Crowdsourcing Behavior in Reporting Civic Issues: The Case of Boston's 311 Systems

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Abstract

Many cities in the United States use civic technologies like 311 systems as part of their public service systems for monitoring non-emergency civic issues. These systems have enhanced the city's monitoring capability by diversifying communication channels. However, the data created through these systems is often biased because of differences in people's use of technology (i.e., digital divide) and individuals' behavioral patterns in providing types of information to the systems. If civic data is used by local governments in making informed decisions, these data-driven services could be skewed towards the heavy technology users, and not reflect citizens' diverse needs. If individuals share similar behavioral patterns or cultural norms by neighborhood in reporting civic issues, socio-economic or regional inequality could be exacerbated due to the uneven provision of service. This paper aims to explore these aspects of civic technologies by examining the relationship between community characteristics, individuals' data contribution behavior, and the formation of data types. We report results based on Boston's 311 data as a case study.

Keywords: Civic technologies, crowdsourcing behavior, community-level analysis

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1 Introduction

Since 1996, municipalities have used telephone lines to receive non-emergency (i.e., not 911) reports such as potholes, streetlights, and graffiti [44]. These civic technologies have come to be known as "311," referring to the phone number often used. 311 systems now support reporting via diverse channels such as email, websites, and mobile applications. This system of "human sensors" that improve municipalities' capability to detect civic issues aided by voluntary residents' reporting [8]. Because 311 systems are among the most mature and popular technologies deployed in many cities in the United States, they offer rich longitudinal data about non-emergency civic issues that are often unavailable elsewhere. A 311 dataset provides opportunities to study how such technologies are, and could be, integrated into local communities, making them resilient and informed.

Although promoting 311 systems has expanded data contributor, research has found that user motivation is often due to territoriality, not a sense of civic duty, or a desire to preserve and protect private space [33]. As a result, urban inequality such as socio-economic segregation is reinforced, not disrupted, through 311 systems [29]. One driver of such problems might be top-down implementation of 311 technologies, driven by bilateral communication between municipalities and companies, without participation, oversight, or influence from the public [30]. This creates a circular dependency between people's use of technology, 311 data creation, and community characteristics such as socio-economic well-being.

Leveraging a civic technology for monitoring and managing civic issues without considering its impact on human- and community-wide factors could induce biased 311 data that exacerbates existing inequality. This bias can pose two problems. When governments use such data to implement policies or services, service design could reflect the needs, which might not reflect diverse citizens' needs. On the other hand, if individuals' behavioral characteristics are clustered together by neighborhood (e.g., digital divide), the management quality of the city could differ by region due to the uneven monitoring of civic issues. However, it is unclear how individuals' reporting patterns differ by neighborhood and how such behavioral characteristics affect the types and volumes of issues reported. Because previous work regarding 311 systems or, more broadly, crowdsourced civic technologies has focused on either individuals' motivations to contribute to civic technologies or descriptive analysis of existing inequality [33, 10]. Viewing civic data creation from an information provision perspective has been less prominent in the field of information systems, but doing so at the community level clarifies the dependencies between and mechanisms for civic data creation, people's crowdsourcing behavior, and community characteristics.

This paper analyzes Boston's 311 reporting data to examine the relationship between community characteristics, individuals' voluntary crowdsourcing behavior, and the formation of particular 311 reporting types (which could be conceptualized as *information deserts*, a material pre-condition of information inequality at the community level [28]). The analysis was informed by a theory of local information landscapes (LIL theory) from the field of information science as the theoretical framework to conceptualize these information-driven dimensions, because it provides material lens for viewing the community-level structure of information [28]. This view highlights geographically-driven crowdsourcing behavior as an important intermediary process between community characteristics and the material structure of local information. Using computational methods, we generate variables that indicate different crowdsourcing behaviors for civic technologies in geographical regions. Our statistical analysis of variables generated from computational modeling illuminates the dynamics of the 311 data creation process.

Because civic technologies such as 311 systems have not been studied from a material perspective, we provide an overview of civic technology research grounded in the concept of co-production in public management. Then, we articulate the value of studying this domain in information systems through a literature review.

2 Background: Civic Technologies and Co-production

Communities and residents have always been involved with government service provision [4]. Public co-production has increased over time, starting basic civic actions like attending community meetings and voting [47, 49], through residents as customers [22, 34, 47], to residents as partners [35]. These developments often reflected growth or problems with program implementation [15, 41] and shifts in bureaucratic views of the public [37, 36, 39, 4, 5]. Shifting cultural norms have also motivated changes toward co-production with a focus on governance engaging services through networks and values of trust, cooperation, stakeholders, outcomes, and pluralism [35].

Co-production is not a monolithic solution. Brix et al. describe co-production as a complex, social phenomena where, "there are no unambiguous, logical, cause-effect relations between co-production initiatives and their outcomes" (p.180) [5]. Degrees of inclusivity compound this complexity, affecting the amount of power shared in decision making [32] or the range of services co-produced [3]. Only around 20% of studies examined co-production outcomes, even though one aim of co-produced services is to improve end results [50].

Advancements in civic technology enable the practice and study of co-production. Applying technology in civic and public spaces aims to improve public services and experiences and boost public engagement. Researchers have studied civic technology (e.g., 311 systems) for public management and studied its role in public services [8]. Public policy and management researchers have focused on how the residents' civic technology use is related to management tactics such as cities' resource allocation [11], operational aspects of on-demand services [8, 21], government's social media account management [16], and government's equitable responses [10]. Those scholars often conceptualized the technology as an object being *co-produced* as part of public services because municipalities implement public services, but residents contribute to the evolution and quality of the systems [4, 9]. Brandsen and Honingh categorized the dimensions of the co-production of public services based on the extent to which citizens are involved in designing and implementing the services (e.g., citizens as data contributors vs. citizens as technology co-designers) [4]. Public services derived from co-production using technology drives other civic technologies, such as e-governance [43]. Despite the increased presence of 311 and other civic tech over the past 30 years, Wood described the space as "relatively immature" [53]. This is echoed by public managers supporting co-production activities while unawareness of the purpose or their role in the co-production [47].

Yet, 311 as a co-production platform continues to evolve from passive reception of resident feedback and service requests to an interactive system. At its core, 311 relies on the input of residents. People operate as human sensors, understanding and communicating about the city beyond the capacity of local government [9]. By design, 311 could provide rich spatial and temporal data to improve current public services as well as to develop new opportunities. Cities rely heavily on 311 data, not only to resolve individual requests and understand their own performance (e.g., responsiveness and accountability) [44], program popularity [21], and issues such as the digital divide [6]. 311 also serves as a barometer for public satisfaction with city management [12]. However, 311's dependence upon user-provided information means that differences in 311 usage could affect the quality, quantity, and attribution of data collected, which requires understanding the human factors that shape 311 systems use.

