; Flying clubs, recreational; Football clubs, recreational; Galleries, shooting; Girls' day camps (except instructional); Gocart raceways (i.e., amusement rides); Gocart tracks (i.e., amusement rides); Golf courses, miniature; Golf courses, pitch-n-putt; Golf driving ranges; Golf practice ranges; Guide services (i.e., fishing, hunting, tourist); Guide services, fishing; Guide services, hunting; Guide services, tourist; Gun clubs, recreational; Hockey clubs, recreational; Hockey teams, recreational; Horse rental services, recreational saddle; Horseback riding, recreational; Hunting clubs, recreational; Hunting guide services; Ice hockey clubs, recreational; Jukebox concession operators (i.e., supplying and servicing in others' facilities); Kayaking, recreational; Lawn bowling clubs; Miniature golf courses; Mountain hiking, recreational; Nightclubs without alcoholic beverages; Nudist camps without accommodations; Observation towers; Outdoor adventure operations (e.g., white water rafting) without accommodations; Pack trains (i.e., trail riding), recreational; Paintball, laser tag, and similar fields and arenas; Para sailing, recreational; Picnic grounds; Pinball machine concession operators (i.e., supplying and servicing in others' facilities); Ping pong parlors; Pool halls; Pool parlors; Pool rooms; Racetracks, slot car (i.e., amusement devices); Raceways, gocart (i.e., amusement rides); Recreational camps without accommodations; Recreational day camps (except instructional); Recreational sports clubs (i.e., sports teams) not operating sports facilities; Recreational sports teams and leagues; Riding clubs, recreational; Riding stables; Rifle clubs, recreational; River rafting, recreational; Rowing clubs, recreational; Saddle horse rental services, recreational; Sailing clubs without marinas; Sea kayaking, recreational; Shooting clubs, recreational; Shooting galleries; Shooting ranges; Skeet shooting facilities; Slot car racetracks (i.e., amusement devices); Snowmobiling, recreational; Soccer clubs, recreational; Sports clubs (i.e., sports teams) not operating sports facilities, recreational; Sports teams and leagues, recreational or youth; Stables, riding; Summer day camps (except instructional); Tourist guide services; Trail riding, recreational; Trampoline facilities, recreational; Trapshooting facilities, recreational; Waterslides (i.e., amusement rides); White water rafting, recreational; Yacht clubs without marinas; Youth sports league teams	3413692	28640	12.9%
624410	Babysitting services in provider's own home, child day care; Babysitting services, child day care; Child day care centers; **Child day care services**; Child day care services in provider's own home; Child day care, before or after school, separate from schools; Day care centers, child or infant; Day care services, child or infant; Group day care centers, child or infant; **Head start programs**, separate from schools; Infant day care centers; Infant day care services; Nursery schools; Pre-kindergarten centers (except part of elementary school system); **Preschool centers**	7472	58746	12.7%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
711130	Bands; Bands, dance; Bands, musical; Chamber musical groups; Chamber orchestras; Choirs; Classical musical artists, independent; Classical musical groups; Concert artists, independent; Country musical artists, independent; Country musical groups; Dance bands; Drum and bugle corps (i.e., drill teams); Ensembles, musical; Jazz musical artists, independent; Jazz musical groups; Musical artists, independent; Musical groups (except musical theater groups); Musical productions (except musical theater productions), live; Musicians, independent; Opera singers, independent; Orchestras; Popular musical artists, independent; Popular musical groups; Rock musical artists, independent; Rock musical groups; Singers, independent; Soloists, independent musical; Symphony orchestras; Vocalists, independent	932	7566	12.3%
922110	Administrative courts; Circuit courts; City or county courts; Courts of law, civilian (except American Indian or Alaska Native); Courts, civilian (except American Indian or Alaska Native); Courts, small claims; Sheriffs' offices, court functions only; Traffic courts	1277	10513	12.1%
522294	Federal Agricultural Mortgage Corporation; Federal Home Loan Mortgage Corporation (FHLMC); Federal Intermediate Credit Bank; Federal National Mortgage Association (FNMA); FHLMC (Federal Home Loan Mortgage Corporation); Financing, secondary market; FNMA (Federal National Mortgage Association); GNMA (Government National Mortgage Association); Government National Mortgage Association (GNMA); Government-sponsored enterprises providing secondary market financing; Real estate mortgage investment conduits (REMICs) issuing, private; REMICs (real estate mortgage investment conduits) issuing, private; Repackaging loans for sale to others (i.e., private conduits); Secondary market financing (i.e., buying, pooling, repackaging loans for sale to others); SLMA (Student Loan Marketing Association); Student Loan Marketing Association (SLMA)	38	313	12.1%
923120	Cancer detection program administration; Communicable disease program administration; Community health programs administration; Coroners' offices; Environmental health program administration; Food service health inspections; Health planning and development agencies, government; Health program administration; Health statistics centers, government; Immunization program administration; Maternity and child health program administration; Mental health program administration; Public health program administration, nonoperating	915	7592	12.1%
922130	Attorney generals' offices; District attorneys' offices; Legal counsel offices, government; Public defenders' offices; Public prosecutors' offices; Solicitors' offices, government; U. S. attorneys' offices	359	3016	11.9%
926110	**Arts and cultural program administration**, government; Consumer protection offices; Councils of Economic Advisers; Cultural and arts development support program administration; Development assistance program administration; **Economic development agencies**, government; Energy development and conservation agencies, nonoperating; Energy program administration; Enterprise development program administration; General economics statistical agencies; Industrial development program administration; Labor statistics agencies; Small business development agencies; Tourism development offices, government; Trade commissions, government; Trade development program administration	257	2224	11.6%
525110	Employee benefit pension plans; Funds, employee benefit pension; Funds, pension; Pension funds; Pension plans (e.g., employee benefit, retirement); Plans, pension; Retirement pension plans; Union pension funds	98	863	11.4%
524114	Dental insurance carriers, direct; Group hospitalization plans without providing health care services; Health insurance carriers, direct; Hospital and medical service plans, direct, without providing health care services; Hospitalization insurance carriers, direct, without providing health care services; Insurance carriers, health, direct; Insurance underwriting, health and medical, direct; Medical insurance carriers, direct; Medical service plans without providing health care services	397	3497	11.4%

