The Unequal Landscape of Civic Opportunity in America

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Abstract

The hollowing of civil society has threatened effective implementation of scientific solutions to pressing public challenges—which often depend on cultivating pro-social orientations commonly studied under the broad umbrella of social capital. Although robust research has studied the constituent components of social capital from the demand-side (i.e. the orientations people need for collective life in pluralistic societies, such as trust, cohesion, and connectedness), the same precision has not been brought to the supply-side. This paper defines the concept of civic opportunity—opportunities people have to encounter civic experiences necessary for developing such orientations—and harnesses data science to map it across America. We demonstrate that civic opportunity is more highly correlated with pro-social outcomes like mutual aid than other measures, but is unequally distributed, and its sources are under-represented in the public dialogue. Our findings suggest greater attention to this fundamentally uneven landscape of civic opportunity.

Main Text

This paper defines, measures, and describes patterns of civic opportunity in America to try to develop more precise understandings of where social capital can be cultivated. Scholars have long understood social capital to be fundamental to making collective life in pluralistic, democratic societies possible[1-3,5-9]. Particularly in an era characterized by extreme socio-political polarization, distrust, disinformation, and societal fragmentation, understanding how to build the social capital and civic muscles people need to overcome natural instincts towards parochial, ethnocentric, self-interested behavior is more important than ever[10-12]. Yet, social capital does not spontaneously emerge. Instead, it needs an infrastructure of associations and organizations that try to help generate it. French philosopher Alexis de Tocqueville famously called this infrastructure "schools of democracy"[13]. To generate social capital, people need opportunities to join with others in well-designed (virtual or in-person) civic settings that cultivate the capacities needed to strengthen connectedness, cohesion, and collective problem-solving[4,14].

Despite its importance, scholars have also critiqued social capital for being conceptually vague, and hence sometimes tautological in how it is measured[15,16]. Thus additional research has sought to break social capital down into its constituent components, yielding fruitful lines of research on social trust, connectedness, cohesion, volunteerism, norms of reciprocity and obligation, and so on[1-3,6,7,17-21]. Most of this research, however, has focused on the demand-side of social capital—the pro-social orientations that social capital seeks to generate—to unpack the psychological orientations that constitute it. Although many researchers, including those at the United States Senate's Social Capital Project[22], have recognized the distinctiveness and importance of the supply-side of associations and organizations that generate social capital, the measures used to assess it have been relatively blunt. Many of these measures count the number of certain types of organizations in a community (such as "public good" providing organizations[2], or a compilation of religious, civic, professional, political, and recreational organizations[18]) without taking into account research showing that many such organizations are increasingly less likely to actually engage people in civic action[23,24]. Other measures provide deep, textured investigations of particular local communities[3,25-27] without providing a national picture.

Lacking better data on the supply-side, we are left knowing that social capital is needed for solving collective problems, without knowing where to go to cultivate it, or being able to *ex ante* anticipate where it might be strong or weak. We need better data on where opportunities exist for increasing this underlying capacity[10,28-30]. This paper thus focuses on the supply-side by examining *civic opportunity*, which we define as the opportunities people have to encounter the experiences necessary to cultivate the capacities for collective life in pluralistic societies. We develop more direct and comprehensive measures of civic opportunity than previously possible to map it across America. Our data show that civic opportunity is distinct from the demand-side of social capital and distributed unequally across the country. We also demonstrate that in a multivariate analysis, our civic opportunity index is more highly associated with measures of a community's willingness to engage in publicly-oriented, other-regarding behavior like mutual aid than other common measures of social capital. Our data also reveal a mismatch between the kinds of associations commonly discussed in public life, such as professional organizations based in Washington DC, and those that actually generate civic opportunity.

Results

Mapping Civic Opportunity

Mapping patterns of civic opportunity is challenging because of the inherently decentralized nature of civil society. The organizations and public spaces that constitute the landscape of civic opportunity emerged organically in communities across America and thus are distributed in diffuse ways throughout the country. In many ways, their effectiveness depends on their ability to be nested in the specific social contexts and unique local circumstances of people's everyday lives. Yet, this decentralization limited previous attempts to map civic infrastructure. The public availability of big data and digital traces left by these organizations, however, enables this paper to develop a more comprehensive map of civic opportunity in America than previously possible.

To map civic opportunity, we must first identify the entities that constitute civil society. Civil society refers to the formal and informal associations, organizations, networks, and settings where people gather for public action, such as churches, neighborhood groups, community associations, and so on[1,15]. We used the set of non-profit organizations registered with the Internal Revenue Service (IRS) as the starting point for inquiry. This is not a perfect measure because not all social-capital providing organizations are formalized non-profits that report to the IRS. We use it as a starting point, however, and show in our analyses below that it nonetheless provides us with an improved picture of civic opportunity (even if, as we discuss later, it could be improved in the future). The IRS database identifies approximately 1.8 million organizations with non-profit status, along with basic information such as addresses, revenue, and expenditures. We could then geographically map each non-profit organization onto physical space.

Not all non-profit organizations provide civic opportunity, however. Organizations with non-profit status may be oriented towards the public good but they vary widely in if and how they engage people. Non-profit hospitals, for instance, do not provide civic opportunity. Previous measures elided these distinctions, estimating the supply-side of social capital using counts of certain types of organizations in a community without differentiating which ones actually engage people in shared action[2,18], or estimates that elide distinctions between demand-side and supply-side measures of social capital[2]. Our data allow us to develop more precise estimates of civic opportunity at local geographies.

To pinpoint organizations that are sources of civic opportunity, we layered IRS data with data scraped from the Internet to develop a classification scheme. We automated data ingestion to scrape 1,062,554 organizational websites associated with the organizations in the IRS database. We linked these data to the core IRS data as well as additional filings from organizations where available. In addition, we overlayed external data, such as the U.S. Census data, using geo-codes, to gather data about the kinds of communities where these organizations operate.

Our index of civic opportunity emerges from the classification schemes we developed based on this interconnected data. We used natural language processing (NLP) to categorize organizations by focus and activity—what they do and how they do it[25,31]. We built a binary classifier for fifteen categories of possible areas of organizational focus (Supplementary Table 1) based on mission and program descriptions submitted to the IRS and website text on "about" pages, and generated the highest likelihood score for 1,400,002 organizations (Supplementary Table 3) to identify each organization's focus. In scraping websites, we assessed the presence of links for activities such as volunteering and taking civic or political actions (Supplementary Table 5-6) to identify organizational activities. We classify organizations as being generators of civic opportunity if they do one of four things: provide volunteer opportunities, offer membership, offer ways to take civic or political action, or hold community events. Through these methods, we identified 564,559 organizations throughout America that provide civic opportunities. We did not include nonprofits whose primary address is a post office (P.O.) box in this sample because, in such cases, their location is not necessarily linked to their constituency.

We created a civic opportunity index in three steps. First, we created a composite civic opportunity score by averaging dummy indicators of each of the four possible civic-opportunity-generating activities an organization provided. An organization that provided all four of these opportunities scored 1, whereas an organization that offered none of these opportunities scored 0 (Supplementary Figure 1 compares this method of creating an index variable to other approaches and shows that this type of index best captures the distinct dimensions of civic opportunity). Second, we summed these civic opportunity scores for each county and normalized them by dividing these cumulative scores by the estimated 2018 population of the counties. Third, we categorized these counties into equal-sized quintiles with higher numbers indicating a higher density of civic opportunity. Panel A in Figure 1 shows the distribution of this civic opportunity index by county across America, showing that it is unevenly distributed across counties in the United States. For instance, every county in states like Connecticut fall into the top two quintiles of civic opportunity (4 or 5). In contrast, over 86% of counties in Mississippi fall into the bottom two quintiles (1 or 2). Panel B zooms in on Los Angeles county and calculates the civic opportunity index by zip code to show that the disparities exist not only at the county level, but also at more localized levels.

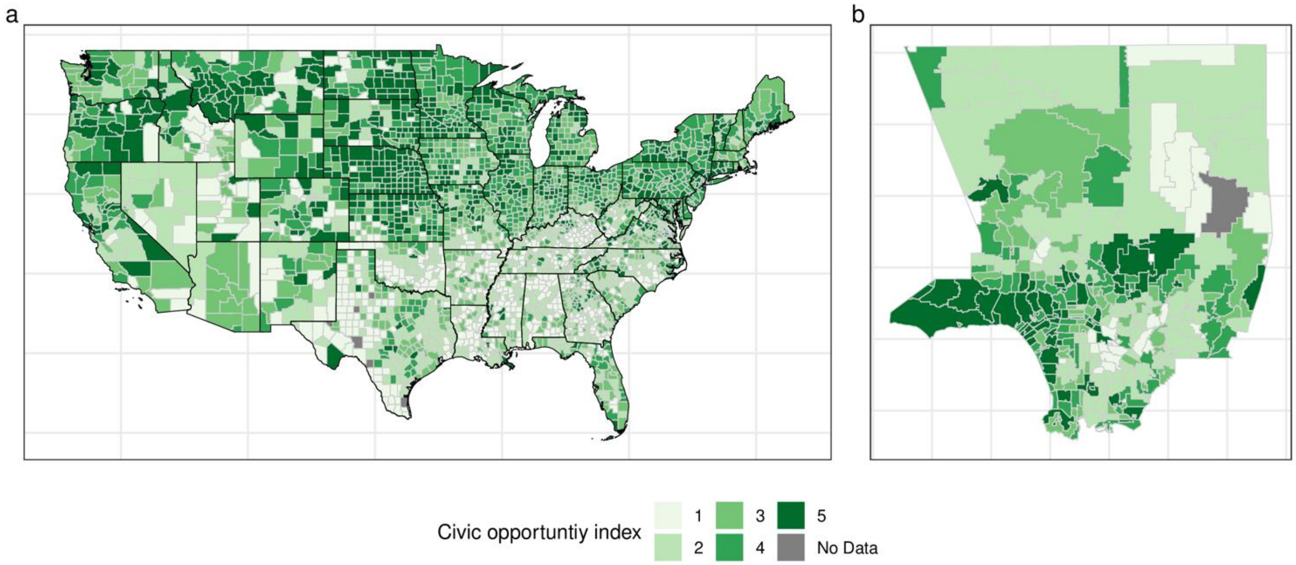

Figure 1: The Geography of Civic Opportunity in the United States. The Civic Opportunity Index ranks counties based on their cumulative civic opportunity scores per capita. Each civic opportunity score represents the range of opportunities (0-1) provided by an organization. The index divides the counties of the continental United States (Panel A) or zip codes of Los Angeles county (Panel B) into five grades: from 1 (low civic opportunity, shaded in white) to 5 (high civic opportunity, shaded in green).

Further analyses demonstrate that these disparities in civic opportunity are systematically present across the country. Figure 2 graphs coefficients of a regression of civic opportunity on measures of demographic disparity in a county—specifically, the federal poverty level in each county, the percentage of those with a college education, and the percentage of the population that identifies as non-Hispanic white. The regression shows that civic opportunity scores per capita decrease as poverty levels (slope=-1.55 [-1.68, -1.42], df = 3127, p = <0.001) increase and the percentage of white (slope=0.47 [0.40,0.52], df = 3127, p = <0.001), college-educated (slope=1.52 [1.42 ,1.64], df = 3127, p = <0.001) residents increases. Wealthier, whiter, better-educated communities are more likely to have civic opportunity. Further, our measure of civic opportunity reveals the inequality in opportunity more clearly than simply examining the density of particular types of organizations in a community. Supplementary Table 7 shows the results of the same regression with the Rupasingha et al[18] measure (which examines a composite of the number of religious, civic, business, political, professional, and labor organizations, as well as the number of bowling centers, recreational sports centers, golf club, country clubs, and sports teams in a community). Supplementary Table 8 compares standardized regression coefficients to show that civic opportunity is associated with measures of educational and socio-economic disparity at a higher rate than Rupasingha's measures for both the federal poverty level and percentage of college-educated residents, allowing us to pinpoint the inequalities more clearly. The difference between the regression coefficients for the two measures is not significant for the comparison to the percentage of non-Hispanic, white residents.