3 Literature Review

3.1 Individual- and Community-level Factors and 311 Reporting

The importance of service co-production as a means to empower citizens led researchers to study people's motivations in contributing to 311 systems and their behavioral patterns. Motivations for reporting to 311 systems include rational action, trust, and empowerment. Some are individual, but others reflect communities [19]. For example, O'Brien *et al.* found 311 reporting was motivated by individuals' territorial management while their engagement in civic activities and voting was positively related to 311 reporting in non-territorial locations

[33]. Minkoff found that the stake people have in the neighborhood (e.g., home-ownership or children at home) also affects 311 reporting behavior [31]. Other individual-level factors include access to the Internet [26], trust in government agencies [48], the influence from household members, friends, and colleagues who use online government services [54]. Furthermore, an individual's existing level of engagement with the government, for instance, a successful experience on their first 311 report, has a significant impact on their continuous reporting [38, 48].

Community-level factors related to 311 reporting have also been studied. Socio-economic status has been negatively correlated with people's use of Boston's 311 systems, which might be related to device type [9]. Eshelmen and Yang discovered a positive correlation between 311-report frequency and local sentiment, as well as government responsiveness (based on geo-tagged Tweets from San Francisco 311 data) [14]. Wang *et al.* found strong correlations between community-level 311 service requests and community wealth, education, unemployment, and housing prices [51]. Cavallo *et al.* found that 311 request frequencies were related to racial composition, percentage of families with children, age, and other socio-demographic status variables, but these relationships varied among the three cities studied [6]. The amount of attention a city pays to different communities (e.g., economic development and council member experience) can also affect community-level reporting [31]. Geographic clusters can be formed based on features from 311 data [51], and often, such features include gender, population density, ethno-racial composition, education levels, typically at the US census tract level [33, 27].

While factors that influence 311 system use and reporting behaviors provide an understanding of a community's co-production process, it is unclear whether and how behaviors are shaped by community characteristics and how such behaviors create the civic issue landscape (i.e., the distribution and characteristics of the entirety of reported issues). Because the civic issues data plays a critical role in public services and the management of neighborhoods, we must understand the processes of civic data creation, its material characteristics, and the impact of reported issues on community well-being. These theoretical gaps between empirical public administration studies on 311 systems might reflect a paucity the needs for community-level crowdsourcing behavior.

3.2 Behavioral Models in Crowdsourcing

Theoretical models for crowdsourcing behavior have largely focused on people's motivations and intentions in the context of online communities. Research has examined the factors that motivate people's crowdsourcing activities such as a collective intention mode whether one is acting as a group member or as an individual [46], the subjective meaning of tasks [7], and incentive structures [24], which are usually conceptualized using the model of intrinsic and extrinsic motivation [2]. Also, technological features such as visibility of the needs and work design have been studied as motivational factors [23].

These motivation-related factors have been examined in the crowdsourcing contexts that are geographically-oriented. Among the many contexts, citizen science is one of the well-known contexts in crowdsourcing in geographical environments. For example, people's passion about learning new things, helping wildlife and environment, spending time outdoors, and exercises were reported as the motivations for geographically-driven crowdsourcing [17]. Particularly in the citizen science context, intrinsic motivations such as environmental concerns, a sense of contribution to science, and enjoyment were found as key contributors to people's crowdsourcing behavior [40].

While it is an important factor to examine citizens' intrinsic and extrinsic motivation to report civic issues to the 311 systems, the focus of this paper is more on the behavioral aspects of crowdsourcing work, which would give rise to the types and quality of reported issues. For example, the typology of behavioral dimensions has been studied in the citizen science contexts. Scholars examined people's contextualized behaviors such as asking questions, using data, and learning protocols [40]. Also, the dimensions that are related to productivity were studied such as multitasking [20], innovative behaviors [55], and attitudes such as whether workers are active or passive [45].

Building upon these models and empirical work, and by deepening the granularity of behavioral patterns in geographical areas, we aim to uncover the variations in people's civic issue reporting patterns and their relationship to the social determinant of community well-being (i.e., poverty). Because civic technologies are less related to learning and education, but more rely on people's citizenship behavior and environmental concerns, this study will be a basis to develop the theoretical models of crowdsourcing behavior in the context of civic technologies.

4 Research Questions

Because the paper focuses on the provision of civic issues to the systems, we use a theory of local information landscapes (LIL theory) as a framework to design the methodology. LIL theory conceptualizes community-level structures and features of local information [28] and provides a model that describes the distribution of information and the relationships between different information sources, making it possible to understand the structural and material characteristics of information as tangible factor. As depicted in Fig. 1, a community's local information landscape is formed by components that embed information (i.e., information sources) and diverse information provision practices. Accordingly, crowdsourcing behavior in the context of civic technologies is often shaped by other community characteristics such as organizational dynamics, community features, and policies.

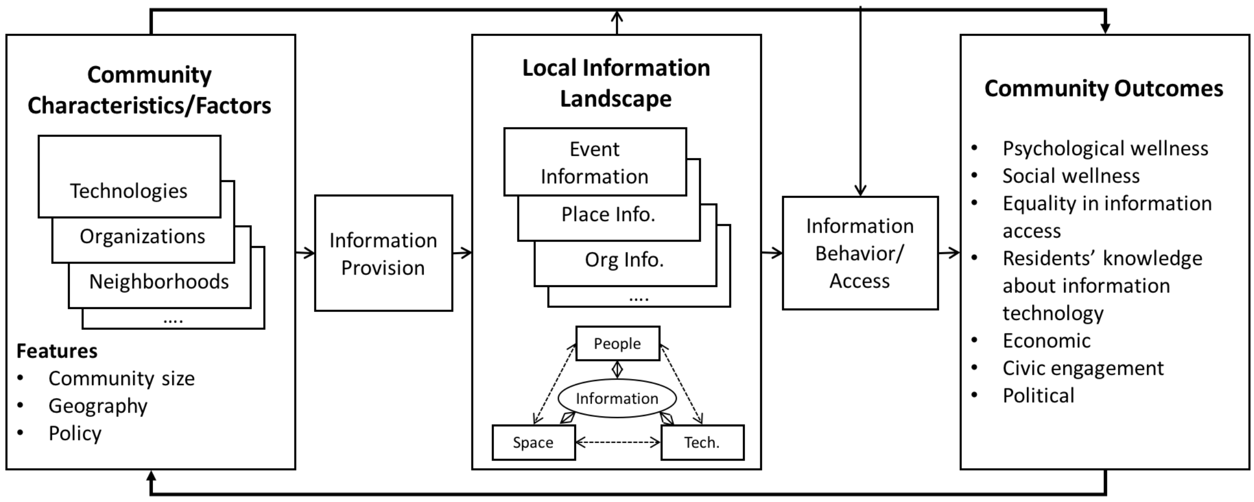

Figure 1: A model-based diagram for a theory of local information landscapes [28].

