

People, Places, and Ties: Landscape of social places and their social network structures

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Due to their essential role as places for socialization, “third places¹”—social places where people casually visit and communicate with friends and neighbors—have been studied by a wide range of fields including network science, sociology, geography, urban planning, and regional studies. However, the lack of a large-scale census on third places kept researchers from systematic investigations. Here we provide a systematic nationwide investigation of third places and their social networks, by using Facebook pages. Our analysis reveals a large degree of geographic heterogeneity in the distribution of the types of third places, which is highly correlated with baseline demographics and county characteristics. Certain types of pages like “Places of Worship” demonstrate a large degree of clustering suggesting community preference or potential complementarities to concentration. We also found that the social

networks of different types of social place differ in important ways: The social networks of ‘Restaurants’ and ‘Indoor Recreation’ pages are more likely to be tight-knit communities of pre-existing friendships whereas ‘Places of Worship’ and ‘Community Amenities’ page categories are more likely to bridge new friendship ties. We believe that this study can serve as an important milestone for future studies on the systematic comparative study of social spaces and their social relationships.

In January 2014, *The New York Times* reported a conflict between a group of local senior citizens and management at a McDonald’s in Queens, New York. The conflict centered around senior citizens who regularly spend time at the store socializing with one another without spending much on food beyond coffee and fries². In other words, the McDonald’s functioned as both a commercial establishment and a community center, an example of what urban theorists dub a “third place”¹, a social place where people can regularly visit and communicate with friends, neighbors, and even strangers, distinctive from home (first place) and the workplace (second place).

Given their ubiquity and essential role as places for socialization, the idea of third places — public spaces in particular — has been studied by a wide range of fields including network science, sociology, geography, urban planning, and regional studies^{3–11}. Empirical studies show that public spaces such as parks and cafes attract people and initiate new social interactions^{4,12,13}, and the accessibility of public spaces is associated with the level of social interaction and friendship formation between people around them^{14–16}. Furthermore, studies show that the rise and decline of local pubs in rural areas drive the corresponding change in the regional social capital and the

level of social cohesion of the rural communities^{1,6,17,18}, especially during disasters or economic hardships¹⁹⁻²². On the other hand, the social infrastructure of an area also have a major impact on the residents' quality of life^{23,24}. Hence, better understanding of social spaces and their function is critical to improve the resilience of communities.

Despite their importance in our social lives, the lack of systematically collected “census” of social places and their social networks has been a significant challenge for understanding the nature and impact of third places. Although nationwide surveys (e.g, County Business Patterns by US Census) produce information on local commercial establishments, they do not cover non-commercial (but essential) public spaces, such as community ammenities and outdoor parks. Most existing studies did not distinguish between various types of local places, such as cafe, bars, and community ammenities, impeding further comparative inquiries. Finally, the interplay between the types of social places and the social networks which they facilitate has been mostly overlooked, primarily due to the lack of appropriate data sources. For instance, what would be the differences in the social network framed around an outdoor parks and another around a restaurant? Would churches and pubs tend to facilitate similar types of social connections?

We address this challenge by investigating *the landscape of social places and their friendship networks* geographically, and demographically, across the United States. We use nationwide, de-identified, and aggregated data from Facebook Pages to measure the distribution of various third places, which allows us to present a systematic perspective of social spaces in the US. Furthermore, we use social network of Facebook followers of third place establishments, to examine the multi-

faceted interaction between third places and social lives.

Results

Representativeness of Facebook pages Facebook friendships provides a meaningful representation of people's social ties. In the United States, the Facebook usage rate is not only high (69% of adults), but also relatively constant across income groups, education groups, and racial groups among online US adults²⁵. Furthermore, previous studies of online social networks have found a significant association between self-reported friendships and Facebook friendships ^{26–28}. However, while the representativeness of friendships in Facebook for real social relationships has been validated by previous studies and surveys, the representativeness of Facebook Pages¹ for offline third places across the US has not been thoroughly examined. To evaluate the representativeness of Facebook Pages, we compare the number of Facebook social place pages to the number of third place establishments observed in the County Business Patterns (CBP) dataset (See Methods). Note that it covers only a fraction of social spaces and thus falls short for our systematic investigation.

Figure 1(a) to (c) show that there is a strong correlation between the logarithm of the number of social place pages and the estimated number of third place establishments per county in the CBP dataset. The Pearson's correlation coefficients range from 0.90 for Bars and Pubs to 0.98 for Restaurants. We also check the correlations of the per-capita numbers (See Supplementary Information), which still show significant correlations across all categories. Despite there still exists potential discrepancy caused by overlapped or fake Facebook Pages, the strong correlations

¹<https://www.facebook.com/business/pages>

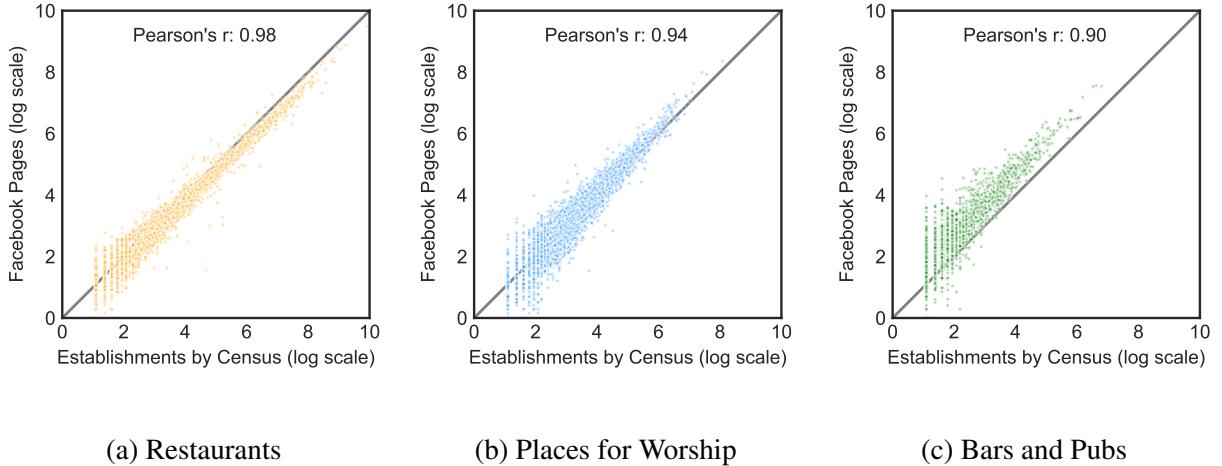


Figure 1: Correlation between the number of establishments surveyed by the US Census and the number of Facebook’s pages in similar categories (See Supplementary Information for per-capita plots, which still show significant correlation). All compared categories show significant correlations, which supports the representativeness of Facebook Pages to reveal the landscape of social places.

between the number of Facebook’s pages and the government-estimated number of businesses is a promising sign that Facebook Pages cover a sizeable number of real-world businesses.

