From phone booths to Wi-Fi kiosks: the spatial inequality of public connectivity in New York City

ABSTRACT

This paper offers the very first examination of the spatial patterns of public Wi-Fi hotspots deployment in New York City. Furthermore, it utilizes the Spatially Aware Technology Utilization Model to investigate what determinants (i.e., demographic and socio-economic factors, digital infrastructure, and political orientation) might impact the spatial distribution of public Wi-Fi hotspot deployment with a Bayesian spatial modeling approach. Through the hot spot analysis, we find that the deployment of public Wi-Fi hotspots is not spatially equal across the five boroughs of New York City. Instead, it is highly clustered in Manhattan as the *hot spot*, while there are a few *cold spots* identified in the other four boroughs. We also find that the deployment of public Wi-Fi hotspots does favor the areas with denser commercial business and with a higher ratio of population who identified as Democrats. We can detect its efforts to mitigate the digital inequalities, such as those neighborhoods with more residentials who do not have high-speed Internet connections. But it does not improve broadband access disparities between digitally marginalized areas and the rest of the city, especially for the census tracts of more population without Internet or broadband subscription. Meanwhile, it also reinforces part of the existing digital divide, such as communities with more population with lower educational attainment. More importantly, the study also offers a spatial perspective, as the relationships identified would not be accurately estimated without incorporating the spatial effects in the modeling processing.

Keywords: Digital inequality, Wi-Fi hotspots deployment, New York City, Hotspot analysis, Bayesian spatial modeling

Introduction

Scholars have pointed out that public Internet access should be treated as essential community infrastructure, rather than potential economic enterprises (Simpsons, 2004). Lately, public Internet infrastructure has never been more indispensable than during the pandemic, as an essential service for working and learning remotely, connecting with friends and families, carrying out daily tasks and accessing telemedicine (McClain et al., 2021). As smart city plans roll out, city-wide infrastructure projects aiming at providing free and secure public Internet access have been launched across the United States in the form of Wireless fidelity (Wi-Fi), which is a wireless technology allowing devices to connect to Internet through access points (Oh et al., 2022). Wi-Fi technology has several advantages over wired telecommunications, as it is easy to install, and less expensive. Meanwhile, Wi-Fi is able to prevent the degradation in service quality during high volumes of mobile traffics (Poularakis et al., 2019). In the U.S., despite concerns over security risks, a customer survey finds that almost half of respondents use public Wi-Fi regularly to save their cellular data usage (Leininger, 2022).

However, public Wi-Fi hotspots deployment could be operated differently on various levels, from large parts or all of a municipal area (i.e., New York City, Washington D.C.), to limited public facilities including public libraries and community centers (i.e., Seattle, Chicago). New York City (NYC), as one of the largest urban conglomerations in the world with a population of over 22 million, however, suffers from digital access inequities. Twenty nine percent of New Yorkers have no home broadband subscription and 46 percent of households in poverty lack both home and mobile broadband (Mayor's Office of the Chief Technology Officer, 2021). Since 2015, then-mayor de Blasio has announced the launch of the project of LinkNYC, which could be the world's largest free public Wi-Fi municipal network, while transforming the old phone booths into the Wi-Fi kiosks across five boroughs

(Pujol, 2022). Furthermore, the *Internet Master Plan*, released by the de Blasio administration in New York City in 2020, aims at bridging the digital divide and delivering equitable internet access in the metropolitan area by investing $157 million. Within the 195 neighborhoods of New York City, 42% have at least one "hotspot" (free Wi-Fi access point) in a commercial area under the LinkNYC project. In total, the free public Wi-Fi has been deployed at 3,319 locations by around 17 providers on streets, open space, transit and public facilities across the five boroughs (Mayor's Office of the Chief Technology Officer, 2021, see Figure 1).

[FIGURE 1 AROUND HERE]

Fuentes-Bautista and Inagaki (2012) argue that the social shaping of the rapid growth in Wi-Fi adoption, is contributed by the partnerships among industry, community organization, academic and research institutions, and local government. However, does the deployment of public Wi-Fi address the digital inequality issue in New York City? Or does it reflect the digital inequality on the contrary? And what factors are driving the (spatial) distribution of these Wi-Fi locations? There are few existing studies have empirically examined the determinants of public Wi-Fi deployment density and distribution in the U.S. context with the geographical data on the specific locations of Wi-Fi access point, while incorporating a spatial dimension. This study presents a very first spatial analysis of the public Wi-Fi deployment in the urban America using one of the most prominent public Internet projects of NYC. The current study is implemented in two steps: (1) It examines the hot (and cold) spots in public Wi-Fi distribution with the Getis-Ord Gi* statistics across the census tracts of New York City. (2) By adopting the Spatially Aware Technology Utilization Model (SATUM, Pick & Sarkar, 2016), it analyzes what demographic, socio-economic, digital infrastructure, and political factors would be associated with the count of public Wi-Fi hotspots deployment. Analytically, a Bayesian spatial modeling with negative binominal regression is utilized while accounting for the spatial random effects. In particular, this study aims at utilizing empirical evidence to investigate the effectiveness of de Blasio administration's Internet Master Plan on serving the broadband unserved/underserved areas and digitally marginalized communities in NYC, with a spatial perspective.

Related literature

Wi-Fi access within a spatial scale

One of the earliest empirical studies investigating the Wi-Fi access point was conducted in Cincinnati, Ohio by Grubesic & Murray (2004), which decomposes the uneven spatial distribution of Wi-Fi density across the neighborhoods. The other case was situated in Baton Rouge, Louisiana (Driskell & Wang, 2009). However, Driskell and Wang (2009) did not focus on the Wi-Fi access point on the public domain like municipal Wi-Fi network that this paper focuses on. Instead, they conceptualize the presence of a Wi-Fi network in a broader sense: the geographical unit with any residentials of a Wi-Fi device, a broadband Internet subscription, and a networking infrastructure. Out of the U.S. context, one empirical study in Shanghai, China by Wang et al. (2016), which mapping out the government-sponsored Wi-Fi hotspots, has identified the spatial inequality as they could not cover the traditional neighborhoods in the central city and sub-districts in remote rural areas in Shanghai, China. Kim (2018) uses the public Wi-Fi locations as a proxy measure of the urban vitality in Seoul, South Korea.

It has been long studies that the municipal Wi-Fi access should have the potentials to support the local communities on economic growth, social interaction, as well as narrowing down the digital divide while enlarging the public sphere with more civic participation (Hampton & Gupta, 2009; Hampton et al., 2010; Lemstra et al., 2010; Torrens, 2008; Yang et al., 2021). However, as Fuentes-Bautista and Inagaki (2012) point out in the case of Austin, Texas Wi-Fi initiatives are mostly serving the best-connected and technologically savvy users of the Internet in the city. Meanwhile, the public access of high-speed wireless services is normally absent amongst the ethnic minority and low-income neighborhoods, which not only reflect the underlying socioeconomic inequalities but also created a new form of inequality in connectivity (Fuentes-Bautista & Inagaki, 2006, 2012). In particular, the Wi-Fi access in urban communities taps on the classic first level of digital inequality or digital divide litearture, as the disparities in digital access on Internet and computers measured as a dichotomous distinction between *haves* or *have-nots* (DiMaggio et al., 2004). Given the limited literature in this specific topic (which has also demonstrated the contribution of the current study), in the next section, we are drawing a broader picture from the literature in the access or availability of digital infrastructure and information and communication technologies (ICTs) within a spatial scale.

