

NBER WORKING PAPER SERIES

SOCIAL CAPITAL AND LABOR MARKET NETWORKS

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

Working Paper 23959  
<http://www.nber.org/papers/w23959>

NATIONAL BUREAU OF ECONOMIC RESEARCH

1050 Massachusetts Avenue  
Cambridge, MA 02138  
October 2017, Revised January 2019

This research was supported by the Russell Sage Foundation. Opinions expressed in this paper are those of the authors and not necessarily those of the U.S. Census Bureau, the Federal Deposit Insurance Corporation, the Russell Sage Foundation, or the National Bureau of Economic Research. Much of the work for this analysis was done while Mark Kutzbach was an employee of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. We are grateful to Andrew Foote, Matt Harding, Christian Hansen, Lisa Hellerstein, Thomas Hegland, Erika McEntarfer, Chun (KC) Kuang, and Arezou Koochi for helpful comments and discussions. This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by National Science Foundation Grants SES-9978093, SES-0339191, and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2017 by Brian J. Asquith, Judith K. Hellerstein, Mark J. Kutzbach, and David Neumark. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Social Capital and Labor Market Networks

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

NBER Working Paper No. 23959

October 2017, Revised January 2019

JEL No. J01,J64,R23

### **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-profit sector establishments at the neighborhood level. We use a machine learning algorithm to identify important 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, police departments, fire and rescue services including volunteer fire departments, country clubs, mayors' offices, chamber music groups, hobby clubs, and museums.

Brian J. Asquith  
W. E. Upjohn Institute  
300 S Westnedge Avenue  
Kalamazoo, MI 49007  
United States  
basquith86@gmail.com

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

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

David Neumark  
Department of Economics  
University of California, 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.”<sup>1</sup> In this paper, we explore the links between measures of social capital and labor market networks 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 type 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 yielding successful labor market outcomes. 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 even more specifically from recent empirical research showing that networks based in residential communities or neighborhoods improve labor market outcomes for local residents, including higher wages, longer tenure, and for individuals displaced from jobs, faster re-employment (Hellerstein et al., 2014, and Hellerstein et al., 2016).<sup>2</sup>

---

<sup>1</sup> See [https://en.oxforddictionaries.com/definition/social\\_capital](https://en.oxforddictionaries.com/definition/social_capital) (viewed August 23, 2017). Portes (1998) discusses the history of the term and reviews how it has been used in the field of sociology.

<sup>2</sup> 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

The goal of our study is to explore the connection between social capital and labor market networks. Given, on the one hand, strong interest in social capital, and, on the other hand, all of the work documenting the importance of neighborhood-based labor market networks to labor market outcomes of its residents, we ask what we view as a fundamental question that has not been explored previously: When social capital is higher in a neighborhood, are neighbors better networked in terms of the jobs they hold? In addressing this question, we make four key contributions to the research literature on both social capital and labor market networks. First, we connect these two literatures by asking how neighborhood levels of social capital are linked to the strength of local labor market networks. Second, we draw on a unique data set – the National Establishment Time Series, or NETS – to construct novel measures of location-based social capital based on the non-profit sector. Third, given that we have many potential social capital measures, we use a machine learning algorithm to select the measures that are predictive of the strength of local labor market networks, rather than making a priori assumptions about which social capital measures belong in our empirical specifications. And fourth, we examine the link between social capital and labor market networks using a local labor market network measure that, as discussed below, we have previously demonstrated to be important for labor market outcomes.

The social capital measures we study have been hypothesized in the previous literature to increase connections among neighbors and should also foster labor market networks as we measure them. We construct neighborhood-level measures of social capital that fit into four broad categories.

First, we construct measures reflecting 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

---

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.

set of variables that could plausibly reflect the extent of 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 use 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 reflection 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.<sup>3</sup> 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 Ferrara, 2002), and, in this case, would indicate that others in your community share your beliefs.

Finally, the major focus of our paper is to build on past work suggesting that civic institutions (e.g., Coleman, 1988; Putnam, 2000), religious organizations (e.g., Putnam, 2000; Putnam and Campbell, 2012), 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. Specifically, we use data on the universe of establishments, from the National Establishment Time Series (NETS), to measure the number and

---

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

composition of non-profits by Census tract, and we explore – using our machine learning methods – which ones are associated with evidence of stronger labor market networks.

To be clear, our main contribution with regard to social capital is our exploration of the role of non-profits, via the introduction of this new data. We use the other social capital measures, derived from the literature, in part to reflect that literature, but also to establish whether the estimated effects of the non-profit-related social capital measures we introduce are likely to reflect variation in social capital that is independent of the proxies for social capital others have proposed. Our inclusion of these other proxies should not be viewed as us insisting that these measures from the literature in fact reflect social capital.

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 matched employer-employee data links persons to residences and, if they are employed in a job covered by Unemployment Insurance, to the locations of establishments of 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.<sup>4</sup>

The measure of clustering we use captures the network connections between neighbors arising from either of these two models. Of course, as in nearly all research on labor market networks, we cannot directly observe the flow of information about jobs or applicants in the labor market. However, our past work has, in our view, validated the measure we use as capturing the effects of this flow of information. In particular, our network measure is associated with higher wages for employed workers and longer job tenure (Hellerstein et al., 2014), both consistent with better labor market matches when our network measure is higher. And it is associated with faster re-employment of workers who lose jobs in mass layoffs, and a higher likelihood of re-employment at a neighbor's employer (Hellerstein et al., 2016), consistent with employed neighbors providing referrals to their employers, or providing information about job vacancies to unemployed workers in their network.

Moreover, our network measure of the extent to which neighbors are clustered at the same employer could potentially reflect other influences. As a result, in our past work we have used rich models to control for other – non-network – sources of relationships between our empirical network measure and these outcomes, mostly related to either variation in the strength of local labor markets, and sorting of workers across geographic locations who likely to experience similar labor market outcomes, including taking similar jobs. For example, in our work on re-employment after mass layoffs (Hellerstein et al., 2016), we control for highly-detailed fixed effects so that we identify the effect of networks from subgroups of workers who experience the same mass layoff at the same employer in the same county, and who differ only in terms of the Census tract in which they reside – and the variation in the network measure across those tracts. And in asking whether our network measure is associated with higher wages or longer job matches (Hellerstein et al., 2014), we net out (via potential controls in our regressions) variation in the network measure that could be explained by neighbors tending to work in the same Census tract – which would inevitably lead to some working at the same employer – because of transportation infrastructure or simple geographic proximity.

---

<sup>4</sup> Jackson (2008, Chapter 10) provides a transparent discussion and comparison of these models.

As a result of these prior analyses, we assume that our empirical network measure is related to the flow of information about jobs between neighbors. 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. While our network measure is an indirect measure of the underlying “construct,” which is the flow of information – in this case, between neighbors – we believe this interpretation of our measure is supported by the extensive prior research we have conducted. We do not 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 et al. (2014), which, in part, examines how factors varying across geographies correlate with upward mobility. More closely related – although focused on 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.<sup>5</sup>

Given the exploratory nature of this paper, and the large number 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

---

<sup>5</sup> 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 – but are included in our data – can play a role in enhancing social capital.

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. Our measure, developed in Hellerstein et al. (2011), uses worker-level data and 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.

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. 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:

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

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.<sup>6</sup>

We 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 a natural metric because it is derived from the individual network measure developed and tested previously by Hellerstein et al. (2011). 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. Then, at the community level, the community network index is the average of the network indexes of each of the neighbors:

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

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  $P$  signifies that this measure is calculated over people, not workers. It is measured as:

---

<sup>6</sup> We define workers at single-employee firms (who have no co-workers) as having an  $NI_{ic}$  of zero.

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

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 networks 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  $NI_c^P$ .

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 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.<sup>7</sup> 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 (Graham et al., 2017). 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 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 approximately 110 million primary jobs that were active on April 1, 2010, where a primary job is defined as the highest earning job that a person holds.<sup>8,9</sup> 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.<sup>10</sup> 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

---

<sup>7</sup> 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.

<sup>8</sup> 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.

<sup>9</sup> 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 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. Our definition of employment omits those who were not employed by the same employer over the two quarters, even if they worked in both quarters; these individuals may have had job-to-job transitions or periods of non-employment.

<sup>10</sup> 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.

networking across groups are not affected by using the imputation.<sup>11</sup> 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  $NI_c^P$ .

### 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. 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. 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).<sup>12</sup>

There are three reasons to include these demographic variables in the analysis. First, for our network measure  $NI_c^P$ , individuals who are not employed contribute a value of zero to the tract average. Their non-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.

---

<sup>11</sup> 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.

<sup>12</sup> 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.

Second, even for the network measure  $NI_c^W$  that excludes the non-employed, previous research (e.g. Hellerstein et al., 2011 and 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 (Portes, 1998). The third reason to include these controls as candidates in our machine learning algorithm is that there is evidence that demographic characteristics are key to producing social capital and social trust (Alesina and La Ferrara, 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.<sup>13</sup>

We 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 whether neighborhood social capital that is school-based also translates into more networked labor markets. We first

---

<sup>13</sup> 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 forfeiting opportunity to expand one's social ties.

overlay a 2010 map of U.S. Census Bureau school district boundaries onto a map of Census tracts.<sup>14</sup> 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 the Census tract level. We view these measures as motivated directly by the social capital literature cited

---

<sup>14</sup> 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.

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 our other data, we use observations on establishments for the year 2010.

The NETS is constructed by Walls & Associates from Dun & Bradstreet (D&B) data.<sup>15</sup> 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 provide information on businesses to the business community, by constructing a set of "predictive indicators" (e.g., the D&B rating and Paydex

---

<sup>15</sup> For more details, see <http://exceptionalgrowth.org/downloads/NETSDatabaseDescription2013.pdf> (viewed November 30, 2017), Neumark (2007), and the appendix of Neumark et al. (2011).

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 well 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 do not appear in the LEHD (Stevens, 2007).<sup>16</sup>

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

---

<sup>16</sup> 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."

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 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 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.<sup>17</sup> And some of the businesses or institutions in the non-profit sector that we study may play this role at a more aggregate level than the Census tract.

#### **IV. Machine Learning: LASSO**

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 (Townsend, 2017).<sup>18</sup> LASSO

---

<sup>17</sup> See, for example, <https://www.usajobs.gov/> (viewed December 4, 2017).

<sup>18</sup> Townsend’s method is itself a STATA implementation of the recommended LASSO algorithm developed in Friedman et al. (2010).

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 (2018), 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, 2018).

The key to understanding LASSO starts by examining the objective function when seeking to estimate a vector of parameters  $\beta$  (Tibshirani, 1996):

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

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  $l$ ).<sup>19</sup> When researchers do not have strong priors as to which observable characteristics belong 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 researcher 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 penalty factor  $\lambda$  is selected by the LASSO algorithm.<sup>20</sup> The LASSO estimation procedure identifies the set of parameters

---

<sup>19</sup> 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.

<sup>20</sup> There are many different methods for calibrating  $\lambda$ , but the Townsend (2017) implementation uses cross-validation. In cross-validation, the sample is randomly split into several, equal-sized “folds.” On  $K-1$  of the folds, the coefficients and penalty factor are calculated, and then on the  $k$ th fold, they are applied as a validation exercise to calculate the out-of-sample error. Repeating this exercise leaving out one fold each time, the penalty factor that minimizes the out-of-sample error is chosen to be reapplied to the entire sample.

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 (Belloni and Chernozhukov, 2013).<sup>21</sup>

The candidate  $x$  variables that we have collected and grouped 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. We sometimes include two other variables in our LASSO algorithm. One is what we call a “transport isolation index” (similar to Hellerstein et al., 2014). This variable 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 information 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 allow for the possibility that observed network isolation 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  $NI_{ic}$  (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

---

<sup>21</sup> A LASSO regression induces shrinkage on the coefficients, relative to what the same coefficient estimates would be under OLS. Performing OLS after model selection has the virtue of eliminating the shrinkage bias while achieving similar convergence properties as the LASSO itself. This result is somewhat dependent on the LASSO selecting an appropriately “sparse” model – i.e., a model where the number of selected variables is small relative to the number of candidate variables. However, even if model does not achieve sparsity, running OLS after LASSO still retains the virtue of eliminating the shrinkage bias.

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 potential control 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 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.

Finally, in order to control for state fixed effects, in some models we first “residualize” both the dependent variable and all the candidate social capital measures by regressing each of them individually on the fixed effects (Frisch and Waugh, 1933; Lovell, 1963). We then run the LASSO procedure on the residualized variables, effectively partialling out the state fixed effects, and using only the remaining within-state variation in those models. For all of the variables we include in the models (with the exception of the state fixed effects), we allow the LASSO procedure to pick the variables that remain, and then we re-estimate the model using OLS with just these variables. Both the variable selection and the ensuing estimated coefficients tell us whether and which of the social capital proxies are related to neighborhood labor market networks.

