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Exploring the imprint of social media networks on neighborhood community through the lens of gentrification

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Abstract

Gentrification, the rise of affluent socioeconomic populations in economically depressed urban neighborhoods, has been accused of disrupting community in these neighborhoods. Social media networks meanwhile have been recognized not only to create new communities in neighborhoods, but are also associated with gentrification. What relation then does gentrification and social media networks have to urban communities? To explore this question, this study uses social media networks found on Twitter to identify communities in Washington, DC. With space-time analysis of 821,095 geo-tagged tweets generated by 77,528 users captured from 15 October 2015 to 18 July 2016, we create a location-based interaction measure of tweets which overlays the social networks of the comprising users based on their followers and followees. We identify gentrifying neighborhoods with the 2000 Census and the 2010–2014 American Community Survey at the block group level. We then compare the density of location-based interactions between gentrifying and nongentrifying neighborhoods. We find that gentrification is significantly related to these location-based interactions. This suggests that gentrification indeed is associated with some communities in neighborhoods, though questions remain as to who has access. Making novel use of big data, these results demonstrate the important role built environment has on social connections forged "online."

Keywords

Gentrification, space-time analysis, social networks, big data, livability

Introduction

From Jacobs (1961) to Appleyard (1981) and beyond, the vibrancy of local community has been viewed by urban planners and scholars alike to be a seminal benchmark for understanding the quality of life of any neighborhood. New social media like Twitter, made readily available through dynamically networked handheld technologies, is creating

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new possibilities to build local community. These technologies foster social networks between users that allow far greater mobility regarding where and how people interact in cities (Hampton and Wellman, 2003; Ling, 2008; Rainie and Wellman, 2012). Moreover, social media offers new opportunities to study local communities beyond resource-intensive surveys. However, there is comparatively little research on how local community born from social media networks relates to the demographics or built environment of a neighborhood. This is a key omission given the role these forces are thought to have in the endurance of vibrant urban communities (Jacobs, 1961; Sampson, 2012). To address this limitation, we explore the relationship of social media and community through the lens of one of the most controversial issues facing cities today—gentrification.

Gentrification, the increasing presence of affluent populations in previously economically depressed neighborhoods (Kennedy and Leonard, 2001), is a logical vantage point to examine how local context relates to social media networks given gentrification's recognized association with new media (Hristova et al., 2016). Social media platforms like Twitter and Yelp are outlets through which gentrifying neighborhoods are promoted and assessed (Zukin et al., 2015). There is, however, much uncertainty as for what relation gentrification has with local communities. Many argue gentrification harms community (Betancur, 2011; Freeman, 2005, 2006; Newman and Wyly, 2006), but would this harm extend to community derived from social media networks?

The goal of this article is to explore whether gentrification and social media networks converge to affect communities in neighborhoods. The relation of gentrification and social media networks raises important questions not only for how gentrification affects communities, but also for how cyberspace relates to physical space. If social media networks prove to have an inverse association with gentrification, it supports the argument that gentrification disrupts community. However, if gentrification is positively associated with social media networks, it might instead demonstrate that gentrification does not unilaterally disrupt urban communities.

To identify local community from social media networks, we make novel use of location-based interaction networks which identify proximal "interactions" between Twitter users occupying the same area at the same time (Cho et al., 2011; Yuan and Nara, 2015; Yuan et al., 2014). These networks are derived from geo-tagged Tweets in gentrifying and nongentrifying neighborhoods in Washington, DC. We identify how socially "close" location-based interaction networks are based on whether the users that constitute them are followed and/or followed by one another. Further, we use word clouds of the commonly used terms found in Tweets by neighborhood to gain an impression of the kinds of communities that can be found in gentrifying and nongentrifying areas. In so doing, we can evaluate if gentrifying areas indeed have a unique relationship with communities forged through new media.

This paper makes several important contributions to urban studies. It builds on the gentrification literature by offering more subtext as for how communities are affected by neighborhood change. What is more, our methodology lays the groundwork for the use of network-oriented research based on big data as a way to understand urban quality and neighborhood dynamics. Through the use of big data, urban planners and researchers alike can explore small granular relationships between neighborhood effects and social networks.

Background

Gentrification and community

The existing literature appears in agreement that gentrification negatively relates to community. Gentrification is often accused of physically displacing existing residents who can no longer afford the rising costs of their neighborhoods (Chapple, 2009; Freeman, 2005; Freeman and Braconi, 2004), thus dismantling the existing local community. However, there is a lack of quantitative evidence that wide scale displacement of this sort takes place (Ding et al., 2015). Even if residents are not being physically displaced, there are other ways gentrification can affect the community of a neighborhood. First, gentrification may impact communities through the influx of new populations (Betancur, 2011; Freeman, 2006; Hwang, 2016b; Newman and Wyly, 2006). The social networks which constitute community require time to develop and new residents may not have resided in these places long enough to develop relationships with longstanding residents (Freeman, 2006; Sampson, 2012). Second, gentrification can disrupt communities through the replacement of locally rooted stores, restaurants, and community oriented nonprofits, with chain stores and high-end restaurants. Longstanding low income residents report alienation from these new establishments, feeling they are not meant for them due to their higher costs and the race of their perceived clientele (Freeman, 2006; Sullivan and Shaw, 2011; Zukin et al., 2009). The newer residents for their part will be more drawn to these establishments while at the same time be unaware or dismissive of the pre-exising establishments (Hwaing, 2016b; Zukin et al., 2015). This change in local businesses is important for community as local establishments have been identified as a pivotal site for social capital formation and maintenance (Putnam, 2000; Sanchez-Jankowski, 2008).

Another key factor related to both gentrification and community is that of racial/ethnic composition. Ample research has documented that local racial/ethnic composition directly influences where connections form, usually along racial ethnic lines (Neal, 2015; Portes and Vickstrom, 2011). Putnam (2007) notably argued that community is more inhibited in racially/ethnically mixed communities, where common ground is typically more elusive. Racial/ethnic composition also has an important role as to where gentrification occurs, often times in places that are racially diverse to begin with (Hwang, 2016a). Does this mean that gentrifying areas lack community because of their diverse racial/ethnic character?