The spatiality of ICT access

Adopting from the media ecologist schools, Adams and Jansson (2012) have called for the construction of the research paradigm in the interdisciplinary communication geography, addressing the spatial turn of communication studies (Falkheimer & Jansson, 2006). Some scholars argue that one of the advantages brought by the development of ICTs s is that it breaks the constraints of space as mobile-seamless while increasing the spatial flexibility of daily activities (Martínez-Cerdá, 2020; Schwane & Kwan, 2008). However, there are also scholars concerning the physical space or the place-based attributes that might affect people's ICTs practices as well (Fast et al., 2019; Liu, 2019). The argument of *end of geography* in technology (Graham, 1998) could be rebutted since Internet and the latecomer social media is still dependent on the physical space, as the phsyciallity of the virtuality (Dourish & Bell, 2007; Tranos, 2013). ICTs should be "situated, localized and specialized" in space (Rodriguez-Amat & Brantner, 2016, p.15), as Adams and Janssons (2012) further explicated the so-called "media/communication" in spaces (or ICTs in spaces) as emphasizing the fixed communication infrastructure, which should be better interpreted as the information channels, or the flow patterns.

Especially when comes to the wireless Internet technology like Wi-Fi, the spatiality of information channels or flows is constructed by the information infrastructure. As Dourish (2006) argues, ICTs are involved in the operation and emergence of the social and cultural production of space when the human agents encounter space as a collective form. In other words, the uses of ICTs and ICTs themselves, are fully posited within and affected by our daily activities (Dourish, 2006, p.304). Furthermore, the geography of ICT (i.e., the spatial location of Wi-Fi), provide a tangible representation of information infrastructure in the urban space (Kim, 2018). Therefore, epistemologically, spatial thinking should be allowed in the setting of ICTs practices. To integrate space in ICTs assumes that space would be of help to better understand and predict human behavior.

As the first law of geography claimed by Tobler, “everything is related to everything else, but near things are more related than distant things (1970, p.236)”. Here spatial autocorrelation comes in, as a concept that reflects the relationship between nearby spatial units (Getis, 2010). A positive spatial autocorrelation indicates that if the spatial units are nearer, the more similar their values are; and a negative spatial autocorrelation refers to the situation that when the spatial units are nearer, the less similar their values are. Meanwhile, if there is no spatial autocorrelation, the values of the nearby spatial units are randomly associated (Lee, 2017). A similar construct would be spatial dependence, which means the degree of spatial autocorrelation, and some scholars might use them interchangeably, or spatial association (Getis, 2010).

Scholars in various disciplines such as regional studies and economics, have identified ICTs utilization (e.g., access and use) are spatial dependent based on various geographical units (i.e., state, county, prefecture, region) in the U.S. (Azari & Pick, 2005;

Pick et al., 2015), European (Maurseth & Frank, 2009; Billon et al., 2017), China (Chen & Ye, 2021; Song et al., 2020), and Japan (Nishida et al, 2014). In particular, one of the early attempts that touches on the spatiality of Internet access in the context of U.S. is the spatial taxonomy of broadband region proposed by Grubesic (2006). Through the Local Indicators of Spatial Autocorrelation (LISA), Grubesic identifies four types of spatial clusters of broadband availability: *broadband core*, *broadband periphery*, *islands of inequity*, and *islands of availability* on ZIP code level. Lucendo-Monedero et al. (2019) have also been able to detect the spatial pattern of ICT development of households and individuals in Europe at a regional level, which is operationalized as digital development index, which draws data from different sources, such as access to the Internet at home, use of the Internet by individuals, e-government, and e-commerce. In this study, we pose our first research question here:

RQ1: What is the spatial pattern of the public Wi-Fi hotspots deployment in New York City?

The determinants of ICT access

In the long history of digital divide/digital inequality, demographic and socio-economic factors have been empirically tested out frequently across different countries and culture, to be related to ICT access (Pick & Azari, 2008). However, what have been missing in the digital divide/digital inequality literature is the presence of spatial effects, as the geographical unit with high or low values of ICT access or utilization could be influenced by their neighboring units with similar value of ICT practices. Given the spatial emphasis of this study, we will be using Spatially Aware Technology Utilization Model (SATUM) as the theoretical framework to incorporate the spatial dimension into the analysis of ICT practices, which originates in the Technology Acceptance Model (TAM). While being frequently neglected in previous studies, Pick et al. (2015) propose SATUM to incorporate the spatial dimension into ICT utilization as an enhancement of UTAUT (Unified theory of acceptance and use of technology). Previous studies have taken ICT practices as the outcome variables, while ignoring that demographic factors might influence the utilization and availability of ICT within the geographical unit and adjacent units as well, such as average age of the population, employees in professional, scientific and technical sectors, income, GDP per capita, education, gender, race and ethnicity (Azari & Pick, 2005; Billon et al., 2017; Song et al., 2020). While acknowledging the role of the determinants in ICT practices as mentioned previously, SATUM further proceeds with spatial autocorrelation analysis (for each variable), confirmatory analysis with OLS, diagnostic testing for the OLS regression residuals, and spatial regression models. As an inductive reasoning-based model of ICT practices, SATUM is capable of explaining digital inequality within a geographical scale since its explanatory variables such as socioeconomic factors are also implicitly spatial. This has been empirically tested at the U.S. domestic level as well at the international level, in Latin America and Europe (Pick et al., 2021; Pick & Nishida, 2015; Sarkar et al., 2019). In the past literature, two types of basic spatial econometric models are used in the next section accounting for spatial dependence deriving from OLS regression with Anselin's approach (Anselin, 2013). One of them is termed the spatial lag model, which adds a spatially lagged (or "neighboring") dependent variable as part of the explanatory factors, correcting for the biased and inconsistent estimation (application in ICT access see Billon et al., 2017; Chen & Ye, 2021). The other one is called the spatial error model, which adds a spatial lagged error term, assuming the unobserved errors in the model are spatially correlated as correcting for the inefficient estimation (application in ICT access can be referred to Maurseth & Frank, 2009; Noh & Yoo, 2008). Nonetheless, we will discuss more about why we are choosing Bayesian spatial modeling in the study over the traditional spatial econometric model in the method section.

Since there is no existing study has examined the spatial distribution of public Wi-Fi hotspot in the urban American context, this study offers the very first investigation under the framework of SATUM. Furthermore, focusing on the community needs for digital infrastructure, we mainly utilize the demographic and socio-economic factors which could reflect the demanding side of public Wi-Fi hotspot in our analysis. Race and ethnicity have been found for long to be significant factors in relation to digital inequality. Previous studies found that the percentage of the Asian population is positively related to Internet access and usage, while percent African American population and Hispanic population are negatively associated with Internet access and usage (Campos-Castillo, 2015; Zahnd et al., 2022). In particular, racially and ethnically segregated neighborhoods correspond with the cost barrier of access toward Internet (Mossberger et al., 2012). However, unlike Internet subscription at home, the Wi-Fi deployment is situated in the public domain, rather than owned by private household. Therefore, the relationship between the race/ethnicity and the deployment of Wi-Fi hotspot is not clear yet. We here ask:

RQ2: What is the relationship between (a) the Asian American population; (b) the African American population; (c) Hispanic population and the Wi-Fi hotspot deployment on census tract level in NYC?