One current limitation of LASSO is that conducting proper inference can be challenging. Computing standard errors from LASSO coefficients themselves is non-trivial, because the LASSO function is a non-linear and non-differentiable function, even when  $\lambda$  is fixed (Tibshirani, 1996). Post-LASSO OLS coefficients, while computable, do not incorporate the fact that the first-stage of the LASSO preselects the covariates ( $x$ 's) for the second stage. That is, each coefficient's distribution for these is conditional on both the covariates and on  $\hat{M} = M$ , where  $\hat{M}$  is the OLS regression model selected out of all

the possible candidate OLS models  $M$  that could come out of the first stage LASSO. We deal with this in two different ways. First, we report the usual OLS standard errors, disregarding the model selection from the LASSO. This should result in standard errors that are too small. In most OLS applications, this would be a problem, and in our context, what this means in practice is that we might incorrectly infer that too many social capital measures are related to our labor market network measure than is actually the case. But given that the LASSO procedure excludes many of our candidate social capital measures to begin with, and given that we interpret our results with appropriate caution, we are not too concerned about this.

Nonetheless, we also report 95-percent confidence intervals on our OLS estimates as constructed using a second method. In a recent paper, Lee et al. (2016) (hereafter, LSST) showed that under the assumption that the error term in the second-stage regression model is normally distributed, conditioning on  $\hat{M} = M$  gives the estimated coefficients a truncated normal distribution. They outline an algorithm for finding the left and right truncation points of that distribution, which we implement to create adjusted confidence intervals for the coefficient estimates. We note that these confidence intervals also are only an approximation for two reasons. First, the set of candidate models  $M$  is defined by assuming we have included in the LASSO all possible social capital measures that may be related to our network measure. Second, LSST's results rely on an assumption of normality, which in our setting is clearly only an approximation since our network measure is actually bounded. In practice, it turns out that the statistical inferences are nearly identical using these two methods, indicating that the OLS standard errors are likely not problematic.

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 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**

### *Descriptive statistics*

Table 1 reports descriptive statistics for all 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.<sup>22</sup> Our network 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  $NI_c^W$ );<sup>23</sup> 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  $NI_c = 0$ . 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.<sup>24</sup>

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 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 90 of the 6-digit NAICS industries with at least 10 percent of establishments coded as non-profits, drawn from the universe of establishments with non-

---

<sup>22</sup> 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 25<sup>th</sup>, 50<sup>th</sup>, and 75<sup>th</sup> percentiles of our tracts, by population, having 2,886, 3,966, and 5,190 persons, respectively. Given this similar sizing and the nature of our evaluation, we do not weight our estimates by population, so each Census tract serves as an observation.

<sup>23</sup> 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. Hellerstein et al. (2011 and 2014) 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 in an absolute sense.

<sup>24</sup> 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.

missing legal status (see the on-line appendix for full descriptions of each industry). The entries are ordered in terms of NAICS codes. The maximum percentage of establishments coded as non-profits is above 50 percent (for NAICS code 813219), and is high for industries including charities, humane societies, hospitals and clinics, athletic 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 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 pre-specify 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). Although we have not yet discussed the estimation results, Table 2 provides a preview, as we indicate in boldface industries (or a subset of the full NAICS definition) that are retained in at least some of our LASSO estimations. We later describe and summarize the industries that, according to our LASSO estimations, increase labor market network connections.

### *Preliminary regressions*

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) that are based on prior research. We use simple OLS in this table and not LASSO, and we just include this smaller set of potential social capital measures (and not the non-profit sector establishment counts). 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 most 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 – 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 more than 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  $NI_c^P$ .<sup>25</sup>

We also find that our network measure is higher when residential mobility is lower (where residential mobility – or lack thereof – is captured by the share of residents that did not move in the previous year). There is also evidence, especially 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 likely to

---

<sup>25</sup> 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.

have been at the same address longer, or 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 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.<sup>26</sup>

#### *LASSO regressions*

In Table 4 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 social capital variables (and other variables) belong in the OLS regression. We report estimates from six specifications. First, using  $NI_c^W$  – the network measure that is constructed using only workers – we show results excluding and then including (potentially, if chosen by LASSO) the tract-level isolation index and establishment count, and for each of these cases, excluding and then including (via residualization) the state fixed effects. Then, using  $NI_c^P$ , the network measure based on population, we repeat the specifications including the tract-level isolation index and establishment count (both because these are selected by LASSO, and are strongly significant), with and without fixed state effects. The specifications including the transport isolation measures, which are also sensitive to employment, should help to control for employment-related effects on our networking measure (though transport isolation may also over-control, as hiring to the same location, even if not the same firm, may also be a product of networks).

---

<sup>26</sup> 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 popular support for institutions that provide social capital at a more aggregate level.

The first panel of the table covers the demographic and commuting controls. One interesting result is that the estimates for these variables are not very different from those in the corresponding specifications in Table 3, and the variables generally not selected by LASSO are those whose effects in Table 3 were quite small, with only a couple of exceptions.

The second panel covers the potential schooling and voting social capital variables. LASSO retains the variables related to number of districts and the Democratic vote share in all specifications. At the other extreme, voter turnout is retained in only one specification. The estimated magnitudes of the schooling and voting variables are similar to Table 3, and the signs are always the same. Thus, the estimates indicate that neighborhoods with smaller districts and schools are more networked, as are neighborhoods where fewer schoolchildren qualify for free or reduced-price lunch. The majority vote share results indicate that more politically homogeneous neighborhoods – on this metric – have stronger labor market networks. And again, a higher Democratic vote share lessens labor market network connections.

The last set of results – which begin below the schooling and voting variables – pertain to the counts of non-profit establishments in the 90 industries with a large share of such establishments.<sup>27</sup> Comparing column (1) to column (3), column (2) to column (4), and column (2') to column (4') indicates that there are many industries that are selected by the LASSO procedure whether or not we include fixed state effects. Similarly, comparing column (1) to column (2), and column (3) to column (4) – and the same is true for  $NI_c^P$  – indicates that many of the same industries are retained whether or not the tract-level isolation index and the establishment counts are included as potential controls.

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:<sup>28</sup>

---

<sup>27</sup> The order of the industries is the same as in Table 2, sorted by NAICS codes.

<sup>28</sup> Note that we use a subset of all the industry definitions from Table 2, chosen to try to best characterize the NAICS industry. One has to exercise caution in characterizing these industries, as the on-line appendix indicates that for some NAICS codes there is a much longer list of business types within the code.

- union health and welfare funds (NAICS code 525120)
- elementary, junior, and secondary schools (NAICS code 611110)
- chamber music groups (NAICS code 711130)
- museums (NAICS code 712110)
- country clubs and golf courses (NAICS code 713910)
- camps (NAICS code 721214)
- churches, mosques, etc. (NAICS code 813110)
- charitable trusts (NAICS code 813211)
- hobby clubs, civic associations, Scouts, PTAs, etc. (NAICS code 813410)
- labor unions (NAICS code 813930), and
- fire and rescue services, including volunteer fire departments (NAICS code 922160).

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 industries such as: ambulance and rescue services (NAICS code 621910); nursing homes (NAICS code 623110); city and mayors' office (NAICS code 921110); and police departments (NAICS code 922120). These industries might be best characterized as providing public goods, in which case a high establishment count may reflect 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, the local presence of these public goods facilities may be a more indirect indicator of communities that are smaller, with more community involvement and monitoring (e.g., Ostrom, 1990), and hence more

ties that can enhance labor market networks.

Finally, to be sure, there are some findings – especially negative ones – that seem harder to interpret. The industries with persistent negative effects include: distribution of electric power (NAICS code 221122); social science research and development services (NAICS code 541720); fundraising campaign organization services (NAICS code 561499); humane societies (NAICS code 813312); professional associations (NAICS code 813920); campaign organizations (NAICS code 813940); homeowners’ associations (NAICS code 813990); and arts/cultural or economic development administration (NAICS code 926110). One possible explanation of these latter findings is that these kinds of industries are associated with hiring that tends not to be local (such as government jobs, or professional jobs).

We cannot explain all of our findings, and indeed we did not expect to be able to do so. We are, after all, using a machine learning algorithm that picks out predictors of our network measures, and we have not imposed theoretical constraints or priors on the potential predictors (other than restricting to establishments in industries with a higher share of non-profits). Overall, however, we regard the industries selected by the LASSO procedure that are positively associated with either the worker-based network measure ( $NI_c^W$ ) or the population-based network measure ( $NI_c^P$ ) 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. To provide the reader with a better sense of this result, Table 5 lists the full NAICS definitions for the industries with positive (and significant) effects in five or more specifications in the LASSO estimates reported in Table 4.

The magnitudes of the estimated relationships between some of our social capital measures are non-trivial. For example, in column (3) of Table 4, the estimated coefficient on hobby clubs, Scouts, PTAs, etc. (NAICS code 813410) is 0.0224. In Table 6, we show the standard deviations of the non-profit sector counts; for this industry, the standard deviation is 1.939. Thus, a one standard deviation change would increase  $NI_c^W$  by about 0.0434, and given a mean of  $NI_c^W$  of 1.609, the implied effect is about 2.7 percent. The implied effects is about twice as larger for churches, mosques, synagogues, etc. (NAICS code 813110);

the estimated coefficient in column (3) is about the same magnitude, but the standard deviation is twice as large. Similarly, although the estimated coefficient for country clubs and golf courses (NAICS codes 713910) is much larger (e.g., 0.173 in column (3)), the standard deviation is much lower (0.337), leading to a similar size effect.

In contrast, the implied effects of some of the sectors that have negative effects on the network measures are smaller. For example, the implied effect of establishments in the distribution of electric power (NAICS code 221122) in column (2) is 0.0162, and the implied effect for establishments in campaign organizations, etc. (NAICS code 813940) in column (3) is 0.0187. Indeed, the average standard deviation is more than 50 percent larger (0.22 versus 0.13) for industries with a positive effect on the network measures than for industries with a negative effect, based on Table 6.

We note that the list of industries with positive estimated effects on our network measures are not simply the industries that have the highest share of non-profits or, alternatively, the largest industries with a non-profit component (as specified in the NETS – see the % Non-Profit and Total Estab.’s fields, respectively, in Table 2 and the on-line appendix). Such a finding might have been consistent with non-profits simply being a byproduct of social largesse (in that they must operate on a non-profit basis), which might be related to our networking measure, or 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), only one – charitable trusts and community foundations (NAICS code 813211) – appears consistently with positive effects on our network measures (see Table 5). The industry with the greatest share non-profit, community chests (NAICS code 813219), has no discernable effect on labor market networks in any specification.

## **VI. Conclusions**

Our goal in this paper is to conduct empirical analyses to identify characteristics of neighborhoods (Census tracts) that may facilitate the development of social capital leading to 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 good job market matches and better 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, police departments, fire and rescue services including volunteer fire departments, country clubs, mayors' offices, chamber music groups, hobby clubs, and museums. 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 are successful at fostering interactions between residents that build social capital to create labor market connections among neighbors.

## **VII. Discussion**

There is a long-standing interest in social capital in sociology, political science, and economics, and a burgeoning interest in labor market networks in both sociology and economics. We believe our study contributes to and strengthens this literature in four significant ways. Most important, we connect the two, asking how neighborhood levels of social capital are linked to the strength of local labor market networks. Second, we draw on a new data set to construct novel measures of social capital based on the representation, in the neighborhood, of businesses in the non-profit sector. Third, given the multiplicity of

social capital measures – especially when we introduce non-profit counts across a large number of industries, we use a machine learning algorithm to select the measures that are predictive of the strength of local labor market networks. And fourth, we use a local labor market network measure that we have validated in our past research showing that it is correlated with better job matches, faster re-employment after mass layoffs, etc., and that it explicitly measures and captures the influence of the role of one’s neighbors in helping one find a job.

That said, there are potential limitations, mainly related to trying to address these questions in a large-scale, quantitative study. First, we do not – nor do most network researchers – observe direct network connections between agents.<sup>29</sup> Second, and as a corollary, the network measure we use does not capture other types of network connections that may influence job finding, such as connections to former workers, university alumnae, or military service members (e.g., Cingano and Rosolia, 2012; Laschever, 2016; Oyer and Schaefer, 2012). And third, we cannot identify the explicit ways in which social capital – as reflected in the measures we use – enhance labor market networks. Fourth, social capital has many possible dimensions that we may fail to capture in our social capital measures, such as trust and norms (Coleman, 1988), and social capital that “bridges” – connecting dissimilar people – as opposed to “bonding” – connecting similar people (e.g., Kim et al., 2006; Putnam, 2000).