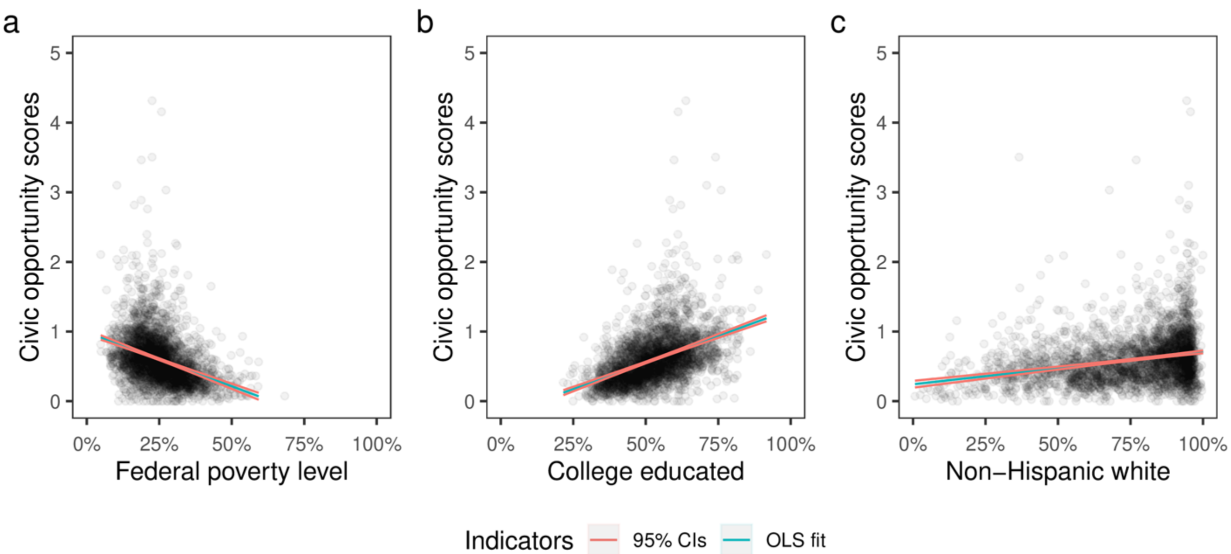

Figure 2: Inequality of Civic Opportunity. Plots graph the regression coefficients and 95% confidence intervals of a univariate OLS regression of civic opportunity scores per capita on measures on inequality in a county, specifically, a. the federal poverty rate (-1.552 [-1.693, -1.410] p = <0.001, n=3127) , b. the percentage of college-educated people (1.525 [1.416, 1.634] p = <0.001, n=3127) , and c. the percentage of non-Hispanic Whites 0.466 [0.403, 0.528] p = <0.001, n=3127 in a county. The jittered points each represent one county, and the lines display the OLS regression.

The Relationship of Civic Opportunity to Civic Action

We also find that this patterned inequality in civic opportunity is related to indicators of a community's ability to come together to solve shared problems. Communities with limited civic opportunities may lack the necessary infrastructure to take collective action when it is most needed. The emergence of mutual aid in response to the coronavirus pandemic is a good example, as it illustrates people's willingness to take actions that assist their community members. In Figure 3, we explore the connection at the county level between civic opportunity and the emergence of COVID-19 mutual aid organizations during the global coronavirus pandemic of 2020-2021. Panel A in Figure 3 shows the association between the emergence of mutual aid and per capita civic opportunity scores from a multivariate regression that also controls for urbanicity, partisanship, poverty, education, and race (, 0.052 ; 95% CI [0.020, 0.083], df = 3025, p = <0.001 see Supplementary Table 10). Counties with higher per capita civic opportunity scores were more likely to have mutual aid organizations emerge during the pandemic.

We also compare our measure of civic opportunity with other commonly used measures of social capital to see what the association is between different social capital measures and the emergence of mutual aid. We draw on one measure that is a composite index of 19 widely used indicators of social capital[20] and two other measures that focus particularly on the supply-side of social capital: Chetty et al's[2] measure of "public good" organizations, and the Rupasingha et al[18] composite measure of social-capital providing organizations. Based on the Pearson's two-tailed correlation method, they are each correlated with our civic opportunity scores per capita at r = 0.32 (95% CI [0.284, 0.374], df = 3125, p < 0.001,), r = 0.48 (95% CI [0.45, 0.504], df = 3125, p

< 0.001) and 0.32 (95% CI [0.292, 0.355], df = 3125, p < 0.001), respectively. Panel B in Figure 3 shows that there is no significant positive association between Kyne and Aldrich's social capital index and the emergence of mutual aid (-0.037 ; 95% CI [-0.080, 0.007], df=3025, p = 0.096), and Panels C and D shows the same for Chetty et al's measure of "public good" organizations (which is measured as the number of Facebook pages predicted to be "Public Good" pages per 1,000 users in the community) (-0.021 ; 95% CI [-0.054, 0.013], df = 3025, p = 0.237) and Rupasingha et al's measure (0.013 ; 95% CI [-0.045, 0.018] , df = 3025, p = 0.411) (Supplementary Table 10). Moreover, the positive association we find between our measure of civic opportunity and the emergence of mutual aid is significantly greater in magnitude to those of the other measures shown in Figure 3, when comparing standardized regression coefficients using a t-test (Kyne and Aldrich, t=3.131, p=0.0017, df=6052 ; Chetty, et al., t=2.771, p=0.0056, df=6052 ; Rupasingha, et al., t=2.355, p=0.0186, df=6052, and Supplementary Table 11). Our measure of civic opportunity, in sum, appears to be more strongly associated with a community's likelihood to engage in behaviors like mutual aid than other measures of both demand and supply-side social capital.

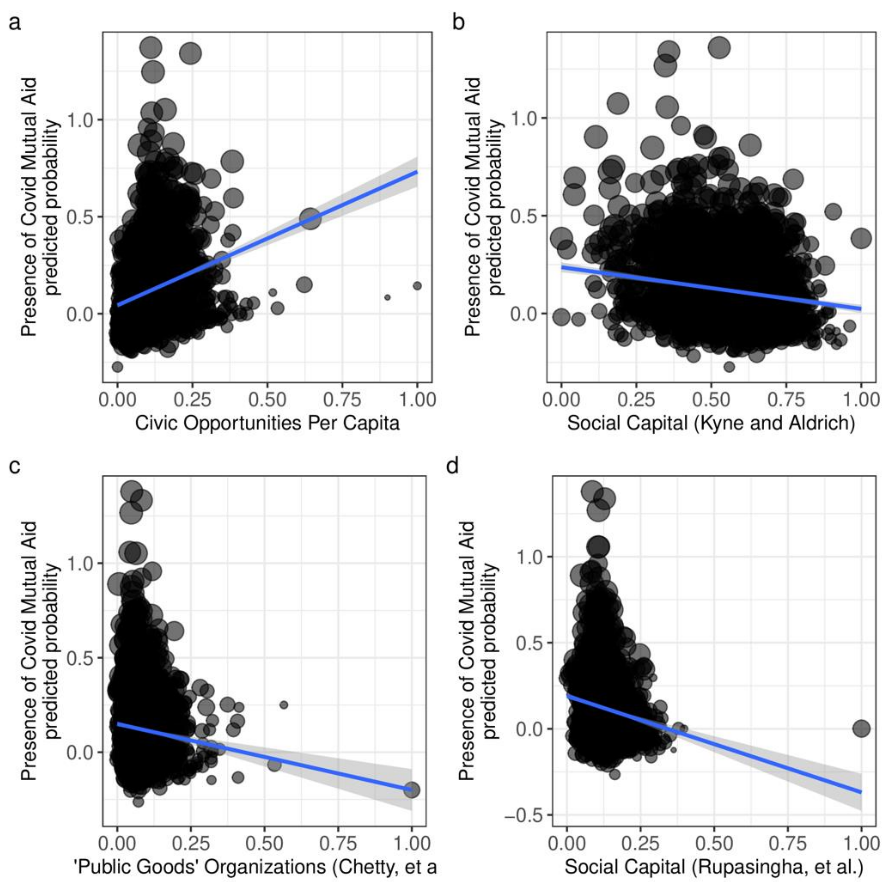

Figure 3: Relationship of per capita civic opportunity scores (Panel A), Kyne and Aldrich's composite measure of social capital (Panel B), Chetty et al's "public good" organizations per capita (Panel C), and Rupasingha et al's index (Panel D) with COVID-19 mutual aid instances at the county level. The indices given on the x-axis are all normalized to be in a range of 0 to 1. Each dot represents a single county. The blue line shows the partial correlation between the two variables after adjusting for partisanship, age, ethnicity, poverty rates, education, and urbanity of the counties. The shaded area corresponds to a 95% confidence interval. For full results, please refer to Supplementary Table 10.

Furthermore, our measure of civic opportunity is associated with other indicators (beyond mutual aid) of the ability of a community to act towards solving public problems. Supplementary Tables 10-14 show that civic opportunity is associated with a range of outcomes, including a decrease in vaccine hesitancy (Supplementary Table 12), even when controlling for local misinformation (Supplementary Table 13), and an increase in vaccine uptake at both the county (Supplementary Table 14) and zip code levels (Supplementary Table 14) in multivariate regressions that include individual characteristics such as partisanship, education, race, income, and insurance status.

These results suggest that measuring civic opportunity this way helps us observe a community's willingness to engage in public-spirited actions. These effects are consistent with what democratic theorists predicted from the earliest days of the republic[14,32]. Yet, if civic opportunity is related to so many salutary behaviors in a community, why has it become so uneven?

Sources of Civic Opportunity

One potential reason civic opportunity may have become so uneven is because there is a mismatch between the types of organizations producing civic opportunity and the types of organizations that get public attention. In our data, the most common organizations providing civic opportunity across America are social-fraternal organizations (Rotary Clubs, fraternities, sororities, ethnic clubs, etc.) and religious (churches, temples, mosques, etc.) organizations. Together, they make up 37% of all civic opportunity organizations. In 85% of counties, they are the top providers of civic opportunity. Yet, those are not the kind of organizations most likely to emerge or get attention in the modern era.

Panel A in Figure 4 shows how the landscape of civic opportunity has shifted over time. If we examine IRS data that identifies the year each organization received non-profit status (proxy to a founding year), social-fraternal and religious organizations went from being 62% of civic opportunity organizations (among organizations founded before 1960) to 28% (among organizations founded after 2010). In contrast, after 2010, the kinds of organizations more likely to emerge have reflected a much broader range of non-profit activities, including political, professional, and research organizations, as well as issue-specific organizations (such as housing, economic, and education organizations) and community-based organizations (such as arts, sports & hobby, and youth organizations). Supplementary Table 18 shows the proportion of different types of organizations providing civic opportunity.

In addition, Panel B shows that the kinds of organizations providing civic opportunity are strikingly different from those represented in Washington DC. We focus on organizations in Washington D.C. because these organizations are more likely to have a presence with policymakers, and have the scale needed to be covered in media[33,34]. The media is much more likely to cover an advocacy organization lobbying for a new policy than a hobby association meeting for board games on a Thursday night. Panel B in Figure 4 compares the kinds of organizations with offices in Washington DC to the kinds of organizations that provide civic opportunity. We used fuzzy matching to match our list of organizations with data from previous research about organizations with a presence in Washington D.C. (details in Supplementary Table 17)[34]. In contrast with civic opportunity organizations, the largest category of non-profit organizations in Washington D.C. are professional and research-based organizations. Together, these two types of organizations comprise 41% of all lobbying organizations in Washington D.C. but take up only 9% of all civic opportunity organizations.

