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The unequal landscape of civic opportunity in America

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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 (that is, 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. Here we define the concept of civic opportunity—opportunities people have to encounter civic experiences necessary for developing such orientations—and harness data science to map it across America. We demonstrate that civic opportunity is more highly correlated with pro-social outcomes such as mutual aid than other measures, but is unequally distributed, and its sources are underrepresented in the public dialogue. Our findings suggest greater attention to this fundamentally uneven landscape of civic opportunity.

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[1–8]. 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 behaviour is more important than ever[9–11]. 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'[12]. 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[13,14].

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[2,3,6,17–21]. 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 US 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

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exist for increasing this underlying capacity[9,28–30]. In this Article, we thus focus 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 behaviour such as 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 have emerged organically over time, 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 has 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, neighbourhood 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 enquiry. 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[17]. 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 overlaid external data, such as the US Census data, using geocodes, 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 to categorize organizations by focus and activity—what they do and how they do it[25,31]. We built a binary classifier for 15 categories of possible areas of organizational focus (Supplementary Table 1) based on mission and programme 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 Tables 5 and 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 non-profits whose primary address is a post office 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 Fig. 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 equally sized quintiles with higher numbers indicating a higher density of civic opportunity. Figure 1a shows the distribution of this civic opportunity index by county across America, showing that it is unevenly distributed across counties in the USA. For instance, every county in states like Connecticut fall into the top two quintiles of civic opportunity (4 or 5). By contrast, over 86% of counties in Mississippi fall into the bottom two quintiles (1 or 2). Figure 1b 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.

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, 95% CI −1.68 to −1.42, degrees of freedom (d.f.) 3,127, $P \leq 0.001$) increase and the percentage of white (slope 0.47, 95% CI 0.40 to 0.52, d.f. 3,127, $P \leq 0.001$), college-educated (slope 1.52, 95% CI 1.42 to 1.64, d.f. 3,127, $P \leq 0.001$) 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 presents 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 labour organizations, as well as the number of bowling centres, recreational sports centres, 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 the measures described by Rupasingha et al.[18] for both the federal poverty level and percentage of college-educated residents,

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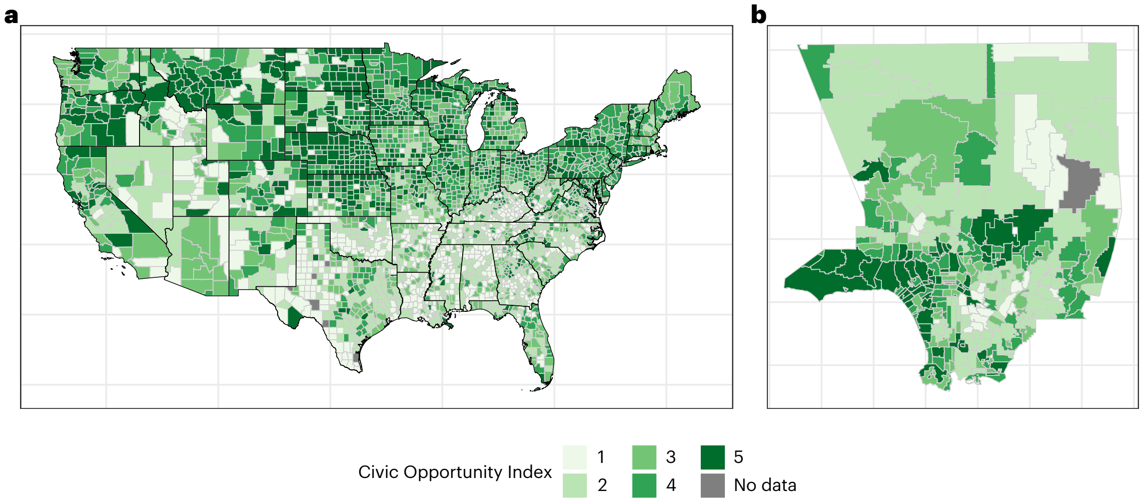

Fig. 1 | The geography of civic opportunity in the USA. a,**b**, The Civic Opportunity Index ranks counties on the basis of their cumulative civic opportunity scores per capita. Each civic opportunity score represents the range of opportunities (0–1) provided by an organization. The index divides the counties of the continental USA (**a**) or zip codes of Los Angeles county (**b**) into five grades: from 1 (low civic opportunity, shaded in white) to 5 (high civic opportunity, shaded in green).