Geographic and Demographic Landscape of Social Places Facebook Pages provide a means for individuals to connect over shared interests in hobbies, causes, businesses, or celebrities, to mention but a few categories which form the subjects of Facebook pages. Facebook Pages includes physical locations, which are of local interests. These pages on local places are arguably well-aligned with the concept of “third places.” Using an existing list of third place categories created by Jeffres et al.²⁹, we systematically identify (See Methods) the pages of social places which connect people locally and may function as “third places.”

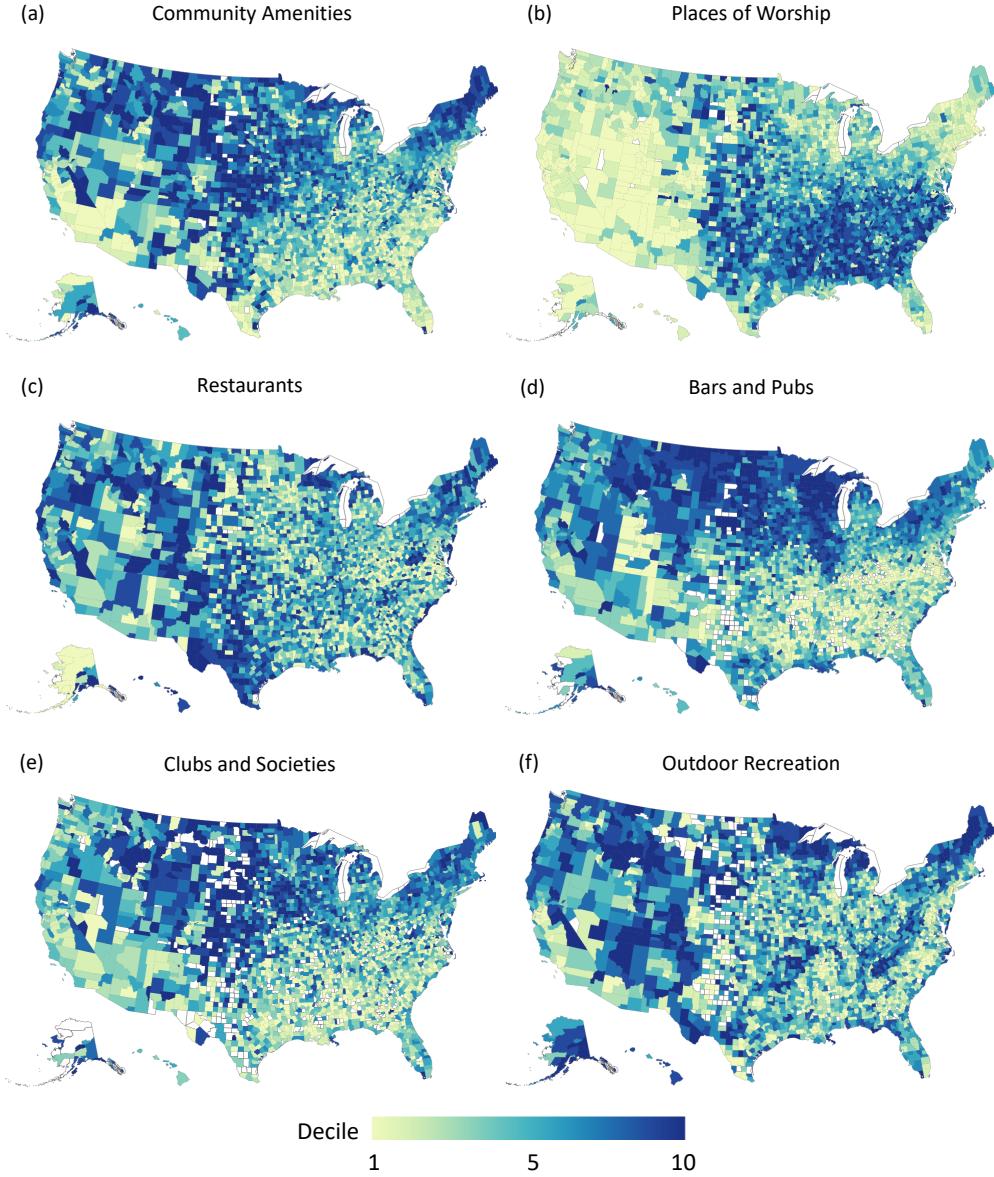


Figure 2: Prevalence maps of different social place categories across the United States. **(a)** Community Amenities, **(b)** Places of Worship, **(c)** Restaurants, **(d)** Bars and Pubs, **(e)** Clubs and Societies, and **(f)** Outdoor Recreation. Prevalence is measured as the number of establishments per 1000 residents for each third place category. For visualization, each US county is assigned into a decile based on its prevalence. There exist several third place types heavily concentrating on a certain part of the US — Places of Worship and Bars and Pubs. Also, the third places for Outdoor Recreation are distributed around famous mountain areas, which shows the association between natural environment and burgeoning types of social places.

The maps of social place distribution exhibit that there is significant geographic heterogeneity between third place categories. ‘Bars and Pubs’ and ‘Clubs and Societies’ are more common in Midwest and Northeast, while Places for worship are more concentrated in the South. On the other hand, Community Amenities and Restaurants are more common in the West and Northeast (Figure 2(a) and (c)). Finally, Outdoor Recreation are distributed around famous mountain and lake areas, including the regions around Rocky Mountains, Appalachian, and Five Great Lakes (Figure 2(f)).