The built-environment of gentrifying communities offers another important vantage point. The relationship of gentrification to the built environment can take a number of shapes, with various implications for community. Neighborhoods with an older, dense, and diverse housing stock of some historical value are a common site of "rehabilitation" gentrification, where most of the built structures are largely superficially designed to preserve their "historic" character, such as "Brownstone Brooklyn" in New York City (Osman, 2011). In addition to their draw for would-be gentrifiers, these older communities are also recognized for their conduciveness for rich social connections that foster community. The dense and diverse housing stock coupled with small, walkable blocks (represented by high densities in streets and intersections) in these places offers various public spaces for people to interact and build networks (Appleyard, 1981; Jacobs, 1961; Whyte, 1980). If gentrification is associated with these kinds of neighborhoods, would the built environment offset potential community disruption of population turnover and storefront change?

Conversely, not all gentrification is associated with the rehabilitation of existing structures. Some have also connected gentrification with the mass demolition of older structures, replaced with new structures targeted toward upper income populations (Curran, 2007). This kind of mass redevelopment has had a notorious reputation in disrupting the social connectedness of urban neighborhoods (Jacobs, 1961), including that of low income ethnic communities (Chapple, 2009).

Social media networks and community

Some argue an outcome of new digital communication is an increasingly networked community less bound by the local context of neighborhoods (Hampton and Wellman, 2003; Rainie and Wellman, 2012; Takhteyev et al., 2012). However, it is not clear how accessible these new technologies are in practice. Sampson (2012) finds that lower income neighborhoods are less prone to use the new media due to cost impedances and a lack of local resources. Other studies have found that while upper income populations have more access to new media, it is consistently used across socioeconomic strata (Duggan, 2015). The bottom line is that even as the use of new media driven social networks grow, neighborhoods maintain a potential role in how this media is used. How then do disparities in physical space affect social media networks and community more broadly?

Research comparing in-person networks to social media networks has found that high levels of Twitter activity parallel high levels of in-person networks (Crandall et al., 2010; Eagle et al., 2009; Ling, 2008; Ye et al., 2012). However, it is not certain how strong the social connections within social media networks are in practice. Twitter tends to be unidirectional instead of reciprocal, with people more likely to share news or social information like where and when to meet up instead of engaging in direct dialog (Alhazmi and Gokhale, 2015; Takhteyev et al., 2012). Nonetheless, the social networks found in Twitter can be a proxy of social cohesion, an essential building block for community (Sampson, 2012). Research has found that the connections through Twitter and similar social networking sites foster social capital (Alhazmi and Gokhale, 2015; Hampton et al., 2011; Hofer and Aubert, 2013; Ye et al. 2012). Borrowing from Putnam (2000), Hofer and Aubert (2013) argue that the amount of followees one has on Twitter is associated with bonding social capital, ties between people with similar social backgrounds, and the number of users one follows is associated with bridging social capital, ties between people with different social backgrounds. Thus, while we cannot say for certain how directly Twitter users interact, examining their networks is a viable way to identify community.

Social media networks may also present a way through which gentrification *builds* community. For one, the young affluent populations typically pegged as gentrifiers are also the group most likely to use social media (Duggan, 2015; Freeman and Braconi, 2004). Moreover, existing research has found that social media has a prominent role in the process of gentrification, with new restaurants and shops being discussed and appraised through social media (Zukin et al., 2015). Indeed, social media usage tends to be stronger in gentrifying neighborhoods (Hristova et al., 2016). In spite of the potential for urban communities derived from social media networks, the relation of gentrification to communities in neighborhoods has not been empirically explored.

Research objectives

The past literature of gentrification and social media networks raises some key questions which motivate this study. Gentrification is associated with changes in the demographic environment and built environment that may impact the community in a neighborhood. Is gentrification in any way related to the community derived specifically from social media networks? The past research has offered some evidence that social media networks might leave an imprint of social capital in physical space. However, while gentrification has a longstanding association with new media, it is not certain how it would relate to social media networks. Given the preliminary nature of Twitter network research in an urban context, this project is primarily exploratory in nature with the following research objectives:

1. Capture complex dynamics of gentrification in a timely manner by utilizing big data and data mining techniques onto Twitter.
2. Examine location-based interactions of geo-tagged Tweets in urban neighborhoods to see if the physical manifestation of social media networks is related to gentrification.
3. Determine how multiethnic communities and other relevant neighborhood characteristics beyond gentrification factor into the relationship of gentrification and social media networks.
4. Directly compare the subject of Tweets dominating gentrifying and nongentrifying areas to see if there is meaningful difference that may explain our results.

Data

We collected geo-tagged Twitter data in Washington, DC from 15 October 2015 to 18 July 2016 for a total of 821,095 Tweets generated by 77,528 users. These tweets are depicted in Figure 1. Gentrifying neighborhoods are identified through the 2000 Census and 2009–2014 American Community Survey (ACS). Block group level data were used as it allows a better capture of the local dynamics of gentrification. One issue with using block group level data in different time periods is that the boundaries change. While there are established methods of interpolation used for census tracts, such as the Neighborhood Change Database, these are not available for block groups. To deal with this issue, we developed a data management tool to automatically interpolate Census 2000 data at the block group level within the Census 2010 block group boundary. We implemented a simple areal interpolation method (Goodchild and Lam, 1980), programmed using Python and Structured Query Language (SQL) for PostgreSQL and PostGIS. Finally, we obtained supplemental data on the built environment from the National Academies of Sciences' new *Livability Calculator* (Appleyard et al., 2016) which uses data from HUD and EPA.

Measures

Neighborhood measures

There is no commonly agreed upon strategy for identifying gentrified neighborhoods (Barton, 2016). Recognizing this, the current study utilized Census and ACS data to replicate the typology of gentrification used by Ding et al. (2015). This method identifies places that have gentrified as well as those with the potential to gentrify but have not done so, allowing a better comparison of gentrification's effects onto a community. Following this approach, we determined first whether neighborhoods were "gentrifiable" in 2000 by identifying block groups that featured a median household income below that of the District of Columbia. From there, we created the categories used in this study which are described in Table 1 and depicted in Figure 2. Using the ACS, we identify *New Construction*, anything built after 2005, as an example of built environment gentrification. Through the *Livability Calculator*, we identify walkability through the commonly used measure of *Intersection density*, or number of walkable intersections per square mile (Appleyard et al., 2016).