NAICS12	NAICS Description	Non-Profit Count	Total Establishments	Percent Non-Profit
485113	Bus line, local (except mixed mode); Bus services, urban and suburban (except mixed mode); Bus transit systems (except mixed mode); City bus services (except mixed mode); Commuter bus operation (except mixed mode); Local bus services (except mixed mode); Suburban bus line services (except mixed mode); Urban bus line services (except mixed mode)	78	696	11.2%
611630	Foreign language schools; **Language schools**; Schools, language; Second language instruction; Sign language instruction; Sign language schools	99	910	10.9%
523991	Administrators of private estates; Bank trust offices; Escrow agencies (except real estate); Fiduciary agencies (except real estate); Personal investments trust administration; Securities custodians; Trust administration, personal investment; Trust companies, nondepository	383	3240	11.8%
611699	Bible schools (except degree granting); Bridge and other card game instruction; Charm schools; CPR (cardiac pulmonary resuscitation) training and certification; Diction schools; First aid instruction; Life guard training; Public speaking training; Self defense (except martial arts) instruction; Speed reading instruction; Survival training instruction; Yoga instruction, camps, or schools	343	3166	10.8%
921140	Executive and legislative office combinations; Legislative and executive office combinations	124	1172	10.6%
621610	Home care of elderly, medical; Home health agencies; Home health care agencies; Home nursing services (except private practices); Hospice care services, in home; Nurse associations, visiting; Nursing agencies, primarily providing home nursing services; Visiting nurse associations	1677	16718	10.0%

Note: Tabulations based on the National Establishment Time Series. Percent non-profit is based on observations with non-missing legal status field. Observations are rank-ordered by this percentage. For descriptions, see https://www.census.gov/eos/www/naics/ (viewed March 30, 2017). In the NETS data, some establishments were never assigned a 6-digit code. So instead of dropping these, we include them as is. One of these (NAICS 4-digit code 6241) appears in our list of industries with a high share of non-profit establishments.