In our view, it is critical to complement the kind of large-scale evidence we have assembled with ethnographic and case study evidence that probes the explicit operation of labor market networks, and that seeks to understand what influences – including explicit manifestations of different types of social capital – the extent to which potential network members share information about jobs and workers and help people find better job matches. One study that has critical elements of both types of evidence is the Kasinitz and Rosenberg (1996) study of network hiring and social capital on the Red Hook, Brooklyn, waterfront.<sup>30</sup> Ultimately, the accumulation of evidence on labor market networks and what makes them stronger and more effective can not only increase our understanding of behavior, but, ideally, also point to ways in

---

<sup>29</sup> A significant exception in which researchers can observe these connections is the Add Health data set (see, e.g., Goodreau et al., 2009).

<sup>30</sup> Portes (1998) discusses other similar studies.

which policymakers or other stakeholders can strengthen labor market networks to improve the inclusion and integration into the labor market of groups that may have less access to good jobs.

There may also be ways to expand on the analysis of the large-scale data we use to refine understanding of social capital measures. For example, there is research suggesting that religious and secular voluntary associations (like our non-profits) have different forms of social capital,<sup>31</sup> and religious denominations may vary in their degree of insularity and hence the type of social capital they create (bonding versus bridging).<sup>32</sup> Furthermore, the value of various sources of social capital may vary across persons in the same neighborhood with different characteristics. In the NETS data, organizations' names (and hence likely identities) are not confidential, so it could be possible to do research that links specific information on these types of organizations with modifications of our labor market network measures that try to capture *which* neighbors are connected. Intersecting institutional and personal characteristics might yield interesting new findings, but the volume of output and demands for interpretation would be substantially greater, so we leave that for future work.

---

<sup>31</sup> See, e.g., Acevado et al. (2014), and Monsma (2009).

<sup>32</sup> See, e.g., Putnam and Campbell (2012).

## *References*

- Abadie, Alberto, and Maximilian Kasy. 2018. "Choosing Among Regularized Estimators in Machine Learning." *Review of Economics and Statistics*, forthcoming.
- Abowd, John M., Bryce Stephens, Lars Vilhuber, Fredrik Andersson, Kevin McKinney, Marc Roemer, and Simon Woodcock. 2009. "The LEHD Infrastructure Files and the Creation of the Quarterly Workforce Indicators." In Timothy Dunne, J. Bradford Jensen, and Mark J. Roberts (Eds.), *Producer Dynamics: New Evidence from Micro Data*. Chicago, IL: University of Chicago Press for the National Bureau of Economic Research, 149-230.
- Acevedo, Gabriel A., Christopher G. Ellison, and Xiaohe Xu. 2014. "Is It Really Religion? Comparing the Main and Stress-Buffering Effects of Religious and Secular Civic Engagement on Psychological Distress." *Society and Mental Health*, 4(2), 111-128.
- Alesina, Alberto, and Eliana La Ferrara. 2002. "Who Trusts Others?" *Journal of Public Economics*, 85(2), August, 207-234.
- Ansolabehere, Stephen, Maxwell Palmer, and Amanda Lee. 2014. "Precinct-Level Election Data." Harvard Dataverse. Available at <https://dataverse.harvard.edu/file.xhtml?fileId=2456565&version=1.0> (viewed March 27, 2017).
- Bayer, Patrick, Stephen Ross, and Giorgio Topa. 2008. "Place of Work and Place of Residence: Informal Hiring Networks and Labor Market Outcomes." *Journal of Political Economy*, 116(6), December, 1150-1196.
- Belloni, Alexandre and Victor Chernozhukov. 2013. "Least Squares After Model Selection in High-Dimension Sparse Models." *Bernoulli*, 19(2), 521-547.
- Brueckner, Jan K., and Ann G. Largey. 2008. "Social Interaction and Urban Sprawl." *Journal of Urban Economics*, 64(1), July, 18-34.
- Calvó-Armengol, Antoni, and Matthew O. Jackson. 2007. "Networks in Labor Markets: Wage and Employment Dynamics and Inequality." *Journal of Economic Theory*, 132(1), January, 27-46.
- Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. 2014. "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *Quarterly Journal of Economics*, 129(4): 1553-1623.
- Cingano, Federico, and Alfonso Rosolia. 2012. "People I Know: Job Search and Social Networks." *Journal of Labor Economics*, 30(2), April, 291-332.
- Coleman, James S. 1988. "Social Capital in the Creation of Human Capital." *American Journal of Sociology*, 94, Supplement, S95-S20.
- Cotton, Kathleen. 1996. "School Size, School Climate, and Student Performance." *School Improvement Research Series*. Northwest Region Educational Laboratory. Available at <http://educationnorthwest.org/sites/default/files/SizeClimateandPerformance.pdf> (viewed August 23, 2017).
- Dugan, Andrew. 2015. "Trust Differs Most by Ideology for Church, Police, Presidency." *Gallup*, June 30<sup>th</sup>. Available at [http://www.gallup.com/poll/183875/trust-differs-ideology-church-police-presidency.aspx?utm\\_source=Politics&utm\\_medium=newsfeed&utm\\_campaign=tiles](http://www.gallup.com/poll/183875/trust-differs-ideology-church-police-presidency.aspx?utm_source=Politics&utm_medium=newsfeed&utm_campaign=tiles) (viewed March 27, 2017).
- Friedman, Jerome, Trevor Hastie, and Robert Tibshirani, 2010. "Regularization paths for Generalized Linear Models via Coordinate Descent," *Journal of Statistical Software* 33, 1-22.
- Frisch, Ragnar and Frederick V. Waugh. 1933. "Partial Time Regressions as Compared with Individual

Trends." *Econometrica*, 1(4), October, 387-401.

Gardner, Pamela W., Shulamit N. Ritblatt, and James R. Beatty. 2000. "Academic Achievement and Parental Involvement as a Function of High School Size." *The High School Journal*, 83(2), December-January, 21-27.

Glaeser, Edward L., David Laibson, and Bruce Sacerdote. 2002. "An Economic Approach to Social Capital." *The Economic Journal*, 112(384), November, F437-F58.

Goodreau, Steven M., James A. Kitts, and Martina Morris. 2009. "Birds of a Feather, or Friend of a Friend? Using Exponential Random Graph Models to Investigate Adolescent Social Networks." *Demography*, 46(1), February, 103-125.

Graham, Matthew R., Mark J. Kutzbach, and Danielle H. Sandler. 2017. "Developing a Residence Candidate File for Use with Employer-Employee Matched Data." U.S. Census Bureau, Center for Economic Studies, Discussion Papers, CES 17-40.

Granovetter, Mark S. 1974. *Getting a Job: A Study of Contacts and Careers*. Cambridge, MA: Harvard University Press.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2004. "The Role of Social Capital in Financial Development." *American Economic Review*, 94(3), June, 526-556.

Guryan, Jonathan, Erik Hurst, and Melissa Kearney. 2008. "Parental Education and Parental Time with Children." *Journal of Economic Perspectives*, 22(3), Summer, 23-46.

Haidt, Jonathan. 2007. "The New Synthesis in Moral Psychology." *Science*, 316(5827), May, 998-1002.

Hellerstein, Judith K., Mark Kutzbach, and David Neumark. 2016. "Labor Market Networks and Recovery from Mass Layoffs: Evidence from the Great Recession Period." NBER Working Paper No. 21262.

Hellerstein, Judith K., Mark Kutzbach, and David Neumark. 2014. "Do Labor Market Networks Have an Important Spatial Dimension?" *Journal of Urban Economics*, 79(3), January, 39-58.

Hellerstein, Judith K., Melissa McInerney, and David Neumark. 2011. "Neighbors and Co-Workers: The Importance of Residential Labor Market Networks." *Journal of Labor Economics*, 29(4), October, 659-695.

Iceland, John, and Daniel H. Weinberg. 2002. "Racial and Ethnic Segregation in the United States: 1980-2000." Available at [https://www.census.gov/hhes/www/housing/resseg/pdf/paa\\_paper.pdf](https://www.census.gov/hhes/www/housing/resseg/pdf/paa_paper.pdf) (viewed March 27, 2017).

Ihlanfeldt, Keith R., 2006. "A Primer on Spatial Mismatch within Urban Labor Markets." In Arnott, R., McMillen, D. (Eds.), *A Companion to Urban Economics*, 404-417. Boston, MA: Blackwell.

Ioannides, Yannis M., and Linda Datcher Loury. 2004. "Job Information, Networks, Neighborhood Effects, and Inequality." *Journal of Economic Literature*, 42(4), December, 1056-1093.

Jackson, Matthew O. 2008. *Social and Economic Networks*. Princeton, NJ: Princeton University Press.

Kasinitz, Philip, and Jan Rosenberg. 1996. "Missing the Connection: Social Isolation and Employment on the Brooklyn Waterfront." *Social Problems*, 43(2), May, pp. 180-196.

Kim, D., S. V. Subramanian, and I. Kawachi. 2006. "Bonding Versus Bridging Social Capital and their Associations with Self Rated Health: A Multilevel Analysis of 40 US Communities." *Journal of Epidemiology & Community Health*, 60(2), 116-122.

Laschever, Ron. 2013. "The Doughboys Network: Social Interactions and the Employment of World War I Veterans." Unpublished paper. [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1205543](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1205543) (viewed

May 24, 2018).

Lee, Jason D., Dennis L. Sun, Yuekai Sun, and Jonathan E. Taylor. 2016. "Exact Post-Selection Inferences, with Application to the LASSO." *The Annals of Statistics*, 44(3), 907-27.

Lochner, Kimberly, Ichiro Kawachi, and Bruce P. Kennedy. 1999. "Social Capital: A Guide to its Measurement." *Health & Place*, 5(4), December, 259-270.

Lovell, Michael C. 1963. "Seasonal Adjustment of Economic Time Series and Multiple Regression Analysis." *Journal of the American Statistical Association*, 58(304), 993-1010.

Meyer, John, W. Richard Scott, and David Strang. 1987. "Centralization, Fragmentation, and School District Complexity." *Administrative Science Quarterly*, 32(2), June, 186-201.

Monsma, Stephen V. 2003. "Nonprofit and Faith-Based Welfare-to-Work Programs." *Society*, 40(2), 13-18.

Montgomery, James D. 1991. "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis." *American Economic Review*, 81(5), December, 1408-1418.

National Center for Education Statistics, 2012. *Common Core of Data*. Available <https://nces.ed.gov/ccd/pubagency.asp> (viewed March 27, 2017).

Neumark, David, Brandon Wall, and Junfu Zhang. 2011. "Do Small Businesses Create More Jobs? New Evidence for the United States from the National Establishment Time Series." *Review of Economics and Statistics*, 93(3), February, 16-29.

Neumark, David, Junfu Zhang, and Brandon Wall. 2007. "Employment Dynamics and Business Relocation: New Evidence from the National Establishment Time Series." *Research in Labor Economics*, 39-83.

Onyx, Jenny, and Paul Bullen. 2000. "Measuring Social Capital in Five Communities." *Journal of Applied Behavioral Science*, 36(1), March, 23-42.

Ostrom, Elinor. 1990. Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge, U.K. Cambridge University Press.

Oyer, Paul, and Scott Schaefer. 2012. "Firm/Employee Matching: An Industry Study of American Lawyers." NBER Working Paper No. 18620.

Portes, Alejandro. 1998. "Social Capital: Its Origins and Applications in Modern Sociology." *Annual Review of Sociology*, 24, 1-24.

Putnam, Robert D., 2007. "*E Pluribus Unum*: Diversity and Community in the Twenty-First Century. The 2006 Johan Skytte Prize Lecture." *Scandinavian Political Studies*, 30(2), 137-174.

Putnam, Robert D. 2000. Bowling Alone: The Collapse and Revival of American Community. New York: Simon & Schuster.

Putnam, Robert D., and David E. Campbell. 2012. American Grace: How Religion Divides and Unites Us. New York: Simon & Schuster.

Putnam, Robert D. 1994. "Social Capital and Public Affairs." *Bulletin of the American Academy of Arts and Sciences*, 47(8), May, 5-19.

Rupasingha, Anil, Stephan J. Goetz, and David Freshwater. 2006. "The Production of Social Capital in U.S. Counties." *The Journal of Socio-Economics*, 35(1), February, 83-101.

Sharkey, Patrick, Gerard Torrats-Espinosa, and Delaram Takyar. 2017. "Community and the Crime Decline: The Causal Effect of Local Nonprofits on Violent Crime." *American Sociological Review*, 82(6), December, 1214-1240.

Stevens, David W. 2007. "Employment that is Not Covered by State Unemployment Insurance Laws." Longitudinal Employer–Household Dynamics, Technical Paper No. TP-2007-04.

Tibshirani, Robert. 1996. "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society. Series B (Methodological)*, 58(1), 267-288.

Townsend, Wilbur. 2017. "ELASTICREGRESS: STATA Module to Perform Elastic Net Regression, LASSO Regression, Ridge Regression." Statistical Software Components S458397, Boston College Department of Economics, revised April 16, 2018.

U.S. Census Bureau. n.d. (a). "Chapter 10: Census Tracts and Block Numbering Areas." Available at <http://www.census.gov/geo/www/GARM/Ch10GARM.pdf> (viewed December 23, 2010).

