Plug In For Lunch: Exploring Dining Options Around American EV Charging Stations

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Abstract

Drivers of Electric Vehicles (EVs) must spend some time around EV Charging Stations (EVCS). This on-site dwelling time can create opportunities for EV drivers to interact with urban amenities and nearby businesses. This driver-business interaction is known to have a positive spillover effect on the local economy by attracting high-income drivers to low-income areas. Using methods in Geographic Information Systems (GIS) and Artificial Intelligence (AI), this paper reviews the status quo of EVCS placement regarding this interaction, across the Contiguous United States. We use dining locations, such as restaurants and bakeries, as a mediator of this interaction. The shortage of dining options is apparent in regions where businesses are sparsely and linearly spread out along the road network without a dense commercial core. A Large Language Model (LLM)-assisted analysis of the type of cuisine each dining location serves reveals room for improvement in the access to certain cuisine types. Based on these observations, this paper proposes an initiative to strategically deploy EVCS around dining locations that serve low-access cuisine types. This can contribute to destination development for EV drivers and encourage driver-business interaction for local business owners, potentially delivering an economic boost to the surrounding community. This paper demonstrates the application of AI and LLM to loosely-formatted, crowdsourced geospatial data and the practice of urban planning.

1 Introduction

Electric Vehicles (EVs) became a mainstream mode of transportation in the United States and other parts of the world. Global EV sales in the year 2024 reached a record high of 17 million units [1], while Electric Vehicle Charging Stations (EVCS), a set of public infrastructure used to recharge EVs, are rapidly expanding [2]. Recent research investigated multiple aspects of EVCS, including demand modeling [3], public perception [4, 5], and site selection analysis [6, 7]. One rarely explored aspect of EVCS is the on-site activity of the drivers while their vehicles are plugged in. Although the charging speed varies by battery capacity and charging infrastructure, drivers using public EVCS must spend some time around the plug. During this dwell time, EV drivers can interact with nearby urban amenities [8]. Surveys show that between 35% and 45% of drivers visit nearby shops [9], and 60% of them prefer to eat food and buy refreshments [10].

This nature of EVCS can provide a unique opportunity for attracting potential customers to communities. Zheng et al. [11] examined the high-level impact of EVCS on the local economy with a spatio-temporal analysis in California, United States. They found that one additional EVCS leads to an incremental increase in annual spending on nearby businesses of $1,478 (+1.4%). This effect was found to be more pronounced when an EVCS is in proximity to Points Of Interest (POI): hotels,

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restaurants, retail shops, and entertainment venues. Even in disadvantaged neighborhoods, the increase in business spending was statistically significant, suggesting that EVCS user experience and driver-business interaction can be an economic catalyst at the neighborhood level. Following this concept, there is a need to assess the status quo of EVCS deployment; are EVCS placed in a way that effectively and equitably actualize this effect? If not, how can we facilitate more interactions between EV drivers and the local businesses around EVCS?

This paper utilizes Artificial Intelligence (AI) and Geographic Information Systems (GIS) for a large-scale analysis of 121,177 dining locations and 27,042 EVCS locations across the Contiguous United States. This paper particularly puts dining locations as a mediator of driver-business interaction because they are one of the short-medium-term destinations (POIs) of EV drivers [12], their unique experiences and cuisine can be effective in destination development [13–16], and it is known that individual preferences and demographic factors on food can create distinct travel patterns [17].

Namely, this paper uses Google's Large Language Model (LLM), *Gemini 2.5 Flash Lite* [18] and its accompanying word embedding model, *gemini-embedding-001* [19], to perform a novel analysis on what type of food each dining location serves. Upon analysis, this paper proposes a strategic urban planning initiative that can better promote driver-business interaction and generate additional revenue for local business owners. This paper demonstrates the application of AI and LLM to (1) loosely-formatted, crowdsourced geospatial data and (2) the practice of urban planning for transportation infrastructure and public policy for economic development.

2 Methods

2.1 Study Area and Data

The study area of this paper is 37 Metropolitan Divisions (MDs) in the Contiguous United States, as shown in Figure A.1. MDs provide better control over overbounding and underbounding issues [20], and systematically represent major cities with adequate granularity. For each MD, we gathered two sets of data: EVCS locations and dining locations. EVCS location data was retrieved from the Alternative Fueling Station Locator by the United States Department of Energy [21]. Dining location data was retrieved from OpenStreetMap (OSM), a geospatial data platform frequently used in urban transportation research [22, 23], via Overpass Turbo. We extracted all features tagged with the key `amenity` and values `restaurant`, `food_court`, `fast_food`, or `cafe` within our study area. For example, data of the Boston Metropolitan Area is shown in Figure A.2.

2.2 Assessing the Quantity of Dining Options Around EVCS

We used ArcGIS Pro 3.4.0 to count the number of unique dining locations within a 0.25-mile (400-meter) radius from each EVCS. This is called *buffer analysis*. 0.25 miles is the distance that a person can walk within 5 minutes, assuming they can walk at 3 miles per hour (distance = speed $\times$ time), in accordance with previous urban planning research [24–27]. We adjusted for differences in the baseline total count of dining locations across MDs by creating a rank-ordered Dining Option Score (DOS). We calculated the DOS of MD i by dividing the mean count of dining options around EVCS by the log-normalized count of total dining locations within that MD, as Equation 1.

$$\text{Dining Option Score}_i = \frac{E(\text{Number of Dining Locations Around EVCS})_i}{\log_{10}(\text{Number of Total Dining Locations})_i} \tag{1}$$

2.3 Assessing the Diversity of Dining Options Around EVCS by Cuisine Type

2.3.1 Defining Cuisine Types with Natural Language Processing

To assess the diversity in dining options by the type of food they serve, we analyzed the key-value pairs of the OSM `cuisine` tag. Among 121,177 dining locations in our data, there were 4,421 unique, non-null cuisine tags. Categorizing dining locations by 4,421 unique cuisine types is ineffective. Thus, we needed to abstract these cuisine tags into a handful of distinct clusters by defining a new categorical system. We approached this task as a Natural Language Processing (NLP) problem. The use of NLP in urban planning research is an emerging concept that provides significant opportunities [28], and has been utilized in previous geospatial research [29], including OSM data analysis [30].

First, we tokenized 4,421 OSM cuisine tags and added contextual information on each of them. For example, a dining location with the cuisine tag `greek;lebanese;seafood` was represented as a sentence: "A dining location that guests tagged with: greek and lebanese and seafood". Then, we used Google Gemini's word embedding model, *gemini-embedding-001* [19], to translate each of these sentences into a vector representation of 768 dimensions. Next, we performed k-means clustering, a popular unsupervised machine learning algorithm [31], on 4,421 vector representations. The value of k was determined with Within-Cluster Sum of Squares (WCSS) values, commonly known as the 'elbow method' [32]. With optimal k=5, results are shown in Figure A.4.

This presented 5 cuisine types: Asian & Pacific (e.g., "Chinese and Japanese and sushi"), Cafe & Desserts (e.g., "donut and coffee_shop"), American Classics (e.g., "American and wings"), Italian (Pizza & Pasta), and Latin American (e.g., "Mexican and Cuban"). Restaurants serving continental European or Mediterranean cuisine were located in the middle, alongside other generic dining locations (e.g., "European"). There were some other cultural cuisines on the left-hand side of the figure (e.g., "Asian and Mexican").

We also incorporate publicly available, expert sources to better support our definition of cuisine types, since 4,421 OSM cuisine tags do not represent all dining locations in our data. About half of the dining locations did not have a tag. Marcus [33], in his book, lists Black American, Asian, Hispanic, Mediterranean, Cajun, Caribbean, Eastern Indian, European, and Indigenous American cuisine as 'global cuisines' that influenced the tastes and health of the United States people. Culinary Arts Academy Switzerland [34], on their website, lists Italian, Japanese, Indian, Chinese, Thai, Mexican, Greek, and French cuisine as 'most popular and widely loved international cuisines'. BBC [35] also has a lengthy list on their website. Balancing between NLP-based clustering and expert sources, we made a comprehensive, combined list of cuisine type category as Table B.2. Note that we added special labels for Quick Service Fast Food & Deli, Vegetarian & Salad & Juice, Other Cultural Cuisine, Contemporary Fusion, and *unknown*, for dining locations that do not fall in any category.

2.3.2 LLM-Assisted Semantic Categorization with Google Gemini

With our combined definition of cuisine types, we prompted an LLM to categorize all 121,177 dining locations by labeling each of them with a cuisine type. Many previous urban planning research employed LLM for text processing [36–40]. The benefit of the LLM approach is that it requires minimal preprocessing compared to classical machine learning approaches, especially with no extensive calibration and domain-specific training [41, 42]. Also, the LLM approach can mimic human judgment, which is useful in understanding cuisine tags. For example, if we want to describe a restaurant that serves `greek;lebanese;seafood` in one word, a knowledgeable human could semantically collapse the three tags as one concept, 'Mediterranean', while a rule-based machine (e.g., regular expression) may not perform as well as needed. We used Google's newest LLM, *Gemini 2.5 Flash Lite* [18]. Via its Python API, we prompted Gemini to read the following OSM tags: `amenity`, `brand`, `cuisine`, and `name`, and return a single label within the preset cuisine list (Section 2.3.1) that best represents each dining location. An overview of this procedure is shown in Figure 1.