Community characteristics and demographics play a large role in which establishments are created and persist. To better understand the relationship between demographics and prevalence of third places, we look at four characteristics and how they influence third place prevalence: urbanization, income, education, and foreign-born population.

The results, shown in Figure 3, reveals that prevalence of the four largest categories — Retail, Beauty, Restaurants, and Places of Worship — indeed varies with regional and demographic characteristics. Counties in the middle of the RUCC urbanization scale have the highest prevalence of retail stores, beauty shops, and restaurants (Figure 3(a)). Places of Worship, Community Amenities, and Outdoor Recreations, in particular, are less prevalent in more urban counties.

The prevalence of Places of Worship shows a stark decrease with increasing income levels. The counties in the lowest income decile tend to have about 2.5 times more places of worship per capita than the counterparts in the highest decile. By contrast, the numbers of beauty places in rich counties are higher than the number in poor counties in general. Other categories, such

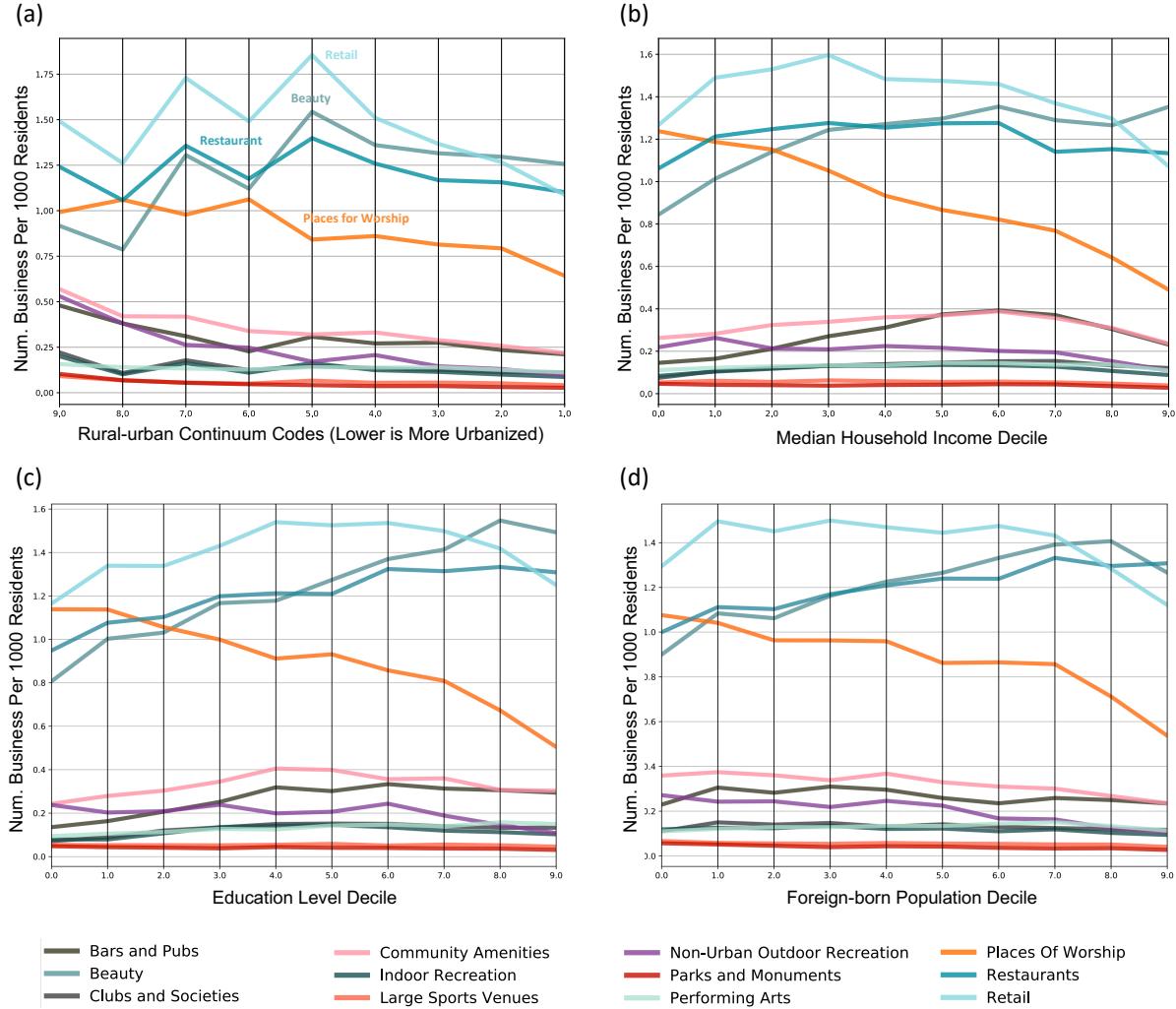


Figure 3: Comparison of the median numbers of each social places per 1000 residents in US counties across different levels of **(a)** urbanization, **(b)** median household income, **(c)** education, and **(d)** foreign-born population. Many third place types show distinct pattern based on demographic characteristics, such as Places of Worship having a dramatic decreasee with increasing urbanization, income, education, and foreign-born population.

as Community Amenities, Bars and Pubs, Retail, and Restaurants, show the inverted-U shape, where the middle-class counties have more of those social places than either richer and poorer counterparts.

As expected from the correlation between income and other demographic characteristics, the prevalence of Places of Worship shows a similar decreasing pattern with education level and foreign-born population. Community Amenities are more prevalent in the regions having medium education level and lower portion of foreign-born population, while the prevalence of Beauty and Restaurants are correlated with both the level of education and the portion of foreign-born population. The heterogeneous prevalence across the types of social place, depending on demographic characteristics of region, reveals the importance of comparative studies, in the future, to understand the role and effect of social places properly.