In addition to the measures of gentrification, we draw on the ACS for our controls. These include the classification of multiethnic neighborhood, which is any block group that is at least 40 percent White, and any other groups (Black, Hispanic, Asian, etc.) are at least 10

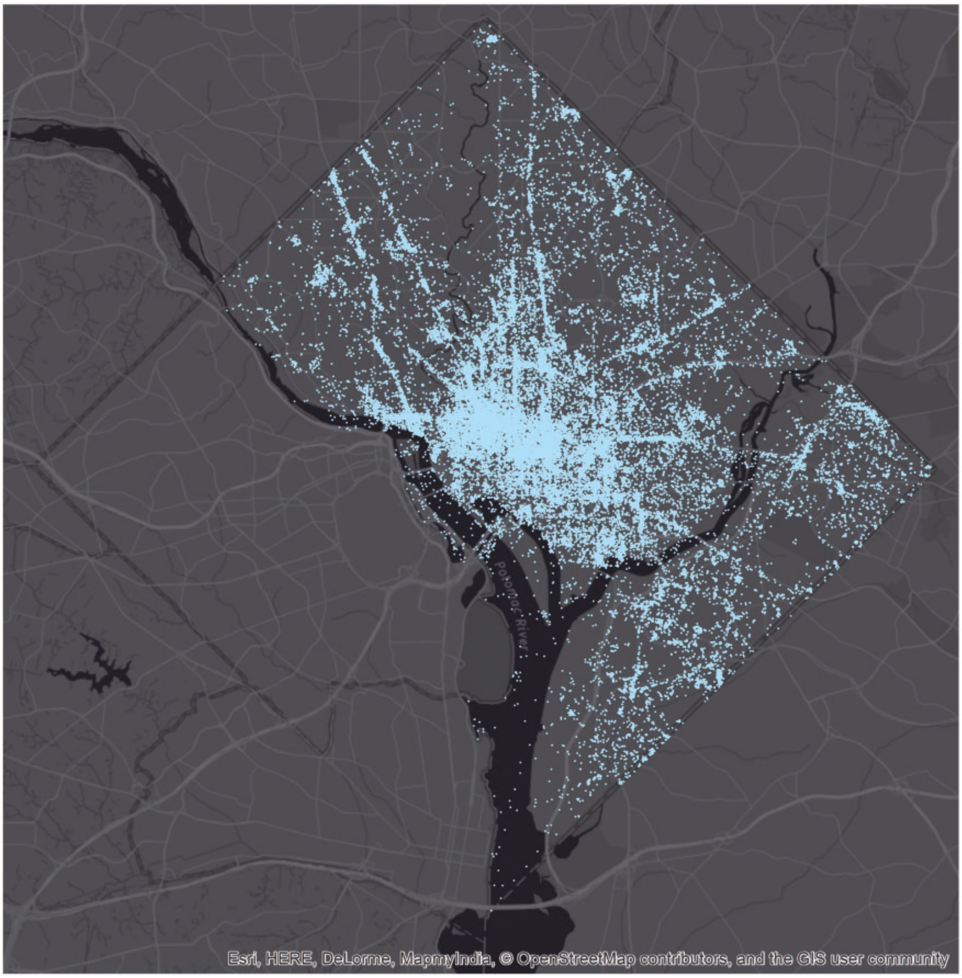

Figure 1. Geotagged tweets in Washington, DC.

Table 1. Demographic gentrification typology.

Type	Neighborhood criteria
Not gentrifiable	Above the citywide median income in 2000
Gentrifiable	Below the citywide median income in 2000
Gentrifying	Increase in gross rent or median income above the citywide median between 2000 and 2014. Grew in the number of college-educated residents above the citywide median between 2000 and 2014
Not gentrifying	Failed to meet the above criteria

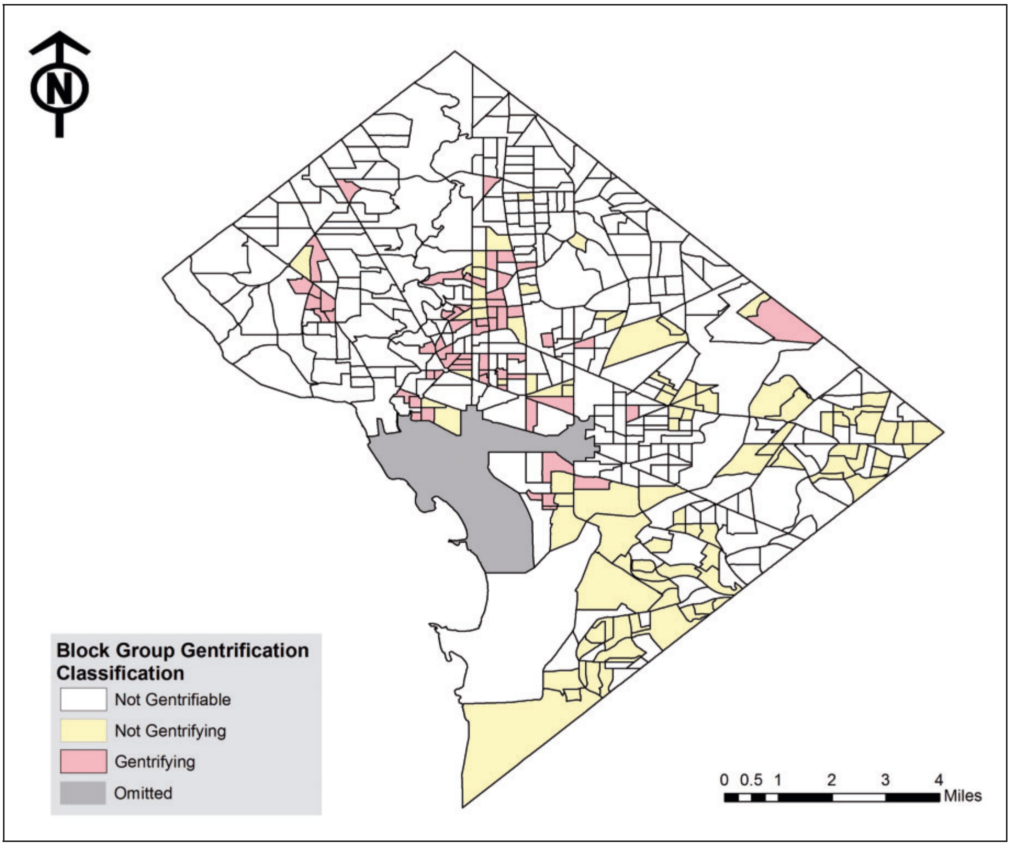

Figure 2. Demographic gentrification in Washington, DC by census block groups.

percent (Friedman, 2008). Also, we include the percent between the ages of 18 and 29, the largest group currently using Twitter (Duggan, 2015). Next, we have measures of neighborhood stability, including *Percent Moved in Five Years* and the *Percent Homeowner*. Finally, we account for population density. We attempted to confine our number of variables to minimize the risk of collinearity. Available upon request, further tests were conducted to ensure acceptable collinearity of variables.

