Are Highways Conduits or Barriers for Urban Travelers? A Welfare Analysis Using Smartphone Data

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Abstract

This paper evaluates the impact of highways on intracity travel using granular smartphone GPS data. I find that urban highways act as barriers to travel: conditional on travel time, destinations reached by crossing highways are 24.9% less likely to be chosen, and those reached by using highways are 23.5% less likely. These effects are equivalent to increasing travel time by 2.4 minutes. The impacts are stronger for short, consumption trips and weaker for commuting. Using a quantitative urban model that integrates both work and consumption travel, I evaluate the welfare effects of two counterfactual highway systems that remove the estimated disamenities. Both scenarios yield substantial welfare gains of at least 9%. These gains arise from improved access to urban amenities, leading to the reallocation of population, employment, and consumption opportunities toward urban centers and away from suburban areas, which enhances amenities in urban areas while diminishing them in suburban areas. Decomposition of the counterfactual equilibrium highlights the importance of modeling consumption travel, a key contribution of this study.

Keywords: Consumption travel, Highways, Amenity, Smartphone data, Quantitative urban model

JEL Codes: R12, R13, R42, R53, R58

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1 Introduction

The economic value of highways to cities is an ongoing topic of discussion. Highways have traditionally been viewed as conduits that reduce transportation costs, stimulate economic growth, and facilitate suburban expansion by enabling faster travel (Baum-Snow, 2007; Duranton and Turner, 2012). However, recent public discussions and urban policy initiatives have brought attention to a competing perspective: highways may also act as barriers, fragmenting neighborhoods, hindering local mobility, and limiting access to urban amenities.[1] Despite growing public interest, academic evidence on the scale of highway disamenities is sparse, and their impacts on intracity travel are unknown, largely due to limited micro-level travel data. Given the high costs of highway infrastructure, understanding its local economic costs and benefits is crucial to urban policy.

This paper evaluates the impacts of highways on urban quality of life in two steps. First, leveraging granular smartphone GPS data, I examine the effects of highway interactions on consumers' travel choices—specifically, how travel routes that involve crossing or using highways affect the probability of visiting a destination relative to routes without such interactions. Understanding consumption travel is important, as it accounts for 80% of all intracity trips in U.S. metropolitan areas (NHTS, 2017).[2] Consumption trips are more likely to be influenced by highways, given the flexibility of choices of these activities compared to the more restricted residential and workplace choices. Second, I ask what the welfare gains would be if consumers lived in a counterfactual economy with alternative highway systems that mitigate these effects. To answer this, I embed the consumer travel model within a general equilibrium model encompassing residence and workplace decisions. The model captures three types of highway disamenities: the impacts on consumption trips, commuting, and residential amenities. This allows for a comprehensive analysis of each channel's impact.

The first question is fundamentally empirical, involving two opposing mechanisms. On the one hand, highways can function as conduits for economic activities, since they enable high-speed, nonstop travel. On the other hand, highways can act as barriers if encountering them during travel imposes disamenities, such as increased noise and emissions, higher risks of accidents, and "freeway phobia"[3]. Therefore, I build a discrete choice model where travelers derive utility from visiting various locations to access consumption opportunities. The costs associated with a visit include a measure of trip length and the potential (dis)amenity from interactions between travel routes and highways. The model features a

[1] For example, the Freeways Without Futures Project by the *Congress for the New Urbanism*, McCormick (2020) from the *Lincoln Institute*, Millsap (2019) from *Forbes*, and Black (2019, 2020) from *The Stranger* all critique highways for their local disamenities, and discuss possible transformations, though without empirical analysis. In terms of current and future policies, the Reconnecting Communities Pilot (RCP) Grant Program, launched by the U.S. Department of Transportation in 2022, awarded $3.3 billion in 2024 to programs aimed at "advancing community-centered transportation connection projects", especially in underserved communities.

[2] See Appendix A.1 for the calculation of this share.