Social Networks of Social Places If types of available social places are strongly associated with geographic and demographic characteristics, how about the social network around each type of social place? Are there certain characteristics of social networks that are associated with each type of social place? For instance, how does the social networks of people who frequent a Restaurant differ from those who frequent a Place of Worship? We answer this question by leveraging the Facebook friendship network of users who follow of a particular page in Facebook Pages, which we call “follower friendship network”. This approach creates a user-to-user graph for each page, which allows us to analyze the structure of social relationships embedded in each social place.

We first characterize the social network topologies around all third place categories by mea-

suring various network features. We sampled 2,500 pages having between 50 and 50,000 followers — to exclude extreme pages — at random, from each of the twelve third place categories. Then, we compute multiple topological statistics of the social network of each sampled page (See Methods for more information on the extraction process). In particular, following a previous study to characterize social networks of US colleges³⁰, we compute the following 18 network measurements with respect to the user-to-user friendship graph connecting followers of each page: density, number of edges, number of nodes, average degree, average clustering coefficient³¹, average degree assortativity³², degree variance, average path length within the largest connected component, algebraic connectivity³³, modularity of modularity-maximizing partition³⁴, and number of k -Cores³⁵ and k -Brace³⁶ for $k \in \{2, 4, 8, 16\}$. These measures examining various aspects in network structure allow us to capture the fragmentation and diversity of social networks, which we expect to differ by type of social place.

We first extract the ‘most representative’ network for each third place category and visualize them (See Figure 4). We find that social networks for Parks and Monuments and Outdoor Recreation are sparser, less-centralized, while those for Clubs and Societies, Bars and Pubs, and Performing Arts venues are highly connected, having multiple cores.

The structures of the representative friendship network reveals about the functional role of the third place type in our social lives. The coverage of the largest connected group of each friendship network may imply whether the type of third place is more for small groups of existing friends or for constructing a bigger community by bridging gaps between strangers. The representative

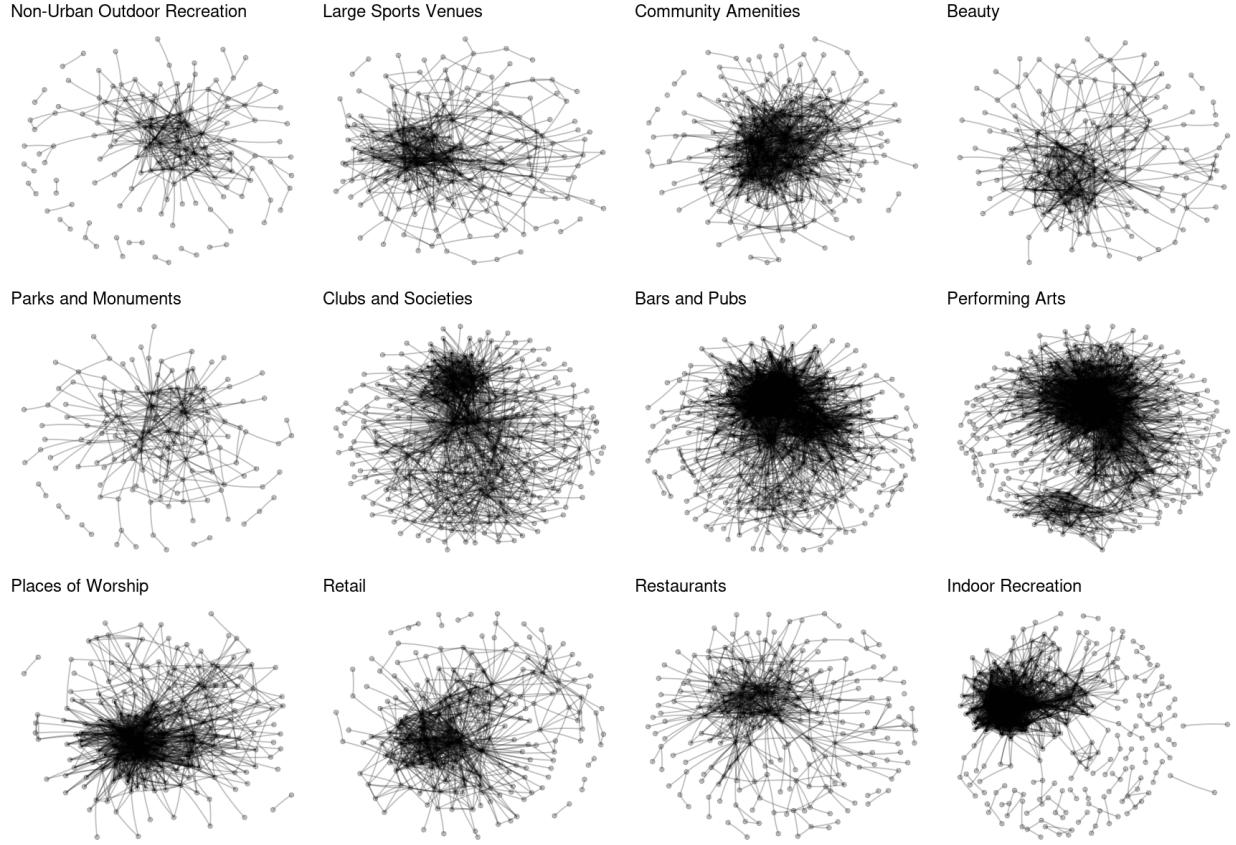


Figure 4: Typical networks for each third place category. Plot shows page follower networks that are nearest to the per-category mean ranks. Distance defined as the L2-norm against the per-category mean rank across all features, weighted by feature importance. The structure of friendship networks can provide hints about the functional role of the third places in our social lives. For instance, the prevalence of dyads and triads separated from a giant component (e.g., Restaurants) coincide with our intuition that restaurant visitors are likely to come with a small group of their existing friends, while less likely to know other people in the place. Also, the existence of core-periphery structure strongly suggests the existence of “regulars”.

networks that exhibit many independent dyads and triads—those of Outdoor Recreation, Indoor Recreation, Restaurant, Parks and Monuments, for instance—potentially indicate that these social places are where people visit with a small group their existing friends. On the contrary, the social networks having a large connected subgraph covering most members may suggest that the social places where many visitors are likely to know each other or to be introduced to each other. Also, the existence of clear division between a group of densely-connected core members and the loosely-connected other members, called core-periphery structure, hints at the presence of “regulars”; The friendship networks of the places having a group of core members who are densely connected to each other — such as Places of Worship, Bars and Pubs, Community Amenities, and Indoor Recreation — is consistent with the story that there are regulars who frequently visit the place, while other non-regulars are likely to be a friend of one of the regulars.