Although the role of education attainment toward Internet access has been long studied, as the early adopters of Wi-Fi technology are usually tech-savvy users with higher education level (Elena-Bucea et al., 2021; Fuentes-Bautista & Inagaki, 2012). However, in the context of Wi-Fi hotspots deployment, the users do not initially choose to adopt or consume. Meanwhile, economic determinants such as income and investment have also been long and widely found to have a positive relationship with Internet access and usage (Dasgupta et al., 2005; Elena-Bucea et al., 2021). Martin and Robinson (2007) find that the odds of access increased most rapidly for individuals with the highest income level and most slowly for individuals with the lowest income level. Similarly, given the public or semi-public nature of Wi-Fi deployment, we would like to ask:

RQ3: What is the relationship between education attainment and the Wi-Fi hotspot deployment on census tract level in NYC?

RQ4: What is the relationship between (a) median household income; and (b) GINI index (income inequality) and the Wi-Fi hotspot deployment on census tract level in NYC?

Meanwhile, previous literature has argued that the proliferation of public Wi-Fi is mostly confined to commercial areas in the urban context since it is strongly associated with the sites of consumption (Fuentes-Bautista and Inagaki 2012; Torrens, 2008). Therefore, we hypothesize that:

H1: The census tract in NYC with more commercial business with have denser Wi-Fi deployment.

Besides, we would also like to evaluate whether the public Wi-Fi hotspot deployment under the Internet Master plan by de Blasio administration is able to better provide equitable internet access for the underserved or unserved neighborhood. Thus, we have also incorporated the digital infrastructure factors in our model. Meanwhile, public Internet usually draws upon a more dirigisme approach, such as the universal service obligations (Leith, 2012). We would like to know does the spatial distribution of public Wi-Fi hotspot favor specific regions affiliated with particular political spectrum? Hence, our last two research questions are put as below:

RQ5: What is the relationship between digital infrastructure and the Wi-Fi hotspot deployment on census tract level in NYC?

RQ6: What is the relationship between political orientation and the Wi-Fi hotspot deployment on census tract level in NYC?

Last but not least, given the focus on spatial perspective in this study, we would also like to ask:

RQ7: Are any relationships above sensitive to spatial structure on census tract level in NYC?

Method

Data collection

In this paper, we are drawing data from multiple sources. For the main dependent variable, the public Wi-Fi location data is retrieved from New York City's Internet Master Plan through NYC Open Data (n = 3319).[1] Integrating the TIGER/Line (Topologically Integrated Geographic Encoding and Referencing) shapefile from Census, we have aggregated all the Wi-Fi hotspots locations with spatial join into the map of New York City, whose unit of analysis is Census tract (see Figure 2, N = 2324).

[FIGURE 2 AROUND HERE]

In our analysis, the geographical region of New York City is defined by five counties or boroughs: Bronx county (Bronx), Kings county (Brooklyn), New York county (Manhattan), Queens county (Queens), Richmond county (Staten Island). Besides, for RQ2, we have further drawn data from multiple sources based on previous literature as follow:

Demographic and socio-economic factors: Population, African American population, Asian American population, Hispanic population, median age, population with less than high school education, GINI index, median income. All the demographic factors are obtained through American Community Survey (ACS) 2016 – 2020 5-Year Estimate.

[1] The data of Wi-Fi deployment distribution under the Internet Master Plan can be accessed from: https://data.cityofnewyork.us/City-Government/NYC-Wi-Fi-Hotspot-Locations/yjub-udmw/data

Commercial density: the density of point of interest categorized in the commercial domain. The density is measured by the aggregated number of the commercial business in the particular census tract collected through NYC's open data portal.[2]

Digital infrastructure: household without any devices (i.e., computer/smartphone/tablet) at home; household without any broadband subscription; household without any Internet connection at home, which are gathered through latest American Community Survey (ACS) 2016 – 2020 5-Year Estimate. Additionally, we also include the Internet availability in the model, which is operationalized as the residential with fixed high-speed connections over 200 kbps in at least one direction per 1000 households collected from Federal Communication Commissions Form 477 data.[3]

Political orientation: we are also interested whether the political orientation of the geographical region would affect the spatial distribution of public Wi-Fi hotspots location. Therefore, we have collected the population affiliated with Democrats and Republicans in that census tract through ESRI's ArcGIS Business Analyst. The descriptive statistics of each variable for NYC and each borough are presented in Table 1.

[TABLE 1 AROUND HERE]

Analytical strategy

In order to answer RQ1 to investigate the spatial pattern of Wi-Fi hotspots location, we have utilized Geti-Ord Gi^* statistics to perform hots pot (and cold spot) analysis (Getis & Ord, 2010). Specifically, the z-score of Geti-Ord Gi^* could indicate where the variable is highly clustered spatially as hot spot (with a positive value) or not. It can be expressed as:

[2] The data of commercial point of interest of NYC can be accessed from: https://data.cityofnewyork.us/City-Government/Points-Of-Interest/rxuy-2muj

[3] Additionally, we have tested out another measure of Internet availability (with a higher threshold) in the final model as well, as the residential with fixed high-speed connections at least 10 Mbps downstream and at least 1 Mbps upstream per 1000 Households. But both measures yield similar results, so we decided to only include the less conservative measure of broadband speed in the final results.

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{ij} x_j}{\sum_{j=1}^{n} x_j} \tag{1}$$

Where: x_i and x_j = the count of Wi-Fi hotspots at the census tract i .

w_{ij} = diagonal matrix of weight factors (spatial weight matrix).

To investigate the relationship between demographic and socio-economic factors, commercial density, digital infrastructure and political orientation, and the spatial pattern of public Wi-Fi hotspots locations, we choose to use a Bayesian spatial modeling framework given the nature of dependent variable as a count data. Additionally, through a likelihood ratio test for overdispersion, we find a negative binomial distribution fits better for our dependent variable compared to a Poisson distribution (Lawless, 1987), which can be expressed as the following equation:[4]

$$\overline{y_i} = \exp\left(\beta_0 + \sum_{j=1}^{n} \beta_j x_{ij}\right) \tag{2}$$

Where: $\overline{y_i}$ = the mean of the Wi-Fi hotspot count at the census tract i.

β_j = the parameters examining the relationship between factor x_j and $\overline{y_i}$ at the census tract i.

In particular, we use integrated nested Laplace approximation (INLA) approach in the R-INLA package to attain the Bayesian estimates in spatial modeling which has been widely utilized in the domains of public health and epidemiology (Rue et al., 2009; Yang et al., 2021). Instead of a frequentist spatial econometrics approach or a conventional spatial regression method, a Bayesian spatial generalized linear modeling is more suitable for count data which does not follow a normal distribution. Meanwhile, compared to the common approach to perform Bayesian inference like Markov Chain Monte Carlo (MCMC), INLA is computationally much less expensive while obtaining robust and comparative performance in

[4] The Chi-square test statistics is 2256.8 ($p < 0.001$, with all the covariates included), and 5707.91 ($p < 0.001$ without any covariates) respectively.

spatial and spatio-temporal (Blangiardo et al., 2013). Moreover, since the current study cares less about the spillover effect, such as the influences of the variable of interests from the neighboring geographical units, the spatial autoregressive (lag) model or spatial Durbin model would not be helpful in the analytical strategy (LeSage & Pace, 2009). In this paper, we are focusing more on controlling the potential bias led by the spatial structure. Therefore, we are incorporating two more error terms based on equation (2):

$$\overline{y_i} = \exp\left(\beta_0 + \sum_{j=1}^{n} \beta_j x_{ij} + \delta_i + \varepsilon_i\right), \tag{2}$$

$$where\ \delta_i \sim \mathbb{N}(0, \tau_\mu)\ and$$

$$\varepsilon_i | \varepsilon_{-i} \sim \mathbb{N}\left(\frac{\sum_{j\sim i} \varepsilon_i}{n_i}, \frac{1}{n_i \tau_\varepsilon}\right)$$

Where: δ_i = a random error for the corresponding census tract i, which is independent and identically distributed (IID) that follows a normal distribution with a mean of 0 and a variance parameter; and τ_μ = a precision parameter for the IID component.