[3] Freeway phobia refers to driving anxiety on freeways, which represent highly complex and demanding traffic conditions. The literature on psychology and traffic accidents agrees that the higher mental workload of driving on highways leads to driving anxiety and fatigue. See Hidalgo-Muñoz et al. (2023) for a review.

gravity equation, which I estimate using data on consumer visit flows between census tracts (CTs) in the Seattle metropolitan area.[4]

Consumer visit flows are aggregated from smartphone GPS data, which provides features of individual Places of Interest (POI)[5] and visit patterns to each POI, such as the number of visits from specific home locations. I assume the home locations are the origins of the visits and aggregate the POI-level visits to obtain the visit flows between CT pairs. I obtain travel time and the interaction between routes and highways by computing the path that minimizes travel time based on OpenStreetMap (OSM), assuming all travelers take the shortest routes. Data on mean travel speed from Uber Movement is employed in route finding to incorporate the impact of traffic conditions.

The gravity estimation indicates that highways primarily function as barriers to consumption travel. Conditional on travel time, destinations accessed by traveling on or across a highway experience a 17% decrease in the probability of being visited, equivalent to a 12% increase in travel time. This disamenity is not specific to Seattle's unique geography. Similar impacts are found in the consumption travel data in other major Metropolitan Statistical Areas (MSAs) across the U.S., collectively accounting for 21% of the national population.[6] The effects are particularly large for short trips in high-density urban zones. Specifically, destinations reached by crossing urban highways are 24.9% less likely to be chosen, and those reached by using urban highways are 23.5% less likely. These effects are equivalent to increasing travel time 18% or 2.4 minutes. In contrast, suburban highways are associated with minor and insignificant disamenities.

These findings imply the broader impact of highways on urban mobility and welfare. The welfare effects of alternative urban highways depend on how much highway intrusions disrupt daily travel.[7] To evaluate welfare empirically, I build a quantitative urban model that incorporates commuting and consumption trip choices and consequently reflects determinations of employment, population, and supply of consumption amenities across space. Notably, the model captures three key mechanisms through which highways affect urban welfare: the impact on consumption travel, the influence on commuting patterns, and the role of highways in shaping residential amenities. Additionally, I also find the disamenities of living near a highway, as in Brinkman and Lin (2024), and the disamenities experienced during commuting. By incorporating these multiple channels, the model provides a more holistic assessment of how

[4] I consider both travel time and travel distance as alternative measures of trip length in the gravity estimation. The preferred specification uses travel time, consistent with the structural model, as time costs directly enter the consumer's indirect utility. Specifications using travel distance offer a complementary perspective, revealing the benefits of higher travel speed enabled by highways. Together, these approaches provide a comprehensive understanding of the dual roles of highways as both conduits and barriers.

[5] The smartphone data source defines a Place of Interest (POI) as a specific physical location that someone may find interesting. Table A.2 shows examples of POIs by category.

[6] As shown in Section C.4, the other sample MSAs are New York City (NYC), Los Angeles (LA), Chicago, San Francisco (SF), Dallas, Houston, and Miami.

[7] If a significant share of travel is affected, redesigning highways could bring substantial welfare gains, justifying large-scale investments. However, if most travel remains unaffected or if new highways slow down movement in dense areas, welfare losses may occur. Traffic changes could also reshape the spatial distribution of work and consumption within the city. Together, these mechanisms highlight the need for welfare analysis using general equilibrium models.

highway modifications influence consumer welfare.

A key innovation in this framework is the explicit modeling of endogenous amenities arising from consumption travel. Unlike traditional urban models that proxy amenities with residential population density (E.g. Allen and Arkolakis, 2014; Ahlfeldt et al., 2015; Almagro and Domínguez-Iino, 2024), this model recognizes that the amenities of living in a location are shaped by the accessibility of consumption opportunities, as well as local environments. Additionally, it accounts for the interdependence between consumer travel and the spatial distribution of POIs. Consumers prefer to visit locations with a greater variety of POIs, while businesses locate themselves in areas with higher consumer traffic. This bidirectional relationship is strongly supported by the travel data and generates agglomeration in consumption, amplifying the effects of highway interventions on urban welfare.