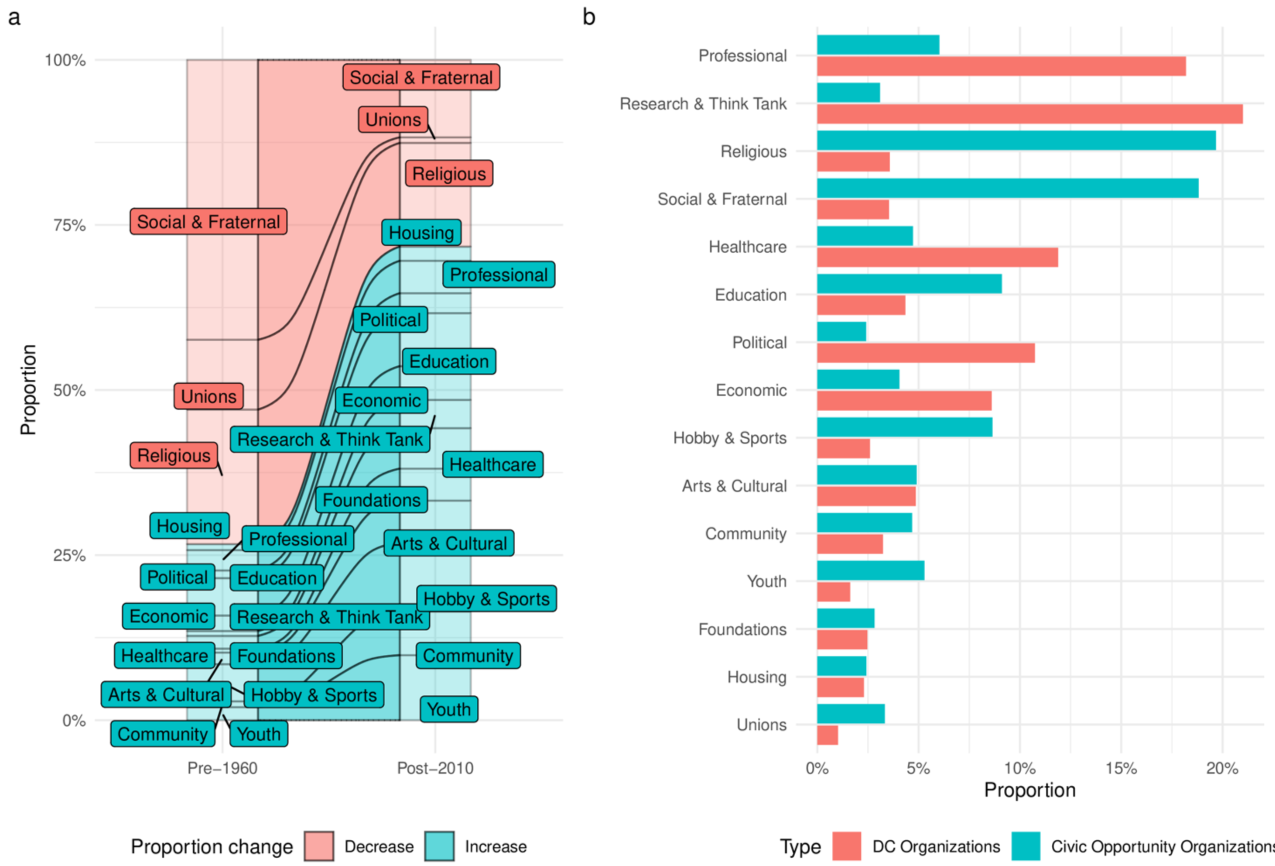

Figure 4: Sources of Civic Opportunity. Panel A: Historical Shifts in the Types of Civic Opportunity Organizations Founded pre-1960 and post-2010. **Panel B:** Proportion of Different Types of Organizations Providing Civic Opportunity versus those represented in Washington DC

Limitations

More research is needed to better elucidate the relationship between civic opportunity and public willingness to engage in behaviors directed towards the common good. Not all civic opportunity will produce democratic behaviors. Historical research shows that civic associations can be carriers of democracy or authoritarianism[35,36], and we need better data to understand the conditions under which civic opportunity promotes public-spirited behavior instead of undermining it. In addition, developing measures of civic opportunity that combine both offline and online organizations, and both formal and informal associations would improve our understanding of civic opportunity. Our data also leaves open an understanding of the mechanisms through which civic opportunity promotes pro-democratic behavior.

Discussion

This paper uses data and analytic tools to sharpen our conceptual and empirical understanding of civic opportunity as a constituent element of supply-side social capital. Examining the data shows that civic opportunity is associated with our ability to solve public problems like engaging in mutual aid and vaccine uptake, even in the face of threats to democracy like hyper-partisanship and disinformation. The association between civic opportunity and pro-democratic community behaviors suggests that more attention to civic opportunity is warranted, especially if examining the infrastructure of civic opportunity can identify communities vulnerable to erosions in social capital. The distinctions between the types of organizations that provide civic opportunity and the types of organizations that engage in public affairs, however, implies that there may be a gap in our understanding of which organizations can be vehicles for democratic renewal in America.

Prior research shows that people are less likely now than in the past to encounter civic opportunity[23,24] suggesting people may be less willing to engage in public-spirited behavior because the supply of opportunities that people need to develop these proclivities have become emaciated. Although copious research has demonstrated the importance of factors like social cohesion and capital in promoting other-regarding behavior,[10-12] relying only on *ex-post* measures of social cohesion or social capital in a community limits our ability to develop solutions. Reform demands tools to assess *ex-ante* which communities are likely to exhibit these factors, or which processes, practices, and societal entities can help develop this social fabric. The concept of civic opportunity identifies the civic associations that can generate these publicly-spirited orientations in a community and offers indications of where investments in civic infrastructure might be needed. In a moment when global societies seem vulnerable to authoritarianism, perhaps investing in the infrastructure of civic opportunity could build more resilience against anti-democratic backsliding.

Methods

ORGANIZATIONAL DATA COLLECTION

We obtained a list of all recognized non-profits from the IRS Exempt Organizations Business Master File (accessed: Aug 24, 2020). The organizations were geocoded using the Texas A&M (TAMU) University Geoservices Online.[37]

Mission and program statements were extracted from IRS 990 filings using code available in the "MapAgora" package (ver 0.08): https://snfagora.github.io/MapAgora/ However, the package is currently unable to access the IRS 990 filings as the IRS has discontinued its public dataset on Amazon Web Services as of December 31, 2021.

Organizational websites were identified using automated searches through the Bing Search API. The text from "About" pages on these websites was extracted using the code in the R package "MapAgora."

CLASSIFYING ORGANIZATIONAL TYPE

To classify organizations by their area of focus, we employed natural language processing and machine learning techniques. Specifically, we labeled organizations based on their mission and program descriptions submitted to the IRS and their "About" page text, using fifteen categories described in Supplementary Table 1. The training data consisted of 9,112 labeled observations in total.

We first built 15 binary classifiers (1 = Yes, 0 = No) using labeled training data for each of the fifteen categories. These models were then applied to 1,400,002 organizations for which we assembled descriptive text data. A likelihood score between 0 and 1 was assigned to each model, and a final categorization was produced based on the highest modeled score (see Supplementary Table 2).

To increase the accessibility and usability of their automated text classification code w have documented and packaged the entire process into an R package called "autotextclassifier" (ver 0.05): https://snfagora.github.io/autotextclassifier/ This package increases the accessibility and usability of our replication code, which is built upon the "tidymodels" package in R.

The process consists of five steps:

1. Feature engineering, which involves tokenizing texts, removing stop words, and applying tf-idf to normalize text length. The user can also choose to use word embedding for feature extraction.
2. Splitting data, where, by default, 80% of the human-labeled data is used for the training set, and the rest is used for the test set. The user can adjust this ratio.
3. Hyperparameter tuning, where we tune the penalty term for LASSO regression, and for XGBoost, they tune multiple factors including the number of trees to fit, the depth of the decision tree, learning rate, the number of randomly selected hyperparameters, the minimum number of observations each tree has before stopping a search, the reduction in the loss function required to split trees further, and the size of the data used for an

iteration. For random forests, they tune the number of randomly selected hyperparameters and the minimum number of observations each tree has before stopping a search.

4. Creating the search space for these hyperparameters using grids (LASSO regression and random forest) and Latin Hypercube sampling (XGBoost) and optimizing them based on the ten-fold cross-validation.
5. Applying the best-fitted model in each algorithm to the training data and evaluating their performances.

We have made the package user-friendly so that individuals without deep technical knowledge of machine learning or R programming can use it to perform each task. We validated individual binary classifiers by assessing their accuracy rates, balanced accuracy rates, and F-1 scores. The final models selected were ensemble models that combined probabilities generated by the LASSO and XGBoost models and used word embedding. We then applied each of the 15 models to the 1,400,002 organizations for which we had obtained text data, generating probability scores from 0 to 1 for each organization for each category. The final assigned category was the category of the model that generated the highest probability score.

CLASSIFYING ORGANIZATIONAL ACTIVITY

In addition to categorizing organizations based on their area of focus, we categorized organizations based on their activities.

To do this, we automated searches of 1,062,554 organizational websites and assessed the presence of links for activities such as volunteering and event hosting (see Supplementary Table 4 for the full list). The matching rules, including the code used for this, are part of the MapAgora R package. A summary of the rules used is provided in Supplementary Table 5.

For volunteering and membership, we also utilized IRS tax returns as they contain the relevant fields. It is worth noting that 13% of the observations in these two categories came exclusively from the IRS tax returns.

CREATING CIVIC OPPORTUNITY SCORES, GRADES, AND INDEX

To measure the latent concept of civic opportunity, we use each of the four organizational activities: holding events, offering membership, volunteering, and taking actions, as an instrument. These activities are all measured by dummy variables. For example, if an organization offers volunteering, the volunteering column has a value of 1, and 0 otherwise. Creating a binary index to categorize organizations into civic opportunity and non-civic opportunity organizations is the simplest method. However, this method does not differentiate the variation within civic opportunity organizations.

To capture the variation within civic opportunity organizations, one alternative is to average these binary variables. This method, however, does not differentiate one kind of opportunity from the other.

Other alternatives include using the inverse covariance matrix or taking the first factor of principal component analysis of these binary variables. These methods give weights to the dimensions that have relatively fewer observations or dimensions that go well together.

Our goal is to construct an index variable that captures all four dimensions well. The standard deviation of the correlation coefficient between these four dimensions and the averaged index is 0.24. This coefficient is lower than that between these dimensions and the binary index (0.29), inverse covariance matrix index (0.32), or the first factor of the principal component analysis index (0.31). Based on this perspective, we have decided to use the averaging method.

These correlation coefficients are presented in Supplementary Figure 1.
Since this index variable aims to capture the supply side of social capital, it should be closer to organizational density, which measures the number of organizations per capita in a county and has conventionally been used to measure the same construct. However, this measure should be distinct from the demand-side of social capital, such as bonding, bridging, linking, and their index versions.

To test this, we first scored each organization by averaging the availability of its four opportunities and aggregated these civic scores at the county level. We then correlated this measure with organizational density and social capital measures. The results show that the measure is highly positively related to organizational density (0.74) and weakly correlated with social capital (0.31).

REGRESSION ANALYSIS
To assess the connection between the density of civic opportunities in an area and community outcomes we performed regression analysis on the emergence of mutual aid instances during the COVID-19 pandemic. The presence of community aid efforts was collated from two sources - https://mutualaid.wiki/ and https://www.mutualaidhub.org/. Both sites collected the location and contact information of mutual aid efforts. The data from the two sites were overlapping but distinct. We manually merged the U.S. data from these two sites into a single data set.
In addition, we performed regression analysis on_both COVID-19 vaccine hesitancy and vaccine uptake. To examine vaccine hesitancy, we made use of the COVID-19 Symptoms Survey conducted by the Delphi group at Carnegie Mellon.[38] This is a voluntary survey drawn from a random sample of Facebook users. Following Pierri, et al. we examine mean hesitancy per county in a window from Jan 4 to March 25, 2021. These data are available in 708 US counties. For vaccine uptake we use data provided by the Center for Disease Control and Prevention (CDC) here https://data.cdc.gov/Vaccinations/COVID-19-Vaccinations-in-the-United-States-County/8xkx-amqh. We specifically look at the number of doses delivered per 1,000 residents of a county for the period March 18 – March 25, 2021.