We then quantify concretely the structural difference between third place categories by measuring network dissimilarity between each pair of third place categories. Here, we measure similarity between two categories as *the difficulty of classification*. If a classifier cannot separate two groups of samples easily, we consider that the graphs that produced them are similar. This approach of measuring similarity with a prediction task has been used in recent studies^{30,37,38}. For each pair of third place categories, we train a random forest classifier. We train the sampled social networks of the two categories using the 18 aforementioned topological characteristics as the features (See Methods for detail information). As a result of all possible pairs of the twelve categories, we obtain the cross-validated area under the curve (AUC) of the model for each pair of third place categories, as a measure of similarity distance between the categories. In other words, if the AUC is close

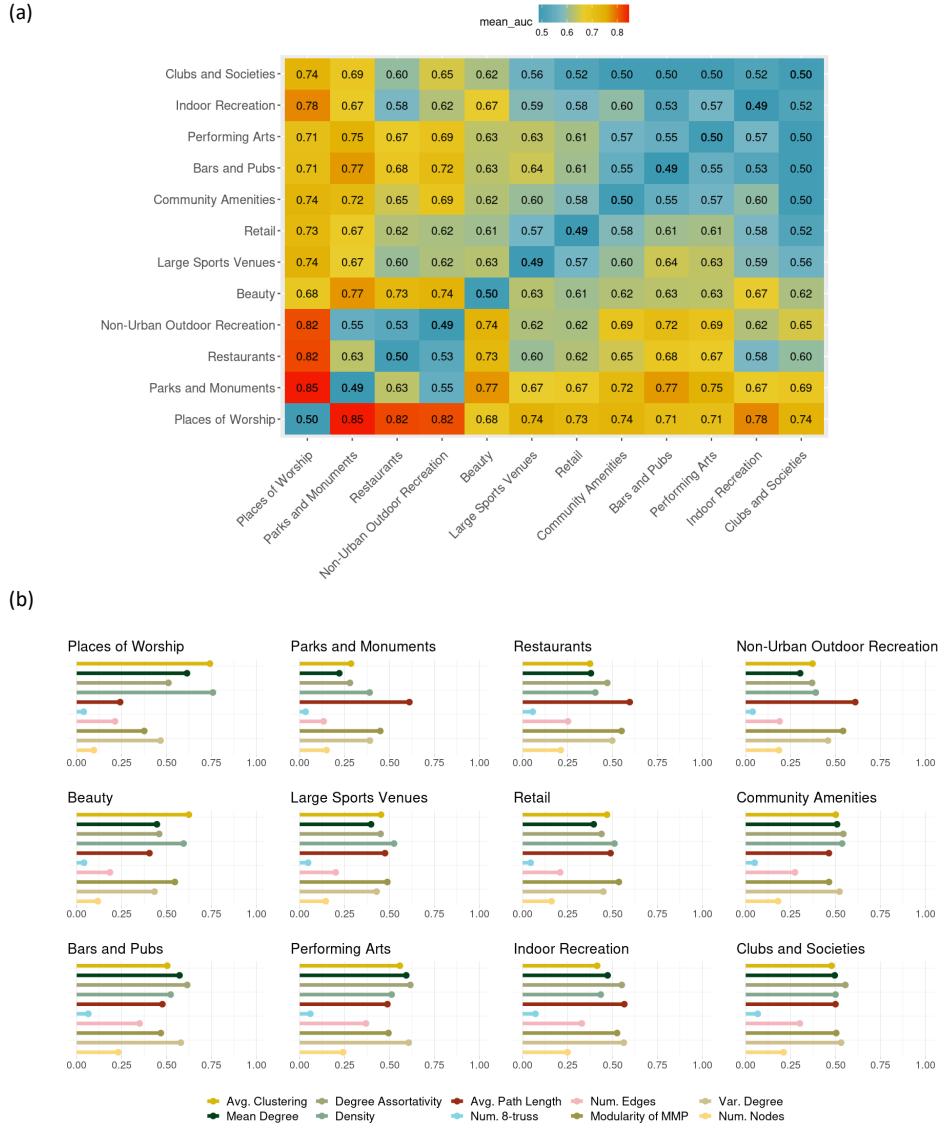


Figure 5: (a) Similarity (AUC) matrix for third place categories based on their social network structure. ROC–AUC of 0.5 represents the maximal similarity (indistinguishable) and ROC–AUC of 1.0 represents the minimal similarity (perfectly distinguishable). The matrix shows roughly two groups: one with Parks and Monuments, Restaurants, and Outdoor Recreation, and the other with most other categories, while Places of Worship exhibit the most distinct structure. (b) Descriptive statistics of the structure of friendship network associated with different third place categories. The statistics are the top ten features by importance, which is presented in Supplementary Information.

to 0.5, the two categories cannot be easily distinguished, which can be considered as similar. On the other hand, if the AUC is close to 1.0, the two categories are easy to distinguish, which can be considered as different.

The ROC–AUC distance matrix, as shown in Figure 5(a), reveals that it is generally possible to distinguish between follower networks corresponding to different third place categories. Also, the matrix shows two clusters of third place categories having similar network structures to each other; 5-category cluster (Clubs and Societies, Indoor Recreation, Performing Arts, Bars and Pubs, and Community Amenities), and 3-category cluster (Outdoor Recreation, Restaurants, Parks and Monuments). **Places of Worship display the most distinctive pattern, indicating that social network around the Places of Worship is highly distinguishable from most other categories.** Figure 5(b) reveals the most informative characteristics of the friendship networks in distinguishing them across categories. We check the descriptive statistics for the top 10 features on average for each type of third place, ranked in order of importance across all classifiers (For the list of feature importance, See Supplementary Information). Aligning with the distant matrix, the topological features show clear similarity between the types within each group, while difference between the groups. Parks and Monuments, Restaurants, and Outdoor Recreation are distinctive based on their Avg. Path Length, while not so regarding clustering measurements, such as Avg. Clustering, Degree Assortativity, and Density. At the same time, the third places in the 5-category cluster is distinguished from the others — Beauty, Large Sports Venues, and Retail — in terms of Variation of Degree, which is probably related to their core-periphery structure.