This study investigates the impact of community characteristics on people's 311 reporting behavior. Particularly, we focus on the community characteristic of socio-economic deprivation, because this was found to be important by much of social science research on civic engagement (e.g., [42, 13]) as well as in empirical studies on 311 systems (e.g., [26]). Crowdsourcing behaviors are modeled based on known 311 reporting behaviors such as territoriality and geographical coverage [33] as well as new constructs such as mobility [25] and subject coverage. By listing the typology of information behavior from a geographical perspective, LIL theory informs the study design and benefits from having concrete dimensions of crowdsourcing behavior in the context of civic technology use. Particularly, through the LIL lens, we ask:

- RQ1: How is socio-economic deprivation related to people's 311 reporting behavior?

Because 311 system users include both residents and government employees, it is unclear how their behaviors differ. Previous studies of 311 data did not distinguish between these two groups. This study 311 reporting patterns with and without government users providing implications for understanding residents' use of civic technologies and governments' interventions in the co-production landscapes. Distinguishing between government users and residents presents a methodological challenge because the 311 data does not provide this information. Therefore, we ask:

- RQ2: How can government users and citizens be identified among 311 users?
- RQ3: How do 311 reporting patterns differ with and without government users with respect to socio-economic status?

Based on RQ1, we develop four hypotheses. Previous studies reported that people's motivation to report issues through 311 systems is territorial rather than civic [33] and people's engagement to civic participation is likely to be weaker in low-income communities due to resource constraints [1]. This indicates that it is the wealthier communities that report more for their territorial issues. Thus, we hypothesize that high socio-economic areas will demonstrate higher territoriality (i.e., lower mobility and narrower geographical coverage in reporting 311 issues with higher concentration of reports near their homes) in managing their environments (H1-1). Conversely, communities with low socio-economic status will have lower territoriality (i.e., higher mobility and broader geographical coverage in reporting 311 issues with a lower concentration of reports nearby their homes) (H1-2). The volume of 311 reports would be higher in high socio-economic areas because of a higher territorial motivation in managing their home environments (H1-3). Finally, we hypothesize that the variety of 311 issues would be higher in areas with low socio-economic status due to a weaker territorial motivation, which may affect timely management of local issues (H1-4).

RQ2 is addressed through methodological approaches and does not yield hypotheses. Regarding RQ3, because government users may actively seek civic issues in the city, we hypothesize that including government users in the 311 reporting landscape will decrease the effects of socio-economic status, suggesting that government interventions would complement the weakness of crowdsourcing mechanisms for monitoring civic issues (H3).

5 Approach

5.1 Data

To answer research questions and test hypotheses, we used two sets of Boston's 311 data and additional demographic information. The City of Boston's 311 system provides access to local public information and accepts requests for services. The city provides open data access to the 311 service request records from 2011 to 2019 with detailed information for more than 1.6 million reports, including the service needed, assignment to city departments for resolution, open and closure timestamps, relevant photos, and other geographic information such as neighborhood, police, and fire districts. On the advice of a Boston employee who worked on BOS:311, we used the data the employee considered generally accurate which is from 2015.

While this data is rich with information central to the 311 call, it is anonymized so cannot provide insights into individual behaviors. We obtained access to a separate, restricted dataset through our research partnership with the City that contains individual-level call characteristics such as a unique caller identifier from which we are able to learn things like repeat caller frequency. The restricted data contains over 260 thousand calls, but only spans call records from January 1, 2015 to January 2, 2016.

Despite each dataset having 29 variables pertaining to call characteristics, only 35% of the variables overlapped. Merging the data would have provided us with an even richer array of call details, but the numerous discrepancies with the unique call identifiers prevented a clean data merge without substantial loss of individual call records. We chose to keep these data separate and focus each to the task of investigating different research questions at the community and individual levels. However, we limited the open data to calls requested in 2015 to match the restricted data timeline and improve comparability between our results.

To better understand the Boston geography and conduct our analysis at different spatial levels, we acquired additional data from the US Census' American Community Survey (ACS) using the 5-year estimate data for 2015, which is the most reliable. From the ACS, we pulled data on population, income, education, housing, employment, foreign born and citizen status, and mean commuting time to work. We matched this data to both the open and restricted 311 call records through geographical aggregation. We obtained the ACS data at the Census tract level, which was later partitioned and re-aggregated to a uniform, hexagon layer.

5.2 Variables

5.2.1 Geographic Unit of Analysis

To explore the geographic distribution of 311 reporting as well as the relationship between individual reporting behaviors and community level variables, we need to identify the geographic units of Boston communities, based on which the individual variables can be geographically aggregated and compared. We used hexagons with a 600-meter diameter instead of existing administrative divisions such as zip codes, wards, or census tracts because of their consistency of covered areas and granularity. Traditional administrative divisions like zip codes can vary significantly in areas and densities (e.g., in Boston, the 02132 zip code is over 140 times larger than 02203 introducing geographical bias when comparing people's behaviors in disparate zip codes). The distances between one hexagon and the six adjacent hexagons are all equal which reduces measurement bias when considering individuals' geographic movement.

In deciding the diameter of hexagons, we considered the size of a city block and the sensitivity of hexagon size to key variables. A city block is usually a group of buildings surrounded by streets and is one of the smallest units that organizes residents' behaviors. The typical width of a block in Boston is from 80m to 200m. The diameter of the hexagon should not significantly deviate from the size of a city block because it defines people's primitive mobility and residential units. A sequence of experimental diameters from 100m to 700m with a 50m interval was used to test the sensitivity of each diameter based on two benchmarks: the percentage of hexagons without 311 reporting and that without population. Among these diameters, 600 meters was the one with the lowest percentage of zero 311 reporting and zero population. Thus, a 600m diameter was chosen to create a hexagon overlay. After aggregation, 568 hexagons were generated for Boston.