To evaluate Gemini's performance, we manually labeled a sample of 300 dining locations, then instructed Gemini to do the same. Gemini labeled 87.33% of dining locations the same as what a human annotator did. The categorization results were imported into ArcGIS. We calculated the number of dining locations that serve each cuisine label. Then, we performed a 0.25-mile buffer analysis around each EVCS and organized the ratio of EVCS accessible to each cuisine type by MD.

To adjust for differences in the baseline cuisine availability across MDs, the ratio of EVCS accessible to each cuisine type of each MD was compared to the baseline ratio of all dining locations within that MD, including ones more than 0.25 miles away from EVCS. We created another score titled Dining Option Diversity Concordance Scores (DODCS) as in Equation 2. It indicates how much EVCS are accessible to each kind of cuisine type, compared to the baseline ratio of dining locations that serve each cuisine type. A value of 1 means that the two ratios are equal. For example, if 10% of dining locations within MD i serve cuisine j, while only 8% of EVCS are accessible to that cuisine via a 5-minute walk, DODCS$_{i,j}$ is 0.8.

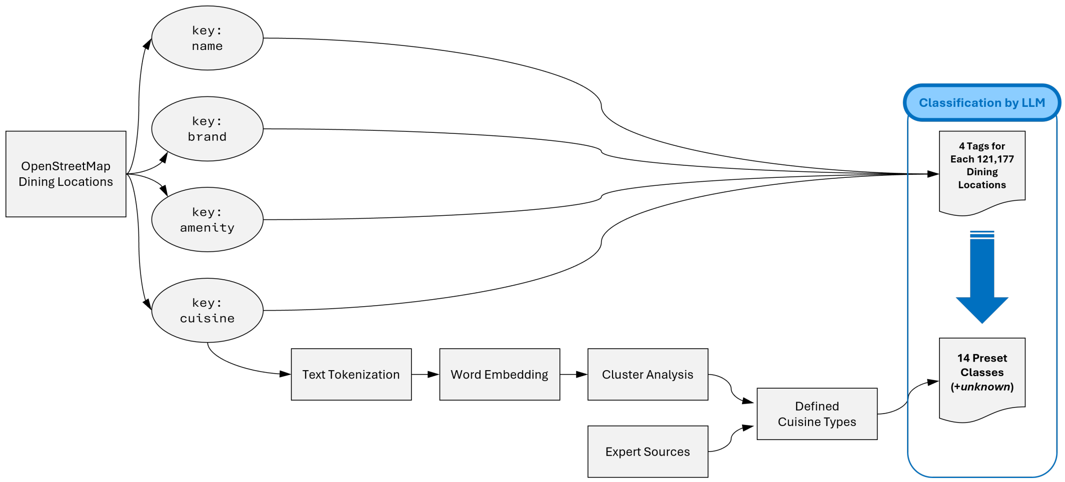

Figure 1: An Overview of Dining Option Diversity Assessment with Google Gemini

$$\text{Dining Option Diversity Concordance}_{i,j} = \frac{\text{Ratio of EVCS Accessible to Cuisine } j \text{ in Region } i}{\text{Ratio of Dining Locations that serve Cuisine } j \text{ in Region } i} \tag{2}$$

3 Results and Discussion

3.1 The Spatial Distribution of Dining Locations Governs EVCS Dining Options

The number of dining locations around each EVCS, by each MD, is shown in Table B.3. At the top of the list, Seattle-Bellevue-Kent (Seattle 2) had an average of 35.22 dining options within a 5-minute walking distance from an EVCS (Adjusted DOS = 9.372). On the other hand, Nassau County-Suffolk County, NY (New York 2) had an average of only 2 dining options within a 5-minute walking distance from EVCS (Adjusted DOS = 0.668). A considerable difference in the count of dining options around EVCS is observable. This suggests geographic heterogeneity in driver-business interactions.

A side-by-side comparison between the good and bad cases suggests that the spatial distribution of commercial establishments is driving the differences in the number of dining options around EVCS. Figures A.5(a) and A.5(b) show EVCS locations and dining locations in Seattle-Bellevue-Kent (Seattle 2) and Nassau County-Suffolk County (New York 2), repsectively. In Seattle 2, dining locations are densely clustered around the downtown area. A few well-placed EVCS can cover many dining locations. EV drivers parking in that area would have a handful of dining options within a 5-minute walking distance. Seattle 2 would have a high EV driver-business interaction, and local businesses would generate additional revenue from these interactions.

On the other hand, New York 2 lacks a central core in which dining locations are clustered. Dining locations are less dense and linearly distributed along the east-west road network. The sparse nature of New York 2 makes a given EVCS location to have few dining locations in proximity. EV drivers in New York 2 are discouraged from interacting with local businesses since they would have to walk a prolonged distance to reach one of their preference. This, in turn, can hinder local businesses from generating additional revenue from EVCS infrastructure.

3.2 Initiative on Deploying EVCS Around Low-access Cusine Types

An easy solution to mitigate this problem is to install more EVCS and make more businesses accessible for EV drivers. However, installing new EVCS is financially limited; EVCS operators must bear a higher operational cost for each new installation. Especially in regions with a sparse distribution of local businesses, like New York 2, more EVCS would be needed to deliver the same driver-business interaction as in denser locations, like Seattle 2. Therefore, there is a need for an alternative, effective EVCS deployment strategy that delivers high interaction with fewer EVCS.

While it is possible to implement engineering solutions, such as the distributed microoutlet depicted in Figure A.6, we leverage this paper's assessment of dining options diversity around EVCS to create a deployment strategy. The baseline ratio of each cuisine type within each MD is shown in Table B.4. The ratio of EVCS that are accessible to each type of cuisine by a 5-minute walk is shown in Table B.5. The Dining Option Diversity Concordance Scores (DODCS) are shown in Table B.6. It indicates the ratio of EVCS that are accessible to each kind of cuisine type, compared to the MD-wide baseline ratio of dining locations that serve each cuisine type (Table B.5 $\div$ Table B.4). Associating dining locations to each EVCS, the Chi-square test of independence yielded $\chi^2(504) = 17407.184$ and $p < .001$, confirming the difference in cuisine diversity across MDs.

Averaging across all 37 MDs, noticeable differences were observed in accessibility from EVCS to each cuisine type. European cuisine other than Italian (DODCS = 1.45), Mediterranean & Middle Eastern (1.26), and Japanese cuisine (1.11) turned out to be more accessible around EVCS than their respective MD-wide baseline. There are not so many dining locations that serve Italian (0.75), Mexican & Latin American (0.81), and non-Japanese East Asian (0.91) cuisines around EVCS, compared to the MD-wide baseline. In addition, as in Figure A.7, each MD has a unique room for improvement in the accessibility from EVCS to each cuisine type. For instance, EVCS placement in Rockingham County-Strafford County (Boston 3) turned out to provide limited access to Mediterranean & Middle Eastern Cuisine in proximity to their EVCS, compared to its MD-wide baseline ratio (DODCS $= 0.263 < 1$).

We propose that urban planners and policymakers consider deploying EVCS around these low-access cuisine types. Improving access to low-access cuisine types (denoted by red crosses in Figure A.7) can foster food tourism and destination development [13–16], encouraging EV drivers to visit further places and interact with local businesses. Also, this can attract more drivers to areas that are less preferred by EVCS operators due to the lack of parking demand and commercial establishments, reducing their financial burden of deploying new EVCS. Implementing this initiative will deliver opportunities for generating additional revenue to local business owners and communities where EVCS operators pay less attention.

4 Conlcusion

The rapid adoption of EVs introduces economic opportunities to local businesses, particularly from increased interaction between EV drivers and the urban amenities around EVCS. Yet, the number of dining options accessible within a 5-minute walking distance of EVCS was spatially heterogeneous across metropolitan divisions. This variability is attributable to the spatial distribution of urban amenities; some cities have a dense commercial core where dining locations are packed together, while some cities have dining locations sparsely spread across the road network. These variations highlight missed opportunities regarding an economic boost to local business owners, suggesting the inequality of the auxiliary benefits of EVCS, in addition to the infrastructure itself [37].

To maximize this effect from EVCS in those areas, we propose a strategic initiative to deploy new EVCS in proximity to currently low-access cuisine types: ones without an EVCS for their customers to plug in. An urban policy at the metropolitan level that incentivizes the deployment of EVCS around dining locations that serve a cuisine type with DODCS < 1 can catalyze an economic boost to communities. Calculating the DODCS metric is made by employing an LLM to assist the paper's analysis, which is a novel application of AI on dining location data. This initiative can supplement the lack of driver demand by attracting more drivers, reducing the financial burden of EVCS operators, and contributing to equitable urban economic development.

The biggest limitation of this paper is the difficulty in predicting and quantifying the monetary potential of the proposed strategy. Our DODCS metric indicates how much a cuisine type is inaccessible from EVCS, not how much additional revenue it can generate by making it accessible to EV drivers. While it is shown that EVCS can generate additional revenue for communities [11], the amount and strength of this revenue should differ across regions, neighborhoods, cuisine types, and latent interaction with other urban amenities.

Future research can also incorporate (1) more geospatial data, such as other POIs, user reviews, and street view images, and (2) build a stronger semantic foundation for the LLM to better identify cuisine types, such as a knowledge graph for Retrieval Augmented Generation (RAG). This will contribute to the development of Geospatial Artificial Intelligence (GeoAI) [43].