It is noteworthy that the similarity of social network between third place categories is not much correlated with the types of activity or behavior in the places. For instance, social activities and behaviors in Restaurants are more similar to those in Bars and Pubs than Community Amenities. However, in terms of the topology of friendship network, Bars and Pubs is closer to Community Amenities than Restaurants, which is aligned with previous studies about the social role of pubs in rural area^{12,17,18}. Hence, our results here imply that it is essential to take the cultural and environmental factors into account, beyond the type of activity, when studying the third places.

Conclusion

In this study, we present a systematic measurement on the prevalence of various third places across the United States, by leveraging Facebook Pages dataset. Our results reveal differences in geographical distribution of social places (e.g. places of worship in the South, and bars in the Midwest), as well as the distribution with respect to demographic features, including the levels of urbanization, income, education, and foreign-born population. Our results also reveal that different kinds of third places draw upon (or facilitate) heterogeneous social network structures among the “followers” of their pages. For instance, Places of Worship tend to be associated with social networks that are highly clustered and feature short path lengths. Parks and Monuments, by contrast, have low clustering and longer path length, indicating a more sparsely-organized networks. Certain third place categories (e.g. Indoor Recreation and Clubs and Societies) have more similar social networks than others, and social networks systematically differ across categories.

We expect that our study marks an important milestone towards the understanding of our social infrastructure and their roles in our society by exploring a unique dataset that covers all major types of social spaces and spans a whole country. Since our findings are decidedly descriptive, more work is required to ascertain the extent to which certain kinds of third places also help create and maintain social ties, as well as the extent to which third places benefit from existing social networks. A dynamic view is thus called for in future research, examining the interplay between social ties and third places.

There are several limitations of this study. First, even with the strong correlation between the prevalence for third place categories in Facebook Pages and county-level CBP statistics, we cannot completely rule out the potential existence of systematic biases in our dataset. For instance, the delay between the actual opening (closing) of establishments and the creation (deletion) of their Facebook Pages may affect our findings. Second, given the existence of a digital divide, our observations may have been affected by the preferred social places for more online-friendly generations. For example, our ranking of the total number of Facebook pages (See Supplementary Information) are more consistent with the rankings presented in a previous survey based on three college town areas in Massachusetts³⁹, than the social place ranking in another study based on a national telephone survey²⁹. Even if our study could pinpoint the *existence* of social places, it does not necessarily capture their *size* or *usage*. The number of places of worship may not reflect the number of people attending services, since the size of congregations can vary a great deal. Leveraging other datasets may address this issue in the future.

During the last couple of decades, we have experienced a dramatic change in our social lives due to the emergence of a new type of social spaces — social media. As we become more familiar with online social places such as Facebook or Twitter, this new social space becomes more related and embedded into the existing offline social places. As our favorite social places create their own websites and Facebook Pages to interact with customers online and offline social places become more interdependent. Hence, studying online and offline interactions can help us to understand the similarities and differences between these different spaces. Furthermore, examining the changes in the landscape of the social spaces — particularly with respect to the COVID-19 pandemic and increasing interconnectedness of offline and online social lives — as well as studying the associations between the abundance of social places and the characteristics and dynamics of local communities will be fruitful future studies.

Methods

Matching CBP categories with the corresponding categories in Facebook Pages The County Business Patterns (CBP) dataset is created by surveying firms around the US and categorizing them into place categories by self-assessments to estimate the number of establishments in each category.

We manually matched a subset of social place categories with their corresponding North American Industry Classification System (NAICS) codes. For each matched categories, we compare the estimated number of establishments in the CBP dataset to the number of Facebook pages in the category. The matching table between our social place categories and NAICS codes is pre-

sented in Supplementary Information.

Extraction of third place pages in Facebook Pages Since Facebook pages can fall into a number of categories, we create a data-driven taxonomy of Facebook Pages that represents social places. In doing so we made use of a dataset of over 6 million local pages with between 50 and 50,000 US followers, people who clicked “like” or “follow” on the page to follow its posts and updates. In Facebook Pages, page administrators choose up to 3 page categories for their pages — for instance, a page may be identified as both “AMERICAN_RESTAURANT”, “RESTAURANT”, and “FOOD” in the Facebook page category. Using a set of page categories for each page, we trained a word2vec model⁴⁰². For every broad category indicated by a previous work²⁹, we choose a Facebook Pages’ category that could reasonably represent the broader category. For instance, “AMERICAN_RESTAURANT” was chosen for the “restaurants” categories.

The top 300 terms, in terms of their distance in the embedded space were then examined for each category, with the research team filtering categories that were judged to not fit the notion of third place. For instance, categories such as “COMPETITION” were excluded for not indicating a place, whereas “MEDICAL_HEALTH” was excluded due to the ambiguous nature of the category, and so on. We also removed “SCHOOLS” from our consideration as they represent workplace (“second places”, rather than “third places”) for students. Inspection of the data further led us to combine “Restaurants” and “Cafes” into a single category, as we did with Community Centers, Senior Centers, and Libraries. Finally, we opted for a different categorization of recreation venues — instead of distinguishing only between community centers, indoors recreation, and outdoors

²In particular, we applied the implemented version of word2vec model in the gensim package⁴¹

recreation, we focused on Community Amenities, Performing Arts venues, Parks and Monuments, Indoor Recreation, Non-Urban Outdoor Recreation, and Large Sports Venues.

The full results of our categorization exercise are shown in Supplementary Information, which shows the list of the twelve social place categories and the examples of the Facebook page categories corresponding to each social place category. As a result of the previously-outlined procedure, 453 Facebook page categories matched with one of the 12 social place “super-categories.” Altogether these “social place pages” account for 37.3% of all US local Facebook pages with between 50 and 50,000 fans.