U.S. Census Bureau, n.d. (b). "School Districts Cartographic Boundary Files Descriptions and Metadata." Available at [http://www.census.gov/geo/www/cob/sd\\_metadata.html](http://www.census.gov/geo/www/cob/sd_metadata.html) (viewed December 25, 2010).

Zenou, Yves. 2013. "Spatial Versus Social Mismatch." *Journal of Urban Economics*, 74, March, 113-132.

Zenou, Yves. 2008. "The Spatial Mismatch Hypothesis." In Blume, L., Durlauf, S. (Eds.), The New Palgrave Dictionary of Economics, Second Ed. London: MacMillan.

**Table 1: Summary Statistics for Network, Transportation, Population, School, and Voting Variables, Census Tract Level**

Variable	Description	Mean	Std. dev.	25 <sup>th</sup> percentile	Median	75 <sup>th</sup> 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 $\geq$ 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 III. 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  $\geq 10$  Percent of Establishments Non-Profit**

NAICS	NAICS Description (Examples)	Non-Profit Count	Total Estab.'s	% Non-Profit
114210	Animal trapping, commercial; <b>Fishing preserves</b> ; Game preserves, commercial; Game retreats; <b>Hunting preserves</b>	139	1063	13.1%
115111	<b>Cotton ginning</b> ; Ginning cotton	103	728	14.0%
221122	<b>Distribution of electric power</b> ; Electric power brokers; Electric power distribution systems	361	1727	20.9%
221310	Canal, irrigation; Filtration plant, water; <b>Irrigation system operation</b> ; <b>Water distribution</b> (except irrigation)	1744	8586	20.3%
221320	Collection, treatment, and disposal of waste through a sewer system; <b>Sewage disposal</b> plants; Sewage treatment plants or facilities; Sewer systems; <b>Waste collection</b> , treatment, and disposal through a sewer system	292	1938	15.1%
311313	Beet pulp, dried, manufacturing; Molasses made from sugar beets; Sugar, granulated, made from sugar beets	14	51	27.5%
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)	78	696	11.2%
519120	Archives; Bookmobiles; Circulating libraries; Film archives; Lending libraries; Libraries (except motion picture stock footage, motion picture commercial distribution); Motion picture film libraries, archives; Reference libraries	3470	16800	20.7%
522294	Federal Home Loan Mortgage Corporation (FHLMC); Federal National Mortgage Association (FNMA); FNMA ( <b>Federal National Mortgage Association</b> ); GNMA (Government National Mortgage Association)	38	313	12.1%
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	383	3240	11.8%
522130	Corporate credit unions; Credit unions; Federal credit unions; State credit unions; Unions, credit	2962	12821	23.1%
524114	Dental insurance carriers, direct; Group hospitalization plans without providing health care services; <b>Health insurance carriers</b> , direct; Hospital and medical service plans, direct, without providing health care services	397	3497	11.4%
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; <b>Union pension funds</b>	98	863	11.4%
525120	Union health and welfare funds	29	159	18.2%
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%
531311	<b>Apartment managers' offices</b> ; <b>Condominium managers' offices</b> , residential; Cooperative apartment managers' offices; Managers' offices, residential condominium; Managers' offices, residential real estate	663	3239	20.5%
541720	Historic and cultural preservation research and development services; <b>Humanities research and development services</b> ; <b>Social science research and development services</b>	1183	8242	14.4%
561499	Address bar coding services; Bar code imprinting services; <b>Fundraising campaign organization services</b> on a contract or fee basis; Mail consolidation services; Mail presorting services; Teleconferencing services	796	4497	17.7%
561591	Convention and visitors bureaus; Convention bureaus; Tourism bureaus; Tourist information bureaus; Visitors bureaus	211	808	26.1%
611110	<b>Elementary and secondary schools</b> ; High schools; <b>Junior high schools</b> ; Military academies, elementary or secondary; Montessori schools, elementary or secondary; Parochial schools, elementary or secondary	30846	119478	25.8%
611210	Academies, junior college; Colleges, community; Colleges, junior; Community colleges; Community colleges offering a wide variety of academic and technical training; Junior colleges	838	2691	31.1%
611310	Academies, college or university; Business colleges or schools offering baccalaureate or graduate degrees; <b>Colleges</b> (except junior colleges); Colleges, <b>universities</b> , and professional schools; Law schools; Medical schools	5666	17482	32.4%
611513	<b>Apprenticeship training programs</b> ; Carpenters' apprenticeship training; Craft union apprenticeship training programs; Electricians' apprenticeship training; Trade union apprenticeship training programs	426	3241	13.1%
611630	<b>Foreign language schools</b> ; Language schools; Schools, language; Second language instruction; Sign language instruction; Sign language schools	99	910	10.9%

NAICS	NAICS Description (Examples)	Non-Profit Count	Total Estab.'s	% Non-Profit
611699	<b>Bible schools</b> (except degree granting); CPR (cardiac pulmonary resuscitation) training and certification; Diction schools; Life guard training; Public speaking training; <b>Yoga instruction</b> , camps, or schools	343	3166	10.8%
611710	College selection services; Educational guidance counseling services; <b>Educational support services</b> ; Educational testing evaluation services; <b>Educational testing services</b> ; School bus attendant services; Student exchange programs	4544	24088	18.9%
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	619	1420	43.6%
621420	Alcoholism treatment centers and clinics (except hospitals), outpatient; Drug addiction treatment centers and clinics (except hospitals), outpatient; Mental health centers and clinics (except hospitals), outpatient	1926	6128	31.4%
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%
621498	Biofeedback centers and clinics, outpatient; <b>Clinics/centers of health practitioners</b> from more than one industry practicing within the same establishment; <b>Community health centers</b> and clinics, outpatient	907	4453	20.4%
621610	Home care of elderly, medical; <b>Home health agencies</b> ; Home health care agencies; Home nursing services (except private practices); Hospice care services, in home; Nurse associations, visiting	1677	16718	10.0%
621910	Air ambulance services; <b>Ambulance services</b> , air or ground; Emergency medical transportation services, air or ground; Rescue services, air; <b>Rescue services</b> , medical	1197	5342	22.4%
621991	Blood banks; Blood donor stations; Eye banks; Organ banks, body; Organ donor centers, body; Sperm banks, human	427	1570	27.2%
622110	Children's hospitals, general; General medical and surgical hospitals; Hospitals, general medical and surgical; Hospitals, general pediatric; Osteopathic hospitals	3986	9913	40.2%
622210	Alcoholism rehabilitation hospitals; Children's hospitals, psychiatric or substance abuse; Drug addiction rehabilitation hospitals; Hospitals for alcoholics; Hospitals, addiction; Hospitals, substance abuse; Mental health hospitals	794	3191	24.9%
622310	Cancer hospitals; <b>Children's hospitals, specialty</b> (except psychiatric, substance abuse); Chronic disease hospitals; Extended care hospitals (except mental, substance abuse); Eye, ear, nose, and throat hospitals	1004	5632	17.8%
623110	<b>Convalescent homes</b> or convalescent hospitals (except psychiatric); <b>Group homes</b> for the disabled with nursing care; Homes for the aged with nursing care; Hospices, inpatient care; <b>Nursing homes</b> ; Rest homes with nursing care	3291	23883	13.8%
623210	Group homes, intellectual and developmental disability; Hospitals, intellectual and developmental disability; Intellectual and developmental disability facilities (e.g., homes, hospitals, intermediate care facilities), residential	568	1817	31.3%
623220	Alcoholism rehabilitation facilities (except licensed hospitals), residential; Drug addiction rehabilitation facilities (except licensed hospitals), residential; Mental health halfway houses; Substance abuse facilities, residential	534	1227	43.5%
623312	Assisted-living facilities without on-site nursing care facilities; <b>Homes for the aged</b> without nursing care; Homes for the elderly without nursing care; Old age homes without nursing care; Old soldiers' homes without nursing care	706	3266	21.6%
623990	<b>Boot camps</b> for delinquent youth; Boys' and girls' residential facilities (e.g., homes, ranches, villages); Child group foster homes; Children's villages; <b>Group foster homes</b> for children; Homes for unwed mothers	2621	10163	25.8%
6241	Individual and family services			
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	2913	7115	40.9%
624120	Activity centers for disabled persons, the elderly, and persons diagnosed with intellectual and developmental disabilities; <b>Centers, senior citizens'</b> ; Community centers (except recreational only), adult; Senior citizens centers	5305	14778	35.9%
624190	<b>Alcoholism and drug addiction self-help organizations</b> ; Crisis intervention centers; Exoffender rehabilitation agencies; Exoffender self-help organizations; Family social service agencies; Family welfare services	8478	32377	26.2%
624210	Community meals, social services; Food banks; Meal delivery programs; Mobile soup kitchens; Soup kitchens	183	499	36.7%
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	582	1403	41.5%

NAICS	NAICS Description (Examples)	Non-Profit Count	Total Estab.'s	% Non-Profit
624310	Job counseling, vocational rehabilitation or habilitation; Sheltered workshops (i.e., work experience centers); <b>Vocational habilitation job counseling</b> ; Vocational habilitation job training facilities (except schools)	2919	9586	30.5%
624410	Babysitting services in provider's own home, child day care; Babysitting services, child day care; Child day care centers; <b>Child day care services</b> ; <b>Head start programs</b> , separate from schools; <b>Preschool centers</b>	7472	58746	12.7%
711110	Broadway theaters; Comedy troupes; Community theaters; Dinner theaters; Improvisational theaters; Musical theater companies or groups; Opera companies; Puppet theaters; Repertory companies, theatrical; Theaters, musical	1004	2500	40.1%
711120	<b>Ballet companies</b> ; Classical dance companies; Contemporary dance companies; Dance productions, live theatrical; Dance theaters; <b>Dance troupes</b> ; Folk dance companies; Interpretive dance companies; Jazz dance companies	76	155	49.0%
711130	Bands; <b>Chamber musical groups</b> ; Choirs; Classical musical artists, independent; Classical musical groups; Concert artists, independent; Country musical groups; Drum and bugle corps (i.e., drill teams); Symphony orchestras	932	7566	12.3%
711211	<b>Baseball teams</b> , professional or semiprofessional; Basketball teams, professional or semiprofessional; Boxing clubs, professional or semiprofessional; <b>Football teams</b> , professional or semiprofessional	269	2009	13.4%
711310	Air show managers with facilities; <b>Arena operators</b> ; Arts event managers with facilities; Arts event organizers with facilities; Arts festival managers with facilities; Boxing event organizers with facilities; <b>Sports arena operators</b>	367	2695	13.6%
711320	Arts event organizers without facilities; Arts festival organizers without facilities; Arts festival promoters without facilities; Boxing event organizers without facilities; Sports event managers without facilities	1010	4715	21.4%
712110	<b>Art museums</b> ; Community museums; Contemporary art museums; Herbariums; <b>Historical museums</b> ; Marine museums; Natural history museums; Natural science museums; Planetariums; Wax museums	3207	12009	26.7%
712120	Archeological sites (i.e., public display); Battlefields; Heritage villages; Historical forts; Historical sites; Pioneer villages	555	1422	39.0%
712130	Animal exhibits, live; Animal safari parks; Aquariums; Arboreta; Arboretums; Aviaries; Botanical gardens; Conservatories, botanical; Gardens, zoological or botanical; Petting zoos; Wild animal parks; Zoological gardens; Zoos	243	811	30.0%
713910	<b>Country clubs</b> ; Golf and country clubs; <b>Golf courses</b> (except miniature, pitch-n-putt)	2772	13310	20.8%
713990	<b>Amateur sports teams, recreational</b> ; <b>Athletic clubs</b> (i.e., sports teams) not operating sports facilities, recreational; Baseball clubs, recreational; Boating clubs without marinas; Bridge clubs, recreational; Lawn bowling clubs	3413692	28640	12.9%
721214	Boys' camps (except day, instructional); Camps (except day, instructional); <b>Children's camps</b> (except day, instructional); Dude ranches; Girls' camps (except day, instructional); Hunting camps with accommodation facilities	999	4835	20.7%
721310	Boarding houses; Dormitories, off campus; Fraternity houses; Residential clubs; Sorority houses; Workers' dormitories	428	2512	17.0%
812220	Animal cemeteries; <b>Cemeteries</b> ; Columbariums; Crematories (except combined with funeral homes); Mausoleums; <b>Memorial gardens</b> (i.e., burial places); Pet cemeteries	981	5876	16.7%
813110	Bible societies; <b>Churches</b> ; Convents (except schools); <b>Missions</b> , religious organization; Monasteries (except schools); <b>Mosques</b> , religious; Places of worship; Shrines, religious; <b>Synagogues</b> ; Temples, religious	73178	228934	32.0%
813211	<b>Charitable trusts</b> , awarding grants; <b>Community foundations</b> ; Educational trusts, awarding grants; Philanthropic trusts, awarding grants; Trusts, educational, awarding grants; Trusts, religious, awarding grants	4761	12624	37.7%
813219	<b>Community chests</b> ; Federated charities; United fund councils; United funds for colleges	1812	3277	55.3%
813312	Animal welfare associations or leagues; Environmental advocacy organizations; <b>Humane societies</b>	1642	3672	44.7%
813319	Accident prevention associations; Antipoverty advocacy organizations; Aviation advocacy organizations; Community action <b>advocacy organizations</b> ; Drug abuse prevention advocacy organizations; Public safety advocacy organizations	6837	16606	41.2%
813410	Alumni associations; Alumni clubs; Book discussion clubs; Booster clubs; <b>Civic associations</b> ; Classic car clubs; <b>Fraternal organizations</b> ; <b>Parent-teachers' associations</b> ; Retirement associations, social; <b>Scouting organizations</b>	14839	44974	33.0%
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	9376	23707	39.5%
813920	Accountants' associations; Architects' associations; Bar associations; Health professionals' associations; Learned societies; Medical associations; <b>Professional associations</b> ; Scientific associations; Social workers' associations	3946	12231	32.2%