Table 3: Demographic, Prior Social Capital Measures, and Neighborhood Labor Market Network Regressions, Using Per Worker Network Measure NI_c^W and Per Person Network Measure NI_c^P, OLS Estimates

	NI_c^W				NI_c^P			
				+ state FEs				+ state FEs
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Poor	1.083***	1.044***	0.935***	1.101***	0.345***	0.314***	0.390***	0.472***
	(0.184)	(0.187)	(0.122)	(0.114)	(0.098)	(0.098)	(0.062)	(0.060)
Hispanic	-1.128***	-0.645***	-0.534***	-0.564***	-0.728***	-0.363***	-0.285***	-0.284***
	(0.165)	(0.180)	(0.142)	(0.144)	(0.101)	(0.103)	(0.072)	(0.072)
Black, non-Hispanic	-0.753***	-0.397***	0.032	-0.014	-0.577***	-0.347***	-0.017	-0.006
	(0.075)	(0.109)	(0.106)	(0.111)	(0.046)	(0.061)	(0.055)	(0.058)
Asian, non-Hispanic	0.282	0.687**	0.608*	0.487	0.142	0.473**	0.423**	0.366*
	(0.415)	(0.340)	(0.343)	(0.343)	(0.250)	(0.199)	(0.195)	(0.194)
Other race, non-Hispanic	-0.388	0.491	-0.430	-0.585**	-0.881*	-0.254	-0.492**	-0.469***
	(0.748)	(0.656)	(0.322)	(0.237)	(0.473)	(0.369)	(0.192)	(0.113)
Non-native	0.407	0.725***	1.118***	1.039***	0.282	0.464***	0.702***	0.642***
	(0.267)	(0.244)	(0.222)	(0.199)	(0.172)	(0.137)	(0.118)	(0.101)
Currently married	2.747***	1.823***	0.727***	0.817***	1.543***	0.927***	0.313***	0.364***
	(0.275)	(0.252)	(0.134)	(0.122)	(0.149)	(0.136)	(0.070)	(0.064)
Education < high school	0.429***	0.510***	0.696***	0.810***	0.078	0.138	0.326***	0.427***
	(0.209)	(0.190)	(0.133)	(0.117)	(0.135)	(0.112)	(0.073)	(0.065)
Education ≥	0.048	0.211	0.819***	0.938***	-0.052	0.024	0.463***	0.571***
Bachelor's degree	(0.145)	(0.159)	(0.122)	(0.128)	(0.090)	(0.096)	(0.074)	(0.075)
Commute < 10 minutes	5.098***	4.663***	1.065***	1.025***	3.112***	2.825***	0.621***	0.572***
	(0.233)	(0.210)	(0.118)	(0.117)	(0.147)	(0.132)	(0.068)	(0.067)
Commute by driving alone	-0.504***	-0.667***	-0.478***	-0.300**	-0.153	-0.224**	-0.192**	-0.071
	(0.197)	(0.187)	(0.137)	(0.126)	(0.107)	(0.101)	(0.075)	(0.069)
Share did not move	1.083***	1.329***	0.824***	0.433***	0.780***	0.910***	0.574***	0.289***
in last year	(0.237)	(0.171)	(0.114)	(0.096)	(0.150)	(0.096)	(0.069)	(0.055)
Share housing	0.090	0.038	0.282***	0.326***	0.071	0.033	0.178***	0.210***
owner-occupied	(0.150)	(0.121)	(0.103)	(0.107)	(0.085)	(0.064)	(0.055)	(0.058)
Observed tract average	…	…	1.251***	1.263***	…	…	1.233***	1.250***
transport isolation index,			(0.022)	(0.021)			(0.018)	(0.017)
per worker								
Count of NETS	…	…	0.061***	0.064***	…	…	0.035***	0.037***
establishments (100s)			(0.006)	(0.007)			(0.004)	(0.004)
Number of districts	…	0.045***	0.058***	0.059***	…	0.031***	0.040**	0.036**
		(0.013)	(0.012)	(0.012)		(0.008)	(0.008)	(0.008)
Average number of tracts	…	-0.021*	-0.005	-0.006	…	-0.010	-0.002	-0.002
in school district(s)		(0.013)	(0.005)	(0.005)		(0.007)	(0.003)	(0.003)
Student/teacher ratio	…	-0.039***	-0.024***	-0.000	…	-0.032***	-0.019***	-0.002
		(0.008)	(0.008)	(0.009)		(0.005)	(0.005)	(0.006)
Free/reduced-price	…	-0.180*	-0.144**	-0.069	…	-0.204**	-0.147**	-0.100***
lunch share		(0.093)	(0.071)	(0.063)		(0.057)	(0.043)	(0.037)
Majority vote share	…	0.705***	0.002	0.074	…	0.458***	0.000	0.056
		(0.236)	(0.191)	(0.182)		(0.135)	(0.106)	(0.099)
Democratic vote share	…	-1.656***	-0.859***	-0.878***	…	-1.051***	-0.574***	-0.618***
		(0.242)	(0.125)	(0.122)		(0.147)	(0.071)	(0.066)
Voter turnout	…	0.200***	0.039	0.032	…	0.151***	0.042*	0.032
		(0.048)	(0.036)	(0.034)		(0.030)	(0.021)	(0.021)
R^2	0.284	0.322	0.686	0.700	0.326	0.373	0.721	0.734