5.2.2 IV and CVs

The 5-year estimate data for 2015 from ACS on census tract level including population, foreign born and citizenship, education attainment, housing units, and commuter time was retrieved and aggregated into hexagon level based on the weighted-sum of intersections. We generated a deprivation index using principal component analysis (PCA) to measure socio-economic status using populations for income below poverty, unemployed population among people below below the poverty level, renter occupied housing units, and having less than a Bachelor's degree. The first principal component forming the deprivation index captured 58% of the variation from the initial variables. All the variables were prorated by area, with the exception for commuter time, which was prorated by population. The summary statistics are shown in Table 1.

5.2.3 Individuals' Information Provision Behavior

To examine individual users' information provision behavior, the following variables were generated by combining restricted/open 311 data in Boston. We use superscripts a to denote individual-level variables.

1. The reporting frequency (n^a) is the number of 311 requests in the data set associated with a unique individual person identifier.

Table 1: Boston Area Hexagon Level Summary Statistics†

Variables	**Mean**	**SD**	**Min**	**Med**	**Max**
Socio-economic deprivation index	0.0	1.5	-2.9	-0.0	4.6
Total population	1,100	1,208	0	666	6,595
Foreign born pop.	229	390	0	153	4,031
Citizen pop.	945	1,025	0	585	6,032
Mean travel time to work (minutes)	30.8	4.8	17.1	31.4	45.2
Income below poverty pop.	173	246	0	64	1,747
Income below poverty and unemployed pop.	21	30	0	6	181
Income above poverty and unemployed pop.	31	40	0	17	211
Total housing units	433	521	0	258	3,777
Owner occupied housing units	148	171	0	111	1,438
Renter occupied housing units	284	392	0	126	2,616
Less than Bachelor's degree	402	470	0	248	3,520
311 reporting per 100 people	14.7	11.1	0.3	13.3	112

† There are 568 hexagonal areas in the region

2. Average distance ($\bar{D}^a$) between the reporting locations of each user, which captures the average geographic range of individual information provision behavior in 311 reporting. To calculate this variable, every pair of reporting locations of a given user is considered. For instance, for a user with three 311 reports with locations recorded as a set A, B, C, a set of distances AB, AC, BC are generated and then the mean value of this set is calculated. In other words, $\bar{D}^a$ is calculated as:

$$\bar{D}^a = \frac{1}{C_2^{n^a}} \sum_{i=1}^{n^a} \sum_{j=i+1}^{n^a} |\overrightarrow{P_i P_j}| \tag{1}$$

where P_i and P_j are two 311 positions reported by a given user, while n^a the 311 reporting frequency of the given user, $|\overrightarrow{P_i P_j}|$ denoting the distance between the two positions P_i and P_j, and $C_2^{n^a}$ is the number of combinations of 311 reports filed by the given user.

3. The maximum, mean, and median distances (d^a_{max}, $\bar{d}^a$, d^a_{median}) of an individual user's 311 reporting locations as measured from his/her home quantify how far the sites of the reported issues are in general from the reporter's home if the home address is registered in the 311 system. These three variables can provide insights into the territoriality aspect of the individual's information provision behavior regarding 311 reporting [33].

4. The radius of gyration (r^a_g) captures an individual's movement in terms of 311 reporting behavior. The radius of gyration in [18] is defined as:

$$r^a_g = \sqrt{\frac{1}{n_a} \sum_{i=1}^{n_a} (\vec{r_i^a} - \vec{r^a_{cm}})^2} \tag{2}$$

where $\vec{r_i^a}$ is the vector of $i = 1, 2, ..., n_a$ positions for user a in a given time, while $\vec{r^a_{cm}}$ denotes the center of mass of trajectory $\vec{r_i^a}$. It is interpreted as the "characteristic distance travelled" by a user [18]. The radius of gyration has been typically used to measure individual-level mobility [18]. This measure is defined as the standard deviation of the set of all distances a user traveled when reporting to 311, as measured from the center of one's 311 reporting locations.

5. The subject coverage of an individual (C^a_s) indicates how many categories a user's 311 reports cover. 311 systems vary in categorizations across different cities. In Boston, there are three hierarchical levels of categories: 14 subjects, 54 reasons, and 208 types. The subject of a 311 case usually indicates which government department the issue will be assigned to, for instance, Boston Police Department or Animal Control. The

variety of the 311 categories tells us the range of problems that affect the residents care about.

6. The Herfindahl-Hirschman Index (HHI) of the subjects covered by an individual user (HHI_s^a) measures the heterogeneity or diversity of the user's reporting categories. HHI is a measure initially for market concentration in economic studies. In this study, the subject HHI of a user is calculated as:

$$HHI_s^a = 1 - \sum_{i=1}^{C_s^a} s_i^2 \tag{3}$$

where C_s^a is the subject coverage of the user, while s_i is the percentage of a subject in all the 311 reports by the given user. Traditionally, a low HHI shows diversity, but we use the Gini-Simpson index (i.e., a reversed form of HHI) so a higher HHI_s^a indicates a higher diversity.

5.2.4 Community Level Information Provision Behavior Variables

As mentioned in previous sections, we identified 568 hexagons with 600-meter diameters as units to represent communities in Boston. We aggregated all the individual-level variables to the hexagon level to run the regressions. We use superscript H to denote the hexagon-level variables to distinguish from individual level variables. For instance, $\bar{D}^a$ denotes the average distance of an individual user while $\bar{D}^H$ the aggregated average distance of all the users who have reported in a hexagon.

The community-level variables are aggregated in a weighted manner. For an individual level variable V^a, the corresponding community-level variable V^H is calculated as:

$$V^H = \sum_{a=1}^{P^H} (V^a \frac{n_a^H}{N^H}) \tag{4}$$

where P^H is the number of users who have reported in the given hexagon, n_a^H the number of 311 reports a user filed in the given hexagon, N^H the total number of considered 311 reports in the given hexagon. For instance, let's say, hexagon No.187 has 105 reports and 23 users have reported in this hexagon, then, the community-level radius of gyration of hexagon No.187 (r_g^{187}) is calculated as:

$$r_g^{187} = \sum_{a=1}^{23} (r_g^a \frac{n_a^{187}}{105})$$

In this way, hexagon-level variables are generated, including aggregated average distance ($\bar{D}^H$), aggregated mean, max, and median distances from home ($\bar{d}^H$, d_{max}^H, d_{median}^H), aggregated radius of gyration (r_g^H), aggregated reporting frequency (n^H), aggregated hexagon coverage (C_h^H), aggregated subject coverage (C_s^H), and aggregated subject HHI (HHI_s^H).