I evaluate two counterfactual scenarios. The first one considers an economy in which urban highways are placed underground, inspired by real-world projects such as the *Big Dig* in downtown Boston and the M-30 tunnel project in downtown Madrid. I implement this experiment by removing the disamenities associated with crossing or living near urban highways while retaining the speed of highways and the effects of using them. The second exercise considers an economy where urban highways are replaced with primary surface roads[8], mimicking scenarios like the Embarcadero Freeway removal in downtown San Francisco. To implement this experiment, I modify two features of urban highways to align them with primary roads: First, I eliminate all highway-related disamenities. Second, I set counterfactual travel speeds to match the observed travel speeds on actual urban primary roads, and recompute travel routes using these counterfactual travel speeds. Consequently, travel within urban areas becomes slower.

The findings reveal that burying highways leads to a welfare increase of 10.2%, a gain equivalent to transferring $9,591 to each Seattle resident in 2019. Decomposition of this counterfactual experiment shows that the gain from consumption travel is larger than that from work travel, as the estimated disamenities from highway interactions are three times greater for consumption trips than for commuting. The second counterfactual, replacing highways with primary roads, generates a slightly smaller welfare gain of 9.0%, equivalent to transferring $8,462 to each Seattle resident. By decomposing the counterfactual exercise, I find that the welfare gain from consumption travel is larger than the welfare loss from commuting. The latter is mainly due to longer commuting times. These findings are robust when incorporating increased congestion due to slower traffic. To account for increased congestion, I impose additional speed reduction on all actual and counterfactual primary roads and use the corresponding travel times to solve the counterfactual equilibrium. Although welfare gains decline with increasing congestion, the lower bound remains substantial at 7.9%. Moreover, the gains from consumption travel consistently exceed the losses from commuting.

The counterfactual city without urban highways partially aligns with Jacobs (1961)'s vision of vibrant,

[8] I use OSM's definition of primary roads, which is the fastest type of surface roads, with a median speed limit of 35 mph.

pedestrian-friendly streets. In both scenarios, substantial improvements in urban amenities attract population inflows and increase consumption opportunities, generating benefits amplified by consumption agglomeration. However, these changes also drive up urban land prices and diminish suburban amenities in a closed city with a fixed land supply. These results reflect the trade-offs involved in urban highway design. While highways help expand cities and improve regional connectivity, they also introduce considerable disamenities that degrade local travel experiences and neighborhood quality of life.

Literature and contribution. This paper contributes to the following strands of literature.

First, numerous studies have examined the impacts of transportation networks, particularly highways, on the growth and welfare of cities, such as Baum-Snow (2007), Duranton and Turner (2012), Hall (2018), and Allen and Arkolakis (2022). Especially, Severen (2023), Brinkman and Lin (2024), Bagagli (2024), and Weiwu (2024) examine the segregation and quality of life effects of the Interstate Highway System. The closest work to this paper is Brinkman and Lin (2024), which uses a spatial economic framework to examine the influence of highways on home–workplace choices. This paper takes a different perspective, focusing on the local impact of highways in the context of consumers' travel decisions, offering a complementary point of view to Brinkman and Lin (2024). It also exploits a new type of disamenity, highlighting the role of highways as physical barriers for travel; whereas in Brinkman and Lin (2024), highways decrease local quality of life by reducing the value of living close to them and destinations benefit from being close to highways because of better job access. However, in my framework, proximity to highways partially disadvantages destinations because traveling on or across them imposes disamenities on consumers. Moreover, the welfare evaluation in this paper includes multiple types of highway impacts, partially overlapping with those discussed in Brinkman and Lin (2024).