Identifying social media networks in urban neighborhoods

We measure the imprint of Twitter networks on a neighborhood community by analyzing geographic and geosocial affiliations in Twitter space. We identify these affiliations by two types of proximal "interactions" between Twitter users, (a) location-based interactions, and (b) location-based social interactions. Both types of interaction are represented as links in networks. Each link consisting of two Twitter users (or nodes) represents a dyad. The LN is created if two Twitter users posted geotagged Tweets in a same census block group within the same hour and day (e.g., 1:00–1:59) (Cho et al., 2011; Yuan and Nara, 2015; Yuan et al., 2014). The LN suggests possible social interactions of Twitter users due to their physical proximity. However, LNs do not firmly establish the presence of social connection in the dyad, nor its strength. LSNs, on the other hand, are LNs that measure social networks by capturing whether Twitter users within the dyad follow, or are followed by, one another on Twitter.

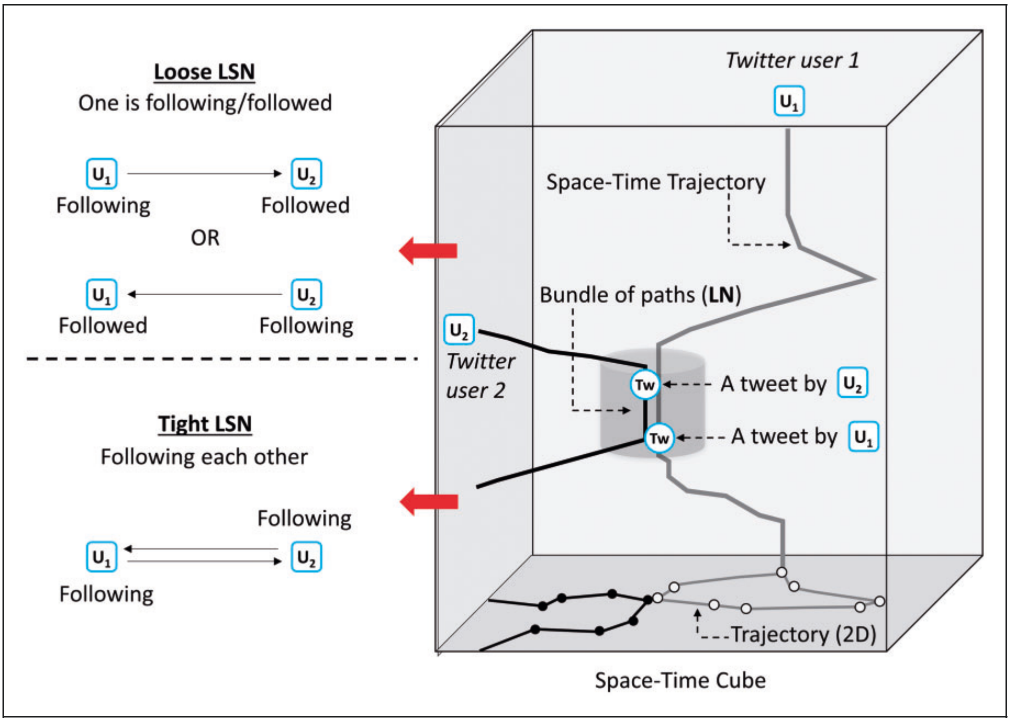

Figure 3. Diagram of Twitter social network on location-based interaction network.

As depicted in Figure 3, LSNs are extracted from dyads in an LN by establishing whether the geosocial link is either asymmetric (one direction) or mutual (both directions). These connections are represented by a directed graph, or digraph for short. If only one of two nodes in dyads in an LN is following the other (asymmetric dyads) on Twitter, these are considered weakly tied relationships, or a "loose" LSN. Conversely, if two nodes in dyads in an LN are both following each other (mutual dyads), these are considered strongly tied relationships constructing a "tight" LSN.

Thus, LNs and LSNs allow us to measure the physical imprint of community derived from social media networks in a neighborhood by finding location-based Twitter "interactions" in similar space and time. How "strong" this community proves to be in practice depends on whether they are LNs, loose LSNs, or tight LSNs, which essentially reflects the local presence of social media networks. However, we cannot say for certain from LNs or even LSNs that the Twitter users which compose them directly know one another, nor can we say that users are actually meeting in person when the location-based "interactions" take place. Nevertheless, loose LSNs can suggest at least a trace sense of community. It is reasonable to assume that one user knows the other user given they are following or being followed by the other member of the dyad and occupying the same space at roughly the same time. To this end, tight LSNs suggest an even stronger sense of community as both users are following, or being followed by, one another. While we do not distinguish bonding or bridging social capital in LSNs, tight LSNs assume the strongest social capital among users given the symmetric nature of the dyad (Hofer and Aubert, 2013).

Another issue with location-based interactions is they are correlated with population—more links will be found in higher population areas. To account for this and

Table 2. Descriptive statistics.

Variables	Demographic gentrification		
	Not gentrifiable	Gentrifying	Not gentrifying
Twitter networks			
LN	543.73	13612.00	1036.83
Loose LSN	13.71	39.45	16.71
Tight LSN	2.51	7.42	3.31
Built environment gentrification			
Percent recent development	0.49	2.19	1.47
Intersections density	89.38	108.67	64.09
Demographics			
Percent multiethnic neighborhood	6.77	15.20	2.08
Percent age 18–29	21.00	29.93	23.56
Population density	0.00	0.01	0.01
Stability			
Percent moved in five years	72.70	65.70	59.58
Percent homeowner	55.76	22.74	34.01
Total	295	59	96

LN: location-based network; LSN: location-based social network.

normalize the data, two steps are taken: first, we include a measure of *Population Density* derived from the ACS; second, we omit block groups without residential components.

Results

Gentrification and network quality

In Table 2, we describe the overall characteristics of our sample by demographic gentrification classification, comparing the differences between neighborhoods classified as gentrifying and not gentrifying. First, the average number of total LNs and LSNs is greater in *gentrifying* block groups compared to *nongentrifying* block groups. This supports the notion that a direct relation between gentrification and LN and LSNs exists. This relationship is visualized in Figures 4 through 6 which map out LN and LSNs based on strength, adjusting the number of links by block group population and overlaying the measures of gentrification. These figures show that while LNs, loose LSNs, and tight LSNs are strongest near the core of the city, they also have a presence throughout the District of Columbia.