Table 2: Pearson's correlation between key variables on hexagon level (considering the 311 reporting by users who reported more than twice).

	2	3	4	5	6	7	8	9
1. N^H	-0.34	-0.35	-0.33	-0.34	-0.29	-0.22	-0.19	-0.14
2. $\bar{D}^H$		0.92	0.97	0.85	0.95	0.69	0.77	0.56
3. $\bar{d}^H$			0.94	0.98	0.87	0.59	0.68	0.52
4. d^H_{max}				0.86	0.96	0.69	0.78	0.57
5. d^H_{median}					0.80	0.54	0.63	0.48
6. r^H_g						0.73	0.81	0.58
7. n^H							0.86	0.56
8. C^H_s								0.80
9. HHI^H_s								

Table 3: Pearson's correlation between key variables on hexagon level (considering the 311 reporting by non-government users who reported more than twice).

	2	3	4	5	6	7	8	9
1. N^H	-0.28	-0.28	-0.24	-0.26	-0.19	-0.04	-0.03	-0.08
2. $\bar{D}^H$		0.81	0.93	0.69	0.88	0.56	0.55	0.39
3. $\bar{d}^H$			0.88	0.96	0.72	0.46	0.51	0.40
4. d^H_{max}				0.75	0.90	0.59	0.63	0.44
5. d^H_{median}					0.58	0.40	0.44	0.34
6. r^H_g						0.62	0.66	0.46
7. n^H							0.73	0.37
8. C^H_s								0.77
9.HHI^H_s								

5.2.5 Identifying Government Users

A registered 311 user could be an individual who reports civic issues voluntarily, but also could be government employee(s) who report 311-related issues on behalf of citizens who seek information or need assistance submitting service requests. These two user groups behave differently. To answer RQ2, we label a user as a government user if his/her home address is within 10-meter range of any fire stations, local government offices, city halls, or police stations. The user generated home addresses were all cleaned up manually by comparing them with Google Maps. Then, the government-related buildings' locations were detected through Google Maps' Place APIs to calculate the precise distances between them and users' home addresses. This process made it possible to approximate government users from the pool of 311 users.

5.2.6 Descriptive Statistics

The Pearson's correlation between key variables on hexagon levels considering two groups of users can be seen in Table 2 and Table 3. The notations of the variables are as follows: 1) N^H: aggregated reports sum in hexagons, 2) $\bar{D}^H$: aggregated average distance, 3) $\bar{d}^H$: aggregated mean distance from home, 4) d^H_{max}: aggregated max distance from home, 5) d^H_{median}: aggregated median distance from home, 6) r^H_g: aggregated radius of gyration, 7)

Table 4: Hexagon Level Dependent Variables Summary Statistics by Subgroup (considering the 311 reporting by users who reported more than twice)

Variables	**Mean**	**SD**	**Min**	**Med**	**Max**
Total reports (N^H)					
all users	121.0	110.4	1.0	102.0	704.0
users with 2+ reports	48.7	47.6	1.0	35.0	327.0
non-govt users	117.3	106.6	1.0	99.0	687.0
non-govt users with 2+ reports	45.3	44.1	1.0	34.0	311.0
Average distance ($\bar{D}^H$)					
all users	754.5	925.5	0.0	468.7	6278.9.0
users with 2+ reports	1,554.9	1,267.6	0.0	1,171.7	6,278.9
non-govt users	439.6	578.1	0.0	284.1	5,823.4
non-govt users with 2+ reports	914.8	886.4	0.0	641.2	6,222.8
Mean distance from home ($\bar{d}^H$)					
all users	873.4	878.1	8.6	572.2	5,380.7
users with 2+ reports	1,418.2	1,116.2	10.3	1,063.9	6,372.0
non-govt users	642.6	719.7	8.6	431.4	5,630.3
non-govt users with 2+ reports	920.0	935.1	10.3	617.8	7,155.5
Max distance from home (d^H_{max})					
all users	1,776.1	1961.8	8.6	1,136.5	12,642.1
users with 2+ reports	3,409.4	2,647.3	10.3	2,655.7	13,050.7
non-govt users	1,143.5	1,355.5	8.6	749.8	14,325.2
non-govt users with 2+ reports	2,105.2	2,049.4	10.3	1,497.8	15,421.0
Median distance from home (d^H_{median})					
all users	811.5	856.4	8.6	525.8	6.866.4
users with 2+ reports	1,271.3	1,113.5	10.3	909.7	7,781.7
non-govt users	601.7	740.4	8.6	391.6	7,485.9
non-govt users with 2+ reports	807.4	976.7	10.3	493.4	7,557.1
Radius of gyration (r^H_g)					
all users	236.6	339.2	0.0	132.4	2,351.9
users with 2+ reports	552.2	487.5	0.0	413.6	2,529.4
non-govt users	108.4	195.9	0.0	59.5	2,435.6
non-govt users with 2+ reports	284.5	316.6	0.0	194.5	2,435.6
Individual reporting frequency (n^H)					
all users	44.9	95.6	1.0	20.4	997.0
users with 2+ reports	101.3	147.5	3.0	57.2	997.0
non-govt users	6.7	11.2	1.0	3.9	182.3
non-govt users with 2+ reports	15.4	21.8	3.0	9.7	272.0
Subject coverage (C^H_s)					
all users	1.7	0.9	1.0	1.5	8.0
users with 2+ reports	2.7	1.2	1.0	2.4	8.0
non-govt users	1.5	0.5	1.0	1.4	5.7
non-govt users with 2+ reports	2.1	0.8	1.0	2.0	7.0
HHI of subjects (HHI^H_s)					
all users	0.8	0.1	0.2	0.8	1.0
users with 2+ reports	0.6	0.1	0.2	0.6	1.0
non-govt users	0.8	0.1	0.2	0.9	1.0
non-govt users with 2+ reports	0.3	0.1	0.2	0.3	0.8

n^H: aggregated individual reporting frequency, 8) C^H_s: aggregated subject coverage, 9) HHI^H_s: aggregated subject HHI.