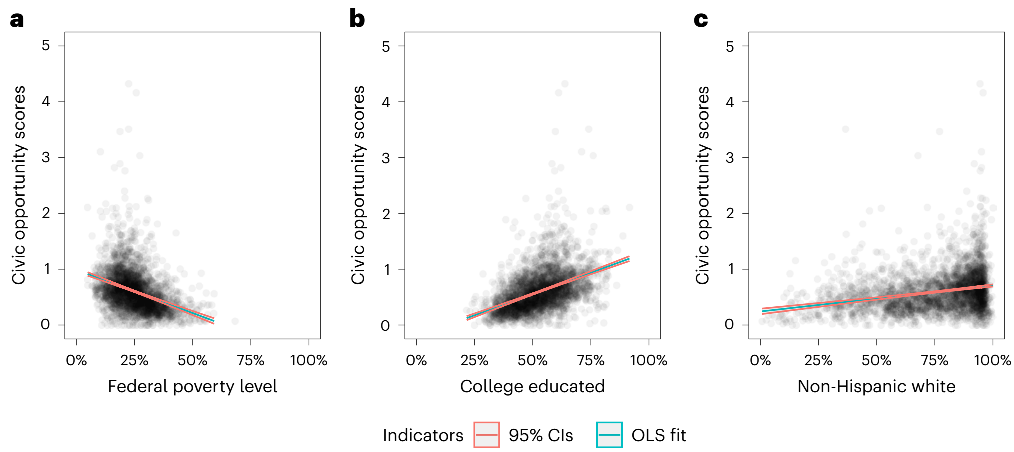

Fig. 2 | Inequality of civic opportunity. a–**c**, Plots graphing the regression coefficients and 95% CIs of a univariate ordinary least squares (OLS) regression of civic opportunity scores per capita on measures on inequality in a county: the federal poverty rate (−1.552, 95% CI −1.693 to −1.410, $P \leq 0.001$, $n = 3{,}127$) (**a**), the percentage of college-educated people (1.525, 95% CI 1.416 to 1.634, $P \leq 0.001$, $n = 3{,}127$) (**b**) and the percentage of non-Hispanic white residents (0.466, 95% CI 0.403 to 0.528, $P \leq 0.001$, $n = 3{,}127$) (**c**) in a county. The jittered points each represent one county, and the lines display the OLS regression.

allowing us to pinpoint the inequalities more clearly. The difference between the regression coefficients for the two measures, however, is not statistically significant for the comparison with the percentage of non-Hispanic, white residents.

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 Fig. 3, we explore the connection at the county level between civic opportunity and the emergence of mutual aid organizations during the global coronavirus pandemic of 2020–2021. Figure 3a 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 to 0.083, d.f. 3,025, $P \leq 0.001$; 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 2 other measures that focus particularly on the supply side of social capital: the measure of 'public good' organizations described by Chetty et al.[2], and the composite measure of social-capital-providing organizations described by Rupasingha et al.[18]. 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 to 0.374, d.f. 3,125, $P < 0.001$,), $r = 0.48$ (95% CI 0.45 to 0.504, d.f. 3,125, $P < 0.001$) and 0.32 (95% CI 0.292 to 0.355, d.f. 3,125, $P < 0.001$), respectively. Figure 3b shows that there is no significant positive association between Kyne and Aldrich's social capital index[17] and the emergence of mutual aid (−0.037, 95% CI −0.080 to 0.007, d.f. 3,025, $P = 0.096$), and Fig. 3c,d shows the same for the