NAICS	NAICS Description (Examples)	Non-Profit Count	Total Estab.'s	% Non-Profit
<b>813930</b>	Federation of workers, labor organizations; Federations of labor; Industrial labor unions; Labor federations; <b>Labor unions</b> (except apprenticeship programs); Trade unions, local; Unions (except apprenticeship programs), labor	2892	11966	24.2%
<b>813940</b>	<b>Campaign organizations</b> , political; Local <b>political organizations</b> ; PACs (Political Action Committees); Political action committees ( <b>PACs</b> ); Political campaign organizations; Political organizations or clubs; Political parties	328	1857	17.7%
<b>813990</b>	Athletic associations, regulatory; Condominium owners' associations; Cooperative owners' associations; <b>Homeowners' associations</b> ; Sports governing bodies; Tenants' associations (except advocacy)	7886	17947	43.9%
<b>921110</b>	<b>Advisory commissions</b> , executive government; <b>City and town managers' offices</b> ; Executive offices, federal, state, and local (e.g., governor, mayor, president); Governors' offices; <b>Mayor's offices</b>	6387	29792	21.4%
<b>921120</b>	Advisory commissions, legislative; Boards of supervisors, county and local; <b>City and town councils</b> ; Congress of the United States; County commissioners; Legislative assemblies; Study commissions, legislative	829	5369	15.4%
<b>921130</b>	<b>Assessor's offices</b> , tax; Budget agencies, government; Federal Reserve Board of Governors; Internal Revenue Service; Property tax assessors' offices; <b>Taxation departments</b> ; Treasurers' offices, government	1026	6165	16.6%
921140	Executive and legislative office combinations; Legislative and executive office combinations	124	1172	10.6%
<b>921190</b>	<b>Auditor's offices, government</b> ; <b>Civil rights commissions</b> ; Civil service commissions; Election boards; General public administration; Human rights commissions, government; Indian affairs programs, government	1167	7710	15.1%
922110	Administrative courts; Circuit courts; City or county courts; Sheriffs' offices, court functions only; Traffic courts	1277	10513	12.1%
<b>922120</b>	DEA (Drug Enforcement Administration); Drug enforcement agencies and offices; Federal Bureau of Investigation (FBI); <b>Housing police</b> , government; <b>Park police</b> ; <b>Police departments</b> (except American Indian or Alaska Native);	3125	14154	22.1%
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%
<b>922160</b>	Ambulance and fire service combined; <b>Fire and rescue service</b> ; <b>Firefighting</b> (except forest), government and <b>volunteer</b> (except private); Firefighting services (except forest and private)	4715	18083	26.1%
922190	Criminal justice statistics centers, government; Disaster preparedness and management offices, government; Law enforcement statistics centers, government; Public safety statistics centers, government	371	2585	14.4%
923110	Certification of schools and teachers; County supervisors of education (except school boards); Education program administration; Education statistics centers, government; State education departments; Teacher certification bureaus	385	2691	14.3%
<b>923120</b>	Community health programs administration; Coroners' offices; Environmental health program administration; Food service health inspections; <b>Health planning and development agencies, government</b> ; Health program administration	915	7592	12.1%
<b>924110</b>	Enforcement of environmental and pollution control regulations; <b>Environmental protection program administration</b>	1033	5232	19.7%
<b>925110</b>	Building standards agencies, government; Housing authorities, nonoperating; <b>Housing programs, planning and development</b> , government	1268	5119	24.8%
925120	Community development agencies, government; County development agencies; Land redevelopment agencies, government; Redevelopment land agencies, government; Regional planning and development program administration	501	1852	27.1%
<b>926110</b>	<b>Arts and cultural program administration</b> , government; Consumer protection offices; <b>Economic development agencies</b> , government; Energy development and conservation agencies, nonoperating; Trade commissions, government	257	2224	11.6%
<b>926130</b>	<b>Communications commissions</b> ; Federal Communications Commission (FCC); Irrigation districts, nonoperating; <b>Licensing and inspecting of utilities</b> ; Regulation of utilities; Sanitation districts, nonoperating	275	1167	23.6%

Note: Tabulations based on the National Establishment Time Series. Percent non-profit is based on observations with non-missing legal status field. For more complete descriptions, see on-line appendix and <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. Industries highlighted in boldface were retained in the Elastic Net estimation, with significant effects, as explained in notes to Table 4.

**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**

Variables	$NI_c^W$				$NI_c^P$			
	(1)	(2)	(3)	+ state FEs (4)	(5)	(6)	(7)	+ state FEs (8)
Poor	1.080*** (0.099)	1.040*** (0.096)	0.935*** (0.058)	1.100*** (0.058)	0.345*** (0.054)	0.314*** (0.053)	0.390*** (0.031)	0.472*** (0.031)
Hispanic	-1.130*** (0.056)	-0.645*** (0.060)	-0.534*** (0.044)	-0.564*** (0.053)	-0.728*** (0.032)	-0.363*** (0.033)	-0.285*** (0.023)	-0.284*** (0.029)
Black, non-Hispanic	-0.753*** (0.032)	-0.397*** (0.041)	0.032 (0.027)	-0.014 (0.033)	-0.577*** (0.019)	-0.347*** (0.024)	-0.018 (0.015)	-0.006 (0.019)
Asian, non-Hispanic	0.282** (0.106)	0.687*** (0.108)	0.608*** (0.094)	0.487*** (0.106)	0.142** (0.061)	0.473*** (0.061)	0.423*** (0.053)	0.366*** (0.061)
Other race, non-Hispanic	-0.388 (0.424)	0.491 (0.418)	-0.430*** (0.140)	-0.585*** (0.189)	-0.881*** (0.212)	-0.254 (0.205)	-0.492*** (0.074)	-0.469*** (0.096)
Non-native	0.407*** (0.094)	0.725*** (0.093)	1.102*** (0.081)	1.040*** (0.085)	0.282*** (0.054)	0.464*** (0.053)	0.702*** (0.044)	0.642*** (0.047)
Currently married	2.750*** (0.135)	1.820*** (0.128)	0.727*** (0.062)	0.817*** (0.061)	1.540*** (0.075)	0.927*** (0.072)	0.313*** (0.035)	0.364*** (0.034)
Education < high school	0.429** (0.101)	0.510*** (0.100)	0.696*** (0.065)	0.810*** (0.066)	0.078 (0.060)	0.138** (0.058)	0.326*** (0.037)	0.427*** (0.038)
Education ≥ Bachelor's degree	0.048 (0.055)	0.211*** (0.057)	0.819*** (0.042)	0.938*** (0.043)	-0.052 (0.033)	0.024 (0.033)	0.463*** (0.024)	0.571*** (0.025)
Commute < 10 minutes	5.100*** (0.121)	4.660*** (0.118)	1.070*** (0.072)	1.020*** (0.072)	3.110*** (0.073)	2.820*** (0.071)	0.621*** (0.040)	0.572*** (0.040)
Commute by driving alone	-0.504*** (0.074)	-0.667*** (0.073)	-0.478*** (0.044)	-0.300*** (0.046)	-0.153*** (0.041)	-0.224*** (0.040)	-0.192*** (0.024)	-0.071*** (0.025)
Share did not move in last year	1.080*** (0.094)	1.33*** (0.094)	0.824*** (0.061)	0.433*** (0.063)	0.780*** (0.054)	0.910*** (0.054)	0.574*** (0.036)	0.289*** (0.038)
Share housing owner-occupied	0.090* (0.052)	0.038 (0.050)	0.282*** (0.032)	0.326*** (0.033)	0.072** (0.031)	0.033 (0.030)	0.178*** (0.019)	0.210*** (0.020)
Observed tract average transport isolation index, per worker	...	...	1.250*** (0.014)	1.260*** (0.015)	...	...	1.230*** (0.011)	1.250*** (0.011)
Count of NETS establishments (100s)	...	...	0.061*** (0.006)	0.064*** (0.006)	...	...	0.035*** (0.003)	0.037*** (0.004)
Number of districts	...	0.045*** (0.008)	0.058*** (0.007)	0.059*** (0.007)	...	0.031*** (0.005)	0.040** (0.005)	0.036*** (0.005)
Average number of tracts in school district(s)	...	-0.021*** (0.002)	-0.005** (0.002)	-0.006*** (0.002)	...	-0.010*** (0.001)	-0.002 (0.001)	-0.002** (0.001)
Student/teacher ratio	...	-0.039*** (0.002)	-0.024*** (0.002)	-0.0004 (0.003)	...	-0.032*** (0.001)	-0.019*** (0.001)	-0.002 (0.002)
Free/reduced-price lunch share	...	-0.180*** (0.032)	-0.144*** (0.022)	-0.069*** (0.023)	...	-0.204*** (0.019)	-0.147*** (0.013)	-0.100*** (0.014)
Majority vote share	...	0.705*** (0.093)	0.002 (0.057)	0.074 (0.058)	...	0.458*** (0.055)	0.0002 (0.033)	0.056* (0.034)
Democratic vote share	...	-1.660*** (0.076)	-0.859*** (0.046)	-0.878*** (0.055)	...	-1.050*** (0.045)	-0.574*** (0.027)	-0.620*** (0.032)
Voter turnout	...	0.200*** (0.030)	0.039* (0.022)	0.032 (0.022)	...	0.151*** (0.018)	0.042*** (0.013)	0.032** (0.013)
R <sup>2</sup>	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. There are approximately 34,000 Census tract observations. See Tables 1 and 2 for variable definitions. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, or 10% level.

**Table 4: Social Capital and Neighborhood Labor Market Network Regressions, Using Per Worker Network Measure  $NI_c^W$  or Per Person Network Measure  $NI_c^P$ , Elastic Net with Alternative Controls**