5.3 Analytical Models

We used Bayesian multi-variate linear regressions to estimate parameters for deprivation index and other variables. We included other community demographic information that may give rise to people's mobility and engagement patterns to control for variance in the model. We tested each dependent variable in four models representing different considerations for all users, non-government users, and user participation frequency. We assessed the 568 600-meter community-level hexagons using aggregated individual information. Given the availability of address individual address information, not all hexagons were valid observations in the regression, with model sample sizes ranging from 365 to 388 hexagons. We examined the geographic coverage density of individual information per hexagon to ensure the ones used in the regression would be representative of our sample. Coverage was consistent and there were no concerns found for any of the modeled subsampled groups.

6 Results

The regression results appear in Tables 5–14 in Appendix. The first three dependent variables pertain to 311 reporting frequency within a hexagonal community and reveal mixed results, which test H1-3. There is an impact on 311 reporting among all the users, with or without addresses. A one-standard deviation increase in the poverty deprivation index corresponds to approximately 47 fewer 311 reports on average within a hexagon and accounted for 63% of variance in the model, all else equal (Table 6). Conversely, when limiting the samples to only individuals with known addresses, there is a general, but not significant, decrease in 311 reporting as a community becomes more socio-economically deprived (Table 5). Similar results appear when weighting the number of 311 reports by individual participation, although the coefficients trended positively to increase 311 reporting after including government users (Table 7). This rejects the null hypothesis of H1-3, only when considering all users including non-registered users.

People within hexagons having higher socio-economic deprivation correspond to higher radius of gyration across all four models, but confidence is limited to all users (Table 8). Among all users, the radius of gyration increased 21.5 units on average with each additional standard deviation on the socio-economic deprivation index, controlling for all other variables in the model. Among users reporting more than twice, the radius of gyration increased another 18.1 units, nearly doubling variation in the gyration distance. R^2 for models accounted for 15.8% and 14.7% of the variance respectively. Also, users are traveling much greater distances between the 311 reports they submit (Table 9). These results rejects the null hypothesis of H1-2. Especially when it comes to including government users, the effect of deprivation increases, suggesting that government officials complement people's mobility in reporting civic issues, rejecting the null hypothesis of H3.

The next dependent variables pertain to territoriality (H1-1). All show strong, substantial increases in mobility from homes as socio-economic deprivation rises, with some exceptions on the confidence among non-government users reporting more than twice (Tables 11 - 12). Results for mean and median distances between reporting locations and individual home addresses range around 40 median 45 mean meters among non-governmental users to 80 median and 84 mean meters among all users that report frequently, when one unit of deprivation index increases. Maximum distances from 311 reports to home have an expected farther reach, where a one standard deviation increase in socio-economic deprivation is associated with an additional low-end 88 meter average increase among non-governmental users and high-end 222 meter average increase among all users that report frequently. These results reject the null hypothesis of H1-1, confirming the findings from previous studies' findings that wealthy areas tend to be more territorial in reporting civic issues.

The final two dependent variables pertain to the subject classification of 311 reports (Tables 13 - 14). Boston has 14 mutually exclusive subjects for their 311 report classifications. Socio-economic status in the community does not appear to have big influence on the subject coverage even though some results are statistically significant. Similarly, despite reasonable confidence across most models for HHI, the near zero coefficients mean that changes in socio-economic status within the community have trivial influence on subject diversity in the 311 reports. These results reject the null hypothesis of H1-4, but the impact is very weak).

Overall, the impact of community socio-economic status has mixed results on our 311 variables. Control variables helped account for model variation and often had meaningful coefficient results to be explored later.

7 Discussion and Limitations

Overall, the findings provide important implications for the literature on co-production of civic technologies and crowdsourcing behavior. A lack of resource-based model in the co-production literature can benefit from this study by understanding theoretical models, a typology of reporting behaviors, and community-level effects on 311 reporting behaviors. By knowing this systematic process, civic practitioners and co-production researchers can deepen understanding of the roles civic technologies play in creating civic data and their material impact.

Information systems scholars can benefit from this study by extending and contextualizing the typology of crowdsourcing behavior in the civic technology domain. Crowdsourcing behavior has been understood in a contextualized environment, which often led to a qualitative examination of it. However, this study indicates that crowdsourcing behaviors can be quantified at the community level by observing geographical and subject-driven digital footprints. Several dependent variables derived from 311 usage illustrate behaviors that provide insight contributing factors of the information landscape that reinforce the 311 data. Individual mobility, understood through the radius of gyration and distance measures, are key characteristics of these behaviors. The strong, positive impact of socio-economic status upon radius of gyration was substantially higher for all users compared to non-government users. The job duties of government users, particularly among frequent reporters, might be one possible explanation. They may generate reports independently or on behalf of people within those communities, with 311 call center operation unaffected by location and the mobile nature of field work by city employees.

Behavior within communities lends support to notions of territoriality, which we can view through 311 reporting distances. Findings for average distance between reports strongly resemble distances to homes with similar reporting concentrations within the community. Yet, because data is aggregated to a community region, it is difficult to say if these distances travel across nearby hexagons. On the other hand, given the 600 meter hexagon size, it is reasonable that most average distances between reports suggest reporting to concentrate within the hexagonal community. Given this relative community concentration and positive distance coefficients, the results also support reporting locations tightens closer to home and each other as communities become more affluent on the socio-economic index.

Despite these new findings, other measures not included here still need to be explored. One limitation is the number of variables capturing community characteristics. Future work will consider race and ethnicity, highly important measures to help account for many of the racial justice and other similar challenges being voiced in society today. Additionally, all of our 311-related variables serve as dependent variables when there could also be leveraged as predictors. Other work classified 311 reports by their functional and representative use to individuals, society, and structural systems [33, 31, 52, 6]. Including these classifications in future work may help reveal other patterns in information behavior and describe the information landscape.

Additionally, we can also shift more use of 311-related variables as predictors to understand how usage features impact other system and service aspects. Lastly, although we discovered sizable differences in 311 data provision based on our sub-sampling across numerous models, our identification of government users was a data-driven approximation. To verify and further isolate the impact of (non-)government users, it will become increasingly important to have metadata from the system administrators that confirm this user type.

Extra metadata to signal if government users specifically enter 311 reports on behalf of someone else, such as a city resident, or as part of their individual duties can further clarify our results and help provide guidance to city officials.