ε_i = a spatially structured error that follows a normal distribution conditional on the neighboring census tract ε_{-i}; and τ_ε = a precision parameter for the spatial component, while $j{\sim}i$ denotes the census tract j is a neighboring census tract of the census tract i; and n_i is the total number of the neighboring geographical unit of the census tract i.

INLA uses vague priors and it puts a log-gamma on the precisions (τ_μ and τ_ε) by default. In the analytical section, beyond the baseline negative binomial model, we have three types of model specifications: (1) only incorporating the IID component, as the IID model; (2) only incorporating the spatial component, as the intrinsic conditional autoregressive (ICAR) model; and (3) incorporating both the IID component and the spatial component, as the Besag-York-Mollié (BYM) model (Besag et al., 1991). Specifically, we use Deviance

Information Criterion (DIC), Watanabe–Akaike Information Criterion (WAIC), Conditional predictive Ordinate (CPO; specifically, the negative of the mean natural logarithm of the CPO values), to compare the models and decide the best model, as normally a model with a lower DIC, WAIC or CPO will be preferred. Meanwhile, unlike the frequentist approach, no *p*-value will be used in the results. However, the mean estimates (before exponentiation) and the 95% credible regions (CR) will be presented for each variable. If zero is not involved within the 95% CR, the corresponding variable will be considered as being associated with our dependent variable, the Wi-Fi deployment count.

Results

Hot spot analysis

In particular, we are using Queen's (instead of Rook's) continuity to construct our spatial weight matrix, which assumes regions with contiguous boundaries with sideways or corners are neighbors (see demonstration in Figure 3). The Moran's *I* of the counts of public Wi-Fi hotspots is 0.463 and statistically significant under the Monte-Carlo simulation with a randomization of 999 permutations ($p < .001$), which indicates a positive spatial autocorrelation across New York City. In other words, the spatial distribution of public Wi-Fi hotspots is not equal in our study area. Furthermore, as Figure 3 shows, the z-scores of Geti-Ord Gi^* statistics has identified the spatial cluster of high values of Wi-Fi hotspots count is mainly located in Manhattan and a smaller cluster in Brooklyn Height and the pier. Meanwhile, the "cold spot", or the regions with low count of Wi-Fi hotspots are pretty scattered in the rest of four boroughs other than Manhattan (the blue area in Figure 4).

[FIGURE 3 AND 4 AROUND HERE]

Bayesian spatial modeling

As the baseline model, we first fit a negative binominal regression with all variables described above. To better deal with the multicollinearity issue, we have removed some variables based on the high correlation with other variables and theoretical explanative power, including the variables of population, and household without any devices (i.e., computer/smartphone/tablet) at home. Also, before performing any analysis, we have also standardized the variables since they are measured on different scales.

The Moran's I index has indicated the spatial heterogeneity of the count of public Wi-Fi hotspots presents, which also indicates we should formally incorporate the spatial structure in our modeling process otherwise it might introduce bias for the inference. As the Bayesian negative binomial regression results show in Table 2, based on the lowest DIC, WAIC and CPO, we can conclude the BYM model with both IID and spatial component is the best model after correcting the random error and spatial structured error. Among the demographic factors, we can find the Hispanic population in the census tract is constantly and positively associated with Wi-Fi hotspots deployment across four models. In the final BYM model, one unit of increase in the Hispanic population in the census tract is related to 51.1% increase in the count of Wi-Fi hotspots deployment [odd ratio = 1.511, 95% CR = (1.247, 1.831) after exponentiation], and the odd ratio does not change dramatically compared to model (48.1%). Meanwhile, the population with less than high school education in the census tract is constantly and negatively associated with the Wi-Fi hotspots deployment across four models. In our model 4, one unit of increase in the population with less than high school education in the census tract results in 26.2% decrease in the count of Wi-Fi hotspots deployment [odd ratio = 0.738, 95% CR = (0.582, 0.934) after exponentiation]. Before incorporating the spatial random error (model 1), the odd ratio is even lower as 0.682. Meanwhile, after incorporating the spatial structured errors, either GINI index or the median income is related to the Wi-Fi hotspots deployment anymore (model 3 and 4). Nonetheless, the commercial density in the census tract is constantly and positively associated with the number of Wi-Fi hotspots deployment across four models. One unit of increase in the commercial density is associated with 13.3% increase of the Wi-Fi hotspots deployment [odd ratio = 1.133, 95% CR = (1.059, 1.213) after exponentiation] although the odd ratio drops from 1.313 compared to model 1. Amongst the digital infrastructure factors, only the number of residential with high-speed Internet connections is constantly and negatively associated with the number of Wi-Fi hotspots deployment. One unit of increase in the number of residential with high-speed Internet connections is related to 23.7% decrease of the Wi-Fi hotspot deployment [odd ratio = 0.763, 95% CR = (0.698, 0.834) after exponentiation]. And for the political factors, the results show that the population affiliated with Democrats is consistently and positively associated with the number of Wi-Fi hotspots deployment but not for Republicans. One increase in the population affiliated with Democrats is related to 44.8% increase of Wi-Fi hotspots deployment [odd ratio = 1.448, 95% CR = (1.242, 1.687) after exponentiation]. Without incorporating the spatial structure in model 1, the spatial random effect is in charge of 30.8% change in the association between population affiliated with Democrats and the count of Wi-Fi hotspots deployment [odd ratio = 1.756, 95% CR = (1.483, 2.081) after exponentiation].

[TABLE 2 AROUND HERE]

To further visually examine the non-spatially structure (i.e. the IID) and the spatially structured effect, we have mapped out the IID and spatial random error in Figure 5 and 6. If we only consider the IID component as shown in Model 2 and Figure 5, our independent variables are able to explain why some census tracts in the boroughs have a higher count of Wi-Fi hotspots deployment since the IID effects have are smaller for those areas with high numbers than those with lower numbers. However, when we incorporate both IID and spatial random error (i.e., the ICAR), Figure 6 tells us about the spatial structure among the census tracts is essential to explain the spatial distribution of Wi-Fi hotspots deployment in NYC and we can find high spatially correlated variance in our data. The census tracts in the blue areas of Figure 6 are more likely to be influenced by their neighbors, such as the whole Manhattan, and the neighborhoods next to Manhattan in Bronx (Mott Haven, Port Morris, Melrose; Belmont, Bathgate, West Farms, East Tremont; University Heights, Morris Heights, Mount Hope, Fordham). Also, the spatial dimension plays a more important role in certain areas of Queens (Hunter's point, Long Island city, Astoria, Woodhaven, Richmond Hill, Richmond Hill, Jamaica Center, Jamaica), as well as the pier closer to water in Brooklyn (Red Hook, Brooklyn Height, Williamsburg, Greenpoint). In short, the distribution of Wi-Fi hotspot deployment is more spatially connected throughout the whole Manhattan Island compared to other boroughs.