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A Supplementary Figures

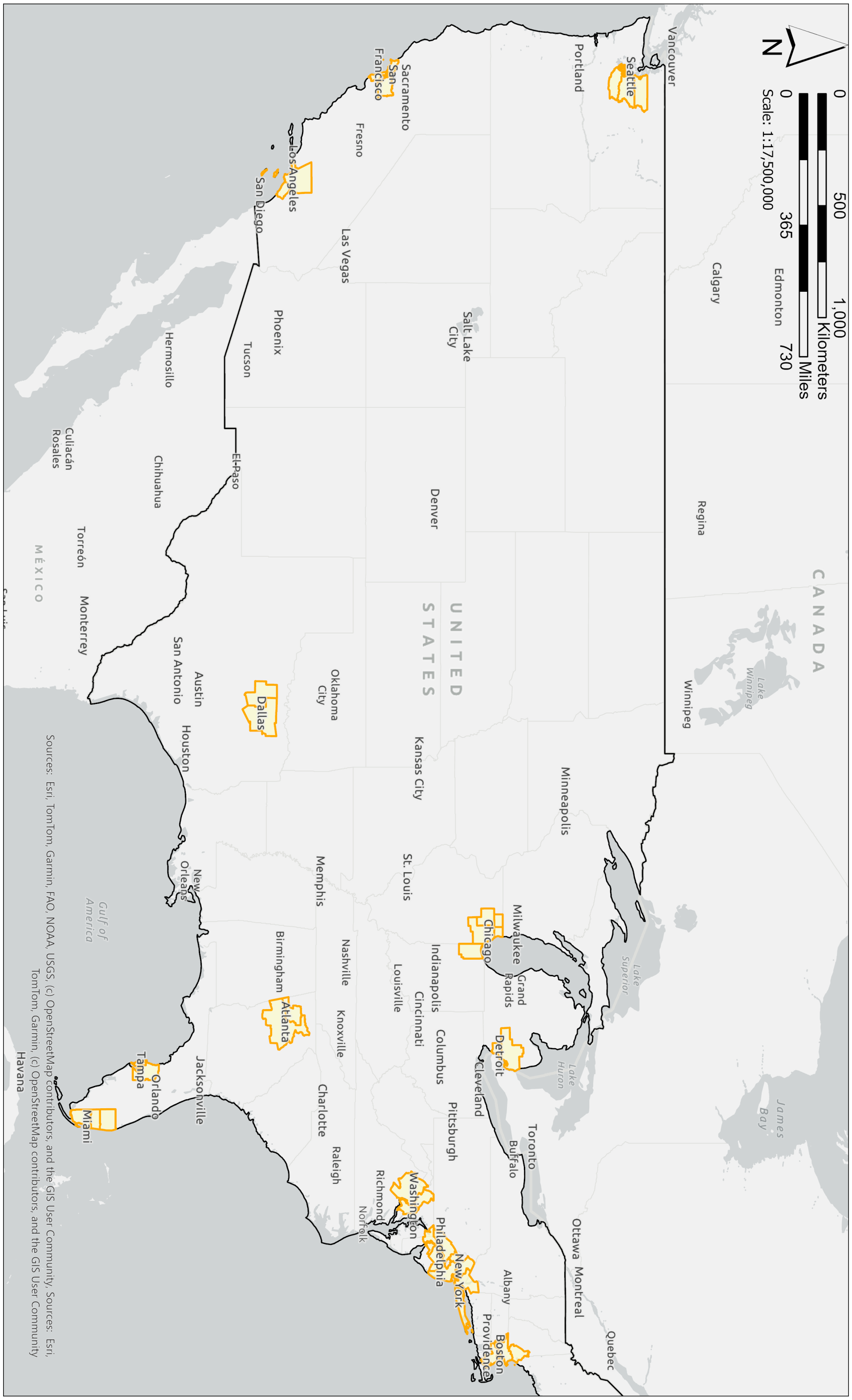

Figure A.1: 37 Metropolitan Divisions (MDs) in the contiguous United States colored in yellow

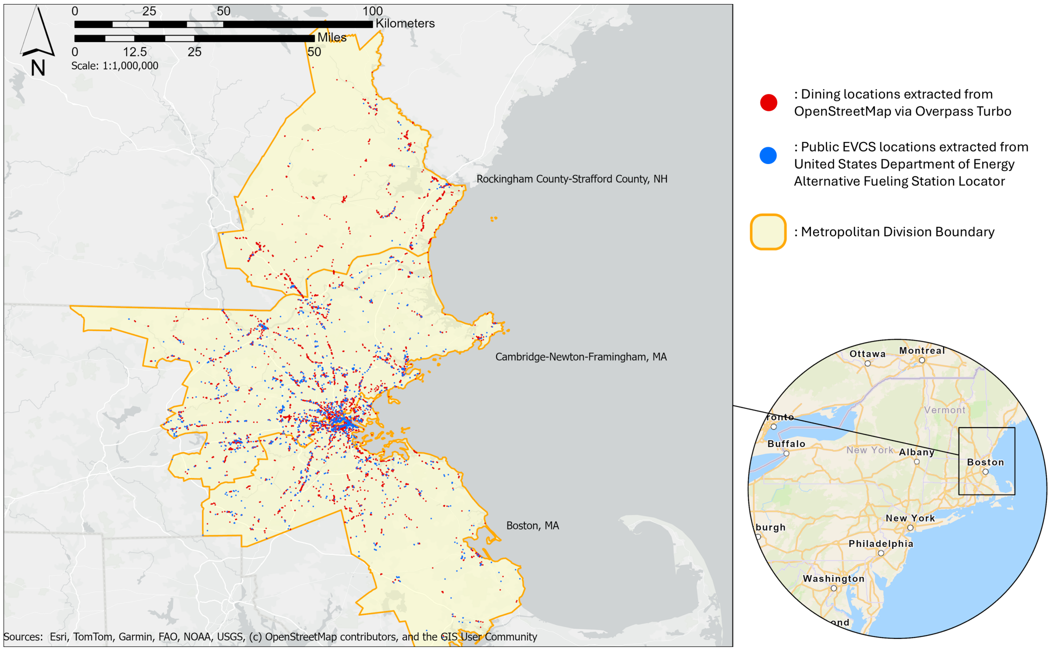

Figure A.2: Dining locations (red) and EVCS locations (blue) in the Boston Metropolitan Area, Massachusetts

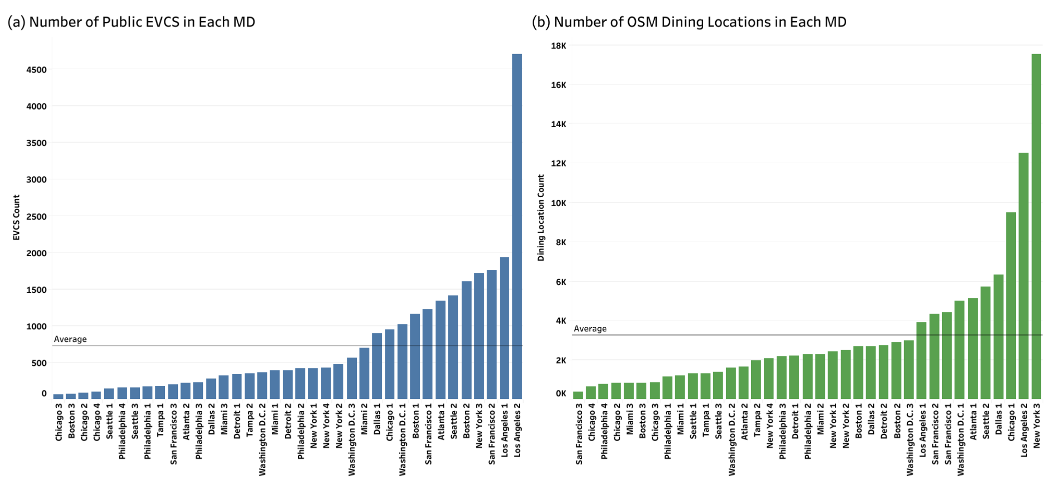

Figure A.3: Count of EVCS and Dining Locations by Metropolitan Division; Sorted Ascending