8 Conclusion

If crowdsourcing behavior types and 311 category/types are confounded, this means the broadening population is very important, otherwise, reporting tends toward increased bias. Thus, 311 systems have enhanced the city's monitoring capability by diversifying communication channels such as phone calls and mobile apps. However, discrepancies still exist in people's use of technology as well as their behavioral patterns in providing particular types of information to the systems. Data created through these systems is often biased so local governments that leverage a civic technology for monitoring and managing civic issues without considering human- and community-wide factors could exacerbate existing inequality. This study provide implications for this potential risk. A broader data partnership with municipalities and cities will make this kind of approach more useful by providing contextualized and comparative understanding of cities and civic technologies.

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Appendix: Regression Tables

Table 5: DV: Total number of 311 reports from users with known addresses

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	-197.032	-335.809	-58.913	-16.709	-80.878	49.687	-204.676	-353.356	-55.342	-30.161	-97.128	35.656
Socio-economic deprivation index	-4.209	-8.681	0.322	-1.560	-3.505	0.374	-3.896	-8.486	0.722	-1.290	-3.372	0.784
Foreign born population (%)	-58.519	-178.946	61.047	-48.316	-106.477	7.947	-49.442	-183.376	85.913	-38.242	-95.524	20.055
Citizen population (%)	75.811	-62.958	216.483	-12.803	-79.480	53.094	90.917	-62.463	246.038	4.497	-61.594	71.810
Mean travel time to work (min)	4.791	3.495	6.123	1.221	0.623	1.828	4.578	3.202	5.949	1.093	0.467	1.719
Total population	0.076	0.071	0.081	0.030	0.028	0.032	0.079	0.073	0.084	0.033	0.030	0.035
log-fit ratio	-0.000	-0.047	0.044	-0.000	-0.050	0.048	-0.001	-0.047	0.046	-0.000	-0.048	0.048
R^2	0.638	0.597	0.678	0.586	0.538	0.629	0.647	0.604	0.685	0.613	0.568	0.654
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 6: DV: Total number of 311 reports with or without known addresses

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
	–	–	–	–	–	–	234.135	-642.449	1091.528	–	–	–
Socio-economic deprivation index	–	–	–	–	–	–	-46.673	-72.106	-19.744	–	–	–
Foreign born population (%)	–	–	–	–	–	–	-708.494	-1470.987	55.721	–	–	–
Citizen population (%)	–	–	–	–	–	–	-77.921	-947.494	822.945	–	–	–
Mean travel time to work (min)	–	–	–	–	–	–	-0.602	-8.914	7.444	–	–	–
Total population	–	–	–	–	–	–	0.425	0.394	0.457	–	–	–
log-fit ratio	–	–	–	–	–	–	-0.000	-0.048	0.048	–	–	–
R^2	–	–	–	–	–	–	0.633	0.590	0.673	–	–	–
N (600m hexagons)	–	–	–	–	–	–	374	–	–	–	–	–

Table 7: DV: Total number of 311 reports, weighted per individual

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	19.393	-4.301	43.509	58.200	11.405	106.242	109.728	2.147	214.537	421.727	135.676	707.542
Socio-economic deprivation index	-0.008	-0.786	0.758	-0.061	-1.539	1.413	2.470	-0.797	5.636	4.519	-4.005	12.942
Foreign born population (%)	10.866	-10.413	31.910	18.911	-24.379	59.915	80.703	-11.655	173.890	-12.324	-251.203	230.900
Citizen population (%)	1.823	-22.992	25.712	-6.998	-56.362	40.230	33.046	-74.324	141.686	-163.052	-447.377	115.819
Mean travel time to work (min)	-0.534	-0.766	-0.313	-1.273	-1.746	-0.805	-3.611	-4.630	-2.627	-4.769	-7.262	-2.203
Total population	-0.000	-0.001	0.000	-0.001	-0.003	0.001	-0.007	-0.011	-0.003	-0.021	-0.031	-0.011
log-fit ratio	0.007	-0.052	0.068	0.006	-0.056	0.069	0.006	-0.052	0.065	0.006	-0.053	0.068
R^2	0.054	0.024	0.090	0.079	0.040	0.124	0.111	0.068	0.157	0.069	0.035	0.108
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 8: DV: Radius of Gyration

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	273.867	-115.154	651.024	847.467	191.779	1509.265	717.080	220.036	1215.730	1804.208	866.410	2742.674
Socio-economic deprivation index	9.345	-2.627	21.390	16.052	-4.591	36.968	21.515	6.084	37.300	39.670	10.670	68.828
Foreign born population (%)	122.690	-218.494	467.511	179.693	-401.416	738.992	246.341	-189.343	683.913	42.191	-781.623	859.618
Citizen population (%)	132.426	-245.313	524.378	90.669	-580.843	746.002	147.879	-366.620	655.883	-218.331	-1169.453	744.447
Mean travel time to work (min)	-8.953	-12.558	-5.372	-19.323	-25.658	-13.114	-19.967	-24.610	-15.356	-29.480	-38.087	-20.785
Total population	-0.023	-0.036	-0.009	-0.055	-0.078	-0.032	-0.049	-0.067	-0.031	-0.111	-0.144	-0.078
log-fit ratio	0.006	-0.052	0.066	0.006	-0.055	0.070	0.005	-0.053	0.062	0.005	-0.053	0.066
R^2	0.066	0.033	0.106	0.103	0.059	0.152	0.158	0.109	0.209	0.147	0.096	0.199
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 9: DV: Average Distance Between Reports

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	813.025	-227.511	1859.858	1981.426	174.247	3886.007	2098.026	708.639	3535.409	4473.072	1959.606	6995.162
Socio-economic deprivation index	36.271	4.258	68.614	41.684	-13.802	97.536	73.093	29.477	117.386	101.993	28.763	176.846
Foreign born population (%)	613.413	-322.095	1492.495	749.353	-936.593	2394.574	823.643	-442.715	2063.128	362.260	-1843.162	2562.503
Citizen population (%)	467.724	-590.144	1516.127	739.790	-1149.950	2572.828	385.905	-1030.490	1804.731	-153.675	-2636.014	2387.724
Mean travel time to work (min)	-27.504	-37.263	-18.013	-53.062	-70.824	-34.819	-56.639	-69.632	-43.715	-79.730	-101.923	-57.338
Total population	-0.077	-0.114	-0.040	-0.178	-0.246	-0.110	-0.147	-0.197	-0.098	-0.305	-0.389	-0.220
log-fit ratio	0.006	-0.054	0.066	0.006	-0.054	0.071	0.003	-0.058	0.063	0.005	-0.055	0.066
R^2	0.083	0.046	0.127	0.109	0.064	0.160	0.170	0.118	0.224	0.154	0.104	0.207
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 10: DV: Mean Home Distance