Notes: Results are for Ordinary Least Squares with robust standard errors in parentheses, with clustering at the county level (590 counties). There are approximately 33,000 Census tract observations. See Tables 1 and 2 for variable definitions.

Table 4: Social Capital and Neighborhood Labor Market Network Regressions, Using Per Worker Network Measure NI_c^W, LASSO with Alternative Controls

			+ state FEs	
Variables	(1)	(2)	(3)	(4)
Poor	1.126***	0.983***	1.510***	1.112***
	(0.185)	(0.112)	(0.182)	(0.111)
Hispanic	-0.599***	-0.632***	-0.560***	-0.563***
	(0.178)	(0.140)	(0.199)	(0.141)
Black, non-Hispanic	-0.410***	0.102	-0.412***	-0.017
	(0.094)	(0.089)	(0.088)	(0.098)
Asian, non-Hispanic	0.627*	0.472	0.459	0.501
	(0.322)	(0.368)	(0.311)	(0.341)
Other race, non-Hispanic	0.534	-0.591	-0.086	-0.598***
	(0.652)	(0.388)	(0.679)	(0.227)
Non-native	0.738***	1.145***	0.572**	1.053***
	(0.241)	(0.266)	(0.224)	(0.198)
Currently married	2.008***	0.806***	2.052***	0.818***
	(0.245)	(0.128)	(0.247)	(0.125)
Education < high school	0.129	0.576***	0.329*	0.725***
	(0.185)	(0.133)	(0.185)	(0.117)
Education ≥ Bachelor's degree	0.163	0.840***	0.396***	0.950***
	(0.149)	(0.107)	(0.136)	(0.122)
Commute < 10 minutes	4.043***	1.127***	3.811***	0.999***
	(0.198)	(0.115)	(0.186)	(0.113)
Commute by driving alone	-0.722***	-0.543***	-0.431***	-0.332***
	(0.192)	(0.145)	(0.163)	(0.127)
Share did not move in last year	1.300***	0.831***	0.741***	0.447***
	(0.162)	(0.144)	(0.145)	(0.098)
Share housing owner-occupied	0.131	0.352***	0.233*	0.340***
	(0.117)	(0.118)	(0.119)	(0.108)
Observed tract average transport isolation index, per worker	…	1.263***	…	1.256***
		(0.023)		(0.022)
Count of NETS establishments (100s)	…	0.070***	…	0.064***
		(0.007)		(0.007)
Number of districts			0.052***	0.057***
			(0.012)	(0.012)
Average number of tracts in school district(s)	-0.017*			-0.006
	(0.010)			(0.004)
Student/teacher ratio	-0.034***			
	(0.008)			
Free/reduced-price lunch share				
Majority vote share				
Democratic vote share	-1.243***	-0.846***	-1.334***	-0.819***
	(0.196)	(0.128)	(0.153)	(0.140)
Voter turnout				

Continued on next page.

Table 4 (continued): Non-Profit Industries Selected, and Estimated Effects, NI_c^W