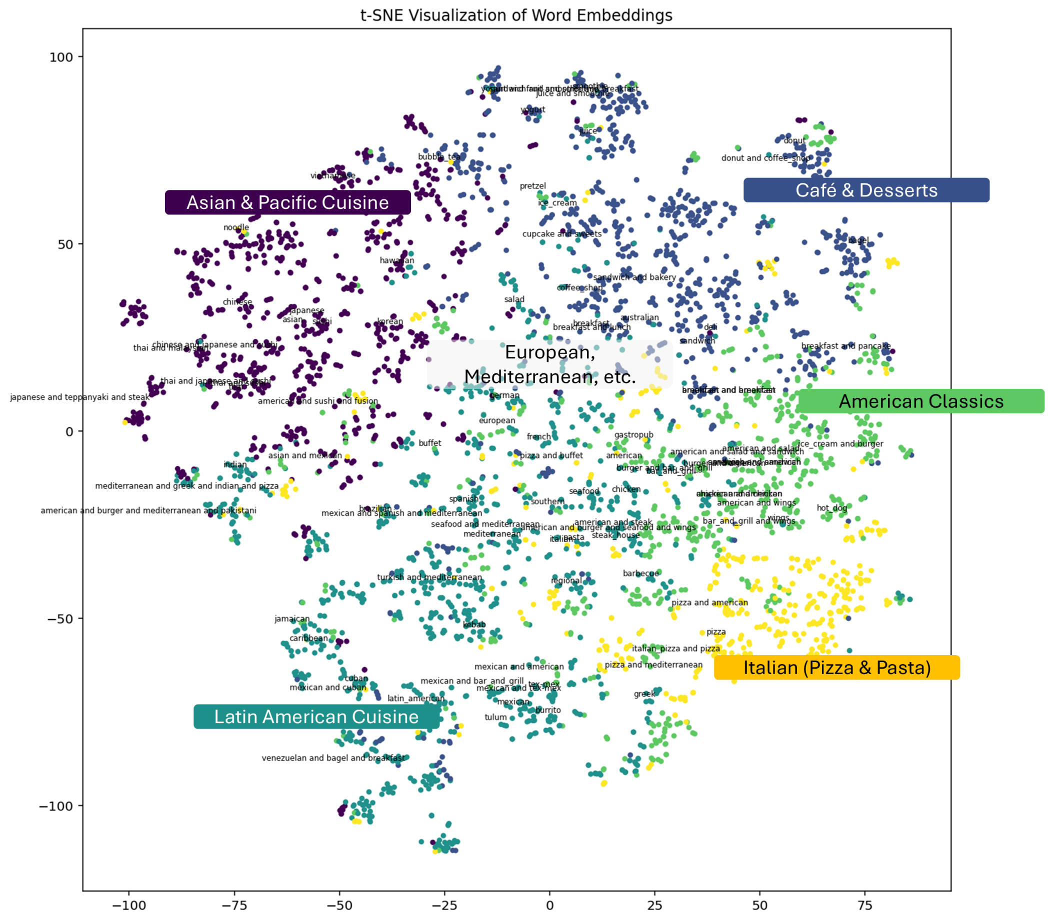

Figure A.4: Clustering OSM cuisine tags as word embeddings; dimensionality reduced from 768 to 2 via t-Distributed Stochastic Neighbor Embedding (t-SNE)

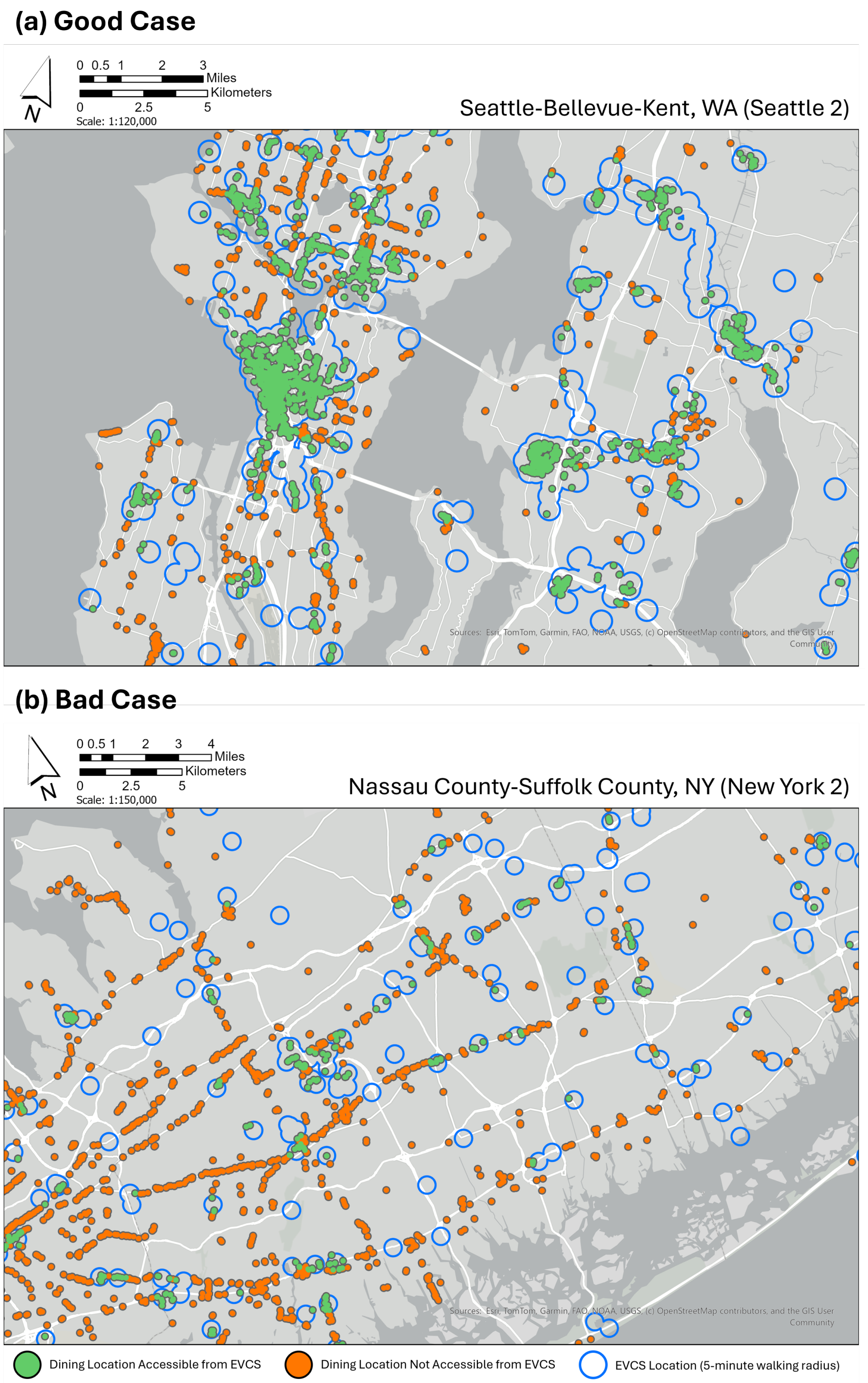

Figure A.5: A comparison between regions with the highest and the lowest DOS. Green circles indicate dining locations that are located within a 5-minute walking radius from one or more EVCS, while orange circles indicate those that are not.

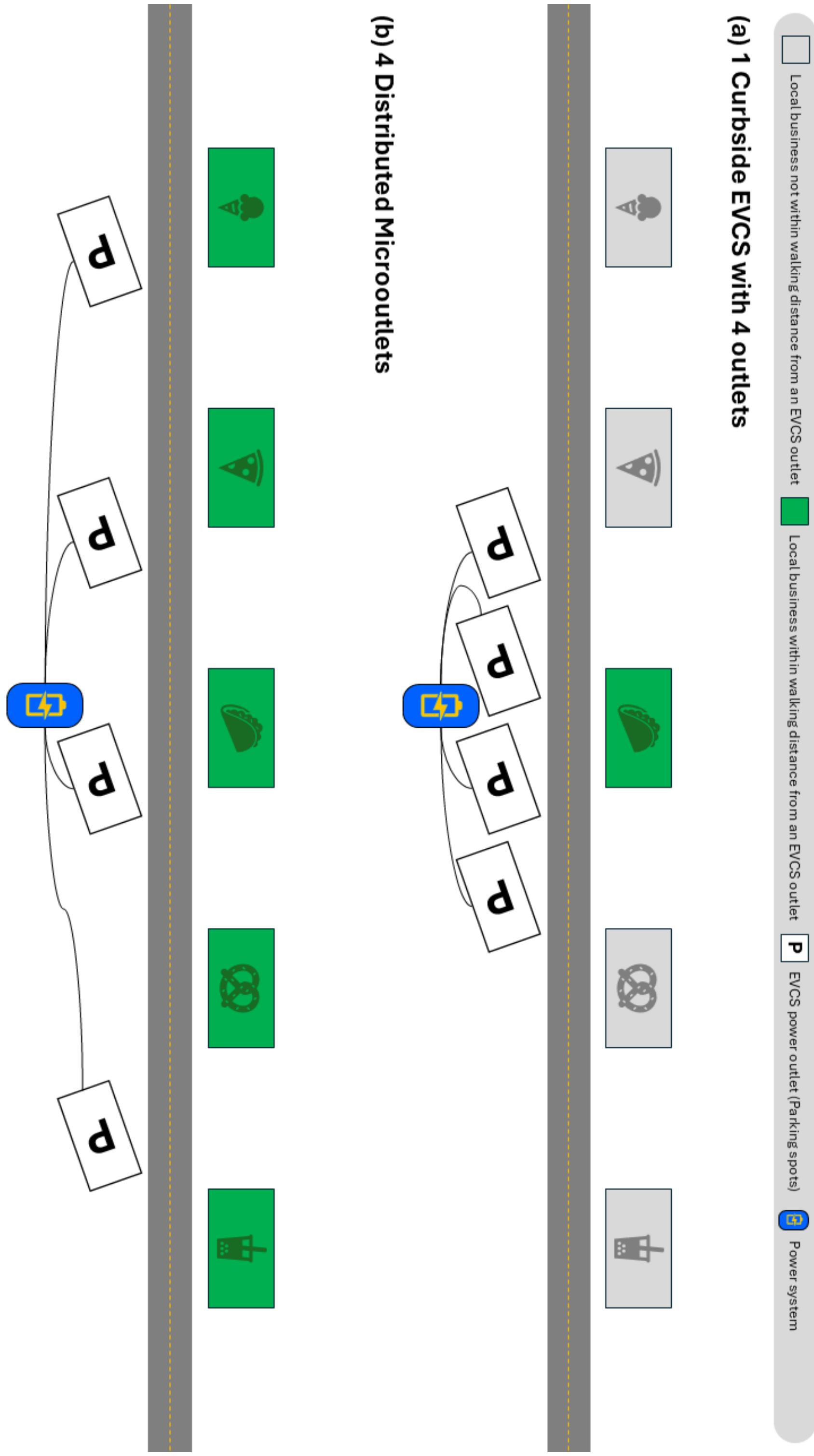

Figure A.6: The Microoutlet Concept. Distributing charging outlets apart from each other and along the street can increase the number of local businesses that are within walking distance of EV parking spots.