[FIGURE 5 AND 6 AROUND HERE]

Discussion and conclusion

This study provides the very first examination on the spatial patterns of public Wi-Fi hotspots deployment in the urban America context and also offer empirical results to evaluate the effectiveness of Internet Master Plan in New York City while incorporating the spatial structure. Our analysis has identified the spatial inequality of the deployment of the public Wi-Fi hotspots in New York City under the then-mayor de Blasio's administration through the hotspot analysis. Utilizing the SATUM framework, we are able to identify the association between some demographic, socio-economic, digital infrastructure, and political factors, and the number of public Wi-Fi hotspots deployment in the New York City. Admittedly, the Internet Master Plan helps some communities with deprivation, such as Hispanic neighborhoods, which is not sensitive to spatial structure. However, the African American population in the census tract is not related to the public Wi-Fi deployment at all, which has created another layer of access barrier in the racially and ethnically segregated neighborhoods (Mossberger et al., 2012). Meanwhile, the finding is also contradictory to the positive relationship between Asian American population and Internet access in the previous literature. We can also detect its efforts to mitigate the digital inequalities. For instance, the number of Wi-Fi hotspots deployment is higher in those neighborhoods with more residentials who do not have high-speed Internet connections. But it does not improve broadband access disparities between digitally marginalized areas and the rest of the city, especially for the census tracts of more population without Internet or broadband subscription. Meanwhile, it also reinforces part of the existing digital divide, such as communities with more population with lower educational attainment.

As expected, the commercial density as measured by the number of places of interests under the commercial category, is associated with the count of public Wi-Fi hotspots deployment, echoing with previous findings (Fuentes-Bautista & Inagaki, 2012; Torrens, 2008). Nonetheless, the BYM model shows that it is also related to the spatial structure as the estimate drops 18% when spatial random effects are considered. In other words, the census tracts with a higher commercial density would have a higher number of public Wi-Fi hotspots and it would affect the count of public Wi-Fi deployment in the neighboring census tract as well. Meanwhile, the positive relationship between median income as well as the income inequality and Wi-Fi deployment, as reflected in the model 1 and model 2, no longer exists after incorporating the spatial structure. In other words, the Wi-Fi hotspot deployment does not quite help with those communities who might not have the capability to access Internet by themselves. Also, the Wi-Fi deployment under the Internet Master Plan also favors communities with more people who self-identify themselves as Democrats. But as the results of model 4 show, the relationship is also subject to the spatial relationship among the census tracts in NYC as the estimate changes from 75.6% to 44.8%. Without considering the spatial dimension, the relationships as above would not be accurately estimated. These findings confirm the role of space in shaping the inequality of ICT access in the form of public Wi-Fi deployment while supporting the utility of spatially informed modeling strategies in future research studying ICT access as well.

However, like many other studies, there are a few limitations that needs to be addressed in the future studies. First of all, we only use the raw count of public Wi-Fi hotspots, as we did not differentiate the type of Wi-Fi hotspots, and we did not incorporate the speed, coverage, or quality of each location either. The count of Wi-Fi hotspots certainly should not be treated as the quality of Internet access, as the second level of digital inequality. Secondly, there are quite a few missing values in the variable of political orientation collected through ESRI's ArcGIS Business Analyst, as our unit of analysis reducing from 2324 to 1972 census tracts, which might impact the performance and even the results of the modeling. A higher-level analysis of geography (i.e., zip codes) should be tested as sensitivity analysis to avoid modifiable areal unit problem. Thirdly, there could be an interaction effects between the explanatory variables that could also significantly influence the deployment of public Wi-Fi hotspots, which is not studied in the current paper. And we believe an interactional approach to understand the spatial variation in ICT access would be an interesting area worth further examination.

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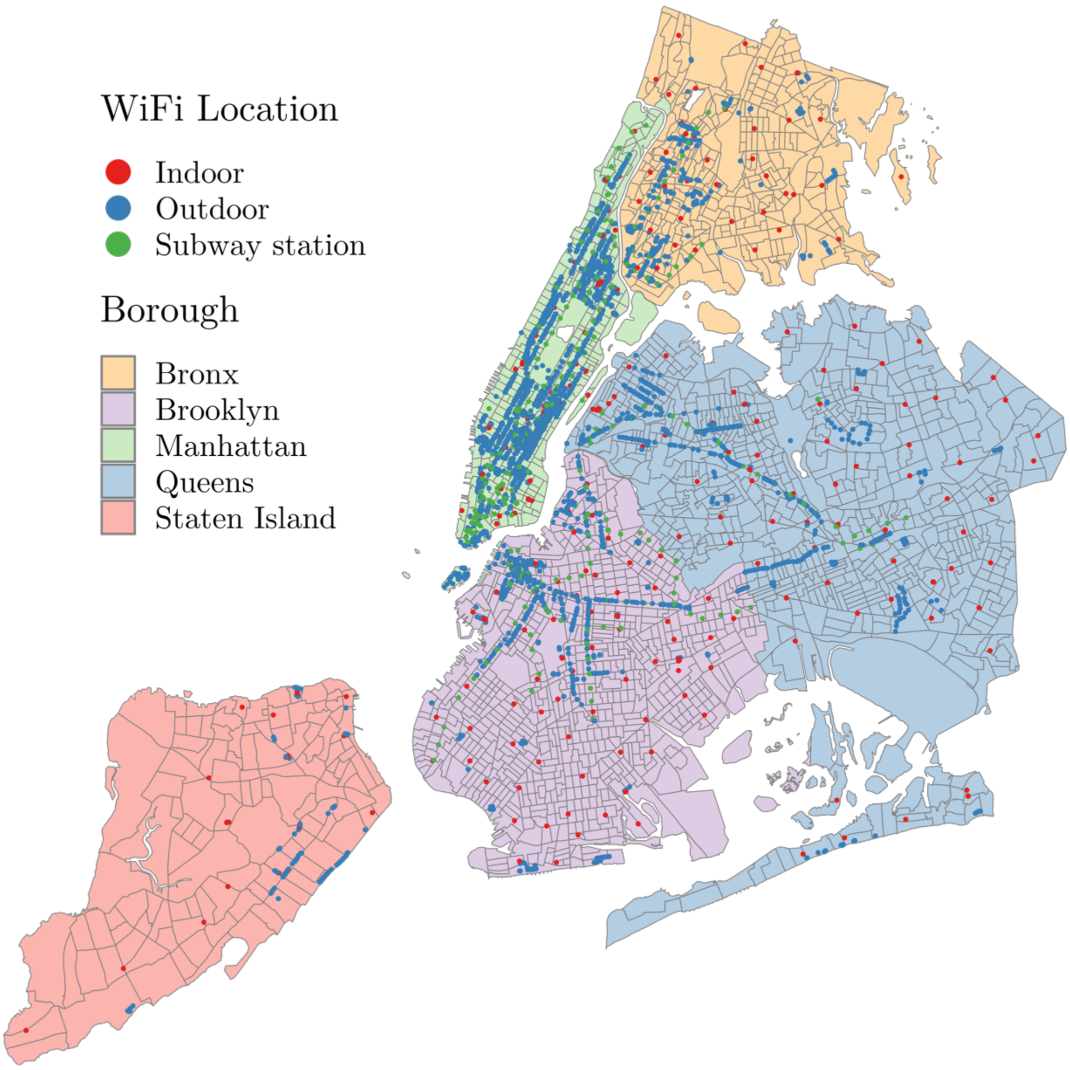
Figure

Figure 1. *The deployment location of public Wi-Fi hotspots under Internet Master Plan in New York City.*



Source: The New York City Internet Master Plan

Figure 2. *The spatial distribution of public Wi-Fi hotspots on census tract level in New York City (after spatial join)*