Variables	$NI_c^W$				$NI_c^P$	
	(1)	(2)	+ state FEs		(2')	(4')
			(3)	(4)		
Poor	1.100 <sup>†</sup> (0.057)	0.921 <sup>†</sup> (0.046)	1.420 <sup>†</sup> (0.059)	1.080 <sup>†</sup> (0.046)	0.392 <sup>†</sup> (0.027)	0.470 <sup>†</sup> (0.028)
Hispanic	-0.593 <sup>†</sup> (0.039)	-0.484 <sup>†</sup> (0.030)	-0.560 <sup>†</sup> (0.045)	-0.518 <sup>†</sup> (0.033)	-0.262 <sup>†</sup> (0.017)	-0.264 <sup>†</sup> (0.020)
Black, non-Hispanic	-0.532 <sup>†</sup> (0.035)	0.0871 <sup>†</sup> (0.025)	-0.574 <sup>†</sup> (0.038)			
Asian, non-Hispanic	0.745 <sup>†</sup> (0.072)	0.637 <sup>†</sup> (0.051)	0.506 <sup>†</sup> (0.079)	0.534 <sup>†</sup> (0.056)	0.440 <sup>†</sup> (0.031)	0.388 <sup>†</sup> (0.033)
Other race, non-Hispanic		-0.308 <sup>†</sup> (0.105)	-0.328 (0.179)	-0.537 <sup>†</sup> (0.125)	-0.416 <sup>†</sup> (0.062)	-0.436 <sup>†</sup> (0.075)
Non-native	0.631 <sup>†</sup> (0.071)	1.130 <sup>†</sup> (0.053)	0.690 <sup>†</sup> (0.077)	1.050 <sup>†</sup> (0.056)	0.706 <sup>†</sup> (0.032)	0.642 <sup>†</sup> (0.034)
Currently married	2.030 <sup>†</sup> (0.066)	0.746 <sup>†</sup> (0.051)	2.080 <sup>†</sup> (0.068)	0.808 <sup>†</sup> (0.051)	0.321 <sup>†</sup> (0.030)	0.354 <sup>†</sup> (0.031)
Education < high school		0.519 <sup>†</sup> (0.063)		0.645 <sup>†</sup> (0.063)	0.239 <sup>†</sup> (0.037)	0.333 <sup>†</sup> (0.038)
Education ≥ Bachelor's degree		0.806 <sup>†</sup> (0.033)		0.918 <sup>†</sup> (0.032)	0.467 <sup>†</sup> (0.019)	0.578 <sup>†</sup> (0.019)
Commute < 10 minutes	4.040 <sup>†</sup> (0.077)	1.000 <sup>†</sup> (0.056)	3.730 <sup>†</sup> (0.076)	0.964 <sup>†</sup> (0.055)	0.575 <sup>†</sup> (0.033)	0.545 <sup>†</sup> (0.033)
Commute by driving alone	-0.664 <sup>†</sup> (0.049)	-0.486 <sup>†</sup> (0.035)	-0.410 <sup>†</sup> (0.052)	-0.344 <sup>†</sup> (0.036)	-0.206 <sup>†</sup> (0.021)	-0.119 <sup>†</sup> (0.022)
Share did not move in last year	1.280 <sup>†</sup> (0.062)	0.735 <sup>†</sup> (0.050)	0.673 <sup>†</sup> (0.072)	0.402 <sup>†</sup> (0.052)	0.516 <sup>†</sup> (0.030)	0.272 <sup>†</sup> (0.031)
Share housing owner-occupied		0.315 <sup>†</sup> (0.027)	0.223 <sup>†</sup> (0.038)	0.336 <sup>†</sup> (0.027)	0.195 <sup>†</sup> (0.016)	0.221 <sup>†</sup> (0.016)
Observed tract average transport isolation index, per worker	...	1.250 <sup>†</sup> (0.007)	...	1.250 <sup>†</sup> (0.007)	1.230 <sup>†</sup> (0.006)	1.240 <sup>†</sup> (0.006)
Count of NETS establishments (100s)	...	0.074 <sup>†</sup> (0.003)	...	0.073 <sup>†</sup> (0.003)	0.047 <sup>†</sup> (0.002)	0.048 <sup>†</sup> (0.002)
Number of districts	0.033 <sup>†</sup> (0.006)	0.053 <sup>†</sup> (0.005)	0.043 <sup>†</sup> (0.007)	0.055 <sup>†</sup> (0.005)	0.035 <sup>†</sup> (0.03)	0.032 <sup>†</sup> (0.003)
Average number of tracts in school district(s)	-0.017 <sup>†</sup> (0.002)	-0.005 <sup>†</sup> (0.002)	-0.020 <sup>†</sup> (0.002)	-0.006 <sup>†</sup> (0.002)	-0.002 (0.001)	-0.002 (0.001)
Student/teacher ratio	-0.035 <sup>†</sup> (0.002)	-0.022 <sup>†</sup> (0.001)	-0.027 <sup>†</sup> (0.004)		-0.018 <sup>†</sup> (0.001)	
Free/reduced-price lunch share	-0.111 <sup>†</sup> (0.029)	-0.135 <sup>†</sup> (0.020)		-0.059 (0.020)	-0.133 <sup>†</sup> (0.012)	-0.089 <sup>†</sup> (0.012)
Majority vote share	0.753 <sup>†</sup> (0.067)		0.952 <sup>†</sup> (0.067)			
Democratic vote share	-1.510 <sup>†</sup> (0.052)	-0.790 <sup>†</sup> (0.033)	-1.700 <sup>†</sup> (0.059)	-0.789 <sup>†</sup> (0.031)	-0.514 <sup>†</sup> (0.018)	-0.536 <sup>†</sup> (0.019)
Voter turnout					0.038 <sup>†</sup> (0.012)	
NAICS codes (description, see Table 2)						
114210 (fishing preserves, hunting preserves)	0.084 <sup>†</sup> (0.038)		0.094 <sup>†</sup> (0.037)			
115111 (cotton ginning)	0.245 <sup>†</sup> (0.123)	0.101 (0.086)	0.296 <sup>†</sup> (0.119)	0.131 (0.084)	0.061 (0.051)	0.080 (0.050)
221122 (distribution of electric power)		-0.131 <sup>†</sup> (0.028)		-0.117 <sup>†</sup> (0.028)	-0.068 <sup>†</sup> (0.017)	-0.061 <sup>†</sup> (0.017)
221310 (irrigation system operation, water distribution)	0.051 <sup>†</sup> (0.013)		0.046 <sup>†</sup> (0.013)			
221320 (sewage disposal, waste collection)	0.126 <sup>†</sup> (0.035)		0.093 <sup>†</sup> (0.004)			

*Continued on next page.*

**Table 4 (continued)**

NAICS codes (description-see Table 2)	$NI_c^W$				$NI_c^P$	
	(1)	(2)	+ state Fes		(2')	+ state FEs
			(3)	(4)		
522294 (Federal National Mortgage Association, etc.)		-0.062 (0.036)		-0.059 (0.036)	-0.023 (0.022)	-0.023 (0.022)
524114 (health insurance carriers)		-0.015 (0.010)	-0.030 <sup>†</sup> (0.014)	-0.010 (0.010)		
525110 (union pension funds)					0.031 <sup>†</sup> (0.013)	
525120 (union health and welfare funds)	0.102 (0.082)	0.231 <sup>†</sup> (0.058)	0.124 (0.080)	0.236 <sup>†</sup> (0.056)	0.171 <sup>†</sup> (0.035)	0.170 <sup>†</sup> (0.034)
531311 (apartment managers offices, condominium managers offices)	0.029 (0.016)	-0.013 (0.011)	0.023 (0.016)	-0.031 <sup>†</sup> (0.011)		-0.015 (0.007)
541720 (social sciences research and development services)		-0.020 <sup>†</sup> (0.007)		-0.022 <sup>†</sup> (0.007)	-0.018 <sup>†</sup> (0.004)	-0.016 <sup>†</sup> (0.004)
561499 (fundraising campaign organization services)		-0.022 <sup>†</sup> (0.092)		-0.019 <sup>†</sup> (0.009)	-0.012 <sup>†</sup> (0.006)	-0.011 (0.005)
611110 (elementary, junior, secondary schools)	0.045 <sup>†</sup> (0.004)	0.013 <sup>†</sup> (0.003)	0.040 <sup>†</sup> (0.004)	0.010 <sup>†</sup> (0.002)	0.009 <sup>†</sup> (0.002)	0.007 <sup>†</sup> (0.002)
611310 (colleges, universities)	-0.012 <sup>†</sup> (0.003)	-0.004 (0.002)	-0.014 <sup>†</sup> (0.003)	-0.003 (0.002)		-0.002 (0.001)
611513 (apprenticeship training programs)	-0.063 <sup>†</sup> (0.017)	-0.025 <sup>†</sup> (0.012)	-0.059 <sup>†</sup> (0.016)	-0.027 <sup>†</sup> (0.012)	-0.012 (0.007)	-0.012 (0.007)
611630 (foreign language schools)				-0.031 (0.017)	-0.046 <sup>†</sup> (0.010)	-0.042 <sup>†</sup> (0.010)
611699 (Bible schools, yoga instruction)	0.024 (0.012)	-0.023 (0.017)	0.039 <sup>†</sup> (0.012)			
611710 (education support and testing services)	0.014 <sup>†</sup> (0.005)	-0.004 (0.004)	0.014 <sup>†</sup> (0.005)	-0.006 (0.004)	-0.008 <sup>†</sup> (0.002)	-0.007 <sup>†</sup> (0.002)
621498 (clinics/centers of health practitioners, community health centers)	-0.034 <sup>†</sup> (0.016)	-0.012 (0.011)	-0.027 (0.016)	-0.011 (0.011)	-0.009 (0.007)	-0.009 (0.007)
621610 (home health agencies)		-0.018 <sup>†</sup> (0.005)		-0.014 <sup>†</sup> (0.005)	-0.010 <sup>†</sup> (0.003)	-0.008 <sup>†</sup> (0.003)
621910 (ambulance or rescue services)	0.070 <sup>†</sup> (0.016)	0.027 <sup>†</sup> (0.011)	0.056 <sup>†</sup> (0.016)		0.019 <sup>†</sup> (0.007)	
622310 (children's hospitals)		0.022 <sup>†</sup> (0.009)	0.022 (0.013)	0.021 <sup>†</sup> (0.010)	0.015 <sup>†</sup> (0.006)	0.012 <sup>†</sup> (0.006)
623110 (nursing homes, group homes, convalescent homes)	0.032 <sup>†</sup> (0.006)	0.010 <sup>†</sup> (0.004)	0.033 <sup>†</sup> (0.006)		0.008 <sup>†</sup> (0.003)	0.008 <sup>†</sup> (0.003)
623990 (boot camps, group foster homes)		-0.016 <sup>†</sup> (0.007)		-0.017 <sup>†</sup> (0.007)	-0.009 <sup>†</sup> (0.004)	-0.009 <sup>†</sup> (0.004)
6241 (individual and family services)		-0.009 <sup>†</sup> (0.003)		-0.011 <sup>†</sup> (0.003)		-0.007 <sup>†</sup> (0.002)
624190 (alcoholism and drug addiction self-help organizations)		-0.006 <sup>†</sup> (0.002)	-0.007 (0.003)		-0.005 <sup>†</sup> (0.001)	
624310 (vocational habilitation job counseling)		-0.019 <sup>†</sup> (0.008)		-0.015 (0.007)	-0.014 <sup>†</sup> (0.005)	-0.010 <sup>†</sup> (0.004)
624410 (child care and preschool centers, Head Start)	0.005 <sup>†</sup> (0.003)	-0.030 <sup>†</sup> (0.002)	0.015 <sup>†</sup> (0.003)	-0.019 <sup>†</sup> (0.002)	-0.018 <sup>†</sup> (0.001)	-0.011 <sup>†</sup> (0.001)
711120 (ballet companies, dance troupes)	-0.249 <sup>†</sup> (0.079)		-0.204 <sup>†</sup> (0.076)	-0.076 (0.054)		
711130 (chamber music groups)	0.021 <sup>†</sup> (0.005)	0.011 <sup>†</sup> (0.003)	0.025 <sup>†</sup> (0.005)	0.012 <sup>†</sup> (0.003)	0.005 <sup>†</sup> (0.002)	0.006 <sup>†</sup> (0.002)
711211 (baseball teams, football teams)	-0.045 <sup>†</sup> (0.017)		-0.031 (0.017)			-0.011 (0.007)
711310 (arena operators, sports arena operators)	-0.034 (0.018)					
712110 (art museums, historical museums)	0.012 (0.007)	0.016 <sup>†</sup> (0.005)	0.015 <sup>†</sup> (0.007)	0.013 <sup>†</sup> (0.005)	0.006 <sup>†</sup> (0.003)	

Continued on next page.