Turning to other characteristics, in keeping with past gentrification research we find that gentrifying block groups are racially mixed, having the largest share of multiethnic neighborhoods (Hwang, 2016a). The measures of built environment are also consistent with past research. Gentrifying areas are more dense, as measured by population density, boast more new construction, and have smaller, more walkable blocks (as represented by intersection density). Also, the population of gentrifying areas tends to be younger, with a disproportionately high share of people in the 18–29 age group. Finally, while gentrifying areas have a higher percentage of residents who moved in the past five years, they also have comparatively fewer residents who own their homes.

To more carefully examine the relation of gentrification to LNs and LSNs, we conduct negative binomial estimations, presented in Table 3. Foremost, we found that gentrifying block groups carry a significant and positive relation with all forms of location-based interactions. This suggests that gentrifying areas have a significantly stronger association to

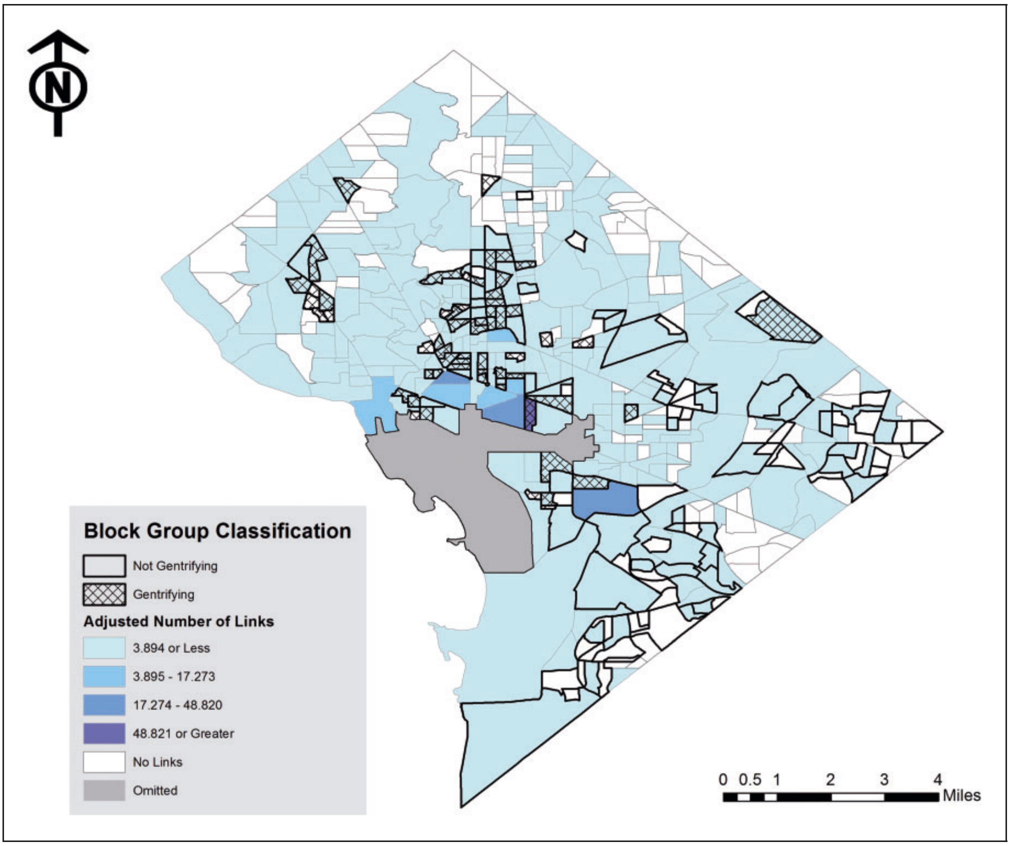

Figure 4. Location-based networks and neighborhood gentrification.

new media derived community in neighborhoods than nongentrifying areas. Nongentrifiable areas are significantly associated with LNs and loose LSN links, but not tight LSNs. This indicates social-affluence alone does not drive LSNs, as nongentrifiable areas had enough socioeconomic resources initially not to be gentrifiable. Turning to built-environment measures, while new construction is not related to location-based interactions (LNs or LSNs), intersection density is related to all forms—which highlights an interesting association between Twitter social networks and walkability. Multiethnic neighborhoods have a marginally significant association with loose LSNs and tight LSNs. In supplemental analysis available on request, we found this relation to be fully significant when gentrification was not included in the models, offering further indication of gentrification's relation to racially/ethnically mixed communities. LNs and LSNs were also associated with young neighborhood residents, those in the 18–29 age group. Also of note, the presence of people who recently moved has a negative relation with all forms of location-based interaction measured, reinforcing the notion that instability harms even mobile networks.

Gentrification community character

To better understand why gentrifying areas are positively associated with community derived from Twitter, we offer some qualitative evaluation of the Tweets in these