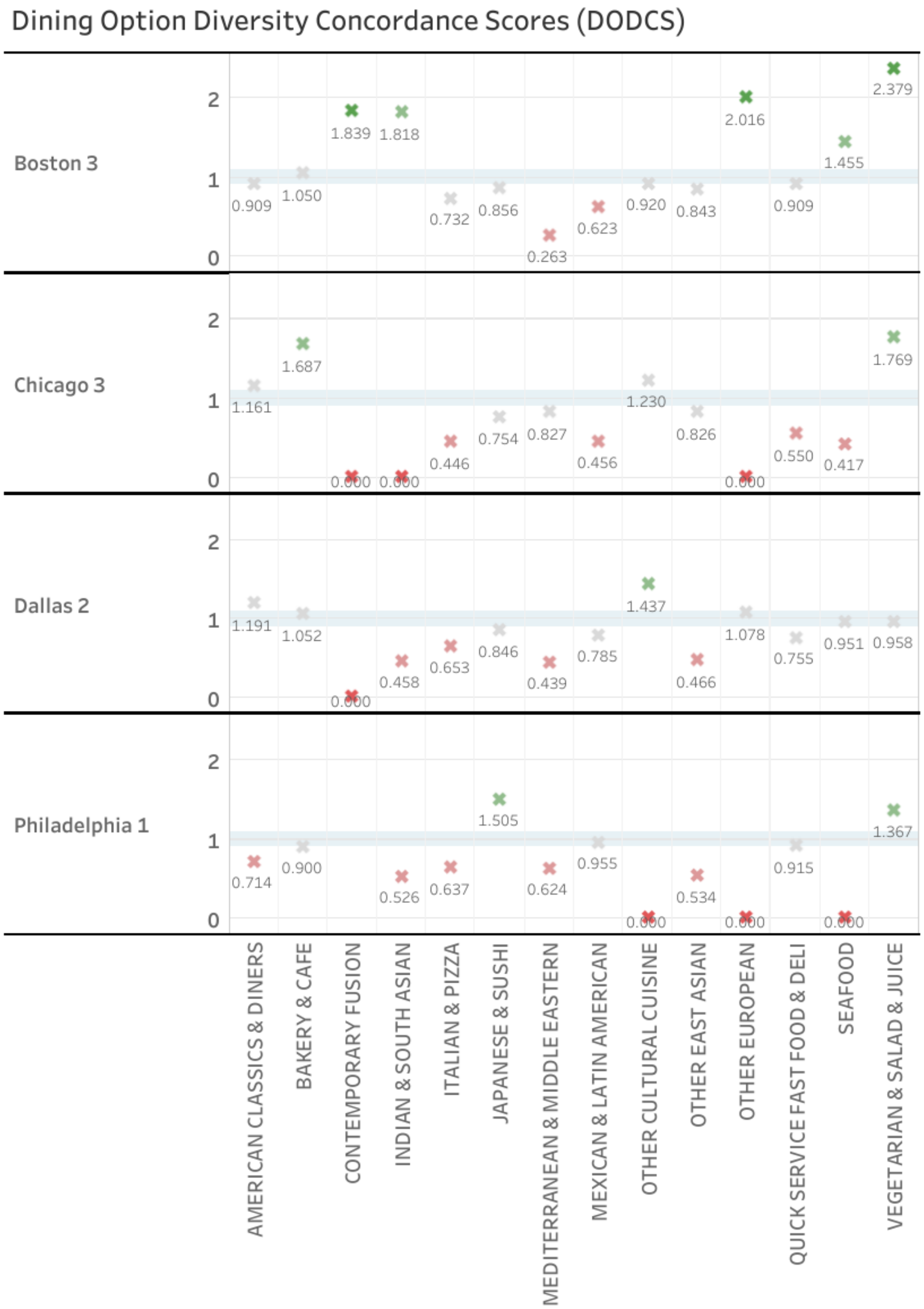

Figure A.7: Dining Option Diversity Concordance Scores of select MDs. Red crosses indicate low-access cuisines, for which the ratio of EVCS that serve that cuisine type is lower than that of the MD's baseline ratio of dining locations that serve it (DODCS < 1). Green crosses indicate the opposite (DODCS > 1).

B Supplementary Tables

Table B.1: Count of Dining Locations and EVCS by Metropolitan Division

Code	Metropolitan Division	Dining Locations	EVCS
Atlanta 1	Atlanta-Sandy Springs-Roswell	5,131	1,344
Atlanta 2	Marietta	1,637	218
Boston 1	Boston	2,685	1,161
Boston 2	Cambridge-Newton-Framingham	2,907	1,609
Boston 3	Rockingham Co.-Strafford Co.	836	80
Chicago 1	Chicago-Naperville-Schaumburg	9,491	951
Chicago 2	Elgin	827	87
Chicago 3	Lake Co.	863	70
Chicago 4	Lake Co.-Porter Co.-Jasper Co.	655	109
Dallas 1	Dallas-Plano-Irving	6,346	900
Dallas 2	Fort Worth-Arlington-Grapevine	2,694	280
Detroit 1	Detroit-Dearborn-Livonia	2,210	346
Detroit 2	Warren-Troy-Farmington Hills	2,752	398
Los Angeles 1	Anaheim-Santa Ana-Irvine	3,891	1,932
Los Angeles 2	Los Angeles-Long Beach-Glendale	12,512	4,696
Miami 1	Fort Lauderdale-Pompano Beach-Sunrise	1,201	390
Miami 2	Miami-Miami Beach-Kendall	2,282	700
Miami 3	West Palm Beach-Boca Raton-Delray Beach	828	325
New York 1	Lakewood-New Brunswick	2,449	427
New York 2	Nassau Co.-Suffolk Co.	2,496	479
New York 3	New York-Jersey City-White Plains	17,508	1,718
New York 4	Newark	2,095	431
Philadelphia 1	Camden	1,134	169
Philadelphia 2	Montgomery Co.-Bucks Co.-Chester Co.	2,277	419
Philadelphia 3	Philadelphia	2,181	233
Philadelphia 4	Wilmington	781	160
San Francisco 1	Oakland-Fremont-Berkeley	4,399	1,229
San Francisco 2	San Francisco-San Mateo-Redwood City	4,345	1,755
San Francisco 3	San Rafael	395	206
Seattle 1	Everett	1,322	146
Seattle 2	Seattle-Bellevue-Kent	5,727	1,415
Seattle 3	Tacoma-Lakewood	1,394	167
Tampa 1	St. Petersburg-Clearwater-Largo	1,337	179
Tampa 2	Tampa	1,974	355
Washington D.C. 1	Arlington-Alexandria-Reston	5,015	1,022
Washington D.C. 2	Frederick-Gaithersburg-Bethesda	1,630	369
Washington D.C. 3	Washington	2,970	567
Average		3,275	731
Total		121,177	27,042

Table B.2: Definition of Cuisine Types

Source	Category of Cuisine Types
NLP (Word Embedding and Clustering)	Asian & Pacific, Cafe & Desserts, American Classics, Italian (Pizza & Pasta), Latin American
Marcus [33]	Black American, Asian, Hispanic, Mediterranean, Cajun, Caribbean, Eastern Indian, European, Indigenous American
Culinary Arts Academy Switzerland [34]	Italian, Japanese, Indian, Chinese, Thai, Mexican, Greek, French
BBC [35]	African, American, British, Caribbean, Chinese, East European, French, Greek, Indian, Irish, Italian, Japanese, Korean, Mexican, Nordic, North African, Pakistani, Portuguese, South American, Spanish, Thai and South-East Asian Turkish and Middle Eastern
Combined List of Cuisine Type Category (NLP + Expert Sources)	Bakery & Cafe, Quick Service Fast Food & Deli American Classics & Diners, Italian & Pizza, Mexican & Latin American, Other East Asian, Japanese & Sushi, Mediterranean & Middle Eastern, Vegetarian & Salad & Juice, Seafood, Other European, Indian & South Asian, Contemporary Fusion, Other Cultural Cuisine, *unknown*

Table B.3: Number of dining locations within a 5-minute walk from each EVCS by Metropolitan Division; Sorted by Dining Option Score (DOS) in descending order.