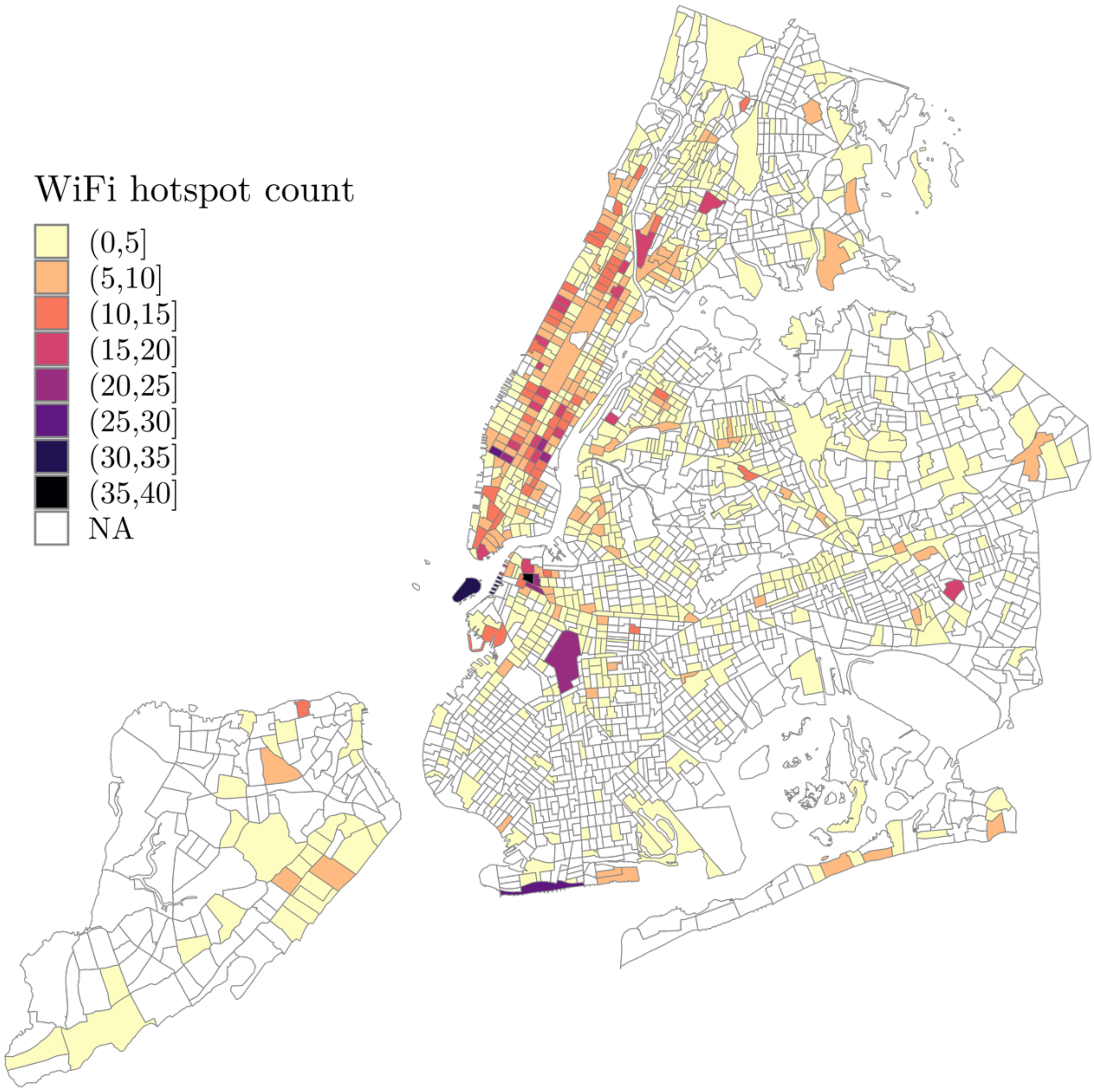


Figure 3. *Demonstration of different continuity: Queen's contiguity (left), Rook's contiguity(middle), and Bishop's contiguity(right)*

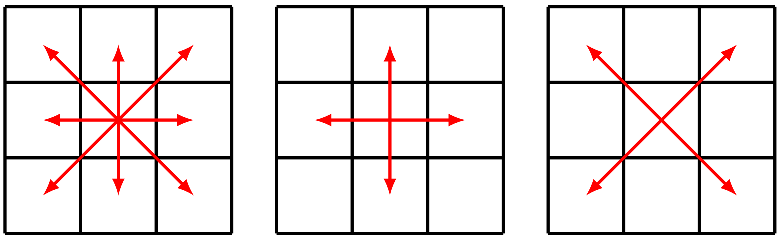


Figure 4. *The hot spots and cold spots distribution of public Wi-Fi hotspots in New York City (Geti-Ord Gi* statistics)*