Based on this table, we then filtered and matched the local places in Facebook Pages belonging each of the following twelve social place categories: places of worship, restaurants, bars, community amenities, performing arts, parks and monuments, indoor recreation, non-urban outdoor recreation, large sports venues, clubs and societies, retail, and beauty. We use the number of pages in a category per one thousand residents, based on the county-level population estimates in 2018 by US Census, which allows us to control for the population of US counties. Since each page in Facebook pages has up to three categories, we adjust the weight of a page for counting, by dividing one by the number of categories that a page has. For instance, if one page has two categories, 0.5 pages are counted for the two categories, respectively.

Demographic records of counties As a proxy of the urbanization level of a county, we use The 2013 Rural-Urban Continuum Codes (RUCC) created by the Office of Management and Budget (OMB) of the United States. RUCC is a classification scheme to distinguish metropolitan counties

Third Place Types	Facebook Pages Category
Places of worship	BUDDHIST_TEMPLE, CHURCH, HINDU_TEMPLE, CATHOLIC_CHURCH, MOSQUE, SYNAGOGUE, CHRISTIAN_SCIENCE_CHURCH, SEVENTH_DAY_ADVENTIST_CHURCH, ASSEMBLY_OF_GOD, CHURCH_OF_CHRIST
Restaurants	AMERICAN_RESTAURANT, ITALIAN_RESTAURANT, EASTERN_EUROPEAN_RESTAURANT, JAPANESE_RESTAURANT, MONGOLIAN_RESTAURANT, BUNSIK_RESTAURANT
Bars	TOPIC_BAR, WHISKY_BAR, TIKI_BAR, IRISH_PUB, BEER_BAR, WINE_BAR
Community Amenities	COMMUNITY_CENTER, MODERN_ART_MUSEUM, SENIOR_CENTER, TOPIC_LIBRARY, TOPIC_MUSEUM, COMMUNITY_MUSEUM, HISTORY_MUSEUM, PUBLIC_GARDEN, COMMUNITY_GARDEN, ART_MUSEUM
Performing Arts	LIVE_MUSIC_VENUE, SYMPHONY, THEATRE, TOPIC_CONCERT_VENUE, COMEDY_CLUB, OPERA_HOUSE, PERFORMANCE_ART, AUDITORIUM, PERFORMING_ARTS
Parks and Monuments	AQUARIUM, ARBORETUM, DOG_PARK, MONUMENT, PICNIC_GROUND, PROMENADE, ZOO, WATER_PARK, PUBLIC_GARDEN, STATUE_FOUNTAIN, RESERVOIR, WILDLIFE_SANCTUARY
Indoor Recreation	BOWLING_ALLEY, MOVIE_THEATRE, DRIVING_RANGE, DRIVEIN_MOVIE_THEATER, HAUNTED_HOUSES, KARAOKE, GO_KARTING
Non-Urban Outdoor Recreation	HIKING_TRAIL, TOPIC_MOUNTAIN, ATV_RENTAL_SHOP, FISHING_STORE, GLACIER, FISHING_CHARTER
Large Sports Venues	FOOTBALL_STADIUM, FIELD, BASEBALL_STADIUM, RUGBY_PITCH, SOCCER_STADIUM, CRICKET_GROUND
Clubs and Societies	GYM, SOCIAL_CLUB, BASKETBALL_COURT, BOWLING_ALLEY, FENCING_CLUB, SALSA CLUB, BOXING_STUDIO
Retail	SHOPPING_MALL, CLOTHING_STORE, SPORTSWEAR_STORE, POPUP_SHOP, FROZEN_YOGURT_SHOP, FASHION_DESIGNER
Beauty	BARBER_SHOP, HAIR_SALON, TANNING_SALON_SUPPLIER, COSMETICS_BEAUTY_SUPPLY, SKIN_CARE_SERVICES, HAIR REPLACEMENT, MASSAGE

Table 1: Third place categories and matched Facebook Pages categories. Top categories for each type are presented in bolded text. See Supplementary Information for full listing.

by the population size of their metro area, and nonmetropolitan counties by degree of urbanization and adjacency to a metro area. Under this scheme, US counties are coded from 1 (Counties in metro areas of 1 million population or more) to 9 (Completely rural or less than 2,500 urban population, not adjacent to a metro area), based on the population and adjacency to a metro area. For regional income, we utilized median household income records for each county from 2018 American Community Survey (ACS). Also, for education and foreign-born population, we use the number of people aged 25 or older who have higher than college degree in each county and the proportion of foreign-born residents in each county, respectively, from 2006-2010 ACS. To visualize demographic patterns in third place distributions, we compute the number of third places per 1000 residents for each county. We then compute the median for each RUCC code and for each decile in terms of the income, education, and foreign-born population proxies.

Extracting social graphs of Facebook Pages For each of 2,500 randomly sampled Facebook Pages of each of the twelve third place categories, we extract the friendship network of the users who are the fan of the page. Then, we map the page to its corresponding third place category, and calculate the topological features of our interests, associated with the category. Finally, after mapping the topological features into each category, all network information is discarded. Since this study is only interested in the topological structure of each third place category, the entire process constitutes appropriate aggregations for each step, which carry no personally identifiable information.

Measuring similarity between social networks We trained 66 binary random forest classifiers — one for each possible pair of different third place categories. The classifiers were trained un-

der 10-fold cross-validation, using the `scikit-learn` Python package⁴² to distinguish between page follower networks coming from either one of the paired categories. Feature importance, averaged across all classifier runs, reveals average clustering, mean degree, and degree assortativity as the most discriminative features. The list of importance for all 18 features are presented in Supplementary Information. This ordering suggests that the classifier is picking up on non-trivial structural differences in the make-up of page follower networks, rather than simply focusing on the number of followers (10/18 in terms of average importance) or density (4/18).