In addition, we consider models that include a term for COVID-19 misinformation. For this we use recent Twitter data derived from the CoVaxxy project by Pierri, et al. These data are available in 543 U.S. counties.

Social capital indices at the county level are from Kyne and Adrich, 2020[17] whereas census tract-level social capital indices are from Fraser, et al. 2022[39].

Data availability: The replication data is available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/TCXRTM

Code availability: The replication code is available at https://github.com/snfagora/map_civic_opportunity.

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Methodology: MdV, JK
Investigation: MdV, JK, HH
Visualization: MdV, JK
Funding acquisition: HH
Project administration: MdV, HH
Supervision: MdV, HH
Writing – original draft: MdV, JK, HH
Writing – review & editing: MdV, JK, HH

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SUPPLEMENTARY INFORMATION

Supplementary Table 1 Codebook for human-labeled classification

Category	**Description**	**Examples**
Arts & Cultural	Arts organizations and cultural organizations, including organizations that protect community heritage	BANGOR SYMPHONY ORCHESTRA, BRICK STORE MUSEUM, CHESAPEAKE SHAKESPEARE COMPANY
Community	Organizations focused on directly helping people in their community and providing community services	WOMENS COMMUNITY CENTER, FAMILY RESOURCE CENTER OF NORTHWEST OHIO, PELLA COMMUNITY FOOD SHELF
Economic	Organizations directly promoting economic improvement in an area.	FALLS CITY CHAMBER OF COMMERCE, NEW ALBANY URBAN ENTERPRISE ZONE, MAIN STREET CORRIDOR DEVELOPMENT CORPORATION
Education	Schools, universities, organizations that support schools, and organizations that provide direct education services.	JOHNS HOPKINS UNIVERSITY, THOMPSON SCHOOL PTO, LITTLE RASCALS PRESCHOOL
Foundations	Organizations focused on granting money or scholarships to others	ROBERT WOOD JOHNSON FOUNDATION, BVS FAMILY FOUNDATION
Healthcare	Organizations that directly deliver care or support healthcare delivery	ST MARYS REGIONAL HEALTH CENTER, SOUTHERN TIER HEALTH CARE SYSTEM INC, CANCER RESOURCES FOR ELKHART COUNTY INC
Hobby & Sports	Shared interested and sports	GARDEN CLUB OF KENTUCKY INC , LAGUNA YOUTH BASEBALL LEAGUE, VILLA PARK BOXING CLUB
Housing	Organizations that provide or manage housing	BELLE APARTMENTS HOUSING DEVELOPMENT FUND CORPORATION,

		CAMPUS TOWERS SENIOR LIVING INC, HABITAT FOR HUMANITY INTERNATIONAL INC
Political	Civic participation organizations and political organizations. Organizations that directly involve people in collective decision making through voting or issue advocacy.	AMERICAN CIVIL LIBERTIES UNION, LEAGUE OF WOMEN VOTERS, ARIZONA ADVOCACY NETWORK
Professional	Professional societies and industry groups.	NATIONAL INDEPENDENT FLAG DEALERS ASSOCIATION, BEEFMASTER BREEDERS CATTLEWOMEN, AMERICAN CANCER ASSOCIATION
Religious	Religious institutions	CROSSROADS CHRISTIAN CHURCH , NEW SPRINGS CHURCH , MANASSAS MOSQUE
Research & Think Tank	Think tanks and research groups.	SOCIETY FOR THE ADVANCEMENT OF MATERIAL AND PROCESS ENGINEERING, INSTITUTE FOR CONSERVATION ADVOCACY RESEARCH AND EDUCATON, AMERICAN COUNCIL FOR CAPITAL FORMATION CENTER FOR POLICY RESEARCH
Social & Fraternal	Organizations that bring people together (often based on shared identity) to be together	KNIGHTS OF COLUMBUS, ROTARY INTERNATIONAL, NATIONAL KAPPA KAPPA IOTA
Unions	Labor unions	AMERICAN FEDERATION OF STATE COUNTY & MUNICIPAL EMPLOYEES, FRESNO CITY EMPLOYEES ASSOCIATION, CIVIL SERVICE EMPLOYEES ASSOCIATION

Youth	Organizations focused on working with and supporting youth	BOY SCOUTS OF AMERICA, NEBRASKA 4-H FOUNDATION, CROSSWALK TEEN CENTER

Supplementary Table 2. Performance results for individual binary classifiers. The final models used were ensemble models that combined Lasso and XGBoost models.

Model	Class	Metric	Estimate
Lasso	Arts & Cultural	Accuracy	0.91
Lasso	Arts & Cultural	Balanced accuracy	0.91
Lasso	Arts & Cultural	F-score	0.91
Random forest	Arts & Cultural	Accuracy	0.91
Random forest	Arts & Cultural	Balanced accuracy	0.91
Random forest	Arts & Cultural	F-score	0.91
XGboost	Arts & Cultural	Accuracy	0.92
XGboost	Arts & Cultural	Balanced accuracy	0.92
XGboost	Arts & Cultural	F-score	0.92
Lasso	Community	Accuracy	0.74
Lasso	Community	Balanced accuracy	0.74
Lasso	Community	F-score	0.74
Random forest	Community	Accuracy	0.79
Random forest	Community	Balanced accuracy	0.79
Random forest	Community	F-score	0.80
XGboost	Community	Accuracy	0.79
XGboost	Community	Balanced accuracy	0.79
XGboost	Community	F-score	0.80
Lasso	Economic	Accuracy	0.96
Lasso	Economic	Balanced accuracy	0.96
Lasso	Economic	F-score	0.96
Random forest	Economic	Accuracy	0.95
Random forest	Economic	Balanced accuracy	0.95
Random forest	Economic	F-score	0.95
XGboost	Economic	Accuracy	0.91
XGboost	Economic	Balanced accuracy	0.91
XGboost	Economic	F-score	0.91
Lasso	Education	Accuracy	0.85
Lasso	Education	Balanced accuracy	0.85
Lasso	Education	F-score	0.85
Random forest	Education	Accuracy	0.90
Random forest	Education	Balanced accuracy	0.90
Random forest	Education	F-score	0.90
XGboost	Education	Accuracy	0.89
XGboost	Education	Balanced accuracy	0.89
XGboost	Education	F-score	0.88
Lasso	Foundations	Accuracy	0.82

Lasso	Foundations	Balanced accuracy	0.82
Lasso	Foundations	F-score	0.81
Random forest	Foundations	Accuracy	0.84
Random forest	Foundations	Balanced accuracy	0.84
Random forest	Foundations	F-score	0.84
XGboost	Foundations	Accuracy	0.83
XGboost	Foundations	Balanced accuracy	0.83
XGboost	Foundations	F-score	0.83
Lasso	Healthcare	Accuracy	0.81
Lasso	Healthcare	Balanced accuracy	0.81
Lasso	Healthcare	F-score	0.82
Random forest	Healthcare	Accuracy	0.87
Random forest	Healthcare	Balanced accuracy	0.87
Random forest	Healthcare	F-score	0.87
XGboost	Healthcare	Accuracy	0.87
XGboost	Healthcare	Balanced accuracy	0.87
XGboost	Healthcare	F-score	0.87
Lasso	Hobby & Sports	Accuracy	0.92
Lasso	Hobby & Sports	Balanced accuracy	0.92
Lasso	Hobby & Sports	F-score	0.92
Random forest	Hobby & Sports	Accuracy	0.92
Random forest	Hobby & Sports	Balanced accuracy	0.92
Random forest	Hobby & Sports	F-score	0.92
XGboost	Hobby & Sports	Accuracy	0.93
XGboost	Hobby & Sports	Balanced accuracy	0.93
XGboost	Hobby & Sports	F-score	0.94
Lasso	Housing	Accuracy	0.89
Lasso	Housing	Balanced accuracy	0.89
Lasso	Housing	F-score	0.89
Random forest	Housing	Accuracy	0.88
Random forest	Housing	Balanced accuracy	0.88
Random forest	Housing	F-score	0.89
XGboost	Housing	Accuracy	0.86
XGboost	Housing	Balanced accuracy	0.86
XGboost	Housing	F-score	0.87
Lasso	Political	Accuracy	0.87
Lasso	Political	Balanced accuracy	0.87
Lasso	Political	F-score	0.88
Random forest	Political	Accuracy	0.83
Random forest	Political	Balanced accuracy	0.83
Random forest	Political	F-score	0.83

XGboost	Political	Accuracy	0.87
XGboost	Political	Balanced accuracy	0.87
XGboost	Political	F-score	0.87
Lasso	Professional	Accuracy	0.86
Lasso	Professional	Balanced accuracy	0.86
Lasso	Professional	F-score	0.87
Random forest	Professional	Accuracy	0.83
Random forest	Professional	Balanced accuracy	0.83
Random forest	Professional	F-score	0.83
XGboost	Professional	Accuracy	0.85
XGboost	Professional	Balanced accuracy	0.85
XGboost	Professional	F-score	0.85
Lasso	Religious	Accuracy	0.89
Lasso	Religious	Balanced accuracy	0.89
Lasso	Religious	F-score	0.89
Random forest	Religious	Accuracy	0.89
Random forest	Religious	Balanced accuracy	0.89
Random forest	Religious	F-score	0.89
XGboost	Religious	Accuracy	0.89
XGboost	Religious	Balanced accuracy	0.89
XGboost	Religious	F-score	0.89
Lasso	Research & Think Tank	Accuracy	0.79
Lasso	Research & Think Tank	Balanced accuracy	0.79
Lasso	Research & Think Tank	F-score	0.82
Random forest	Research & Think Tank	Accuracy	0.87
Random forest	Research & Think Tank	Balanced accuracy	0.87
Random forest	Research & Think Tank	F-score	0.87
XGboost	Research & Think Tank	Accuracy	0.87
XGboost	Research & Think Tank	Balanced accuracy	0.87
XGboost	Research & Think Tank	F-score	0.87
Lasso	Social & Fraternal	Accuracy	0.89
Lasso	Social & Fraternal	Balanced accuracy	0.89
Lasso	Social & Fraternal	F-score	0.88
Random forest	Social & Fraternal	Accuracy	0.87
Random forest	Social & Fraternal	Balanced accuracy	0.87
Random forest	Social & Fraternal	F-score	0.86
XGboost	Social & Fraternal	Accuracy	0.91
XGboost	Social & Fraternal	Balanced accuracy	0.91
XGboost	Social & Fraternal	F-score	0.90
Lasso	Unions	Accuracy	0.94
Lasso	Unions	Balanced accuracy	0.94

Lasso	Unions	F-score	0.94
Random forest	Unions	Accuracy	0.92
Random forest	Unions	Balanced accuracy	0.92
Random forest	Unions	F-score	0.92
XGboost	Unions	Accuracy	0.92
XGboost	Unions	Balanced accuracy	0.92
XGboost	Unions	F-score	0.92
Lasso	Youth	Accuracy	0.82
Lasso	Youth	Balanced accuracy	0.82
Lasso	Youth	F-score	0.82
Random forest	Youth	Accuracy	0.85
Random forest	Youth	Balanced accuracy	0.85
Random forest	Youth	F-score	0.85
XGboost	Youth	Accuracy	0.83
XGboost	Youth	Balanced accuracy	0.83
XGboost	Youth	F-score	0.84

Supplementary Table 3 Performance results for classifiers are pooled by models and metrics

Metrics	**Estimate**
LASSO	
Accuracy	0.86
Balanced accuracy	0.86
F-score	0.87
Random forest	
Accuracy	0.87
Balanced accuracy	0.87
F-score	0.87
XG Boost	
Accuracy	0.88
Balanced accuracy	0.88
F-score	0.88

Supplementary Table 4. Number of organizations in each category labeled by their availability of website data and IRS tax return data.