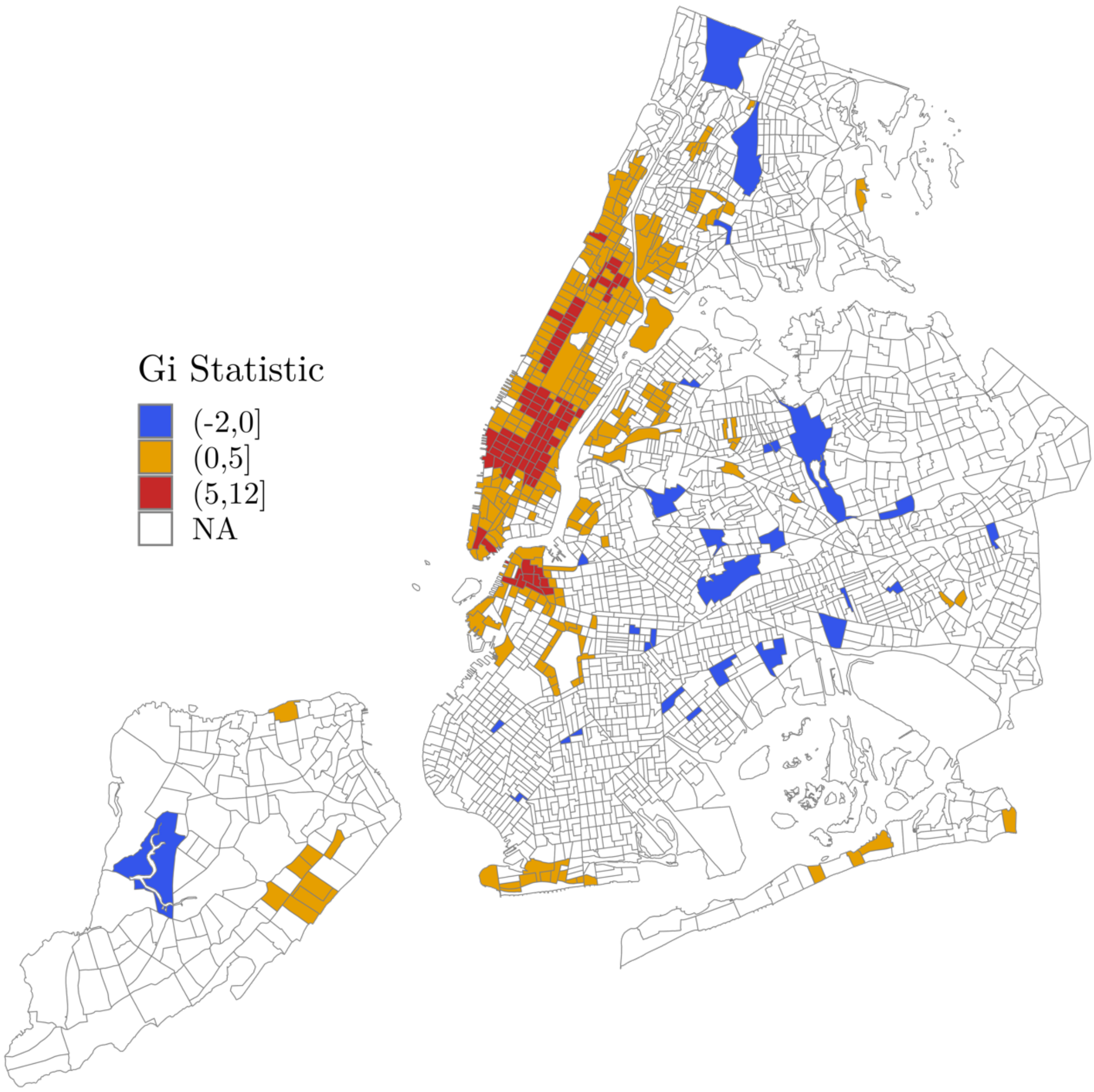


Figure 5. *The non-spatially structured effect of the IID model*

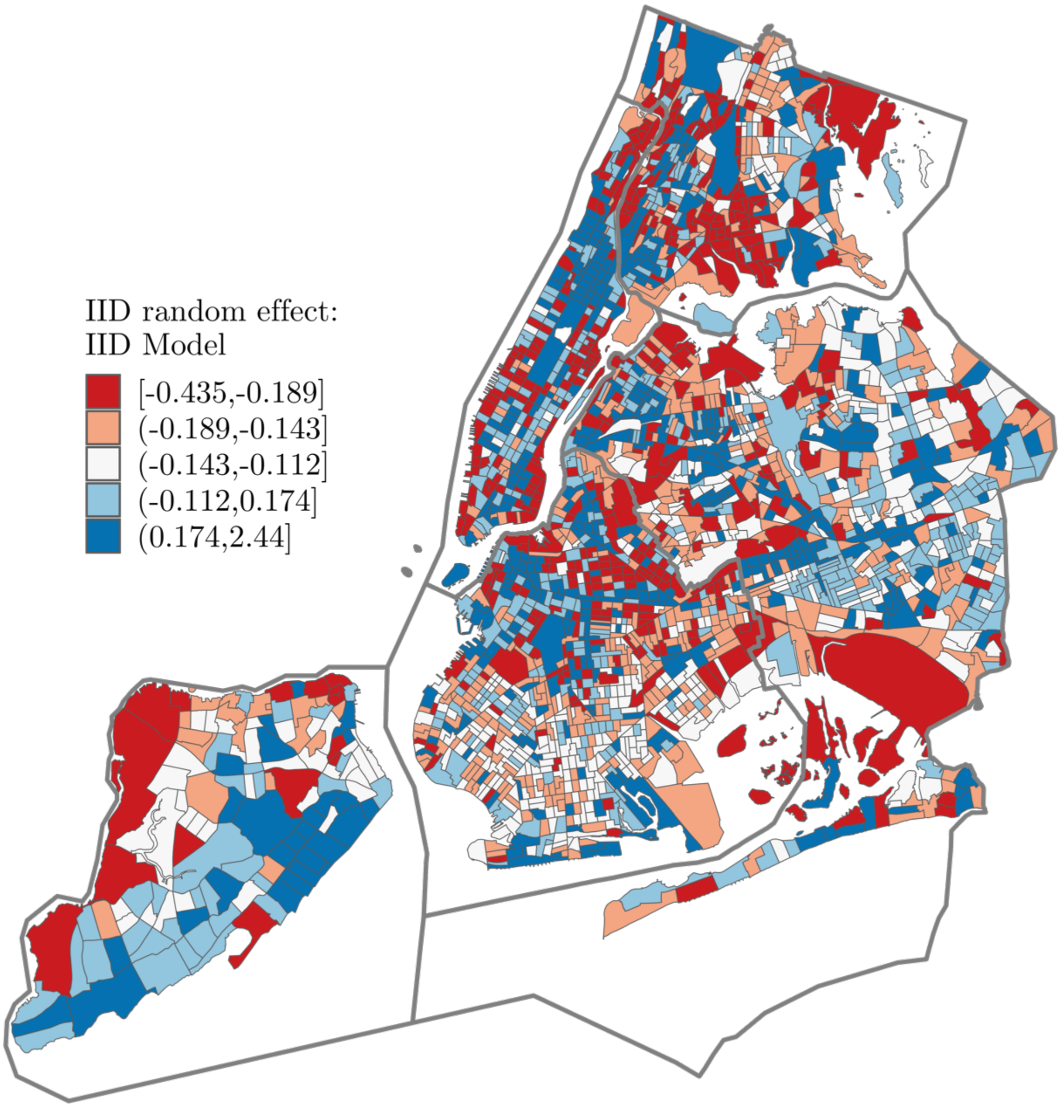
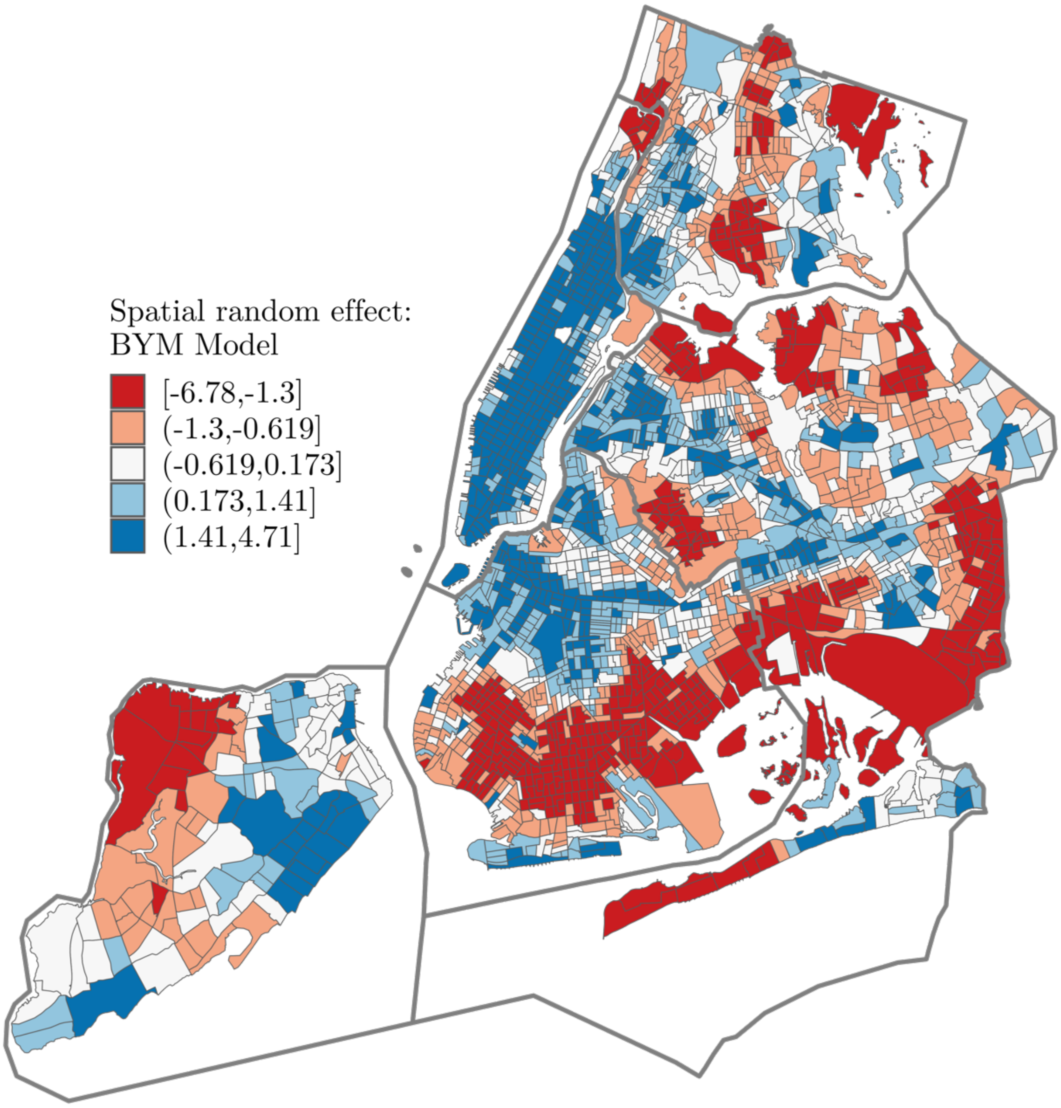