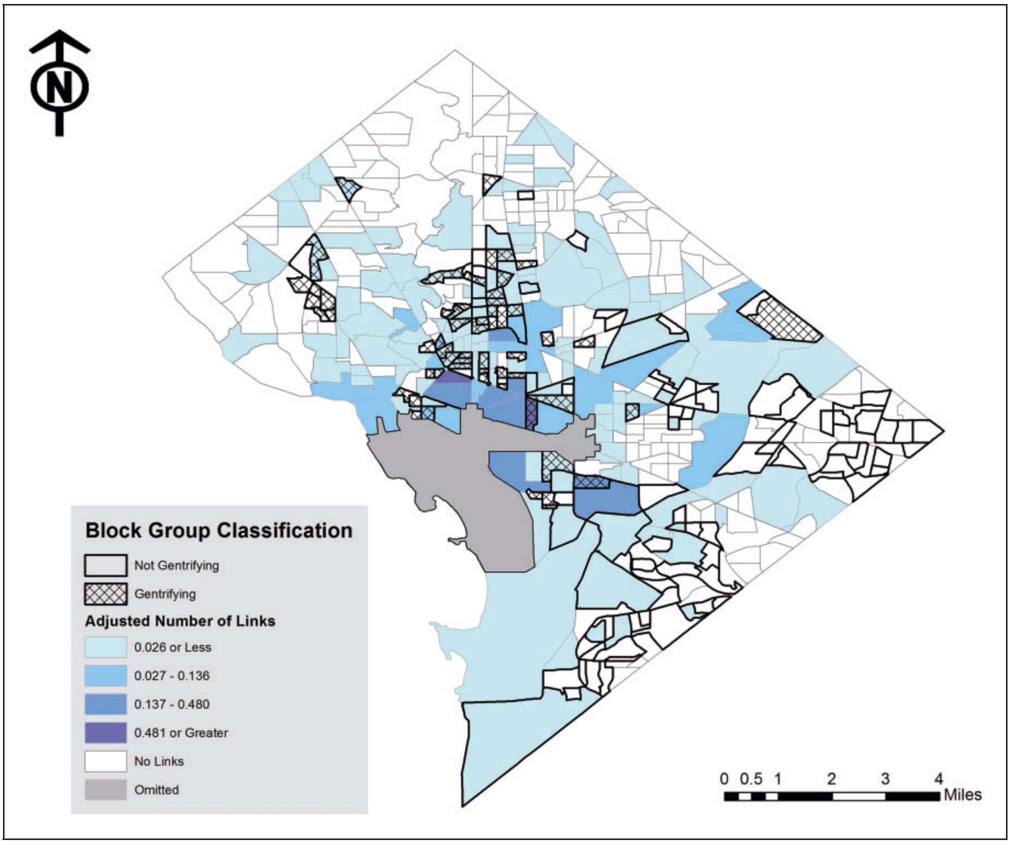

Figure 5. Loose location-based social networks and neighborhood gentrification.

communities to highlight marked differences between these places. Figure 7 presents the word clouds of common terms found in Tweets of four randomly selected block groups identified as gentrifying (the larger the term, the more frequently it is used). Three of the word clouds center on people going out: the most common term in block group 110010028011 "Thip Khao" signifying a local restaurant; for block group 110010042022 "Glens Garden Market" a store/restaurant; and for block group 110010037003 "Meridian Hill Park" a popular urban park. Sample Tweets using these terms in their respective tracts include:

> More breakfast beers, please. - Drinking a Burn the Candle (The Black Mass) by @oliverale at @**glensgardenmkt**
> Really enjoyed this Laotian feast at @**thipkhaodc** tonight with most of my favorite people. @ **Thip Khao**
> Beautiful day at the #park! @ **Meridian Hill Park**

The notable exception to this trend is block group 110010030002, whose conversations are dominated by the D.C. Urban League, indicated as "GWURBANLEAGUE." A sample Tweet includes:

> @**GWURBANLEAGUE** Ms Epperson Director of Special Services discussing employment issues...

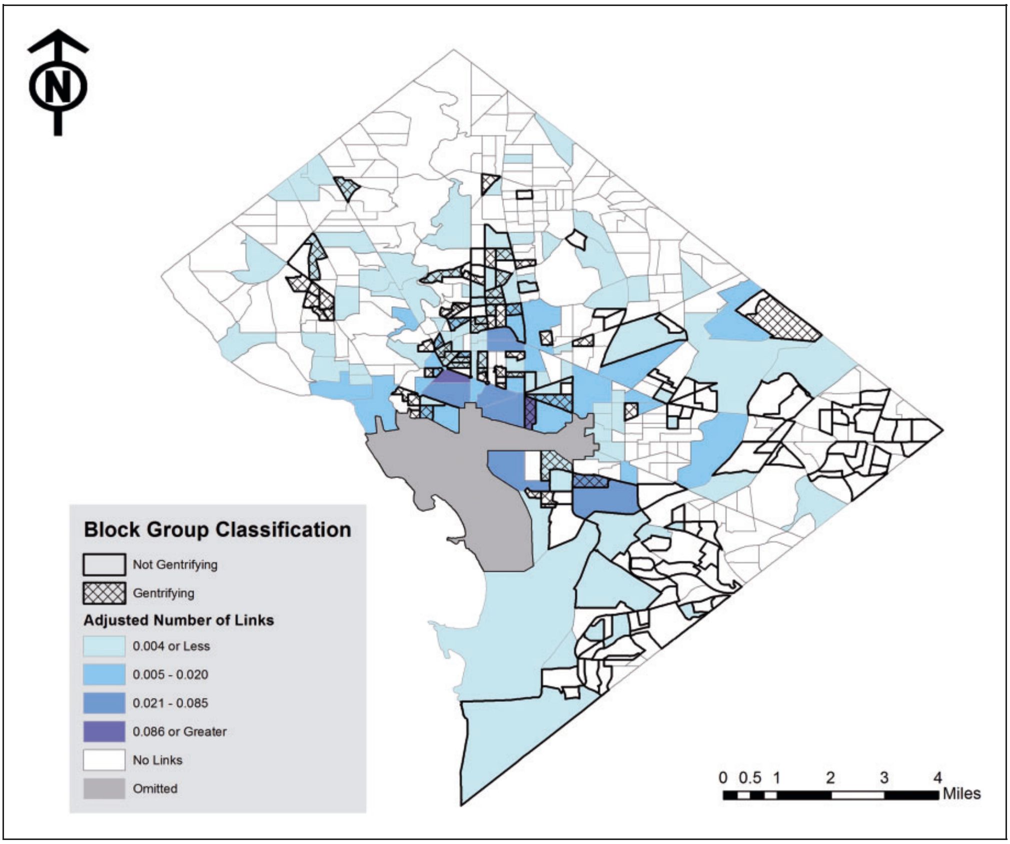

Figure 6. Tight location-based social networks and neighborhood gentrification.

These trends are further supported by Table 4, which lists out the dominating topic by gentrifying and nongentrifying block group based on the most commonly used term in the word clouds. As this table shows, more Tweets in gentrifying block groups are driven by a discernible topic than nongentrifying block groups; disproportionately upscale bars, restaurants or coffee shops.

Overall, the Tweets in nongentrifying areas are notably different in their general content compared to those in gentrifying areas. While Table 4 shows a disproportionate number of nongentrifying block groups are also driven by food and drink Tweets, it is proportionately fewer compared to gentrifying block groups. Also, Tweets in nongentrifying block groups are focused more on generally local issues, as defined by local institutions, nonprofits, or general neighborhood mentions. Figure 8 offers a set of randomly selected word clouds from neighborhoods which did not gentrify. The conversation in block group 110010098031, for example, was dominated by the local high school, **Ballou** High School. A sample Tweet from this area is "*Busy, BUSY weeks at **Ballou**! Parent-teacher conferences. College & career one-on-ones. PSAT test day*... ." Other Tweets seemed fairly random local conversations about routine activities without an overarching narrative. In Block group 110010099051, the word "baby" showed up the most, a sample Tweet being "*Cause if you down @ Cute **Baby**.*" Or in Block Group 110010076052, which lacked a strong discernible term, tended to have Tweets like "*How you my boo but you make my day worse from already having a bad day*."