<table>
<tr><th rowspan="2">Category</th><th rowspan="2">Number of Organizations</th><th rowspan="2">Website Data</th><th colspan="2">IRS Data</th></tr>
<tr><th>990N</th><th>990/EZ/PF</th></tr>
<tr><td rowspan="2">Arts & Cultural</td><td rowspan="2">59,013</td><td rowspan="2">41,075</td><td colspan="2">58,885</td></tr>
<tr><td>32,355</td><td>26,530</td></tr>
<tr><td rowspan="2">Community</td><td rowspan="2">54,709</td><td rowspan="2">34,485</td><td colspan="2">54,363</td></tr>
<tr><td>25,034</td><td>29,329</td></tr>
<tr><td rowspan="2">Economic</td><td rowspan="2">51,049</td><td rowspan="2">31,911</td><td colspan="2">50,825</td></tr>
<tr><td>23,072</td><td>27,753</td></tr>
<tr><td rowspan="2">Education</td><td rowspan="2">111,976</td><td rowspan="2">59,739</td><td colspan="2">109,325</td></tr>
<tr><td>55,664</td><td>56,661</td></tr>
<tr><td rowspan="2">Foundations</td><td rowspan="2">127,841</td><td rowspan="2">27,178</td><td colspan="2">127,531</td></tr>
<tr><td>2</td><td>127,529</td></tr>
<tr><td rowspan="2">Healthcare</td><td rowspan="2">49,527</td><td rowspan="2">33,841</td><td colspan="2">49,206</td></tr>
<tr><td>19,261</td><td>29,945</td></tr>
<tr><td rowspan="2">Hobby & Sports</td><td rowspan="2">129,033</td><td rowspan="2">70,997</td><td colspan="2">128,787</td></tr>
<tr><td>78,594</td><td>50,193</td></tr>
<tr><td rowspan="2">Housing</td><td rowspan="2">32,525</td><td rowspan="2">18,327</td><td colspan="2">32,334</td></tr>
<tr><td>7,769</td><td>24,565</td></tr>
<tr><td rowspan="2">Political</td><td rowspan="2">23,670</td><td rowspan="2">17,572</td><td colspan="2">23,582</td></tr>
<tr><td>12,531</td><td>11,051</td></tr>
<tr><td rowspan="2">Professional</td><td rowspan="2">60,612</td><td rowspan="2">38,116</td><td colspan="2">60,486</td></tr>
<tr><td>33,794</td><td>26,692</td></tr>
<tr><td rowspan="2">Religious</td><td rowspan="2">322,354</td><td rowspan="2">153,289</td><td colspan="2">71,385</td></tr>
<tr><td>39,388</td><td>31,997</td></tr>
<tr><td rowspan="2">Research & Think Tank</td><td rowspan="2">29,663</td><td rowspan="2">21,697</td><td colspan="2">29,522</td></tr>
<tr><td>13,853</td><td>15,669</td></tr>
<tr><td rowspan="2">Social & Fraternal</td><td rowspan="2">260,036</td><td rowspan="2">140,450</td><td colspan="2">258,898</td></tr>
<tr><td>189,400</td><td>69,498</td></tr>
<tr><td rowspan="2">Unions</td><td rowspan="2">37,540</td><td rowspan="2">19,462</td><td colspan="2">37,480</td></tr>
<tr><td>24,510</td><td>12,970</td></tr>
<tr><td rowspan="2">Youth</td><td rowspan="2">51,149</td><td rowspan="2">37,624</td><td colspan="2">50,973</td></tr>
<tr><td>30,941</td><td>20,032</td></tr>
</table>

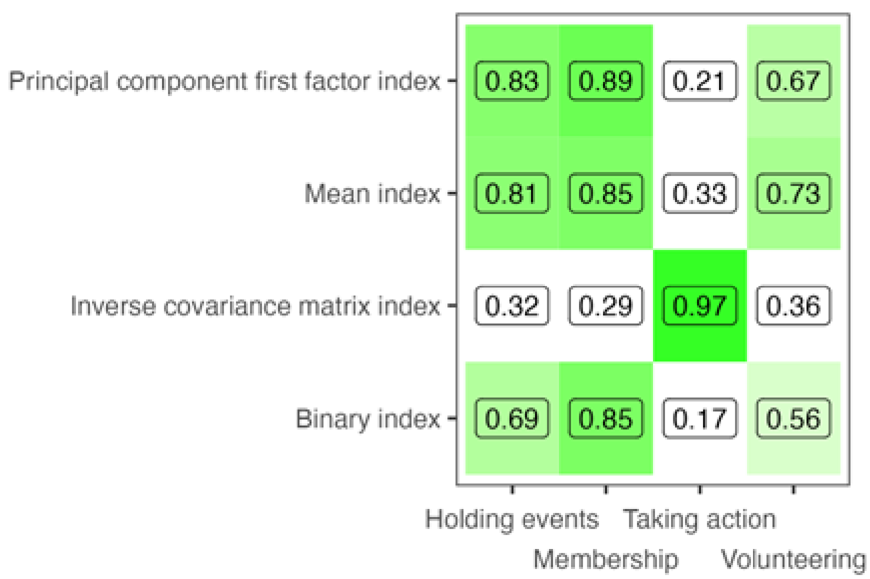
Supplementary Table 5. Rules used to identify organizational activities from website links

Activity	Rule
donations	“donate” ; “give” ; “contribute” ; “support us”
events	“events” ; “calendar” ; “meeting”
membership	"(?<![a-zA-Z])join" ; “member” ; “sign up”
newsletter	“newsletter” ; “bulletin”
volunteer	“volunteer” ; “get involved” ; “getinvolved”
chapters	“chapter”
provide services	“services” ; “get help” ; “gethelp”
take action	“take action” ; “takeaction” ; “justice” ; “social(.?)action”
advocacy	“legislat” ; “election” ; “endorsement” ; “campaigns”; “issues” ; "(?<![a-zA-Z])petition"
visit	“visit” ; “location”
resources	“resource” ; “education” ; “publication” ; “learning” ; “reports”
board	“board”
press	"(?<![a-zA-Z])press" ; "(?<!social(.?))media"

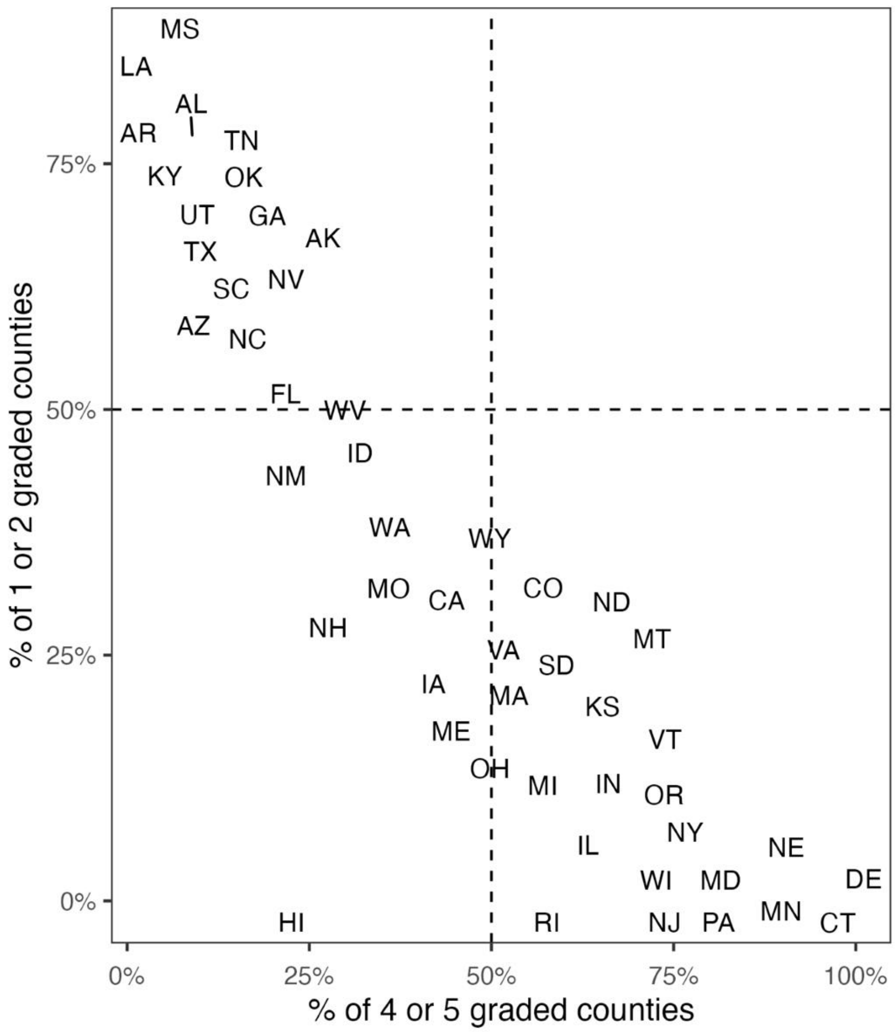
Supplementary Table 6. Number and percentage of organizations identified by their activities, based on their websites.

Category	Number	Percentage
Events	460,226	46.7%
Membership	367,817	37.3%
Donations	327,953	33.4%
Provide Information	315,259	32.0%
Have a board	227,668	23.1%
Volunteers	188,340	19.1%
Services	167,776	17.8%
Come Visit	167,918	17.0%
Press	160,442	16.3%
Advocacy	62,708	6.4%
Chapters	34,451	3.5%
Take Action	28,472	2.9%

Supplementary Figure 1 Correlation matrix between index variables and their components



Supplementary Figure 2 The percentage of high and low civic score counties across states



Supplementary Table 7 Regression results on the associations between three measures of inequality and civic opportunity scores per capita and the Penn State Index.

The standardized (z-scoring) regression coefficients between three measures of inequality and the civic opportunity scores per capita and the Penn State Index (Rupasingha et al 2006) are shown. The unit of analysis is a county. The numbers in parentheses are standard errors. Two-sided p-values are given for each coefficient and are not corrected for multiple comparisons. (*p<0.1 ; **p<0.05 ; ***p<0.01).

	Civic opportunity	Rupasingha et al Index	Civic opportunity	Rupasingha et al Index	Civic opportunity	Rupasingha et al Index
Non-hispanic white					0.253 *** [0.220,0.285] p = <0.001	0.288 *** [0.255,0.321] p = <0.001
Federal poverty level	-0.359 *** [-0.388,-0.329] p = <0.001	-0.309 *** [-0.341,-0.277] p = <0.001				
College educated			0.440 *** [0.407,0.473] p = <0.001	0.282 *** [0.249,0.316] p = <0.001		
Num.Obs.	3127	2814	3127	2814	3127	2814
R2	0.129	0.095	0.194	0.080	0.064	0.083
R2 Adj.	0.128	0.095	0.193	0.079	0.063	0.083
AIC	8448.6	7708.6	8205.9	7757.0	8673.0	7747.0
BIC	8466.8	7726.4	8224.1	7774.8	8691.1	7764.8
RMSE	0.93	0.95	0.90	0.96	0.97	0.96

Supplementary Table 8 Comparison of regression results on the associations between three measures of inequality and civic opportunity scores per capita and the Penn State Index.
The standardized (z-scoring) regression coefficients between three measures of inequality and the civic opportunity scores per capita and the Penn State Index (Rupasingha et al 2006) are shown as in Supplementary Table 7. The differences in standardized coefficients are evaluated using t-tests. (*p<0.1 ; **p<0.05 ; ***p<0.01).