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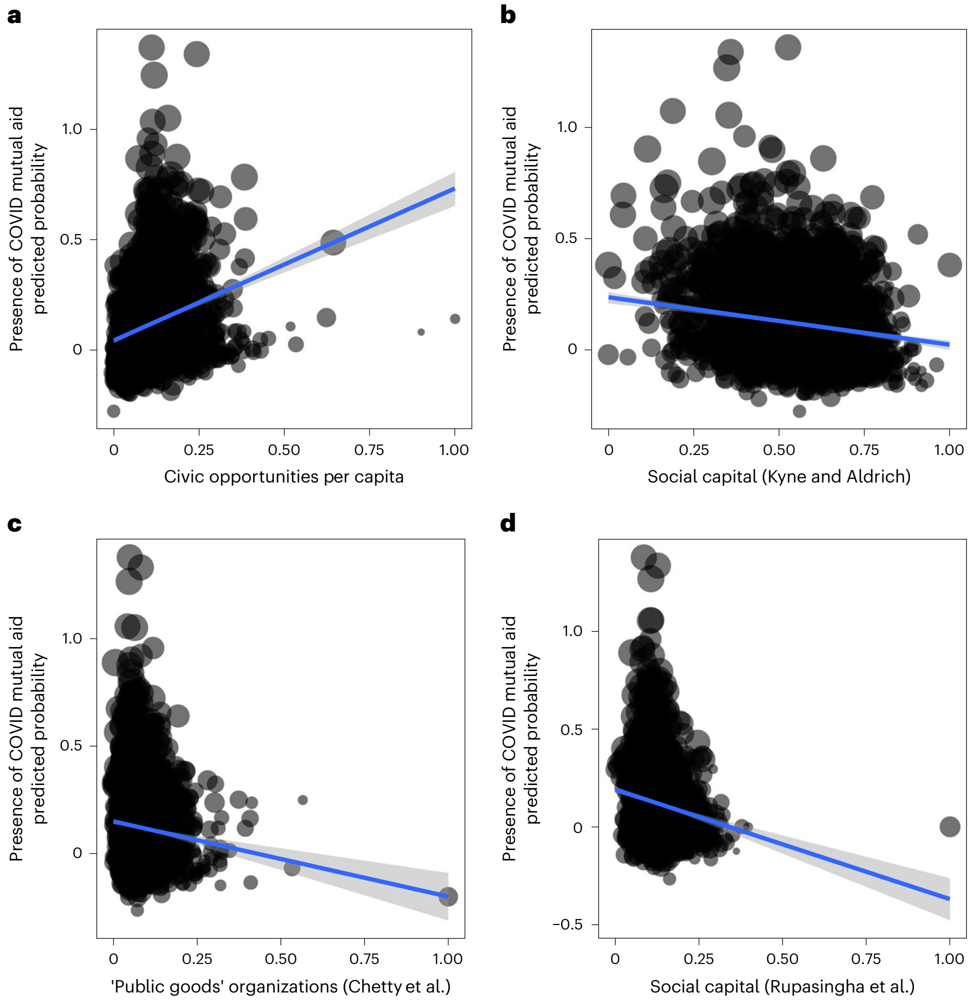

Fig. 3 | The association between civic opportunity and the emergence of mutual aid during COVID. a–**d**, Relationship of per capita civic opportunity scores (**a**), the composite measure of social capital described by Kyne and Aldrich[17] (**b**), the 'public good' organizations per capita reported by Chetty et al.[2] (**c**), and the index described by Rupasingha et al.[18] (**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 0–1. 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% CI. For full results, please refer to Supplementary Table 10.

measure of 'public good' organizations described by Chetty et al.[2] (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 to 0.013, d.f. 3,025, $P = 0.237$) and the measure described by Rupasingha et al.[18] (0.013, 95% CI −0.045 to 0.018, d.f. 3,025, $P = 0.411$) (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 Fig. 3, when comparing standardized regression coefficients using a t-test (Kyne and Aldrich, $t = 3.131$, $P = 0.0017$, d.f. 6,052; Chetty et al., $t = 2.771$, $P = 0.0056$, d.f. 6,052; Rupasingha et al., $t = 2.355$, $P = 0.0186$, d.f. 6,052; Supplementary Table 11). Our measure of civic opportunity, in sum, appears to be more strongly associated with a community's likelihood to engage in behaviours like mutual aid than other measures of both demand- and supply-side social capital.

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 behaviours 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 and so on) and religious (churches, temples, mosques and so on) organizations. Together, they make up 37% of all civic opportunity organizations. In 85% of counties, they are the top providers of civic opportunity.