			+ state FEs	
NAICS codes (description-see Table 2)	(1)	(2)	(3)	(4)
813319 (advocacy organizations)				
813410 (hobby clubs, Scouts, PTAs, civic and fraternal associations)	0.018***		0.016***	
	(0.006)		(0.006)	
813920 (professional associations)		-0.025***		-0.032***
		(0.006)		(0.006)
813110 (churches, mosques, synagogues, missions)	0.028***		0.031***	
	(0.004)		(0.003)	
922160 (fire and rescue services including volunteer fire dept.'s)	0.134***	0.093***	0.098***	0.042***
	(0.019)	(0.013)	(0.017)	(0.011)
611110 (elementary, junior, secondary schools)	0.047***		0.041***	
	(0.006)		(0.005)	
623990 (boot camps, group foster homes)				
621910 (ambulance or rescue services)	0.067***		0.055***	
	(0.023)		(0.020)	
922120 (police departments, park police, housing police)	0.018	0.068***	0.009	0.032***
	(0.016)	(0.012)	(0.015)	(0.010)
921110 (advisory commissions, city, executive, and mayors' offices)	0.021*		0.020*	0.028***
	(0.012)		(0.011)	(0.008)
713910 (country clubs and golf courses)	0.178***	0.123***	0.172***	0.117***
	(0.027)	(0.018)	(0.025)	(0.017)
611710 (education support and testing services)				
813940 (campaign organizations, political organizations, PACs)		-0.050***		
		(0.015)		
812220 (cemeteries, memorial gardens)	0.045***		0.033**	
	(0.015)		(0.014)	
221320 (sewage disposal, waste collection)				
541720 (soc. sci./humanities research and development services)				
923110 (education supervisors and offices)				
623110 (nursing homes, group homes, convalescent homes)	0.034***		0.032***	
	(0.008)		(0.008)	
713990 (amateur/recreational sports teams, and sports-related clubs)	0.049***		0.039***	
	(0.009)		(0.008)	
624410 (child care and preschool centers, Head Start)		-0.026***	0.016***	
		(0.004)	(0.005)	
926110 (arts/cultural, econ. devel., etc., administration)				
611630 (language schools)				
R^2	0.357	0.685	0.394	0.703

Notes: Results are for Ordinary Least Squares with robust standard errors in parentheses, with clustering at the county level (590 counties). There are approximately 33,000 Census tract observations. See Tables 1 and 2 for variable definitions. All models include neighborhood demographic variables (displayed), but only models 3 and 4 include state fixed effects (not displayed). For all models, the included variables for school districts, voting, and non-profits were pre-selected using a LASSO regression (Equation 4) that included all of the displayed variables as well as all of those in Tables 1 and 2 (see text for details).

Table 5: Social Capital and Neighborhood Labor Market Network Regressions, Using Per Person Network Measure NI_c^P, LASSO with Alternative Controls

			+ state FEs	
Variables	(1)	(2)	(3)	(4)
Poor	0.369***	0.425***	0.582**	0.487***
	(0.096)	(0.058)	(0.096)	(0.057)
Hispanic	-0.360***	-0.374***	-0.295***	-0.287***
	(0.103)	(0.072)	(0.109)	(0.074)
Black, non-Hispanic	-0.358***	0.022	-0.290***	0.001
	(0.057)	(0.044)	(0.052)	(0.053)
Asian, non-Hispanic	0.426**	0.276	0.336*	0.379**
	(0.189)	(0.206)	(0.177)	(0.193)
Other race, non-Hispanic	-0.262	-0.574***	-0.517	-0.464***
	(0.378)	(0.270)	(0.350)	(0.110)
Non-native	0.481***	0.768***	0.379***	0.652***
	(0.137)	(0.148)	(0.118)	(0.103)
Currently married	1.064***	0.344***	1.063***	0.388***
	(0.132)	(0.066)	(0.134)	(0.065)
Education < high school	-0.114	0.250***	0.063	0.349***
	(0.117)	(0.075)	(0.117)	(0.065)
Education ≥ Bachelor's degree	0.030	0.531***	0.245***	0.596***
	(0.093)	(0.067)	(0.083)	(0.073)
Commute < 10 minutes	2.459***	0.618***	2.264***	0.561***
	(0.126)	(0.066)	(0.117)	(0.067)
Commute by driving alone	-0.275***	-0.275***	-0.086	-0.104
	(0.104)	(0.083)	(0.089)	(0.071)
Share did not move in last year	0.897***	0.616***	0.501***	0.299***
	(0.092)	(0.086)	(0.086)	(0.057)
Share housing owner-occupied	0.094	0.215***	0.160**	0.224***
	(0.061)	(0.060)	(0.062)	(0.058)
Observed tract average transport isolation index, per person	…	1.248***	…	1.251***
		(0.019)		(0.017)
Count of NETS establishments	…	0.047***	…	0.047***
		(0.004)		(0.004)
Number of districts			0.028***	0.034***
			(0.007)	(0.008)
Average number of tracts in school district(s)	-0.010	-0.012***		-0.004
	(0.006)	(0.004)		(0.003)
Student/teacher ratio	-0.028***			
	(0.005)			
Free/reduced-price lunch share				
Majority vote share				
Democratic vote share	-0.790***	-0.529***	-0.909***	-0.557***
	(0.117)	(0.071)	(0.088)	(0.075)
Voter turnout				

Continued on next page.