	Non-hispanic white	Federal poverty level	College educated
Civic opportunity	0.253 *** [0.220,0.285] p = <0.001	-0.359 *** [-0.388,-0.329] p = <0.001	0.440 *** [0.407,0.473] p = <0.001
Rupasingha et al Index	0.288 *** [0.255,0.321] p = <0.001	-0.309 *** [-0.341,-0.277] p = <0.001	0.282 *** [0.249,0.316] p = <0.001
Difference	-0.042 * [-0.088,0.004] p = 0.0721 df = 6252	-0.055 ** [-0.098, -0.012] p = 0.0122 df = 6252	0.158 *** [0.111, 0.205] p < 0.001 df = 6252

REGRESSION ANALYSES OF CIVIC OPPORTUNITY ON MUTUAL AID AND OTHER OUTCOMES

Supplementary Table 8 describes the additional variables used in regression analysis. Supplementary Tables 9 – 14 show the results of regression of the emergence of mutual aid instances (Supplementary Table 9), vaccine hesitancy (Supplementary Tables 10 – 11) or vaccine uptake (Supplementary Tables 12 – 14) on these covariates. We perform a number of sensitivity analyses and show that these results are robust for different model specifications, different specifications of outcomes, and different geographic specification.

Across all of these models we observe a significant association of increased density of civic opportunities per capita with positive vaccination outcomes at the community level. We see a weaker positive association of just the overall density of non-profits (not accounting for those that offer civic opportunities) with these same outcomes.

Supplementary Table 9 Description of covariates used in regression analysis

Variable	Description	Year	Source
% GOP	The percentage of the Republican presidential vote	2020	https://github.com/tonmcg/US_County_Level_Election_Results_08-20
Covid Mortality	Cumulative Covid-19 deaths per 1000 residents as of March 25, 2021	2021	Center for Disease Control and Prevention
% Poverty	Percentage of county residents in poverty	2010	United States Department of Agriculture (Atlas of Rural and Small-Town America)
% Age 65 and older	Percentage of county residents aged 65 and older	2010	United States Department of Agriculture (Atlas of Rural and Small-Town America)
% Asian Non-Hispanic	Percentage of county residents Asian (non-hispanic)	2010	United States Department of Agriculture (Atlas of Rural and Small-Town America)
% Black	Percentage of county residents in poverty	2010	United States Department of Agriculture (Atlas of Rural and Small-Town America)
% Native American / Indigenous	Percentage of county residents in poverty	2010	United States Department of Agriculture (Atlas of Rural and Small-Town America)
RUCC	Rural Urban Continuum Code	2013	USDA Economic Research Service

misinfo	Mean % of low credibility COVID-19 related tweets	2021	CoVaxxy project, via Pierri, et al.
Linking Social Capital (county)		2018	Kyne and Aldrich, 2019
Bonding Social Capital (county)		2018	Kyne and Aldrich, 2019
Bridging Social Capital (county)		2018	Kyne and Aldrich, 2019
Economic Connectedness		2022	Chetty, et al.. 2022a
Clustering		2022	Chetty, et al.. 2022a
Support Ratio		2022	Chetty, et al.. 2022a
Volunteering Rate		2022	Chetty, et al.. 2022a
Civic Organization Density		2022	Chetty, et al.. 2022a
Social Capital Index		2014	Rupasingha, et al. 2006 with updates

Supplementary Table 10 Weighted least square regression of county-level emergence of mutual aid instances and covariates.

Mutual Aid. Standardized (beta) coefficients from each multivariate regression are shown. Two-sided p-values are given for each coefficient and are not corrected for multiple comparisons. (*p<0.1 ; **p<0.05 ; ***p<0.01). Regressions were also performed with both probit and logit models to test for specification bias.

	base				full			
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Civic opportunity	0.104*** [0.075, 0.132] p = <0.001				0.052** [0.020, 0.083] p = 0.001			
Social capital (Kyne & Aldrich)		0.006 [-0.028, 0.039] p = 0.733				-0.037+ [-0.080, 0.007] p = 0.096		
Civic Organization Density			0.033* [0.004, 0.062] p = 0.028				-0.021 [-0.054, 0.013] p = 0.237	
Social capital (Rupasingha, et al.)				0.023 [-0.008, 0.054] p = 0.147				-0.013 [-0.045, 0.018] p = 0.411
GOP presidential vote (%)	-0.330*** [-0.365, -0.296] p = <0.001	-0.350*** [-0.386, -0.314] p = <0.001	-0.347*** [-0.382, -0.311] p = <0.001	-0.348*** [-0.384, -0.312] p = <0.001	-0.292*** [-0.338, -0.246] p = <0.001	-0.308*** [-0.353, -0.262] p = <0.001	-0.308*** [-0.353, -0.263] p = <0.001	-0.306*** [-0.351, -0.261] p = <0.001
Age 65 or older (%)					-0.014 [-0.053, 0.025] p = 0.492	0.002 [-0.036, 0.041] p = 0.902	0.004 [-0.036, 0.045] p = 0.835	0.002 [-0.040, 0.045] p = 0.915
White Non-hispanic (%)					0.272 [-0.794, 1.338] p = 0.617	0.343 [-0.717, 1.403] p = 0.526	0.325 [-0.739, 1.388] p = 0.550	0.343 [-0.726, 1.413] p = 0.529
Asian (%)					0.224***	0.232***	0.232***	0.236***

					[0.095, 0.352] p = <0.001	[0.104, 0.360] p = <0.001	[0.103, 0.360] p = <0.001	[0.107, 0.364] p = <0.001
Black (%)					0.033 [-0.750, 0.817] p = 0.933	0.070 [-0.708, 0.847] p = 0.860	0.062 [-0.720, 0.844] p = 0.876	0.080 [-0.706, 0.867] p = 0.842
Hispanic (%)					0.141 [-0.574, 0.856] p = 0.699	0.160 [-0.547, 0.867] p = 0.658	0.164 [-0.550, 0.878] p = 0.652	0.178 [-0.540, 0.895] p = 0.627
Native American (%)					0.044 [-0.326, 0.414] p = 0.815	0.065 [-0.303, 0.432] p = 0.730	0.058 [-0.311, 0.426] p = 0.759	0.065 [-0.306, 0.436] p = 0.732
College education rate					0.153*** [0.109, 0.198] p = <0.001	0.168*** [0.122, 0.214] p = <0.001	0.168*** [0.122, 0.213] p = <0.001	0.165*** [0.120, 0.211] p = <0.001
Poverty rate (%)					0.111*** [0.068, 0.155] p = <0.001	0.093*** [0.050, 0.137] p = <0.001	0.099*** [0.056, 0.142] p = <0.001	0.096*** [0.049, 0.142] p = <0.001
Rural/Urban continuity	-0.176*** [-0.208, -0.144] p = <0.001	-0.165*** [-0.197, -0.133] p = <0.001	-0.177*** [-0.209, -0.145] p = <0.001	-0.174*** [-0.209, -0.139] p = <0.001	-0.121*** [-0.162, -0.080] p = <0.001	-0.109*** [-0.149, -0.068] p = <0.001	-0.108*** [-0.148, -0.069] p = <0.001	-0.109*** [-0.150, -0.068] p = <0.001
Num.Obs.	3058	3058	3058	3058	3058	3058	3058	3058
R2	0.209	0.198	0.199	0.199	0.277	0.276	0.276	0.276
R2 Adj.	0.208	0.197	0.198	0.198	0.275	0.273	0.273	0.273
AIC	7971.9	8012.0	8008.5	8010.5	7709.8	7715.2	7716.8	7717.6
BIC	8002.0	8042.2	8038.6	8040.6	7788.1	7793.5	7795.2	7795.9
Log.Lik.	-3980.940	-4001.022	-3999.252	-4000.239	-3841.890	-3844.582	-3845.413	-3845.805
RMSE	0.89	0.90	0.89	0.90	0.85	0.85	0.85	0.85
Std.Errors	HC3	HC3	HC3	HC3	HC3	HC3	HC3	HC3

Supplementary Table 11 Comparison of standardized regression coefficients of social capital measures to civic opportunity. Comparison of standardized regression coefficients from Supplementary Table 9 for social capital measures to those for civic opportunity. The value shown is the difference in beta coefficients. A 95% confidence intervals are given in square brackets. Two-sided p-values are calculated using t-tests.

vs Civic Opportunity	**Social capital (Kyne & Aldrich)**	**Civic Organization Density**	**Social capital (Rupasingha, et al.)**
Base model	0.0982 [0.0524, 0.144] p < 0.0001, df = 6106, t=4.2142	0.071 [0.0244, 0.118] p=0.0028, df = 6106, t=2.9904	0.0812 [0.03414, 0.128] p = 0.0007, df = 6106, t=3.3891
Full model	0.0883 [0.0329, 0.144] p = 0.0017, df = 6090 t=3.1312	0.0722 [0.021, 0.123] p = 0.0056, df = 6090, t=2.7714	0.0651 [0.0108,0.119] p = 0.0186, df = 6090, t=2.3547

Supplementary Table 12 Weighted least square regression of county-level vaccine acceptance (1 – vaccine hesitancy) and covariates. County-level social capital indices are taken from Rupasingha, et al. Two-sided p-values are given for each coefficient and are not corrected for multiple comparisons. (*p<0.1 ; **p<0.05 ; ***p<0.01).

Vaccine Acceptance

	Civic Opportunity (base)	**Civic Opportunity (full)**	**Social Capital (base)**	**Social Capital (full)**
Civic opportunity	0.052*** [0.023, 0.080] p = <0.001	0.031*** [0.017, 0.046] p = <0.001		
Social capital (Rupasingha , et al.)			0.005 [-0.001, 0.011] p = 0.119	0.001 [-0.005, 0.006] p = 0.815
Decile GOP presidential vote (%)	-0.032*** [-0.036, -0.028] p = <0.001	-0.032*** [-0.035, -0.029] p = <0.001	-0.036*** [-0.040, -0.033] p = <0.001	-0.035*** [-0.038, -0.033] p = <0.001
Covid mortality rate		0.004+ [0.000, 0.008] p = 0.059		0.004* [0.000, 0.008] p = 0.029
Age 65 or older (%)		0.002*** [0.001, 0.003] p = <0.001		0.002*** [0.001, 0.003] p = <0.001
White Non-hispanic (%)		0.001 [-0.002, 0.003] p = 0.460		0.001 [-0.001, 0.004] p = 0.342
Asian (%)		0.001 [-0.002, 0.004] p = 0.571		0.001 [-0.002, 0.004] p = 0.468
Black (%)		-0.001 [-0.004, 0.001] p = 0.319		-0.001 [-0.004, 0.002] p = 0.416
Hispanic (%)		0.001 [-0.002, 0.003] p = 0.599		0.001 [-0.002, 0.003] p = 0.574
Native American (%)		0.001 [-0.003, 0.004] p = 0.723		0.001 [-0.003, 0.004] p = 0.722
Percent Poverty		-0.002*** [-0.003, -0.001] p = <0.001		-0.002*** [-0.003, -0.001] p = <0.001
College education rate		0.002*** [0.002, 0.002] p = <0.001		0.002*** [0.002, 0.002] p = <0.001
Rural/Urban continuity		-0.008*** [-0.011, -0.005] p = <0.001		-0.007*** [-0.011, -0.004] p = <0.001
Num.Obs.	708	708	708	708

R2	0.549	0.808	0.528	0.802
R2 Adj.	0.548	0.805	0.527	0.799
AIC	-2186.9	-2773.4	-2154.7	-2750.3
BIC	-2168.7	-2709.5	-2136.5	-2686.4
Log.Lik.	1097.469	1400.686	1081.361	1389.159
RMSE	0.05	0.03	0.05	0.03
Std.Errors	HC3	HC3	HC3	HC3

Supplementary Table 13 Weighted least square regression of county-level vaccine hesitancy and covariates with the inclusion of misinformation. County-level social capital indices are taken from Rupasingha, et al. Two-sided p-values are given for each coefficient and are not corrected for multiple comparisons. (*p<0.1 ; **p<0.05 ; ***p<0.01).