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	1343.863	174.911	2485.757	3861.704	1964.720	5751.944	2238.997	927.479	3530.747	5315.767	3085.415	7514.237
Socio-economic deprivation index	45.119	10.905	80.339	41.157	-16.304	99.073	70.427	28.565	112.761	84.007	15.361	150.804
Foreign born population (%)	881.169	-112.211	1867.209	-1133.390	-2805.052	535.836	898.169	-257.059	2036.997	-1231.037	-3112.836	686.892
Citizen population (%)	623.266	-541.368	1803.788	-1262.515	-3193.060	690.852	484.164	-860.740	1806.305	-1549.443	-3776.557	666.124
Mean travel time to work (min)	-43.464	-53.713	-33.043	-41.048	-58.910	-23.181	-59.996	-72.461	-47.239	-59.835	-79.544	-40.002
Total population	-0.119	-0.159	-0.079	-0.186	-0.253	-0.118	-0.166	-0.212	-0.118	-0.272	-0.348	-0.195
log-fit ratio	0.005	-0.054	0.065	0.007	-0.053	0.068	0.004	-0.052	0.061	0.005	-0.054	0.065
R^2	0.146	0.097	0.196	0.104	0.061	0.153	0.199	0.145	0.256	0.147	0.099	0.200
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 11: DV: Median Home Distance

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	1497.410	405.539	2578.813	4043.322	2059.972	6009.757	2231.463	945.239	3502.786	5509.636	3415.215	7625.920
Socio-economic deprivation index	40.145	8.024	73.817	35.661	-20.780	94.476	66.275	26.142	105.515	80.710	15.092	144.941
Foreign born population (%)	595.852	-344.586	1551.493	-1895.152	-3588.228	-217.918	665.163	-445.566	1772.485	-1861.189	-3760.028	-29.351
Citizen population (%)	351.361	-730.856	1445.792	-1774.607	-3763.266	191.009	316.343	-972.601	1619.246	-2035.902	-4188.213	40.215
Mean travel time to work (min)	-40.250	-49.780	-30.726	-31.161	-49.224	-13.393	-55.461	-67.442	-43.675	-52.632	-72.561	-33.058
Total population	-0.111	-0.150	-0.073	-0.164	-0.231	-0.095	-0.156	-0.201	-0.112	-0.257	-0.330	-0.182
log-fit ratio	0.006	-0.051	0.063	0.007	-0.055	0.070	0.003	-0.057	0.063	0.004	-0.055	0.064
R^2	0.146	0.098	0.196	0.092	0.050	0.139	0.196	0.141	0.250	0.140	0.091	0.191
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 12: DV: Maximum Home Distance

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	1712.411	-821.172	4305.844	5270.919	881.945	9742.693	4189.822	1204.975	7271.296	9880.205	4745.854	14863.554
Socio-economic deprivation index	88.014	12.476	166.270	109.318	-22.573	244.892	157.873	61.136	254.051	223.307	63.506	380.144
Foreign born population (%)	2014.146	-230.913	4233.077	1036.944	-2716.629	4906.041	2254.126	-418.302	4888.552	90.048	-4457.662	4562.759
Citizen population (%)	1716.589	-897.747	4266.053	777.648	-3668.202	5266.522	1423.159	-1669.749	4459.208	-915.507	-5957.577	4262.532
Mean travel time to work (min)	-76.124	-99.599	-52.886	-113.776	-154.632	-73.663	-126.875	-155.085	-99.022	-156.507	-203.753	-110.409
Total population	-0.204	-0.293	-0.114	-0.393	-0.544	-0.242	-0.327	-0.437	-0.217	-0.629	-0.808	-0.446
log-fit ratio	0.007	-0.051	0.069	0.006	-0.052	0.065	0.003	-0.054	0.064	0.006	-0.054	0.065
R^2	0.100	0.058	0.145	0.098	0.056	0.146	0.172	0.119	0.228	0.144	0.093	0.196
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 13: DV: 311 Subject Coverage

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	2.786	1.919	3.665	6.195	4.536	7.827	3.718	2.502	4.934	0.539	0.347	0.736
Socio-economic deprivation index	0.022	-0.006	0.050	0.049	-0.001	0.098	0.047	0.010	0.085	0.009	0.003	0.015
Foreign born population (%)	-0.128	-0.896	0.631	-1.070	-2.516	0.362	0.291	-0.741	1.298	-0.023	-0.190	0.144
Citizen population (%)	-0.769	-1.632	0.115	-2.703	-4.378	-1.054	-0.649	-1.867	0.570	-0.157	-0.357	0.040
Mean travel time to work (min)	-0.019	-0.027	-0.011	-0.042	-0.058	-0.027	-0.046	-0.057	-0.034	-0.007	-0.009	-0.005
Total population	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
log-fit ratio	0.006	-0.051	0.067	0.006	-0.054	0.069	0.004	-0.053	0.065	0.004	-0.052	0.062
R^2	0.084	0.045	0.128	0.137	0.087	0.190	0.159	0.108	0.213	0.154	0.104	0.207
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

Table 14: DV: Subject Diversity (HHI)

	Model 1: Non-Govt Users			Model 2: Non-Govt Users Reporting >2			Model 3: All Users			Model 4: All Users Reporting >2		
	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%	Est.	CI 5%	CI 95%
(Intercept)	0.418	0.231	0.600	1.146	0.852	1.437	8.076	5.907	10.258	1.200	0.915	1.470
Socio-economic deprivation index	0.006	0.001	0.012	0.009	-0.000	0.018	0.088	0.016	0.158	0.011	0.002	0.019
Foreign born population (%)	-0.036	-0.201	0.128	-0.341	-0.594	-0.084	-1.226	-3.209	0.691	-0.340	-0.580	-0.081
Citizen population (%)	-0.141	-0.328	0.054	-0.586	-0.873	-0.289	-3.270	-5.500	-1.066	-0.585	-0.860	-0.291
Mean travel time to work (min)	-0.004	-0.006	-0.002	-0.006	-0.009	-0.003	-0.063	-0.083	-0.043	-0.007	-0.009	-0.004
Total population	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
log-fit ratio	0.007	-0.053	0.069	0.005	-0.054	0.066	0.005	-0.054	0.061	0.005	-0.052	0.064
R^2	0.089	0.050	0.134	0.117	0.071	0.166	0.142	0.095	0.192	0.138	0.091	0.190
N (600m hexagons)	387	–	–	365	–	–	388	–	–	374	–	–

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