Second, this paper contributes to a burgeoning literature using micro-level data, particularly smartphone data, to study urban travel behavior. For example, Chen and Pope (2020), Athey et al. (2020), Agarwal et al. (2020), and Massenkoff and Wilmers (2023) employ different approaches to reveal urban travel patterns and experienced segregation. Davis et al. (2019), Hausman et al. (2023), Cook (2023), and Cao et al. (2024) study consumer welfare in various aspects using trip-level data. This paper contributes by assessing the local impacts of highways on travel and, subsequently, on consumption and social activities in cities. Meanwhile, studies using data from cities in Asian and developing countries focus on rail transit, such as Miyauchi et al. (2021), Lee and Tan (2023), and Tsivanidis (2023). This paper contributes by examining a critical infrastructure for travel in the U.S., as 89% of trips reported in NHTS (2017) occur on roadways.[9]

Third, this paper contributes to the extensive literature on the consumption amenities provided by cities. Jacobs (1961) advocates for human-centered urban design and opposes the construction of central urban highways. In recent studies, Glaeser et al. (2001) highlight the importance of urban density not

[9]See Appendix A.1 for the calculation of this share.

only for its production benefits but also for its role in enhancing consumption opportunities, a perspective that has drawn increasing attention from researchers. A growing body of work, including Handbury and Weinstein (2015), Couture (2016), and Handbury (2021), examines the relationship between city size, population density, the diversity of available goods and services, and consumer welfare, often in the context of intercity comparisons. This paper focuses on the welfare implications within a single closed city, analyzing how its internal road network, particularly highways, shapes consumption choices and urban accessibility. In doing so, this chapter relates to Jacobs (1961), who argues that the vitality and diversity of urban communities arise from frequent, casual interactions among people on vibrant city streets. I provide robust statistical evidence that intracity highways, which prioritize vehicle travel, undermine these interactions.

Fourth, this paper closely relates to the growing literature that uses quantitative frameworks[10] to study endogenous agglomeration and quality of life within urban areas (Allen and Arkolakis, 2014; Ahlfeldt et al., 2015; Monte et al., 2018; Ahlfeldt et al., 2021; Dingel and Tintelnot, 2023). Especially, Ahlfeldt et al. (2015) provide a seminal structural framework and identify a key elasticity that I use in this paper. Notably, Ahlfeldt et al. (2021) and Almagro and Domínguez-Iino (2024) extend the static framework to dynamic models, demonstrating how amenities evolve endogenously. Previous research typically infers amenities indirectly from observed employment, wages, and residential population. This paper leverages detailed smartphone GPS data to directly incorporate consumer travel behaviors as a fundamental element of local amenities, providing a novel and intuitive way to assess endogenous amenities that are especially affected by highways.

The paper proceeds as follows. Section 2 describes the data. Section 3 presents the model of consumer choices. Section 4 explains the methods I use to estimate the demand function. Section 5 analyzes the estimation results. Section 6 develops a quantitative urban model of commuting and consumption travel. Section 7 explains the corresponding estimation and computation methods. Section 8 evaluates the counterfactual exercises. Section 9 concludes.

2 Data and Measurement

This section outlines the data used in this study. I use data mainly from five sources: The primary dataset is the visiting patterns to POIs sourced from SafeGraph, which are aggregated from smartphone GPS pings. Second, road speeds in Seattle are computed with data from Uber Movement and National Household Travel Survey (NHTS, 2017). Third, the computation of travel routes is enabled by OpenStreetMap. Fourth, demographic variables at the census tract level are sourced from the American Community Survey (ACS) in 2019. Fifth, the commuting flows in 2019 are obtained from the Longitudi-

[10]See Redding (2023) for a comprehensive review of the framework.

nal Employer-Household Dynamics, Origin-Destination Employment Statistics (LODES). More details can be found in Appendix A.