1. Oldenburg, R. *The great good place: Cafes, coffee shops, bookstores, bars, hair salons, and other hangouts at the heart of a community* (Da Capo Press, 1999).
2. Maslin Nir, S. & Ham, J. Fighting a mcdonald's in queens for the right to sit. and sit. and sit'. *New York Times* **14** (2014).
3. Jacobs, J. *The Death and Life of Great American Cities* (Random House, New York, 1961).
4. Whyte, W. H. *The Social Life of Small Urban Spaces* (Conservation Foundation, 1980).
5. Lefebvre, H. *The Production of Space, translated by Nicholson-Smith, Donald* (Wiley-Blackwell, 1992).
6. Putnam, R. D. *et al.* *Bowling alone: The collapse and revival of American community* (Simon and schuster, 2000).
7. Gieryn, T. F. A space for place in sociology. *Annual Review of Sociology* **26**, 463–496 (2000).

8. Cho, E., Myers, S. A. & Leskovec, J. Friendship and mobility: user movement in location-based social networks. In *Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining*, 1082–1090 (ACM, 2011).
9. Small, M. L. & Adler, L. The role of space in the formation of social ties. *Annual Review of Sociology* **45** (2019).
10. Dong, X. *et al.* Segregated interactions in urban and online space. *EPJ Data Science* **9**, 20 (2020).
11. Hidalgo, C. A., Castañer, E. & Sevtsuk, A. The amenity mix of urban neighborhoods. *Habitat International* 102205 (2020).
12. Hickman, P. “third places” and social interaction in deprived neighbourhoods in great britain. *Journal of Housing and the Built Environment* **28**, 221–236 (2013).
13. Hampton, K. N., Goulet, L. S. & Albanesius, G. Change in the social life of urban public spaces: The rise of mobile phones and women, and the decline of aloneness over 30 years. *Urban Studies* **52**, 1489–1504 (2015).
14. Abu-Ghazze, T. M. Housing layout, social interaction, and the place of contact in abu-nuseir, jordan. *Journal of environmental psychology* **19**, 41–73 (1999).
15. Lund, H. Testing the claims of new urbanism: Local access, pedestrian travel, and neighboring behaviors. *Journal of the American Planning Association* **69**, 414–429 (2003).

16. Small, M. L. *Unanticipated gains: Origins of network inequality in everyday life* (Oxford University Press, 2009).
17. Cabras, I. Industrial and provident societies and village pubs: exploring community cohesion in rural britain. *Environment and Planning A* **43**, 2419–2434 (2011).
18. Cabras, I. & Mount, M. P. How third places foster and shape community cohesion, economic development and social capital: The case of pubs in rural ireland. *Journal of rural studies* **55**, 71–82 (2017).
19. Browning, C. R., Wallace, D., Feinberg, S. L. & Cagney, K. A. Neighborhood social processes, physical conditions, and disaster-related mortality: the case of the 1995 chicago heat wave. *American sociological review* **71**, 661–678 (2006).
20. Dynes, R. Social capital: Dealing with community emergencies. *Homeland Security Affairs* **2** (2006).
21. Airriess, C. A., Li, W., Leong, K. J., Chen, A. C.-C. & Keith, V. M. Church-based social capital, networks and geographical scale: Katrina evacuation, relocation, and recovery in a new orleans vietnamese american community. *Geoforum* **39**, 1333–1346 (2008).
22. Klinenberg, E. *Heat wave: A social autopsy of disaster in Chicago* (University of Chicago Press, 2015).
23. Carley, M., Kirk, K. & McIntosh, S. *Retailing, sustainability and neighbourhood regeneration* (Citeseer, 2001).

24. Goodchild, B. *Homes, cities and neighbourhoods: planning and the residential landscapes of modern Britain* (Ashgate Publishing, Ltd., 2008).
25. Duggan, M., Ellison, N. B., Lampe, C., Lenhart, A. & Madden, M. Social media update 2014. pew research center, january 2015 (2015).
26. Gilbert, E. & Karahalios, K. Predicting tie strength with social media. In *Proceedings of the SIGCHI conference on human factors in computing systems*, 211–220 (2009).
27. Jones, J. J. *et al.* Inferring tie strength from online directed behavior. *PloS one* **8** (2013).
28. Hampton, K., Goulet, L. S., Rainie, L. & Purcell, K. Social networking sites and our lives. pew internet and american life project. *Retrieved from November 4, 2001* (2011).
29. Jeffres, L. W., Bracken, C. C., Jian, G. & Casey, M. F. The impact of third places on community quality of life. *Applied Research in Quality of Life* **4**, 333 (2009).
30. Overgoor, J., Adamic, L. A. *et al.* The structure of us college networks on facebook. In *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 14, 499–510 (2020).
31. Watts, D. J. & Strogatz, S. H. Collective dynamics of ‘small-world’networks. *nature* **393**, 440–442 (1998).
32. Newman, M. E. Mixing patterns in networks. *Physical review E* **67**, 026126 (2003).
33. Fiedler, M. Algebraic connectivity of graphs. *Czechoslovak mathematical journal* **23**, 298–305 (1973).

34. Clauset, A., Newman, M. E. & Moore, C. Finding community structure in very large networks. *Physical review E* **70**, 066111 (2004).
35. Bollobás, B., Fulton, W., Katok, A., Kirwan, F. & Sarnak, P. Cambridge studies in advanced mathematics. In *Random graphs*, vol. 73 (Cambridge university press New York, 2001).
36. Ugander, J., Backstrom, L., Marlow, C. & Kleinberg, J. Structural diversity in social contagion. *Proceedings of the National Academy of Sciences* **109**, 5962–5966 (2012).
37. Gentzkow, M., Shapiro, J., Taddy, M. *et al.* Measuring polarization in high-dimensional data: Method and application to congressional speech. Tech. Rep. (2016).
38. Bertrand, M. & Kamenica, E. Coming apart? cultural distances in the united states over time. Tech. Rep., National Bureau of Economic Research (2018).
39. Mehta, V. & Bosson, J. K. Third places and the social life of streets. *Environment and Behavior* **42**, 779–805 (2010).
40. Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S. & Dean, J. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, 3111–3119 (2013).
41. Řehůřek, R. & Sojka, P. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*, 45–50 (ELRA, Valletta, Malta, 2010). <http://is.muni.cz/publication/884893/en>.

42. Pedregosa, F. *et al.* Scikit-learn: Machine learning in python. *the Journal of machine Learning research* **12**, 2825–2830 (2011).