	Civic Opportunity (base)	Civic Opportunity (full)	Social Capital (base)	Social Capital (full)
Civic opportunity	0.047** [0.017, 0.077] p = 0.002	0.029*** [0.015, 0.043] p = <0.001		
Social capital (Rupasingha, et al.)			0.007+ [0.000, 0.013] p = 0.053	0.001 [-0.004, 0.007] p = 0.662
Misinformation	-0.012+ [-0.027, 0.002] p = 0.088	-0.013* [-0.024, -0.002] p = 0.016	-0.014+ [-0.029, 0.000] p = 0.052	-0.014* [-0.025, -0.003] p = 0.011
Decile GOP presidential vote (%)	-0.028*** [-0.033, -0.024] p = <0.001	-0.029*** [-0.032, -0.026] p = <0.001	-0.032*** [-0.036, -0.028] p = <0.001	-0.032*** [-0.035, -0.029] p = <0.001
Covid mortality rate		0.003 [-0.001, 0.007] p = 0.151		0.003+ [-0.001, 0.008] p = 0.095
White Non-hispanic (%)		0.001 [-0.001, 0.003] p = 0.423		0.001 [-0.001, 0.004] p = 0.355
Age 65 or older (%)		0.002*** [0.001, 0.003] p = <0.001		0.002*** [0.001, 0.003] p = <0.001
Asian (%)		0.001 [-0.002, 0.004] p = 0.404		0.001 [-0.002, 0.004] p = 0.393
Black (%)		-0.001 [-0.004, 0.001] p = 0.314		-0.001 [-0.004, 0.001] p = 0.355
Hispanic (%)		0.001 [-0.002, 0.003] p = 0.606		0.001 [-0.002, 0.003] p = 0.633
Native American (%)		0.001 [-0.003, 0.004] p = 0.628		0.001 [-0.003, 0.004] p = 0.655
Percent Poverty		-0.001** [-0.002, 0.000] p = 0.007		-0.001* [-0.002, 0.000] p = 0.015
College education rate		0.002*** [0.001, 0.002] p = <0.001		0.002*** [0.002, 0.002] p = <0.001

Rural/Urban continuity		-0.007** [-0.012, -0.003] p = 0.001		-0.007** [-0.011, -0.003] p = 0.002
Num.Obs.	543	543	543	543
R2	0.514	0.816	0.495	0.809
R2 Adj.	0.512	0.811	0.492	0.804
AIC	-1729.3	-2234.9	-1707.7	-2215.8
BIC	-1707.9	-2170.4	-1686.2	-2151.4
Log.Lik.	869.669	1132.448	858.849	1122.920
RMSE	0.05	0.03	0.05	0.03
Std.Errors	HC3	HC3	HC3	HC3

Supplementary Table 14 Ordinary least square regression of vaccine uptake – county (n=2,728). For this analysis we excluded the states of New Hampshire, Colorado, Texas, and Hawaii, which had not fully reported vaccination data to the CDC at that time. Two-sided p-values are given for each coefficient and are not corrected for multiple comparisons. (*p<0.1 ; **p<0.05 ; ***p<0.01).

	Civic Opportunity (base)	**Civic Opportunity (full)**	**Rupasingha et al Index (base)**	**Rupasingha et al Index (full)**
Civic opportunity	7.608*** [4.869, 10.347] p = <0.001	2.834+ [-0.056, 5.724] p = 0.055		
Rupasingha et al Index			2.124*** [1.258, 2.989] p = <0.001	1.017* [0.004, 2.030] p = 0.049
Decile GOP presidential vote (%)	-4.196*** [-4.809, -3.582] p = <0.001	-5.362*** [-6.455, -4.270] p = <0.001	-4.693*** [-5.301, -4.086] p = <0.001	-5.589*** [-6.660, -4.519] p = <0.001
Covid mortality rate		-0.233 [-0.965, 0.499] p = 0.533		-0.231 [-0.963, 0.501] p = 0.536
Age 65 or older (%)		0.691*** [0.404, 0.979] p = <0.001		0.636*** [0.335, 0.937] p = <0.001
Asian (%)		0.339 [-1.088, 1.765] p = 0.642		0.229 [-1.204, 1.662] p = 0.754
Black (%)		0.654 [-0.558, 1.867] p = 0.290		0.518 [-0.703, 1.738] p = 0.406
Hispanic (%)		0.851 [-0.348, 2.051] p = 0.164		0.732 [-0.473, 1.937] p = 0.234
Native American (%)		0.756 [-0.508, 2.021] p = 0.241		0.633 [-0.637, 1.903] p = 0.328
Percent Poverty		-0.617*** [-0.837, -0.398] p = <0.001		-0.584*** [-0.809, -0.360] p = <0.001
College education rate		0.202*** [0.110, 0.294] p = <0.001		0.200*** [0.108, 0.292] p = <0.001
Rural/Urban continuity		-0.266 [-0.706, 0.174] p = 0.236		-0.332 [-0.779, 0.115] p = 0.146
AR	16.244*** [9.358, 23.131] p = <0.001	15.495*** [8.614, 22.376] p = <0.001	15.872*** [8.974, 22.770] p = <0.001	15.094*** [8.203, 21.986] p = <0.001

AZ	12.753* [1.040, 24.465] p = 0.033	2.798 [-9.648, 15.244] p = 0.659	14.406* [2.661, 26.151] p = 0.016	3.310 [-9.136, 15.755] p = 0.602
CA	31.748*** [23.971, 39.525] p = <0.001	21.294*** [11.990, 30.599] p = <0.001	32.432*** [24.652, 40.211] p = <0.001	20.873*** [11.546, 30.199] p = <0.001
CT	24.423** [9.024, 39.822] p = 0.002	13.546+ [-1.795, 28.888] p = 0.084	26.572*** [11.186, 41.958] p = <0.001	13.705+ [-1.631, 29.041] p = 0.080
DC	-26.573 [-68.700, 15.555] p = 0.216	-23.695 [-64.791, 17.401] p = 0.258	-14.398 [-56.034, 27.238] p = 0.498	-19.963 [-60.522, 20.595] p = 0.335
DE	13.197 [-11.018, 37.413] p = 0.285	6.178 [-17.525, 29.881] p = 0.609	15.474 [-8.752, 39.700] p = 0.211	6.695 [-17.000, 30.389] p = 0.580
FL	0.031 [-7.051, 7.112] p = 0.993	-7.037+ [-14.331, 0.258] p = 0.059	0.780 [-6.304, 7.865] p = 0.829	-6.916+ [-14.210, 0.377] p = 0.063
GA	-20.319*** [-26.285, -14.354] p = <0.001	-19.475*** [-25.310, -13.639] p = <0.001	-20.221*** [-26.193, -14.248] p = <0.001	-19.554*** [-25.394, -13.715] p = <0.001
IA	29.305*** [22.786, 35.824] p = <0.001	20.397*** [13.265, 27.530] p = <0.001	27.925*** [21.291, 34.559] p = <0.001	19.293*** [12.046, 26.540] p = <0.001
ID	13.039** [5.064, 21.013] p = 0.001	5.105 [-3.168, 13.379] p = 0.226	13.825*** [5.852, 21.798] p = <0.001	4.922 [-3.363, 13.208] p = 0.244
IL	26.127*** [19.619, 32.635] p = <0.001	19.600*** [12.797, 26.402] p = <0.001	27.064*** [20.580, 33.548] p = <0.001	19.408*** [12.589, 26.227] p = <0.001
IN	22.314*** [15.659, 28.970] p = <0.001	18.052*** [10.971, 25.133] p = <0.001	24.773*** [18.181, 31.364] p = <0.001	18.395*** [11.353, 25.437] p = <0.001
KS	19.961*** [13.367, 26.555] p = <0.001	12.446*** [5.569, 19.323] p = <0.001	20.140*** [13.510, 26.769] p = <0.001	11.944*** [4.968, 18.921] p = <0.001
KY	17.574*** [11.304, 23.845] p = <0.001	17.123*** [10.434, 23.811] p = <0.001	19.189*** [12.890, 25.488] p = <0.001	17.206*** [10.516, 23.897] p = <0.001

LA	4.584 [-2.573, 11.741] p = 0.209	9.000* [1.966, 16.034] p = 0.012	4.583 [-2.584, 11.749] p = 0.210	8.860* [1.821, 15.900] p = 0.014
MA	20.938** [7.470, 34.407] p = 0.002	8.425 [-5.356, 22.207] p = 0.231	20.703** [7.211, 34.194] p = 0.003	7.466 [-6.331, 21.262] p = 0.289
MD	10.327* [0.473, 20.181] p = 0.040	3.296 [-6.523, 13.116] p = 0.510	11.704* [1.874, 21.535] p = 0.020	3.385 [-6.427, 13.197] p = 0.499
ME	56.960*** [45.519, 68.401] p = <0.001	47.074*** [35.068, 59.081] p = <0.001	56.597*** [45.129, 68.064] p = <0.001	46.281*** [34.255, 58.306] p = <0.001
MI	32.920*** [26.123, 39.718] p = <0.001	26.077*** [18.781, 33.372] p = <0.001	34.860*** [28.114, 41.606] p = <0.001	26.356*** [19.076, 33.636] p = <0.001
MN	7.970* [1.135, 14.805] p = 0.022	-1.133 [-8.503, 6.238] p = 0.763	7.598* [0.667, 14.529] p = 0.032	-2.059 [-9.609, 5.491] p = 0.593
MO	9.871** [3.481, 16.261] p = 0.002	7.912* [1.242, 14.583] p = 0.020	11.598*** [5.256, 17.939] p = <0.001	8.006* [1.348, 14.664] p = 0.018
MS	-0.445 [-7.211, 6.321] p = 0.897	2.422 [-4.293, 9.137] p = 0.479	-0.990 [-7.762, 5.782] p = 0.774	2.457 [-4.260, 9.173] p = 0.473
MT	5.181 [-2.348, 12.710] p = 0.177	-0.398 [-8.316, 7.520] p = 0.921	4.436 [-3.198, 12.070] p = 0.255	-1.376 [-9.469, 6.717] p = 0.739
NC	7.349* [0.869, 13.829] p = 0.026	1.610 [-4.884, 8.105] p = 0.627	7.380* [0.891, 13.869] p = 0.026	1.466 [-5.032, 7.964] p = 0.658
ND	6.312 [-1.343, 13.966] p = 0.106	-3.221 [-11.241, 4.799] p = 0.431	5.389 [-2.387, 13.165] p = 0.174	-3.977 [-12.106, 4.152] p = 0.337
NE	13.968*** [6.771, 21.165] p = <0.001	6.864+ [-0.564, 14.292] p = 0.070	16.949*** [10.041, 23.856] p = <0.001	7.350* [0.128, 14.572] p = 0.046
NJ	13.030* [2.673, 23.387] p = 0.014	3.608 [-7.106, 14.323] p = 0.509	15.195** [4.862, 25.528] p = 0.004	3.994 [-6.705, 14.692] p = 0.464
NM	28.944*** [19.147, 38.741] p = <0.001	19.631** [7.833, 31.428] p = 0.001	29.599*** [19.793, 39.405] p = <0.001	19.685** [7.894, 31.476] p = 0.001
NV	3.366 [-7.759, 14.492] p = 0.553	-4.095 [-15.453, 7.262] p = 0.480	4.279 [-6.859, 15.416] p = 0.451	-4.064 [-15.423, 7.295] p = 0.483