Metro Division (Code)	EVCS Count	Total Dining Locations	Dining Options (Min)	Dining Options (Mean)	Dining Options (Median)	Dining Options (Max)	% of EVCS with No Nearby Dining Options	& of EVCS with More Than 5 Dining Options	Dining Option Score
Seattle 2	1,344	5,727	0	35.22	22	151	11.5%	70.3%	**9.372**
Washington D.C. 3	218	2,970	0	29.49	14	129	16.6%	63.0%	**8.492**
New York 3	1,161	17,508	0	26.57	7	288	18.9%	51.6%	**6.262**
Philadelphia 3	1,609	2,181	0	17.51	5	109	14.2%	49.4%	**5.245**
San Francisco 2	80	4,345	0	17.65	5	187	27.2%	45.6%	**4.852**
Boston 1	951	2,685	0	16.2	6	126	30.1%	50.5%	**4.724**
Chicago 1	87	9,491	0	16.99	5	123	21.0%	46.8%	**4.272**
Detroit 1	70	2,210	0	14.17	3	75	24.9%	41.0%	**4.237**
Washington D.C. 2	109	1,630	0	12.57	7	63	20.3%	56.6%	**3.913**
San Francisco 1	900	4,399	0	12.35	3	121	36.7%	43.0%	**3.390**
Washington D.C. 1	280	5,015	0	10.56	6	56	21.6%	52.8%	**2.854**
Boston 3	346	836	0	8.24	3	49	13.8%	42.5%	**2.820**
Los Angeles 2	398	12,512	0	10.92	5	91	20.8%	49.1%	**2.665**
Seattle 1	1,932	1,322	0	7.47	4.5	54	26.0%	41.1%	**2.393**
Tampa 1	4,696	1,337	0	7.2	2	45	41.3%	30.2%	**2.303**
Seattle 3	390	1,394	0	7.22	4	29	20.4%	45.5%	**2.296**
Miami 2	700	2,282	0	7.49	3	57	22.1%	37.6%	**2.230**
Atlanta 2	325	1,637	0	6.17	4	39	22.0%	37.6%	**1.920**
Boston 2	427	2,907	0	6.39	2	53	33.6%	33.6%	**1.845**
Tampa 2	479	1,974	0	5.82	2	33	33.5%	35.5%	**1.766**
Atlanta 1	1,718	5,131	0	6.29	3	62	30.1%	38.2%	**1.695**
San Francisco 3	431	395	0	4.05	2	33	36.9%	25.7%	**1.560**
Los Angeles 1	169	3,891	0	5.31	3	55	27.5%	32.3%	**1.479**
Chicago 3	419	863	0	4.21	2	28	35.8%	25.7%	**1.434**
Dallas 2	233	2,694	0	4.89	2	44	28.6%	30.4%	**1.425**
Chicago 2	160	827	0	3.94	2	22	31.0%	19.5%	**1.350**
Dallas 1	1,229	6,346	0	4.92	2	60	34.6%	33.3%	**1.294**
New York 4	1,755	2,095	0	4.03	1	59	38.8%	18.3%	**1.213**
New York 1	206	2,449	0	4.08	2	51	39.1%	18.5%	**1.204**
Philadelphia 4	146	781	0	3.34	1	44	48.1%	23.1%	**1.155**
Chicago 4	1,415	655	0	3.2	1	16	30.0%	18.6%	**1.136**
Philadelphia 2	167	2,277	0	3.8	1	50	38.7%	22.2%	**1.132**
Detroit 2	179	2,752	0	3.67	1	55	43.7%	20.9%	**1.067**
Miami 3	355	828	0	3.02	1	23	41.5%	18.5%	**1.035**
Miami 1	1,022	1,201	0	2.72	1	24	38.0%	18.0%	**0.883**
Philadelphia 1	369	1,134	0	2.4	1	16	39.6%	12.4%	**0.786**
New York 2	567	2,496	0	2.27	1	40	48.2%	11.3%	**0.668**

Table B.4: Baseline ratio of dining option diversity in each MD; values indicate the ratio of each cuisine type present in the entire MD. Google Gemini was not able to classify 6% of dining locations, due to the absence of, or contradictory information. There also could have been dining locations with very generic information, such as `name` = *John's* with no `cuisine` tag to identify what food it serves.

Code	AMERICAN CLASSICS & DINERS	BAKERY & CAFE	CONTEMPORARY FUSION	INDIAN & SOUTH ASIAN	ITALIAN & PIZZA	JAPANESE & SUSHI	MEDITERRANEAN & MIDDLE EASTERN	MEXICAN & LATIN AMERICAN	SEAFOOD	OTHER EAST ASIAN	OTHER EUROPEAN	OTHER CULTURAL CUISINE	QUICK SERVICE FAST FOOD & DELI	VEGETARIAN & SALAD & JUICE	(unknown)	Total Dining Locations
Atlanta 1	18.75%	11.71%	0.08%	0.84%	9.43%	2.30%	1.48%	10.49%	2.14%	5.03%	0.64%	0.62%	28.42%	1.79%	6.28%	5,131
Atlanta 2	18.51%	10.08%	0.12%	0.98%	10.26%	2.87%	1.28%	12.58%	1.71%	6.11%	0.43%	0.55%	28.89%	2.14%	3.48%	1,637
Boston 1	10.99%	24.88%	0.04%	0.82%	13.26%	3.50%	2.31%	7.00%	3.17%	9.50%	1.01%	0.86%	13.04%	1.27%	8.38%	2,685
Boston 2	12.83%	24.18%	0.21%	1.89%	15.89%	3.10%	1.93%	7.29%	2.48%	7.71%	1.27%	0.62%	13.18%	1.10%	6.33%	2,907
Boston 3	17.46%	23.80%	0.12%	0.48%	15.43%	2.03%	0.84%	4.19%	2.39%	6.70%	1.08%	0.24%	16.51%	1.56%	7.18%	836
Chicago 1	11.41%	18.78%	0.08%	1.21%	11.80%	3.03%	2.35%	10.37%	1.31%	6.13%	1.25%	0.65%	25.15%	1.06%	5.41%	9,491
Chicago 2	15.96%	14.51%	0.00%	0.36%	11.97%	2.30%	0.85%	12.09%	0.48%	4.84%	0.24%	0.24%	29.14%	0.97%	6.05%	827
Chicago 3	16.34%	14.48%	0.12%	0.58%	11.59%	2.67%	1.39%	8.81%	0.70%	3.82%	0.23%	0.46%	27.69%	1.62%	9.50%	863
Chicago 4	19.39%	9.47%	0.00%	0.46%	14.50%	0.76%	1.53%	10.84%	2.29%	1.83%	0.46%	0.31%	33.89%	0.61%	3.66%	655
Dallas 1	13.68%	10.56%	0.06%	1.28%	9.12%	2.47%	1.37%	13.49%	2.00%	5.78%	0.39%	0.49%	31.07%	1.81%	6.41%	6,346
Dallas 2	15.96%	11.10%	0.04%	0.37%	8.95%	1.86%	1.00%	12.44%	1.74%	4.12%	0.48%	0.67%	33.82%	1.00%	6.46%	2,694
Detroit 1	17.29%	12.26%	0.14%	0.50%	12.71%	1.49%	3.35%	8.82%	1.76%	4.12%	0.59%	0.45%	28.64%	1.67%	6.20%	2,210
Detroit 2	17.70%	12.10%	0.04%	0.91%	12.90%	2.40%	3.02%	7.09%	1.45%	5.78%	0.65%	0.18%	28.60%	1.31%	5.89%	2,752
Los Angeles 1	11.51%	16.63%	0.05%	0.75%	8.69%	4.50%	1.80%	13.08%	2.54%	9.25%	0.36%	0.93%	22.00%	2.00%	5.91%	3,891
Los Angeles 2	8.96%	17.23%	0.09%	0.91%	8.50%	5.72%	2.12%	12.70%	1.80%	9.21%	0.63%	1.33%	21.71%	2.53%	6.55%	12,512
Miami 1	14.07%	16.40%	0.00%	0.42%	9.24%	2.50%	1.33%	11.41%	3.16%	4.41%	0.50%	0.50%	28.89%	0.92%	6.24%	1,201
Miami 2	8.33%	13.80%	0.13%	0.39%	12.40%	3.77%	1.88%	16.26%	2.45%	3.46%	1.05%	0.66%	24.76%	2.72%	7.93%	2,282
Miami 3	16.30%	14.49%	0.24%	0.72%	11.11%	3.50%	2.05%	8.57%	3.38%	4.95%	0.24%	0.48%	24.64%	1.69%	7.61%	828
New York 1	14.94%	15.07%	0.08%	2.20%	16.21%	2.78%	1.88%	7.76%	2.65%	7.19%	0.69%	0.57%	19.72%	1.71%	6.53%	2,449
New York 2	12.66%	16.55%	0.28%	1.08%	14.46%	3.73%	2.40%	7.77%	4.05%	6.89%	1.08%	0.68%	16.95%	0.96%	10.46%	2,496
New York 3	7.85%	20.11%	0.13%	2.19%	13.63%	5.09%	3.58%	10.00%	1.40%	11.36%	1.60%	1.55%	13.32%	1.91%	6.28%	17,508
New York 4	14.27%	17.57%	0.00%	1.00%	14.08%	3.25%	1.86%	7.26%	1.00%	6.16%	1.67%	0.76%	18.90%	1.38%	10.84%	2,095
Philadelphia 1	15.08%	18.52%	0.00%	0.97%	16.49%	2.56%	1.23%	6.44%	1.68%	7.67%	0.35%	0.35%	22.13%	1.50%	5.03%	1,134
Philadelphia 2	15.46%	16.12%	0.13%	1.45%	19.32%	2.94%	1.23%	7.42%	1.01%	7.60%	0.57%	0.18%	18.45%	1.67%	6.46%	2,277
Philadelphia 3	11.69%	20.95%	0.14%	1.15%	14.40%	2.75%	2.29%	5.82%	1.42%	10.59%	0.92%	1.33%	17.74%	1.28%	7.52%	2,181
Philadelphia 4	16.90%	15.49%	0.13%	0.51%	16.39%	2.30%	1.15%	7.04%	2.69%	8.32%	0.38%	0.64%	22.02%	1.02%	4.99%	781
San Francisco 1	8.34%	19.28%	0.20%	3.39%	9.23%	5.77%	1.98%	9.93%	1.09%	14.46%	0.50%	2.77%	15.46%	1.61%	5.98%	4,399
San Francisco 2	7.13%	24.05%	0.28%	2.49%	9.02%	7.69%	2.85%	8.88%	1.82%	14.06%	1.59%	2.12%	9.94%	1.66%	6.42%	4,345
San Francisco 3	10.38%	23.04%	0.00%	2.53%	12.91%	3.29%	0.76%	10.13%	2.78%	7.59%	2.03%	0.76%	14.43%	1.52%	7.85%	395
Seattle 1	10.06%	23.83%	0.08%	1.59%	10.97%	5.60%	1.51%	9.46%	1.82%	11.95%	0.30%	0.45%	17.25%	0.61%	4.54%	1,322
Seattle 2	7.87%	25.00%	0.03%	2.41%	9.17%	6.44%	2.67%	9.15%	2.01%	14.28%	0.72%	1.97%	12.22%	1.45%	4.59%	5,727
Seattle 3	12.34%	22.17%	0.14%	0.65%	11.91%	5.02%	0.72%	8.97%	1.29%	7.03%	0.29%	0.50%	22.81%	1.00%	5.16%	1,394
Tampa 1	17.80%	14.96%	0.07%	0.52%	11.52%	3.59%	2.24%	8.53%	5.76%	6.06%	0.90%	0.75%	20.64%	1.35%	5.31%	1,337
Tampa 2	16.26%	12.97%	0.00%	0.71%	11.65%	2.89%	2.53%	9.52%	2.23%	5.02%	0.61%	0.46%	27.86%	1.47%	5.83%	1,974
Washington D.C. 1	13.32%	13.38%	0.08%	1.79%	12.96%	3.21%	3.91%	11.15%	1.46%	11.01%	1.26%	1.42%	20.12%	2.03%	2.91%	5,015
Washington D.C. 2	10.00%	15.71%	0.12%	1.90%	11.96%	4.17%	3.19%	11.72%	1.41%	9.02%	1.10%	2.02%	20.49%	2.21%	4.97%	1,630
Washington D.C. 3	10.47%	16.73%	0.20%	1.92%	10.64%	3.00%	2.86%	9.73%	2.32%	7.68%	1.68%	2.22%	21.25%	2.32%	6.97%	2,970
Average	**13%**	**17%**	**0%**	**1%**	**12%**	**3%**	**2%**	**10%**	**2%**	**7%**	**1%**	**1%**	**22%**	**2%**	**6%**	
Grand Total																121,177