Figure 6. *The spatially structured effect of the BYM model*



Table

Table 1. The descriptive statistics of the five boroughs in New York City

	Bronx (n = 361)		Brooklyn (n = 804)		Manhattan (n=310)		Queens (n = 724)		Staten Island (n = 125)		New York City (n = 2324)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Dependent variable												
Wi-Fi hotspots deployment	0.88	2.15	0.87	2.70	5.39	5.44	0.73	1.80	0.80	2.11	1.43	3.29
Demographic factors												
Population	3953.06	2030.88	3204.94	1421.34	5255.33	2903.42	3136.71	1760.88	3804.77	1717.40	3605.66	2022.25
African American population	1377.57	1141.19	1003.42	1203.35	753.15	1093.82	566.26	961.32	388.98	599.06	858.92	1121.34
Asian American population	153.36	268.68	381.52	526.39	640.90	825.25	813.36	909.46	380.84	362.76	515.17	720.65
Hispanic population	2215.42	1546.45	604.82	667.57	1349.81	1850.53	872.45	893.42	701.86	532.90	1042.97	1245.68
Median age	35.76	7.15	36.79	7.13	38.97	7.35	40.18	6.31	40.52	6.47	38.17	7.11
Population with less than high school education	2061.02	1223.70	1362.50	804.18	1712.46	1338.09	1265.29	811.53	1454.27	696.58	1492.34	1001.67
Socio-economic factors												
GINI index	0.47	0.07	0.46	0.06	0.52	0.07	0.42	0.06	0.43	0.08	0.46	0.07
Income	23610.01	10850.70	36664.97	20311.52	83989.55	52973.23	34199.09	16389.39	38235.17	12041.81	40387.59	30825.52
Commercial density	0.22	1.07	0.30	2.01	1.40	2.80	0.23	0.94	0.78	1.59	0.44	1.79
Digital infrastructure												
Population without any devices (i.e., computer/smartphone/tablet) at home	148.61	113.56	128.69	132.27	187.82	205.32	88.91	96.26	116.63	88.79	126.63	134.10
Population without broadband subscription	45.02	47.79	25.06	31.94	62.19	102.91	21.60	33.78	35.64	34.34	32.60	52.27
Population without Internet	234.83	176.63	177.62	160.07	248.47	263.78	132.14	134.16	170.18	131.28	181.39	176.86
Residential with high-speed Internet	4.25	0.90	4.21	0.79	4.50	1.02	4.65	1.01	4.91	0.55	4.42	0.93
Political orientation												
Population affiliated with Democrats	1521.95	767.74	1264.30	635.90	2403.04	1321.60	1131.31	675.51	1271.76	548.57	1414.35	886.71
Population affiliated with Republicans	216.45	180.76	265.45	178.47	467.44	320.12	360.39	263.44	575.23	360.04	330.85	260.05

Table 2. The Bayesian negative binomial regression results in New York City census tract (*N* = 2324)

	Baseline NB model 1		NB with IID model 2		NB with ICAR model 3		NB with BYM model 4	
	Mean	95% CR	Mean	95% CR	Mean	95% CR	Mean	95% CR
Intercept	-0.097	(-0.181, -0.013)	-0.483	(-0.627, -0.328)	-1.146	(-1.383, -0.940)	-1.258	(-1.374, -1.125)
Demographic factors								
African American population	-0.070	(-0.206, 0.067)	-0.076	(-0.219, 0.066)	-0.102	(-0.273, 0.069)	-0.088	(-0.261, 0.084)
Asian American population	0.096	(-0.016, 0.209)	**0.140**	**(0.024, 0.255)**	0.123	(-0.014, 0.261)	0.119	(-0.019, 0.257)
Hispanic population	**0.393**	**(0.234, 0.553)**	**0.477**	**(0.313, 0.643)**	**0.414**	**(0.224, 0.605)**	**0.413**	**(0.221, 0.605)**
Median age	-0.020	(-0.110, 0.070)	**-0.138**	**(-0.250, -0.027)**	0.020	(-0.091, 0.132)	0.003	(-0.112, 0.118)
Population with less than high school education	**-0.383**	**(-0.599, -0.168)**	**-0.509**	**(-0.741, -0.278)**	**-0.298**	**(-0.530, -0.066)**	**-0.304**	**(-0.541, -0.068)**
Socio-economic factors								
GINI index	**0.142**	**(0.040, 0.245)**	**0.150**	**(0.046, 0.254)**	0.054	(-0.045, 0.154)	0.054	(-0.048, 0.157)
Income	**0.508**	**(0.365, 0.651)**	**0.553**	**(0.423, 0.683)**	0.087	(-0.045, 0.220)	0.117	(-0.019, 0.253)
Commercial density	**0.272**	**(0.156, 0.388)**	**0.239**	**(0.144, 0.335)**	**0.120**	**(0.053, 0.187)**	**0.125**	**(0.057, 0.193)**
Digital infrastructure								
Population without broadband subscription	-0.035	(-0.008, 0.233)	-0.040	(-0.125, 0.046)	-0.016	(-0.100, 0.068)	-0.026	(-0.112, 0.061)
Population without Internet	0.112	(-0.117, 0.047)	**0.148**	**(0.022, 0.273)**	-0.034	(-0.153, 0.086)	-0.020	(-0.143, 0.103)
Residential with high-speed Internet connections	**-0.317**	**(-0.404, -0.229)**	**-0.258**	**(-0.353 , -0.163)**	**-0.299**	**(-0.382, -0.215)**	**-0.271**	**(-0.360, -0.182)**
Political orientation								
Population affiliated with Democrats	**0.563**	**(0.394, 0.733)**	**0.666**	**(0.503, 0.830)**	**0.357**	**(0.207, 0.507)**	**0.370**	**(0.217, 0.523)**
Population affiliated with Republicans	-0.215	(-0.350, -0.080)	-0.230	(-0.375 , -0.086)	-0.062	(-0.205, 0.080)	-0.060	(-0.206, 0.085)
Model hyperparameters								
Overdispersion hyperparameter	0.353	(0.315, 0.394)	0.590	(0.462, 0.728)	7.388	(2.269, 20.93)	13.858	(4.124, 29.825)
Precision for IID component			1.530	(1.086, 2.184)			3.996	(1.482, 10.973)
Precision for spatial component					0.169	(0.141, 0.200)	0.213	(0.163, 0.271)
DIC	6150.91		6023.32		5260.43		5262.84	
WAIC	6158.85		6012.39		5257.2		5452.08	
CPO	1.33		1.65		10.58		9.17	
Marginal log-Likelihood	-3159.61		-3146.11		-4836.40		-2704.29	

Note: NB: negative binomial regression; CR: credible region; IID: independent and identically distributed; ICAR: intrinsic conditional autoregressive regression; BYM: Besag, York, and Mollié.