Table 5 (continued): Non-Profit Industries Selected, and Estimated Effects, NI_c^P

NAICS codes (description-see Table 2)	(1)	(2)	+ state FEs (3)	(4)
813319 (advocacy organizations)		-0.009**		
		(0.004)		
813410 (hobby clubs, Scouts, PTAs, civic and fraternal associations)	0.005		0.005*	
	(0.003)		(0.003)	
813920 (professional associations)				-0.010**
				(0.005)
813110 (churches, mosques, synagogues, missions)	0.016***		0.018***	
	(0.002)		(0.002)	
922160 (fire and rescue services including volunteer fire dept.'s)	0.091***	0.064***	0.067***	0.034***
	(0.011)	(0.008)	(0.011)	(0.007)
611110 (elementary, junior, secondary schools)	0.032***		0.028***	
	(0.004)		(0.003)	
623990 (boot camps, group foster homes)		-0.020***		
		(0.005)		
621910 (ambulance or rescue services)	0.047***		0.038***	
	(0.015)		(0.013)	
922120 (police departments, park police, housing police)	0.006	0.037***		0.027***
	(0.009)	(0.007)		(0.006)
921110 (advisory commissions, city, executive, and mayors' offices)	0.009		0.007	
	(0.007)		(0.006)	
713910 (country clubs and golf courses)	0.114***	0.076***	0.107***	0.071***
	(0.016)	(0.010)	(0.015)	(0.009)
611710 (education support and testing services)		-0.009***		-0.007***
		(0.003)		(0.003)
813940 (campaign organizations, political organizations, PACs)		-0.019**		
		(0.008)		
812220 (cemeteries, memorial gardens)	0.039***		0.030***	
	(0.010)		(0.009)	
221320 (sewage disposal, waste collection)	0.095***			
	(0.029)			
541720 (soc. sci./humanities research and development services)		-0.023***		-0.020***
		(0.006)		(0.006)
923110 (education supervisors and offices)				-0.005
				(0.004)
623110 (nursing homes, group homes, convalescent homes)	0.025***		0.024***	
	(0.005)		(0.005)	
713990 (amateur/recreational sports teams, and sports-related clubs)	0.030***		0.024***	
	(0.0005)		(0.005)	
624410 (child care and preschool centers, Head Start)		-0.015***	0.012***	-0.009***
		(0.002)	(0.003)	(0.002)
926110 (arts/cultural, econ. devel., etc., administration)		-0.041***		-0.039***
		(0.009)		(0.010)
611630 (language schools)		-0.053***		-0.045***
		(0.015)		(0.013)
R^2	0.401	0.719	0.440	0.737

Notes: See notes to Tables 1, 2, and 4.

Appendix Table A1: Non-Profit Counts by Tract, Any NAICS Codes Retained by LASSO

Non-profit counts by tract	Mean	Std. Dev.
813319 (advocacy organizations)	0.34	0.82
813410 (hobby clubs, Scouts, PTAs, civic and fraternal associations)	1.18	1.94
813920 (professional associations)	0.31	1.09
813110 (churches, mosques, synagogues, missions)	4.43	3.88
922160 (fire and rescue services including volunteer fire dept.'s)	0.13	0.42
611110 (elementary, junior, secondary schools)	1.50	1.49
922120 (police departments, park police, housing police)	0.13	0.48
621910 (ambulance or rescue services)	0.07	0.31
713910 (country clubs and golf courses)	0.09	0.34
921110 (advisory commissions, city, executive, and mayors' offices)	0.19	0.78
611710 (education support and testing services)	0.69	1.15
813940 (campaign organizations, political organizations, PACs)	0.06	0.30
812220 (cemeteries, memorial gardens)	0.10	0.36
221320 (sewage disposal, waste collection)	0.02	0.14
541720 (soc. sci./humanities research and development services)	0.19	0.60
623110 (nursing homes, group homes, convalescent homes)	0.35	0.85
713990 (amateur/recreational sports teams, and sports-related clubs)	0.62	0.98
624410 (child care and preschool centers, Head Start)	1.87	1.93
926110 (arts/cultural, econ. devel., etc., administration)	0.03	0.36
611630 (language schools)	0.03	0.21