Table B.5: Dining option diversity; values indicate the ratio of EVCS accessible to each cuisine type by a 5-minute walk.

Code	AMERICAN CLASSICS & DINERS	BAKERY & CAFE	CONTEMPORARY FUSION	INDIAN & SOUTH ASIAN	ITALIAN & PIZZA	JAPANESE & SUSHI	MEDITERRANEAN & MIDDLE EASTERN	MEXICAN & LATIN AMERICAN	SEAFOOD	OTHER EAST ASIAN	OTHER EUROPEAN	OTHER CULTURAL CUISINE	QUICK SERVICE FAST FOOD & DELI	VEGETARIAN & SALAD & JUICE	(unknown)
Atlanta 1	18.24%	14.48%	0.24%	1.46%	8.59%	2.35%	2.66%	7.88%	1.91%	5.55%	1.64%	0.38%	17.94%	3.08%	6.18%
Atlanta 2	19.49%	8.57%	0.00%	0.81%	8.21%	3.07%	1.26%	10.65%	1.35%	8.30%	0.54%	0.27%	22.74%	1.99%	6.86%
Boston 1	10.57%	25.35%	0.02%	1.23%	6.55%	4.62%	3.17%	7.53%	4.16%	6.37%	1.00%	0.57%	13.06%	2.52%	9.84%
Boston 2	11.57%	22.80%	0.50%	1.02%	8.19%	3.60%	3.40%	6.28%	3.41%	5.79%	1.59%	0.48%	11.13%	3.60%	7.82%
Boston 3	15.87%	25.00%	0.22%	0.87%	11.30%	1.74%	0.22%	2.61%	3.48%	5.65%	2.17%	0.22%	15.00%	3.70%	7.39%
Chicago 1	14.18%	22.47%	0.09%	1.36%	7.29%	4.18%	3.22%	7.36%	2.20%	5.06%	2.23%	0.51%	17.34%	2.17%	7.50%
Chicago 2	13.55%	13.19%	0.00%	0.73%	10.26%	2.20%	3.30%	11.36%	0.00%	8.06%	0.00%	0.37%	20.51%	0.00%	5.49%
Chicago 3	18.97%	24.43%	0.00%	0.00%	5.17%	2.01%	1.15%	4.02%	0.29%	3.16%	0.00%	0.57%	15.23%	2.87%	7.76%
Chicago 4	15.43%	10.64%	0.00%	0.53%	18.09%	0.00%	1.60%	7.45%	1.06%	4.26%	4.26%	0.00%	20.74%	0.53%	0.53%
Dallas 1	18.02%	10.23%	0.32%	0.84%	6.90%	2.60%	1.73%	12.96%	1.92%	4.98%	0.76%	0.27%	18.43%	1.43%	8.96%
Dallas 2	19.01%	11.68%	0.00%	0.17%	5.84%	1.57%	0.44%	9.76%	1.66%	1.92%	0.52%	0.96%	25.54%	0.96%	11.60%
Detroit 1	23.15%	17.70%	0.50%	1.43%	6.01%	1.16%	3.72%	5.05%	1.26%	1.03%	0.50%	2.86%	15.44%	4.12%	12.29%
Detroit 2	15.55%	13.54%	0.32%	0.73%	9.51%	3.30%	4.43%	5.32%	2.18%	4.43%	1.69%	0.00%	15.23%	1.21%	6.37%
Los Angeles 1	14.12%	18.58%	0.62%	0.48%	8.47%	3.20%	1.99%	9.90%	2.76%	7.84%	0.23%	0.46%	14.14%	2.60%	5.72%
Los Angeles 2	11.73%	18.49%	0.13%	1.00%	7.24%	6.89%	2.76%	9.52%	2.01%	7.62%	0.74%	1.13%	15.33%	3.63%	8.63%
Miami 1	14.55%	15.02%	0.00%	0.00%	7.37%	2.78%	1.44%	8.90%	2.39%	2.87%	0.19%	0.10%	17.22%	0.86%	10.14%
Miami 2	8.41%	14.53%	0.26%	0.93%	10.70%	4.89%	2.36%	13.08%	2.66%	2.88%	1.02%	0.30%	14.98%	4.19%	14.94%
Miami 3	16.55%	10.03%	0.52%	0.62%	11.38%	4.65%	3.83%	5.07%	4.65%	2.38%	0.52%	0.10%	11.27%	2.07%	11.48%
New York 1	14.75%	14.47%	0.00%	0.71%	11.64%	2.19%	3.60%	8.54%	1.98%	4.66%	0.49%	0.21%	16.73%	1.76%	4.16%
New York 2	10.50%	13.25%	0.00%	0.31%	7.14%	4.18%	0.92%	3.98%	2.96%	4.89%	0.41%	1.43%	13.35%	0.82%	7.65%
New York 3	9.03%	22.25%	0.13%	2.05%	12.89%	6.41%	3.63%	7.35%	1.24%	10.74%	2.22%	1.12%	11.05%	2.62%	5.84%
New York 4	11.17%	19.38%	0.00%	1.25%	12.94%	3.29%	1.97%	5.19%	0.72%	5.06%	0.79%	0.53%	11.37%	2.37%	9.66%
Philadelphia 1	10.77%	16.67%	0.00%	0.51%	10.51%	3.85%	0.77%	6.15%	0.00%	4.10%	0.00%	0.00%	20.26%	2.05%	3.85%
Philadelphia 2	12.87%	15.94%	0.29%	0.79%	12.37%	1.93%	2.07%	7.01%	1.07%	11.15%	0.29%	0.00%	9.72%	1.50%	8.58%
Philadelphia 3	11.54%	22.82%	0.16%	1.52%	6.94%	4.76%	2.85%	6.90%	1.56%	11.62%	0.51%	0.31%	15.99%	1.09%	9.44%
Philadelphia 4	14.58%	18.33%	0.00%	0.83%	9.79%	2.71%	0.63%	5.42%	1.46%	7.08%	0.42%	0.83%	16.46%	2.08%	2.08%
San Francisco 1	6.06%	19.18%	0.14%	2.90%	7.24%	7.70%	3.38%	9.81%	0.58%	12.92%	0.60%	2.88%	10.99%	3.71%	7.45%
San Francisco 2	6.93%	26.63%	0.20%	1.95%	7.30%	6.94%	3.67%	6.52%	1.68%	10.43%	1.14%	1.87%	11.69%	3.36%	7.25%
San Francisco 3	8.15%	21.75%	0.00%	1.14%	7.58%	2.58%	1.00%	9.16%	1.14%	8.73%	0.43%	0.43%	17.45%	1.14%	5.87%
Seattle 1	9.52%	20.45%	0.00%	1.96%	8.68%	4.90%	1.40%	8.82%	3.36%	10.08%	0.00%	0.56%	15.83%	1.26%	5.46%
Seattle 2	7.63%	29.13%	0.49%	2.53%	6.69%	6.12%	3.31%	5.58%	1.94%	12.18%	1.29%	1.29%	9.33%	4.17%	7.43%
Seattle 3	14.03%	26.18%	0.35%	0.71%	8.73%	4.95%	1.18%	5.90%	1.77%	8.02%	0.24%	0.59%	14.27%	0.71%	6.13%
Tampa 1	18.29%	15.65%	0.00%	0.33%	9.39%	7.66%	2.31%	9.97%	5.44%	6.18%	2.72%	0.33%	8.81%	0.66%	5.77%
Tampa 2	15.41%	15.89%	0.00%	0.16%	12.59%	3.47%	1.92%	6.13%	5.07%	6.08%	3.47%	0.37%	16.53%	1.12%	4.69%
Washington D.C. 1	12.43%	19.29%	0.07%	1.32%	10.11%	4.47%	4.18%	9.93%	1.37%	7.37%	1.73%	1.16%	13.65%	5.45%	3.57%
Washington D.C. 2	9.92%	16.70%	0.09%	2.92%	9.07%	6.00%	4.37%	12.75%	1.33%	7.96%	1.66%	1.63%	13.96%	3.89%	4.61%
Washington D.C. 3	10.01%	20.13%	0.21%	1.73%	8.09%	4.50%	4.42%	6.54%	2.38%	6.48%	1.99%	2.05%	17.34%	3.40%	9.70%
Average	13%	18%	0%	1%	9%	4%	2%	8%	2%	7%	1%	1%	15%	2%	7%