Table 3. Negative binomial of Twitter network and community results.

	LN	Loose LSN	Tight LSN
Gentrification			
Demographic gentrification (reference not gentrifying)			
Gentrifying	1.756**	1.849**	1.363*
	(0.561)	(0.550)	(0.536)
Not gentrifiable	0.979*	0.954*	0.549
	(0.410)	(0.403)	(0.398)
Built environment gentrification			
Recent development	0.032	0.027	−0.003
	(0.054)	(0.052)	(0.049)
Intersection density	0.032***	0.019***	0.015***
	(0.003)	(0.003)	(0.002)
Demographics			
Multiethnic	0.263	0.907†	0.898†
	(0.508)	(0.522)	(0.483)
Age 18–29	0.026**	0.036***	0.035***
	(0.009)	(0.010)	(0.009)
Population density	115.131***	83.661***	68.304**
	(20.978)	(23.412)	(24.033)
Stability			
Percent moved in five years	−0.056***	−0.033*	−0.038**
	(0.015)	(0.014)	(0.013)
Percent homeowner	−0.013	−0.008	−0.006
	(0.008)	(0.008)	(0.008)
Constant	5.418***	1.278	0.646
	(1.149)	(1.053)	(0.991)
Observations	450	450	450
Log likelihood	−1821.79	−927.161	−574.215

LN: location-based network; LSN: location-based social network.
†$p < 0.100$; *$p < 0.050$; **$p < 0.010$; ***$p < 0.001$.

An exception to this trend was blockgroup 110010105001, where the Tweets were dominated by a community art and culture center **Blind Whino**. A typical Tweet looking more along the lines of "*#springtime #buds #blooms #art #music #recreation #swdc @ **Blind Whino**.*"

While almost none of the Tweets we collected directly mentioned "gentrification," comparing these Tweets demonstrates important subtle differences between gentrifying and nongentrifying communities. In keeping with past research, most of the discernible Tweets were involved in social sharing (Alhazmi and Gokhale, 2015), and it is through what is being shared that we can suggest the influence of gentrification. Indeed, the discourse in gentrifying areas appeared more tied to visits to often upscale restaurants or bars, places we may associate with gentrification. Meanwhile, the Tweets in nongentrifying areas were more centered on community issues. To be clear, there is much these word clouds do not tell us, such as whether the people Tweeting are locals or the exact composition of businesses can be found in these places. In addition, we cannot say how the Tweet subject directly associates with LN and LSN density. However, they offer a visceral impression of how community activity, as documented by Twitter, is different in gentrifying and nongentrifying areas. We suspect the Tweets in gentrifying areas reflect a community of

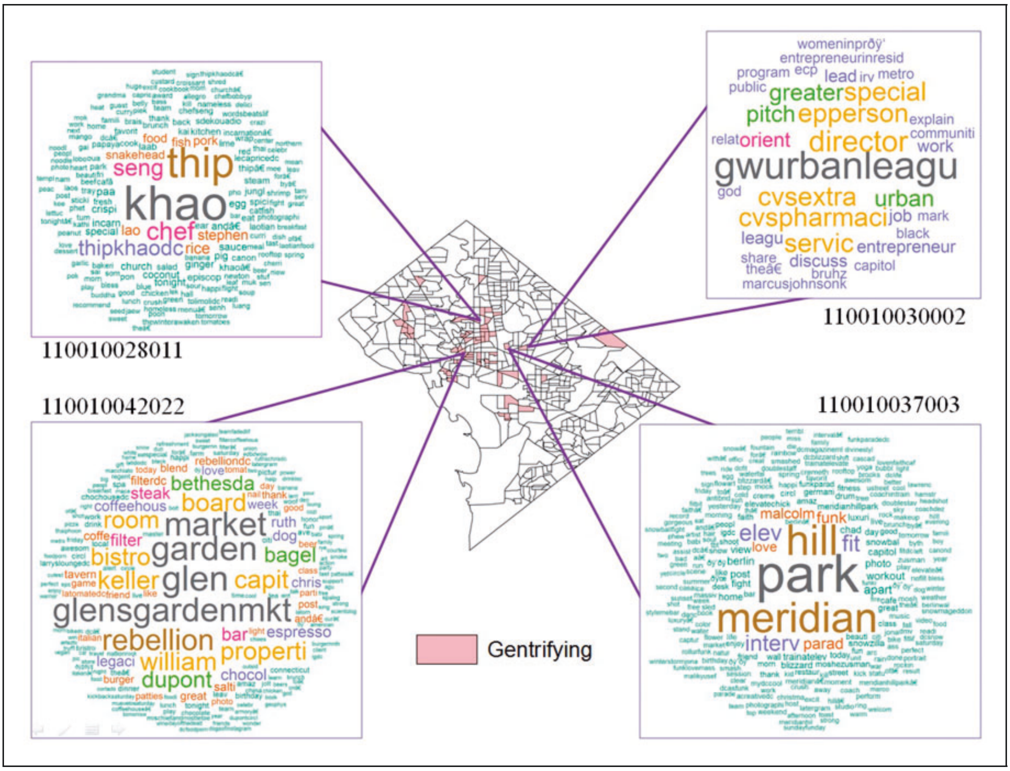

Figure 7. Twitter word clouds for gentrifying block groups.

new residents or visitors drawn to the establishments, as opposed to longstanding residents. The locally oriented Tweets found in areas not gentrifying meanwhile may be more indicative of longstanding residents.

Discussion

This article explored how the forces of gentrification and social media networks converge to affect communities in neighborhoods. To identify this association, we examine if gentrification is meaningfully related to differences in location-based interaction identified by location-based network (LNs) and "loose" or "tight" location-based social networks (LSNs). We did find an association between gentrification and all forms of location-based interactions measured. This is a notable finding given the existing research tends to point to the harmful effects that gentrification carries onto local communities (Betancur, 2011; Freeman, 2005, 2006; Newman and Wyly, 2006). This is not to say these findings are indicative of all forms of community in neighborhoods. While past research argues that location-based interaction corresponds strongly to in-person networks (Crandall et al., 2010; Eagle et al., 2009; Ling, 2008; Ye et al., 2012), we do not have the data on in-person networks to verify this effect. Nonetheless, these results show that gentrifying areas cannot be assumed to unilaterally deflect community. The key question becomes what community is being attracted?