**Table 4 (continued)**

NAICS codes (description-see Table 2)	$NI_c^W$				$NI_c^P$	
	(1)	(2)	+ state FEs		(2')	(4')
			(3)	(4)		
713910 (country clubs and golf courses)	0.170 <sup>†</sup> (0.015)	0.115 <sup>†</sup> (0.010)	0.173 <sup>†</sup> (0.014)	0.113 <sup>†</sup> (0.010)	0.071 <sup>†</sup> (0.006)	0.069 <sup>†</sup> (0.006)
713990 (amateur/recreational sports teams, and sports-related clubs)	0.045 <sup>†</sup> (0.006)		0.039 <sup>†</sup> (0.005)			
721214 (children's camps, vacation camps)	0.071 <sup>†</sup> (0.023)	0.050 <sup>†</sup> (0.016)	0.064 <sup>†</sup> (0.023)	0.051 <sup>†</sup> (0.016)	0.033 <sup>†</sup> (0.010)	0.032 <sup>†</sup> (0.010)
812220 (cemeteries, memorial gardens)	0.045 <sup>†</sup> (0.014)		0.036 <sup>†</sup> (0.013)		0.008 (0.006)	
813110 (churches, mosques, synagogues, missions)	0.027 <sup>†</sup> (0.002)	0.004 <sup>†</sup> (0.001)	0.029 <sup>†</sup> (0.002)	0.006 <sup>†</sup> (0.001)	0.002 <sup>†</sup> (0.001)	0.003 <sup>†</sup> (0.001)
813211 (charitable trusts, community foundations)	0.033 <sup>†</sup> (0.007)	0.026 <sup>†</sup> (0.005)	0.044 <sup>†</sup> (0.007)	0.025 <sup>†</sup> (0.005)	0.009 <sup>†</sup> (0.003)	0.009 <sup>†</sup> (0.003)
813312 (humane societies)		-0.031 <sup>†</sup> (0.013)		-0.027 <sup>†</sup> (0.013)	-0.020 <sup>†</sup> (0.008)	-0.015 (0.008)
813319 (advocacy organizations)	-0.028 <sup>†</sup> (0.004)		-0.022 <sup>†</sup> (0.007)		-0.008 <sup>†</sup> (0.003)	-0.005 (0.003)
813410 (hobby clubs, Scouts, PTAs, civic and fraternal associations)	0.023 <sup>†</sup> (0.004)	0.012 <sup>†</sup> (0.003)	0.022 <sup>†</sup> (0.003)	0.011 <sup>†</sup> (0.002)	0.005 <sup>†</sup> (0.002)	0.005 <sup>†</sup> (0.002)
813920 (professional associations)	-0.023 <sup>†</sup> (0.006)	-0.014 <sup>†</sup> (0.005)	-0.017 <sup>†</sup> (0.006)	-0.013 <sup>†</sup> (0.005)	-0.007 <sup>†</sup> (0.003)	-0.006 <sup>†</sup> (0.003)
813930 (labor unions)		0.011 <sup>†</sup> (0.004)		0.012 <sup>†</sup> (0.004)	0.006 <sup>†</sup> (0.003)	0.007 <sup>†</sup> (0.003)
813940 (campaign organizations, political organizations, PACs)	-0.068 <sup>†</sup> (0.019)	-0.045 <sup>†</sup> (0.013)	-0.061 <sup>†</sup> (0.018)	-0.041 <sup>†</sup> (0.013)	-0.019 <sup>†</sup> (0.008)	-0.019 <sup>†</sup> (0.008)
813990 (homeowners' associations)		-0.008 <sup>†</sup> (0.002)		-0.007 <sup>†</sup> (0.002)	-0.006 <sup>†</sup> (0.001)	-0.005 <sup>†</sup> (0.001)
921110 (advisory commissions, city, executive, and mayors' offices)	0.042 <sup>†</sup> (0.008)	0.031 <sup>†</sup> (0.006)	0.043 <sup>†</sup> (0.008)	0.032 <sup>†</sup> (0.006)	0.019 <sup>†</sup> (0.003)	0.019 <sup>†</sup> (0.003)
921120 (city and town councils)		0.035 <sup>†</sup> (0.012)		0.026 <sup>†</sup> (0.011)	0.023 <sup>†</sup> (0.007)	0.016 <sup>†</sup> (0.007)
921190 (auditor's offices, government, civil rights commissions)	-0.027 <sup>†</sup> (0.010)	-0.023 <sup>†</sup> (0.007)	-0.016 (0.009)	-0.018 <sup>†</sup> (0.007)	-0.011 <sup>†</sup> (0.004)	-0.008 (0.004)
922120 (housing police, park police, police departments)	0.035 <sup>†</sup> (0.012)	0.040 <sup>†</sup> (0.009)	0.030 <sup>†</sup> (0.012)	0.032 <sup>†</sup> (0.009)	0.022 <sup>†</sup> (0.005)	0.019 <sup>†</sup> (0.005)
922160 (fire and rescue services including volunteer fire dept.'s)	0.133 <sup>†</sup> (0.013)	0.063 <sup>†</sup> (0.009)	0.101 <sup>†</sup> (0.012)	0.036 <sup>†</sup> (0.009)	0.043 <sup>†</sup> (0.005)	0.026 <sup>†</sup> (0.005)
923120 (health planning and development agencies)			-0.016 <sup>†</sup> (0.008)	-0.007 (0.006)		-0.006 (0.003)
924110 (environment protection program administration)	0.026 <sup>†</sup> (0.012)	0.021 <sup>†</sup> (0.008)	0.022 (0.012)	0.024 <sup>†</sup> (0.008)	0.012 <sup>†</sup> (0.005)	0.014 <sup>†</sup> (0.005)
925110 (housing programs, planning and development)	0.061 <sup>†</sup> (0.017)	0.019 (0.012)	0.053 <sup>†</sup> (0.016)	0.011 (0.012)	0.005 (0.007)	
926110 (arts/cultural, econ. devel., etc., administration)	-0.060 <sup>†</sup> (0.018)	-0.049 <sup>†</sup> (0.012)	-0.059 <sup>†</sup> (0.017)	-0.050 <sup>†</sup> (0.012)	-0.028 <sup>†</sup> (0.008)	-0.028 <sup>†</sup> (0.007)
926130 (communications commissions, licensing and inspecting of utilities)	-0.076 <sup>†</sup> (0.036)	-0.053 <sup>†</sup> (0.025)	-0.079 (0.035)	-0.040 (0.024)	-0.031 <sup>†</sup> (0.015)	-0.019 (0.015)
R <sup>2</sup>	0.366	0.696	0.347	0.679	0.729	0.709

Notes: Results are for Ordinary Least Squares with robust standard errors in parentheses. For all models, variables are shown if they are selected by the Elastic Net procedure and were statistically significant at the 5-percent level or less based on conventional OLS standard errors; that is, *all* coefficients reported in the table are significant at the 5-percent level based on OLS standard errors. The superscript † indicates that the estimate was statistically significant at the 5% level based on the Lee et al. (2016, LSST) confidence intervals. There are approximately 34,000 Census tract observations. See Tables 1 and 2 for variable definitions. However, columns (4) and (4') are estimated on residualized models where variables are first regressed on the fixed state effects. The R<sup>2</sup> values shown are for these residualized variables. Finally, as in Table 3, we omit from the estimation in columns (1) and (3) the transport isolation index and establishment count controls.

**Table 5: Industries with Consistent Positive Effects of Non-Profit Counts on Network Measures (5+ Specifications in Table 4), Longer NAICS Descriptions**

611110	Academies, elementary or secondary; Boarding schools, elementary or secondary; <b>Elementary and secondary schools</b> ; Finishing schools, secondary; Handicapped, schools for, elementary or secondary; High schools; <b>Junior high schools</b> ; 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; Seminaries, below university grade
623110	<b>Convalescent homes</b> or convalescent hospitals (except psychiatric); <b>Group homes</b> for the disabled with nursing care; Homes for the aged with nursing care; Homes for the elderly with nursing care; Hospices, inpatient care; <b>Nursing homes</b> ; Rest homes with nursing care; Retirement homes with nursing care; Skilled nursing facilities
711130	Bands; <b>Chamber musical groups</b> ; Chamber orchestras; Choirs; Classical musical artists, independent; Classical musical groups; Concert artists, independent; Country musical groups; Drum and bugle corps (i.e., drill teams); Ensembles, musical; Jazz musical groups; Musical artists, independent; 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
712110	Art galleries (except retail); <b>Art museums</b> ; Community museums; Contemporary art museums; Decorative art museums; Fine arts museums; Galleries, art (except retail); Halls of fame; Herbariums; <b>Historical museums</b> ; 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
713910	<b>Country clubs</b> ; Golf and country clubs; <b>Golf courses</b> (except miniature, pitch-n-putt)
721214	Boys' camps (except day, instructional); Camps (except day, instructional); <b>Children's camps</b> (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; <b>Vacation camps</b> (except campgrounds, day instructional); Wilderness camps
813110	Bible societies; <b>Churches</b> ; Convents (except schools); <b>Missions</b> , religious organization; Monasteries (except schools); <b>Mosques</b> , religious; Places of worship; Religious organizations; Retreat houses, religious; Shrines, religious; <b>Synagogues</b> ; Temples, religious
813211	<b>Charitable trusts</b> , awarding grants; <b>Community foundations</b> ; 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
813410	Alumni associations; Automobile clubs (except road and travel services); Book discussion clubs; Booster clubs; Boy guiding organizations; <b>Civic associations</b> ; Classic car clubs; Computer enthusiasts clubs; Ethnic associations; Farm granges; <b>Fraternal organizations</b> ; Fraternities (except residential); Garden clubs; Girl guiding organizations; Golden age clubs; Granges; Historical clubs; Membership associations, civic or social; <b>Parent-teachers' associations</b> ; Poetry clubs; Public speaking improvement clubs; Retirement associations, social; <b>Scouting organizations</b> ; Senior citizens' associations, social; Singing societies; Social clubs; Sororities (except residential); Speakers' clubs; Student clubs; Students' unions; University clubs; Veterans' membership organizations; Women's auxiliaries; Women's clubs; Writing clubs; Youth civic clubs; Youth farming organizations; Youth scouting organizations; Youth social clubs
921110	<b>Advisory commissions</b> , executive government; <b>City and town managers' offices</b> ; County supervisors' and executives' offices; Executive offices, federal, state, and local (e.g., governor, mayor, president); Governors' offices; <b>Mayor's offices</b> ; President's office, United States
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; <b>Housing police</b> , government; Marshals' offices; <b>Park police</b> ; Police academies; Police and fire departments, combined; <b>Police departments</b> (except American Indian or Alaska Native); Sheriffs' offices (except court functions only); State police; Transit police
922160	Ambulance and fire service combined; <b>Fire and rescue service</b> ; Fire departments (e.g., government, volunteer (except private)); Fire marshals' offices; Fire prevention offices, government; <b>Firefighting</b> (except forest), government and <b>volunteer</b> (except private); Firefighting services (except forest and private)
924110	Enforcement of environmental and pollution control regulations; <b>Environmental protection program administration</b> ; NOAA (National Oceanic and Atmospheric Administration); Pollution control program administration; Sanitation engineering agencies, government; Waste management program administration; Water control and quality program administration

See the on-line appendix for full NAICS descriptions.

**Table 6: Non-Profit Counts by Tract, Any NAICS Codes Retained by LASSO**

Non-profit counts by tract	Mean	Std. Dev.	Pos. effects in Table 4
114210 (fishing preserves, hunting preserves)	0.016	0.129	X
115111 (cotton ginning)	0.001	0.039	X
221122 (distribution of electric power)	0.010	0.124	
221310 (irrigation system operation, water distribution)	0.084	0.378	X
221320 (sewage disposal, waste collection)	0.017	0.141	X
522294 (Federal National Mortgage Association, etc.)	0.007	0.099	
524114 (health insurance carriers)	0.076	0.367	
525110 (union pension funds)	0.022	0.174	X
525120 (union health and welfare funds)	0.003	0.059	X
531311 (apartment managers offices, condominium managers offices)	0.068	0.312	
541720 (social sciences research and development services)	0.191	0.599	
561499 (fundraising campaign organization services)	0.127	0.413	
611110 (elementary, junior, secondary schools)	1.501	1.492	X
611310 (colleges, universities)	0.230	1.711	
611513 (apprenticeship training programs)	0.074	0.302	
611630 (foreign language schools)	0.034	0.211	
611699 (Bible schools, yoga instruction)	0.141	0.422	X
611710 (education support and testing services)	0.689	1.148	?
621498 (clinics/centers of health practitioners, community health centers)	0.078	0.315	
621610 (home health agencies)	0.297	0.792	
621910 (ambulance or rescue services)	0.067	0.306	X
622310 (children's hospitals)	0.102	0.382	X
623110 (nursing homes, group homes, convalescent homes)	0.352	0.850	X
623990 (boot camps, group foster homes)	0.215	0.530	
6241 (individual and family services)	0.798	1.369	
624190 (alcoholism and drug addiction self-help organizations)	0.981	2.024	
624310 (vocational habilitation job counseling)	0.187	0.498	
624410 (child care and preschool centers, Head Start)	1.870	1.926	?
711120 (ballet companies, dance troupes)	0.004	0.062	
711130 (chamber music groups)	0.519	1.125	X
711211 (baseball teams, football teams)	0.069	0.293	
711310 (arena operators, sports arena operators)	0.065	0.282	
712110 (art museums, historical museums)	0.227	0.840	X
713910 (country clubs and golf courses)	0.088	0.337	X
713990 (amateur/recreational sports teams, and sports-related clubs)	0.623	0.978	X
721214 (children's camps, vacations camps)	0.042	0.212	X
812220 (cemeteries, memorial gardens)	0.100	0.361	X
813110 (churches, mosques, synagogues, missions)	4.431	3.875	X
813211 (charitable trusts, community foundations)	0.352	0.902	X
813312 (humane societies)	0.053	0.291	
813319 (advocacy organizations)	0.335	0.817	
813410 (hobby clubs, Scouts, PTAs, civic and fraternal associations)	1.182	1.939	X
813920 (professional associations)	0.311	1.090	
813930 (labor unions)	0.270	0.909	X
813940 (campaign organizations, political organizations, PACs)	0.056	0.304	
813990 (homeowners' associations)	0.886	2.225	
921110 (advisory commissions, city, executive, and mayors' offices)	0.190	0.781	X
922120 (housing police, park police, police departments)	0.126	0.479	X
922160 (fire and rescue services including volunteer fire dept.'s)	0.132	0.417	X
923120 (health planning and development agencies)	0.095	0.746	
924110 (environment protection program administration)	0.058	0.516	X
925110 (housing programs, planning and development)	0.063	0.314	X
926110 (arts/cultural, econ. devel., etc., administration)	0.031	0.360	
926130 (communications commissions, licensing and inspecting of utilities)	0.013	0.147	