NY	16.409*** [8.923, 23.895] p = <0.001	8.943* [0.968, 16.918] p = 0.028	18.700*** [11.272, 26.129] p = <0.001	9.142* [1.183, 17.102] p = 0.024
OH	7.244* [0.543, 13.946] p = 0.034	3.893 [-3.224, 11.009] p = 0.284	8.779** [2.117, 15.441] p = 0.010	3.770 [-3.353, 10.894] p = 0.299
OK	13.584*** [6.691, 20.476] p = <0.001	13.287** [4.992, 21.583] p = 0.002	13.626*** [6.724, 20.528] p = <0.001	12.558** [4.193, 20.922] p = 0.003
OR	24.978*** [16.439, 33.516] p = <0.001	14.741** [5.580, 23.902] p = 0.002	24.748*** [16.168, 33.328] p = <0.001	13.861** [4.602, 23.120] p = 0.003
PA	26.501*** [19.319, 33.683] p = <0.001	22.533*** [14.780, 30.286] p = <0.001	28.707*** [21.605, 35.809] p = <0.001	22.774*** [15.060, 30.488] p = <0.001
RI	47.500*** [28.427, 66.574] p = <0.001	32.464*** [13.428, 51.501] p = <0.001	48.698*** [29.612, 67.784] p = <0.001	32.085*** [13.040, 51.129] p = <0.001
SC	8.685* [0.820, 16.551] p = 0.030	7.687+ [-0.005, 15.378] p = 0.050	7.278+ [-0.631, 15.188] p = 0.071	7.100+ [-0.626, 14.826] p = 0.072
SD	30.639*** [23.340, 37.939] p = <0.001	26.425*** [18.615, 34.234] p = <0.001	30.355*** [23.003, 37.707] p = <0.001	25.772*** [17.865, 33.680] p = <0.001
TN	13.659*** [7.096, 20.223] p = <0.001	11.666*** [4.983, 18.348] p = <0.001	15.421*** [8.831, 22.010] p = <0.001	11.974*** [5.288, 18.660] p = <0.001
UT	15.943*** [6.829, 25.058] p = <0.001	7.072 [-2.296, 16.439] p = 0.139	18.099*** [8.950, 27.249] p = <0.001	7.536 [-1.842, 16.915] p = 0.115
VA	-22.766*** [-29.105, -16.428] p = <0.001	-29.021*** [-35.420, -22.622] p = <0.001	-22.030*** [-28.355, -15.705] p = <0.001	-29.082*** [-35.486, -22.678] p = <0.001
VT	-1.795 [-13.988, 10.398] p = 0.773	-13.402* [-26.522, -0.282] p = 0.045	-2.059 [-14.284, 10.166] p = 0.741	-14.273* [-27.425, -1.121] p = 0.033
WA	13.441** [5.146, 21.735] p = 0.002	2.092 [-6.916, 11.099] p = 0.649	12.720** [4.386, 21.055] p = 0.003	1.011 [-8.071, 10.093] p = 0.827
WI	27.659*** [20.609, 34.710] p = <0.001	19.363*** [11.619, 27.108] p = <0.001	27.935*** [20.871, 35.000] p = <0.001	18.810*** [11.005, 26.615] p = <0.001

WV	-7.944* [-15.430, -0.457] p = 0.038	-8.398* [-16.364, -0.432] p = 0.039	-5.937 [-13.422, 1.549] p = 0.120	-8.153* [-16.111, -0.196] p = 0.045
WY	20.272*** [10.303, 30.241] p = <0.001	12.685* [2.570, 22.799] p = 0.014	17.885*** [7.723, 28.048] p = <0.001	10.924* [0.513, 21.335] p = 0.040
Num.Obs.	2726	2726	2727	2727
R2	0.410	0.443	0.409	0.442
R2 Adj.	0.400	0.431	0.398	0.431
AIC	24353.5	24220.0	24369.7	24229.8
BIC	24643.1	24568.7	24659.3	24578.5
Log.Lik.	-12127.758	-12050.976	-12135.840	-12055.891
RMSE	20.70	20.12	20.72	20.13
Std.Errors	HC3	HC3	HC3	HC3

In addition to the county level analyses above we also performed regression analysis on zip code (ZCTA5) level data for individual states. We obtained cumulative zip code level vaccination data from the Minnesota Department of Health for the week of March 22, 2021. We obtained cumulative zip code level vaccination data from the Texas Department of State Health Services for the week of March 23, 2022.

To estimate partisanship at the zip code level, we used "zipcodeR" R package. To estimate electoral data to a target geographic unit (i.e., zip code), we used the following procedure. First, we obtained the 2020 redistricting data files from the ALARM project, the block-level census data using the "blockpop" R package, and the voting-district and block-level shape files using the "tigris" R package. We joined these files together the result will be the combination of the electoral, demographic, and shape data. Finally, we estimated the electoral data to a target geographic unit using race and ethnicity weights.

Other regression variables were obtained from the US Census API as follows. All data are from the American Community Survey 5-year data from 2019:

Supplementary Table 15 Variables used in zip code level regressions

Variable	Census Variable Name	Source
% White Non-Hispanic	B01001H_001E	Detail Tables
% Hispanic	B01001I_001E	Detail Tables
% Black	B01001B_001E	Detail Tables
% Insured	S2701_C02_001E / S2701_C01_001E	SubjectTables
% College Educated	(B06009_005E + B06009_006E) / B06009_001E	Detail Tables
% Poverty	B06012_003E / B06012_001E	Detail Tables
% Vacant Housing	B25002_003E / B25002_001E	Detail Tables
% Age <5	S0101_C02_002E	SubjectTables
% Age ≥65	S0101_C02_015E + S0101_C02_016E + S0101_C02_017E + S0101_C02_018E + S0101_C02_019E	SubjectTables

Supplementary Table 16 Ordinary least square regression for vaccine uptake in zip codes on civic opportunities per capita and other covariates. Vaccine uptake is expressed as the cumulative number of doses per thousand residents. (MN, n=792 ; TX, n=1582 ; NY, n=1516) Two-sided p-values are given for each coefficient and are not corrected for multiple comparisons. (*p<0.1 ; **p<0.05 ; ***p<0.01).

	ZCTA - MN	ZCTA - TX	ZCTA - NY
Civic opportunity	0.002** [0.000, 0.003] p = 0.007	0.016*** [0.011, 0.021] p = <0.001	0.006** [0.002, 0.009] p = 0.002
Democratic vote share presidential vote (%)	0.212*** [0.170, 0.254] p = <0.001	0.129*** [0.078, 0.179] p = <0.001	0.148*** [0.092, 0.204] p = <0.001
population density (log scale)	-0.013*** [-0.016, -0.009] p = <0.001	0.008*** [0.004, 0.012] p = <0.001	0.012*** [0.007, 0.017] p = <0.001
Age 65 or older (%)	0.576*** [0.490, 0.662] p = <0.001	0.433*** [0.328, 0.538] p = <0.001	0.505*** [0.417, 0.594] p = <0.001
Age younger than 5 (%)	-0.163 [-0.404, 0.079] p = 0.187	-0.125 [-0.371, 0.121] p = 0.319	-0.426** [-0.691, -0.161] p = 0.002
College educated (%)	0.189*** [0.140, 0.238] p = <0.001	0.461*** [0.399, 0.523] p = <0.001	0.264*** [0.209, 0.319] p = <0.001
Health insured rate (%)	0.075 [-0.053, 0.204] p = 0.251	-0.012 [-0.108, 0.083] p = 0.798	0.161+ [-0.013, 0.334] p = 0.069
White Non-Hispanic(%)	-0.029 [-0.089, 0.032] p = 0.355	-0.110 [-0.251, 0.031] p = 0.126	-0.199*** [-0.284, -0.114] p = <0.001
Black (%)	0.027 [-0.087, 0.141] p = 0.639	0.157* [0.017, 0.297] p = 0.028	0.040 [-0.060, 0.140] p = 0.433
Hispanic (%)	-0.290*** [-0.417, -0.162] p = <0.001	-0.150+ [-0.305, 0.004] p = 0.056	-0.319*** [-0.411, -0.226] p = <0.001
Num.Obs.	792	1582	1516
R2	0.525	0.519	0.487
R2 Adj.	0.517	0.516	0.483
AIC	-2282.3	-2342.2	-2128.9
BIC	-2216.8	-2267.1	-2054.3
Log.Lik.	1155.126	1185.114	1078.427
RMSE	0.06	0.11	0.12

COMPARING OUR DATA WITH THE WASHINGTON REPRESENTATIVE STUDY

We analyzed the presence of organizations involved in lobbying in different types of organizations using the Washington Representative Study (Organized Interests in Washington Politics, 1981, 1991, 2001, 2006, 2011) and our own data. The Washington Representative Study dataset includes corporations, farms, US governments, foreign governments, international organizations, political action committees, political party organizations, and unknowns, resulting in a total of 40,782 observations.

However, we removed organizations irrelevant to the study of civil society rather than lobbying, which reduced the sample size to 9,673. We assumed that organizations were involved in lobbying if they hired staff or spent money on lobbying, based on the Washington Representative Study. Unfortunately, the names of the organizations in the Washington Representative Study and our database did not match exactly. Therefore, we used a fuzzy matching method called weighted Jaccard match.

Out of 9,673 organizations in the Washington Representative Study, only 2,020 were matched exactly with the organizations in our dataset. However, using the fuzzy matching method, the number of matched organizations increased from 21% to 62% (n=5,968).

In the original Washington Representative Study, 33% of organizations were involved in lobbying. In the fuzzy-matched dataset, 42% of organizations were involved in lobbying.

Supplementary Table 17 Organizations from the Washington Representative Study matched to the Civic Opportunity dataset. The second column indicates the number of organizations of each type, while the third column provides the percentage of organizations engaged in lobbying.

Predicted category	The number of lobbying organizations	The percentage of lobbying organizations
Professional	226	21.1%
Research & Think Tank	214	20.0%
Healthcare	160	15.0%
Political	101	9.4%
Economic	96	9.0%
Education	52	4.9%
Arts & Cultural	45	4.2%
Social & Fraternal	32	3.0%
Community	30	2.8%
Religious	28	2.6%
Housing	26	2.4%
Foundations	17	1.6%
Hobby & Sports	16	1.5%
Unions	14	1.3%
Youth	13	1.2%

Supplementary Table 18 Distribution of civic opportunity organizations across organization types. Pre-1960 organization are those that received IRS non-profit designations prior to 1960. Post-2010 are organizations that received non-profit designations after Jan 1, 2010. The IRS incorporation year is used as a proxy for organizational foundation year.

Predicted category	**All civic opportunity organizations**	**Post-2010 civic opportunity organizations**	**Pre-1960 civic opportunity organizations**
Arts & Cultural	13905	1321	12584
Community	13815	667	13148
Economic	11923	1771	10152
Education	20235	4269	15966
Foundations	10068	447	9621
Healthcare	13654	1467	12187
Hobby & Sports	25062	4253	20809
Housing	4974	683	4291
Political	6892	885	6007
Professional	12076	2331	9745
Religious	46588	15393	31195
Research & Think Tank	9071	561	8510
Social & Fraternal	55372	32025	23347
Unions	9671	7986	1685
Youth	21030	1485	19545

Supplementary Table 19 OLS regression of civic opportunity scores per capita on measures on inequality in a county, depicted in Figure 2. 95% confidence intervals are shown in brackets. Two-sided p-values are given for each coefficient and are not corrected for multiple comparisons. (*p<0.1 ; **p<0.05 ; ***p<0.01).

	DV: Civic opportunity	DV: Civic opportunity	DV: Civic opportunity
Federal poverty level (%)	-1.552*** [-1.693, -1.410] p = <0.001		
College educated (%)		1.525*** [1.416, 1.634] p = <0.001	
White Non-hispanic (%)			0.466*** [0.403, 0.528] p = <0.001
Num.Obs.	3127	3127	3127
R2	0.129	0.194	0.064
R2 Adj.	0.128	0.193	0.063
AIC	2220.6	1977.9	2444.9
BIC	2238.7	1996.0	2463.1
Log.Lik.	-1107.295	-985.951	-1219.462
F	461.157	750.567	212.895
RMSE	0.34	0.33	0.36