While our brief examination of Tweets cannot offer in precise terms what is motivating the positive association of gentrification to location-based interactions; we can make some

Table 4. Most tweeted subject by gentrifiable block groups.

		Block group		
Category	Description	Gentrifying	Not gentrifying	Total
Attraction	Parks, public events, monuments	6	6	12
Boutique	Shops	1	2	3
College	General mention, sports teams	3	0	3
Community	Local institutions, nonprofits	2	5	7
Food and Drink	Bars, restaurants, coffee shops	17	7	24
Hotel	Hotels, motels, bed, and breakfasts	4	2	6
Neighborhood	General neighborhood mentions	5	6	11
Other	No distinguishable subject	21	68	89
Total gentrifiable block groups		59	96	155

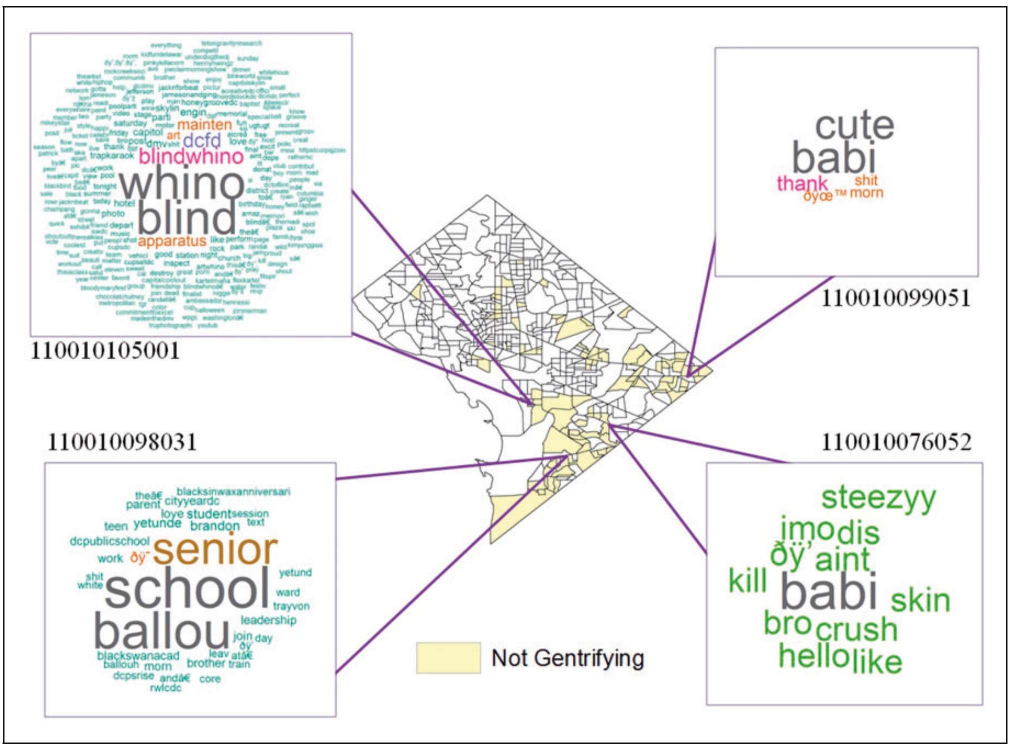

Figure 8. Twitter word clouds for not gentrifying block groups.

informed postulations as for the implications of these findings. The common subjects found in gentrifying neighborhoods reflect people enjoying the resources found in these places, such as a hot restaurant or bar. Gentrifying neighborhoods could thus be providing a space where social media networks centered on consumption physically manifests. Thus, local establishments appear to be maintaining their role in fostering community in gentrifying places (Sanchez-Jankowski, 2008).

Who has access to this new media-driven community? We speculate that the pre-existing communities of gentrifying neighborhoods are not strongly factoring into the LSNs we identified in gentrifying neighborhoods. We can infer from past research that longstanding residents of gentrifying neighborhoods would likely feel alienated by the kinds of establishments associated with this Twitter activity (Freeman, 2006; Sullivan and Shaw, 2011; Zukin et al., 2009). However, we cannot state with certainty the socioeconomic background of the people Tweeting. While Twitter users tend to be of middle and upper income (Duggan, 2015), it would be ecological fallacy to assume affluence for all of those connected into location based interaction networks in gentrifying neighborhoods. What is more, we cannot say from our results whether those Tweeting are "gentrifiers," longstanding residents, or outsiders altogether. Nonetheless, these results point to key difference in community and social media based on neighborhood socioeconomic status which should be explored further in future research.

This article lays the groundwork for new efforts on Twitter social networks using the neighborhood as a lens to understand how social media networks unfold on the ground. Our approach will enable academics and planners to identify at a granular level how gentrification is interacting with the local community and then be able to implement policies in response to certain conditions, such as anti-displacement strategies, rental assistance, and even programs to support and maintain locally serving nonprofits. While there is much work to be done to develop the use of big data in urban analysis, these efforts would eventually allow planners to better adapt to the changes presented by in this increasingly connected age. In this way, big data can enable more targeted corrective efforts to minimize gentrification's potential disruption to preexisting communities. The potential of our approach is not limited to gentrification; it could be employed to other aspects of city life which are well documented through Twitter, such as mass social movements.

To facilitate these efforts, we close with several suggestions for future research. For one, the geographic origin of Twitter users should be identified to see how one's neighborhood impacts their Twitter behavior. There are a number of relevant demographic measures that should be used in future studies, such as employment. In addition, more measures beyond gentrification should be considered, such as racial/ethnic segregation and socioeconomic disadvantages like poverty. Next, more should be done to analyze the content of local Twitter activity. One approach would be more systematized methods like topic modeling to identify underlying themes in Tweets. Also, how social media networks relate to other physical aspects of the built environment must be more thoroughly evaluated. For example, more information on the existing businesses in a neighborhood would provide more subtext as for why people may be Tweeting more about food and drink in gentrifying areas. Finally, our research only presented a cross-sectional snapshot of gentrification and Twitter activity. Future research should further analyze Twitter activity over time to allow space-time analysis which could point to even more granular trends.

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