**On-line Appendix Table: NETS Tabulations of 6-Digit NAICS Industries with  $\geq 10$  Percent of Establishments Non-Profit (Corresponds to Table 2, with Full NAICS Descriptions)**

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non-Profit
114210	Animal trapping, commercial; <b>Fishing preserves</b> ; Game preserves, commercial; Game propagation; Game retreats; <b>Hunting preserves</b>	139	1063	13.1%
115111	<b>Cotton ginning</b> ; Ginning cotton	103	728	14.0%
221122	<b>Distribution of electric power</b> ; Electric power brokers; Electric power distribution systems	361	1727	20.9%
221310	Canal, irrigation; Filtration plant, water; Impounding reservoirs, irrigation; <b>Irrigation system operation</b> ; <b>Water distribution</b> (except irrigation); Water distribution for irrigation; Water filtration plant operation; Water supply systems; Water treatment and distribution; Water treatment plants	1744	8586	20.3%
221320	Collection, treatment, and disposal of waste through a sewer system; <b>Sewage disposal</b> plants; Sewage treatment plants or facilities; Sewer systems; <b>Waste collection</b> , treatment, and disposal through a sewer system	292	1938	15.1%
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%
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%
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%
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 ( <b>Federal National Mortgage Association</b> ); 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%
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%
522130	Corporate credit unions; Credit unions; Federal credit unions; State credit unions; Unions, credit	2962	12821	23.1%
524114	Dental insurance carriers, direct; Group hospitalization plans without providing health care services; <b>Health insurance carriers</b> , 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%
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%
525120	Union health and welfare funds	29	159	18.2%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non-Profit
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%
531311	<b>Apartment managers' offices; Condominium managers' offices</b> , 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%
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; <b>Humanities research and development services</b> ; Language research and development services; Learning disabilities research and development services; Psychology research and development services; <b>Social science research and development services</b> ; Sociological research and development services; Sociology research and development services	1183	8242	14.4%
561499	Address bar coding services; Bar code imprinting services; <b>Fundraising campaign organization services</b> on a contract or fee basis; Mail consolidation services; Mail presorting services; Teleconferencing services; Videoconferencing services	796	4497	17.7%
561591	Convention and visitors bureaus; Convention bureaus; Tourism bureaus; Tourist information bureaus; Visitors bureaus	211	808	26.1%
611110	Academies, elementary or secondary; Boarding schools, elementary or secondary; <b>Elementary and secondary schools</b> ; 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; <b>Junior high schools</b> ; 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%
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%
611310	Academies, college or university; Academies, military service (college); Business colleges or schools offering baccalaureate or graduate degrees; <b>Colleges</b> (except junior colleges); Colleges, <b>universities</b> , 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%
611513	<b>Apprenticeship training programs</b> ; 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 Estab.'s	% Non-Profit
611630	Foreign language schools; Language schools; Schools, language; Second language instruction; Sign language instruction; Sign language schools	99	910	10.9%
<b>611699</b>	<b>Bible schools</b> (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; <b>Yoga instruction</b> , camps, or schools	343	3166	10.8%
<b>611710</b>	College selection services; Educational consultants; Educational guidance counseling services; <b>Educational support services</b> ; Educational testing evaluation services; <b>Educational testing services</b> ; School bus attendant services; Student exchange programs; Test development and evaluation services, educational; Testing services, educational	4544	24088	18.9%
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%
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%
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%
<b>621498</b>	Biofeedback centers and clinics, outpatient; <b>Clinics/centers of health practitioners</b> from more than one industry practicing within the same establishment; Clinics/centers of health practitioners with multi-industry degrees; <b>Community health centers</b> 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%
<b>621610</b>	Home care of elderly, medical; <b>Home health agencies</b> ; 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%
<b>621910</b>	Air ambulance services; <b>Ambulance services</b> , air or ground; Emergency medical transportation services, air or ground; Rescue services, air; <b>Rescue services</b> , medical	1197	5342	22.4%
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%
622110	Children's hospitals, general; General medical and surgical hospitals; Hospitals, general medical and surgical; Hospitals, general pediatric; Osteopathic hospitals	3986	9913	40.2%
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%
<b>622310</b>	Cancer hospitals; <b>Children's hospitals, specialty</b> (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%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non- Profit
623110	<b>Convalescent homes</b> or convalescent hospitals (except psychiatric); <b>Group homes</b> for the disabled with nursing care; Homes for the aged with nursing care; Homes for the elderly with nursing care; Hospices, inpatient care; <b>Nursing homes</b> ; Rest homes with nursing care; Retirement homes with nursing care; Skilled nursing facilities	3291	23883	13.8%
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%
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%
623312	Assisted-living facilities without on-site nursing care facilities; <b>Homes for the aged</b> 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%
623990	<b>Boot camps</b> 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; <b>Group foster homes</b> 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%
<b>6241</b>	Individual and family services			
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%
624120	Activity centers for disabled persons, the elderly, and persons diagnosed with intellectual and developmental disabilities; <b>Centers, senior citizens'</b> ; 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%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non- Profit
<b>624190</b>	<b>Alcoholism and drug addiction self-help organizations;</b> 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%
624210	Community meals, social services; Food banks; Meal delivery programs; Mobile soup kitchens; Soup kitchens	183	499	36.7%
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%
<b>624310</b>	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); <b>Vocational habilitation job counseling;</b> 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%
<b>624410</b>	Babysitting services in provider's own home, child day care; Babysitting services, child day care; Child day care centers; <b>Child day care services;</b> 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; <b>Head start programs,</b> separate from schools; Infant day care centers; Infant day care services; Nursery schools; Pre-kindergarten centers (except part of elementary school system); <b>Preschool centers</b>	7472	58746	12.7%
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%
<b>711120</b>	<b>Ballet companies;</b> Ballet productions, live theatrical; Classical dance companies; Contemporary dance companies; Dance companies; Dance productions, live theatrical; Dance theaters; <b>Dance troupes;</b> 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%
<b>711130</b>	Bands; Bands, dance; Bands, musical; <b>Chamber musical groups;</b> 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%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non- Profit
711211	Baseball clubs, professional or semiprofessional; <b>Baseball teams</b> , professional or semiprofessional; Basketball clubs, professional or semiprofessional; Basketball teams, professional or semiprofessional; Boxing clubs, professional or semiprofessional; Football clubs, professional or semiprofessional; <b>Football teams</b> , 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%
711310	Air show managers with facilities; Air show organizers with facilities; Air show promoters with facilities; <b>Arena operators</b> ; 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; <b>Sports arena operators</b> ; 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%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non- Profit
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%
<b>712110</b>	Art galleries (except retail); <b>Art museums</b> ; Community museums; Contemporary art museums; Decorative art museums; Fine arts museums; Galleries, art (except retail); Halls of fame; Herbariums; <b>Historical museums</b> ; 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%
712120	Archeological sites (i.e., public display); Battlefields; Heritage villages; Historical forts; Historical ships; Historical sites; Pioneer villages	555	1422	39.0%
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%
<b>713910</b>	<b>Country clubs</b> ; Golf and country clubs; <b>Golf courses</b> (except miniature, pitch-n-putt)	2772	13310	20.8%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non-Profit
713990	<b>Amateur sports teams, recreational;</b> 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; <b>Athletic clubs</b> (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%
721214	Boys' camps (except day, instructional); Camps (except day, instructional); <b>Children's camps</b> (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; <b>Vacation camps</b> (except campgrounds, day instructional); Wilderness camps	999	4835	20.7%
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; <b>Cemeteries</b> ; Cemetery associations (i.e., operators); Cemetery management services; Columbariums; Crematories (except combined with funeral homes); Mausoleums; <b>Memorial gardens</b> (i.e., burial places); Pet cemeteries	981	5876	16.7%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non-Profit
813110	Bible societies; <b>Churches</b> ; Convents (except schools); <b>Missions</b> , religious organization; Monasteries (except schools); <b>Mosques</b> , religious; Places of worship; Religious organizations; Retreat houses, religious; Shrines, religious; <b>Synagogues</b> ; Temples, religious	73178	228934	32.0%
813211	<b>Charitable trusts</b> , awarding grants; <b>Community foundations</b> ; 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%
813219	<b>Community chests</b> ; Federated charities; United fund councils; United funds for colleges	1812	3277	55.3%
813312	Animal rights organizations; Animal welfare associations or leagues; Conservation advocacy organizations; Environmental advocacy organizations; <b>Humane societies</b> ; Natural resource preservation organizations; Wildlife preservation organizations	1642	3672	44.7%
813319	Accident prevention associations; Antipoverty advocacy organizations; Aviation advocacy organizations; Community action <b>advocacy organizations</b> ; 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%
813410	Alumni associations; Alumni clubs; Automobile clubs (except road and travel services); Book discussion clubs; Booster clubs; Boy guiding organizations; <b>Civic associations</b> ; Classic car clubs; Computer enthusiasts clubs; Ethnic associations; Farm granges; Fraternal associations or lodges, social or civic; Fraternal lodges; <b>Fraternal organizations</b> ; Fraternities (except residential); Garden clubs; Girl guiding organizations; Golden age clubs; Granges; Historical clubs; Membership associations, civic or social; <b>Parent-teachers' associations</b> ; Poetry clubs; Public speaking improvement clubs; Retirement associations, social; <b>Scouting organizations</b> ; 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%
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%
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; <b>Professional associations</b> ; Professional membership associations; Professional standards review boards; Psychologists' associations; Scientific associations; Social workers' associations; Standards review committees, professional	3946	12231	32.2%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non-Profit
813930	Employees' associations for improvement of wages and working conditions; Federation of workers, labor organizations; Federations of labor; Industrial labor unions; Labor federations; <b>Labor unions</b> (except apprenticeship programs); Trade unions (except apprenticeship programs); Trade unions, local; Unions (except apprenticeship programs), labor	2892	11966	24.2%
813940	<b>Campaign organizations</b> , political; Constituencies' associations, political party; Local <b>political organizations</b> ; PACs (Political Action Committees); Political action committees ( <b>PACs</b> ); Political campaign organizations; Political organizations or clubs; <b>Political parties</b>	328	1857	17.7%
813990	Athletic associations, regulatory; Athletic leagues (i.e., regulating bodies); Condominium corporations; Condominium owners' associations; Cooperative owners' associations; <b>Homeowners' associations</b> ; Homeowners' associations, condominium; Property owners' associations; Sports governing bodies; Sports leagues (i.e., regulating bodies); Tenants' associations (except advocacy)	7886	17947	43.9%
921110	<b>Advisory commissions</b> , executive government; <b>City and town managers' offices</b> ; County supervisors' and executives' offices; Executive offices, federal, state, and local (e.g., governor, mayor, president); Governors' offices; <b>Mayor's offices</b> ; President's office, United States	6387	29792	21.4%
921120	Advisory commissions, legislative; Boards of supervisors, county and local; <b>City and town councils</b> ; 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%
921130	<b>Assessor's offices</b> , 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; <b>Taxation departments</b> ; Treasurers' offices, government	1026	6165	16.6%
921140	Executive and legislative office combinations; Legislative and executive office combinations	124	1172	10.6%
921190	<b>Auditor's offices, government</b> ; <b>Civil rights commissions</b> ; 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%
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%
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; <b>Housing police</b> , government; Marshals' offices; <b>Park police</b> ; Police academies; Police and fire departments, combined; <b>Police departments</b> (except American Indian or Alaska Native); Sheriffs' offices (except court functions only); State police; Transit police	3125	14154	22.1%
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%
922160	Ambulance and fire service combined; <b>Fire and rescue service</b> ; Fire departments (e.g., government, volunteer (except private)); Fire marshals' offices; Fire prevention offices, government; <b>Firefighting</b> (except forest), government and <b>volunteer</b> (except private); Firefighting services (except forest and private)	4715	18083	26.1%
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%

NAICS12	NAICS Description	Non-Profit Count	Total Estab.'s	% Non-Profit
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%
<b>923120</b>	Cancer detection program administration; Communicable disease program administration; Community health programs administration; Coroners' offices; Environmental health program administration; Food service health inspections; <b>Health planning and development agencies, government</b> ; 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%
<b>924110</b>	Enforcement of environmental and pollution control regulations; <b>Environmental protection program administration</b> ; 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%
<b>925110</b>	Building standards agencies, government; Housing authorities, nonoperating; <b>Housing programs, planning and development, government</b>	1268	5119	24.8%
<b>925120</b>	<b>Community development agencies, government</b> ; 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%
<b>926110</b>	<b>Arts and cultural program administration, government</b> ; Consumer protection offices; Councils of Economic Advisers; Cultural and arts development support program administration; Development assistance program administration; <b>Economic development agencies, government</b> ; 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%
<b>926130</b>	<b>Communications commissions</b> ; Communications licensing commissions and agencies; Energy development and conservation programs, government; Federal Communications Commission (FCC); Irrigation districts, nonoperating; <b>Licensing and inspecting of utilities</b> ; 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%

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.