Table B.6: Adjusted Dining Option Diversity Concordance Scores (DODCS); Values are EVCS ratio (Table B.5) divided by baseline ratio (Table B.4). *#N/A* values are divide-by-zero errors.

Code	AMERICAN CLASSICS & DINERS	BAKERY & CAFE	CONTEMPORARY FUSION	INDIAN & SOUTH ASIAN	ITALIAN & PIZZA	JAPANESE & SUSHI	MEDITERRANEAN & MIDDLE EASTERN	MEXICAN & LATIN AMERICAN	SEAFOOD	OTHER EAST ASIAN	OTHER EUROPEAN	OTHER CULTURAL CUISINE	QUICK SERVICE FAST FOOD & DELI	VEGETARIAN & SALAD & JUICE
Atlanta 1	0.97	1.24	3.08	1.74	0.91	1.02	1.80	0.75	0.89	1.10	2.55	0.61	0.63	1.72
Atlanta 2	1.05	0.85	0.00	0.83	0.80	1.07	0.98	0.85	0.79	1.36	1.26	0.49	0.79	0.93
Boston 1	0.96	1.02	0.54	1.50	0.49	1.32	1.37	1.08	1.31	0.67	0.99	0.67	1.00	1.99
Boston 2	0.90	0.94	2.42	0.54	0.52	1.16	1.76	0.86	1.38	0.75	1.25	0.78	0.84	3.27
Boston 3	0.91	1.05	1.84	1.82	0.73	0.86	0.26	0.62	1.45	0.84	2.02	0.92	0.91	2.38
Chicago 1	1.24	1.20	1.07	1.12	0.62	1.38	1.37	0.71	1.68	0.83	1.78	0.78	0.69	2.04
Chicago 2	0.85	0.91	*#N/A*	2.01	0.86	0.96	3.90	0.94	0.00	1.67	0.00	1.53	0.70	0.00
Chicago 3	1.16	1.69	0.00	0.00	0.45	0.75	0.83	0.46	0.42	0.83	0.00	1.23	0.55	1.77
Chicago 4	0.80	1.12	*#N/A*	1.16	1.25	0.00	1.05	0.69	0.46	2.33	9.30	0.00	0.61	0.87
Dallas 1	1.32	0.97	5.08	0.66	0.76	1.05	1.26	0.96	0.96	0.86	1.93	0.55	0.59	0.79
Dallas 2	1.19	1.05	0.00	0.46	0.65	0.85	0.44	0.78	0.95	0.47	1.08	1.44	0.76	0.96
Detroit 1	1.34	1.44	3.68	2.87	0.47	0.78	1.11	0.57	0.71	0.25	0.85	6.32	0.54	2.46
Detroit 2	0.88	1.12	8.81	0.80	0.74	1.38	1.47	0.75	1.50	0.77	2.58	0.00	0.53	0.92
Los Angeles 1	1.23	1.12	12.06	0.64	0.98	0.71	1.11	0.76	1.08	0.85	0.64	0.50	0.64	1.30
Los Angeles 2	1.31	1.07	1.48	1.10	0.85	1.20	1.30	0.75	1.12	0.83	1.17	0.85	0.71	1.43
Miami 1	1.03	0.92	*#N/A*	0.00	0.80	1.11	1.08	0.78	0.76	0.65	0.38	0.20	0.60	0.94
Miami 2	1.01	1.05	1.98	2.36	0.86	1.30	1.25	0.80	1.08	0.83	0.97	0.46	0.61	1.54
Miami 3	1.02	0.69	2.15	0.86	1.02	1.33	1.87	0.59	1.38	0.48	2.15	0.21	0.46	1.22
New York 1	0.99	0.96	0.00	0.32	0.72	0.79	1.92	1.10	0.75	0.65	0.71	0.37	0.85	1.03
New York 2	0.83	0.80	0.00	0.29	0.49	1.12	0.38	0.51	0.73	0.71	0.38	2.10	0.79	0.85
New York 3	1.15	1.11	1.03	0.93	0.95	1.26	1.01	0.74	0.89	0.95	1.38	0.72	0.83	1.37
New York 4	0.78	1.10	*#N/A*	1.25	0.92	1.01	1.06	0.72	0.72	0.82	0.47	0.69	0.60	1.71
Philadelphia 1	0.71	0.90	*#N/A*	0.53	0.64	1.51	0.62	0.96	0.00	0.53	0.00	0.00	0.92	1.37
Philadelphia 2	0.83	0.99	2.20	0.55	0.64	0.66	1.68	0.94	1.06	1.47	0.51	0.00	0.53	0.90
Philadelphia 3	0.99	1.09	1.16	1.33	0.48	1.73	1.24	1.18	1.10	1.10	0.56	0.23	0.90	0.85
Philadelphia 4	0.86	1.18	0.00	1.62	0.60	1.18	0.55	0.77	0.54	0.85	1.09	1.30	0.75	2.03
San Francisco 1	0.73	0.99	0.68	0.86	0.78	1.33	1.71	0.99	0.53	0.89	1.20	1.04	0.71	2.30
San Francisco 2	0.97	1.11	0.72	0.78	0.81	0.90	1.29	0.73	0.92	0.74	0.72	0.88	1.18	2.03
San Francisco 3	0.79	0.94	*#N/A*	0.45	0.59	0.78	1.32	0.90	0.41	1.15	0.21	0.57	1.21	0.75
Seattle 1	0.95	0.86	0.00	1.23	0.79	0.88	0.93	0.93	1.85	0.84	0.00	1.23	0.92	2.08
Seattle 2	0.97	1.16	14.03	1.05	0.73	0.95	1.24	0.61	0.97	0.85	1.80	0.65	0.76	2.88
Seattle 3	1.14	1.18	2.44	1.10	0.73	0.99	1.64	0.66	1.37	1.14	0.84	1.17	0.63	0.71
Tampa 1	1.03	1.05	0.00	0.63	0.82	2.13	1.03	1.17	0.94	1.02	3.03	0.44	0.43	0.49
Tampa 2	0.95	1.23	*#N/A*	0.23	1.08	1.20	0.76	0.64	2.27	1.21	5.71	0.81	0.59	0.76
Washington D.C. 1	0.93	1.44	0.88	0.74	0.78	1.39	1.07	0.89	0.94	0.67	1.38	0.82	0.68	2.68
Washington D.C. 2	0.99	1.06	0.73	1.54	0.76	1.44	1.37	1.09	0.94	0.88	1.50	0.81	0.68	1.76
Washington D.C. 3	0.96	1.20	1.04	0.90	0.76	1.50	1.54	0.67	1.02	0.84	1.18	0.92	0.82	1.46
Average	0.99	1.08	2.30	0.99	0.75	1.11	1.26	0.81	0.97	0.91	1.45	0.87	0.73	1.47

C Code and Data for Reproduction

The code and data for reproducing the results of this paper are available on Google Drive via This Link, or upon request.