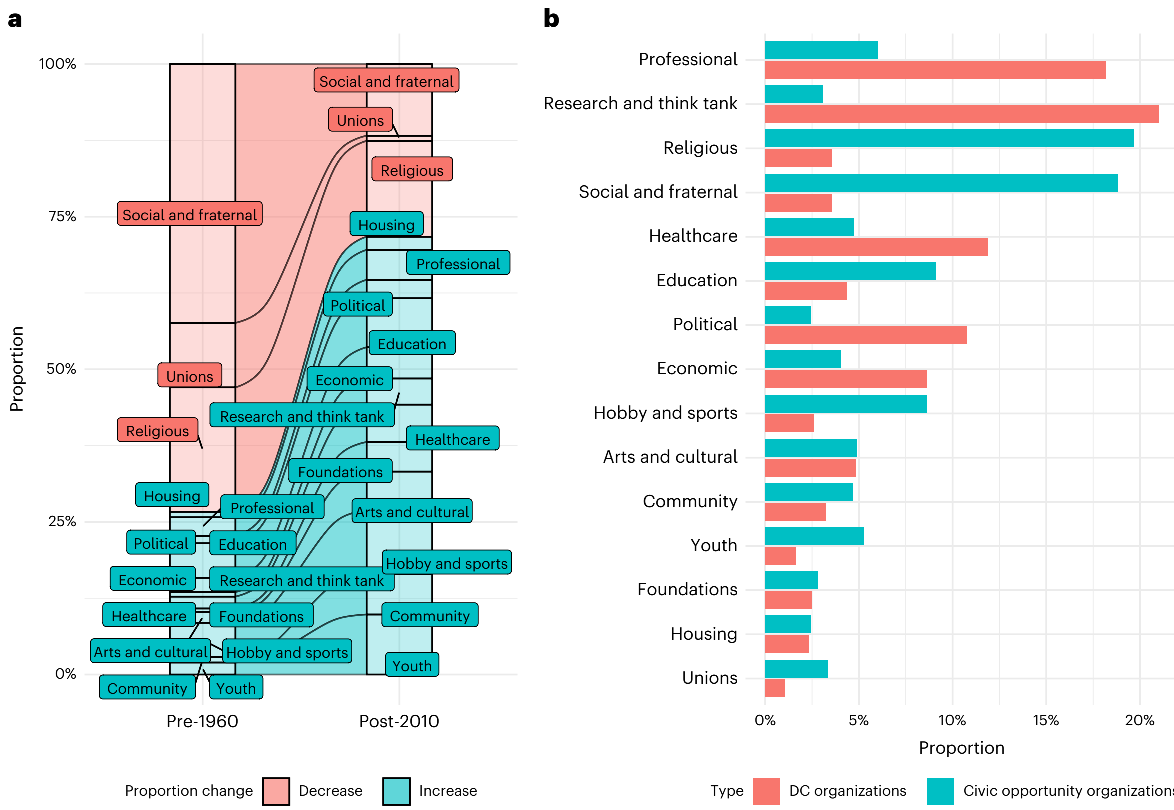

Fig. 4 | Sources of civic opportunity. a, Historical shifts in the types of civic opportunity organizations founded pre-1960 and post-2010. **b**, Proportion of different types of organizations providing civic opportunity versus those represented in Washington DC.

Yet, those are not the kind of organizations most likely to emerge or get attention in the modern era.

Figure 4a shows how the landscape of civic opportunity has shifted over time. If we examine IRS data that identify 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). By 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 and hobby, and youth organizations). Supplementary Table 18 presents the proportion of different types of organizations providing civic opportunity.

In addition, Fig. 4b shows that the kinds of organizations providing civic opportunity are strikingly different from those represented in Washington DC. We focus on organizations in Washington DC 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. Figure 4b compares the kinds of organizations with offices in Washington DC with 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 DC (details in Supplementary Table 17)[33]. In contrast to civic opportunity organizations, the largest category of non-profit organizations in Washington DC are professional and research-based organizations. Together, these two types of organization account for 41% of all lobbying organizations in Washington DC but make up only 9% of all civic opportunity organizations.

Limitations

More research is needed to better elucidate the relationship between civic opportunity and public willingness to engage in behaviours directed towards the common good. Not all civic opportunity will produce democratic behaviours. 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 behaviour 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 leave open an understanding of the mechanisms through which civic opportunity promotes pro-democratic behaviour.

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 such as engaging in mutual aid and vaccine uptake, even in the face of threats to democracy such as hyper-partisanship and disinformation. The association between civic opportunity and pro-democratic community behaviours 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 behaviour 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 behaviour[9–11], 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 24 August 2020). The organizations were geocoded using the Texas A&M University Geoservices Online[37].

Mission and programme statements were extracted from IRS 990 filings using code available in the 'MapAgora' package (v.0.08)[38]. 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 31 December 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 labelled organizations on the basis of their mission and programme descriptions submitted to the IRS and their 'About' page text, using 15 categories described in Supplementary Table 1. The training data consisted of 9,112 labelled observations in total.

We first built 15 binary classifiers (1, yes; 0, no) using labelled training data for each of the 15 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 on the basis of the highest modelled score (Supplementary Table 2).

To increase the accessibility and usability of their automated text classification code, we have documented and packaged the entire process into an R package called 'autotextclassifier' (v.0.05)[39]. 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-labelled 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 on the basis of 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 on the basis of 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 (for the full list, see Supplementary Table 4). 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 shown in Supplementary Fig. 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 US data from these two sites into a single dataset.

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[40]. This is a voluntary survey drawn from a random sample of Facebook users. Following Pierri et al.[28], we examine mean hesitancy per county in a window from 4 January to 25 March 2021. These data are available in 708 US counties.

For vaccine uptake we use data provided by the Center for Disease Control and Prevention at ref. 41. We specifically look at the number of doses delivered per 1,000 residents of a county for the period 18 March to 25 March 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.[28]. These data are available in 543 US counties.

Social capital indices at the county level are from Kyne and Adrich[17], whereas census tract-level social capital indices are from Fraser et al.[42].

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The replication data are 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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