2.1 Smartphone data

I obtain visits to POIs from SafeGraph, a company that collects GPS pings from smartphones. By processing geo-coded data, SafeGraph identifies specific POIs in space and defines a visit to a POI as the GPS ping staying in the POI for more than four minutes. By aggregating the identified visits, SafeGraph provides monthly visiting patterns to POIs, as well as features of individual POI across the United States. I use data from 2019 and aggregate the monthly data to annual visits to mitigate seasonal fluctuations.

The Seattle MSA is the primary sample in this study, mainly due to the availability of Uber Movement data[11]. Additionally, the city's road network has a prominent characteristic: its mostly-used highway passes directly through downtown and several natural choke points created by its unique geography. As a result, the city's traffic conditions are among the worst in the U.S. Finally, vehicle travel predominates due to limited public transit options. For the above reasons, residents have been advocating for the conversion of downtown highways to reconnect neighborhoods.[12] I also use data from seven other major U.S. cities to support the external validity of the findings.

My analysis mainly relies on two features in the smartphone data: the locations and industries of the POIs and the number of visits originating from specific home census tracts.[13] I use two strategies to include visits that are likely related to consumption behavior. First, I select a subsample of POIs that provide consumption amenities for local residents[14]. Second, I keep the visits that stay at the POI for less than 4 hours, which accounts for 84% of the total visits in the raw data. I then aggregate the POI-level visits to generate annual visit flows from the home census tract, where the pings from underlying devices are found during nighttime, to the destination census tract, where a group of POIs is located.

2.2 Maps and GIS data

I obtain the shapefiles of census tracts and U.S. roads from the U.S. Census Bureau's Topologically Integrated Geographic Encoding and Referencing Database (TIGER). The highways in this study are the "Primary Roads" defined by TIGER, including interstate and intrastate highways and highway links. Figure 1 depicts the map of census tracts and highways in Seattle. I define three major municipalities—Seattle, Tacoma, and Bellevue—and their respective surrounding towns as urban zones. The remaining tracts are classified as suburban zones. The red lines represent highways in the MSA, with solid lines

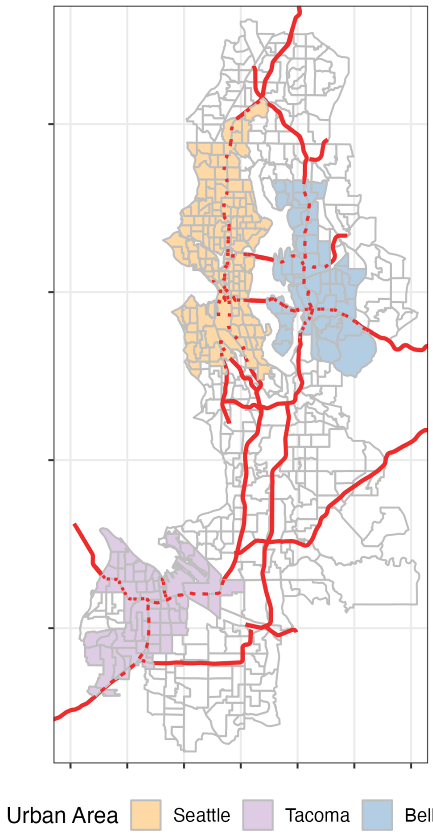
[11] See Subsection 2.3 for discussion

[12] See media articles, such as Black (2019, 2020); Argerious (2021) and a series of studies and campaigns to reconnect neighborhoods by building a lid on top of Interstate-5 at Lid I-5. Allen and Arkolakis (2022) also uses Seattle as a test case to examine the welfare impacts of road investments, highlighting its extensive traffic congestion and limited transit options.

[13] Home location is identified by SafeGraph based on the nighttime location of the device.

[14] See Table A.2 for a full list of POIs in the sample.

Figure 1: Census Tracts, Cities, and Highways in Seattle MSA



Note: This figure depicts a map of the census tracts and highways in the Seattle metropolitan area. Urban areas encompass the three core municipalities: Seattle, Tacoma, and Bellevue, along with their nearby towns. The remaining census tracts are classified as suburban areas. Highways are represented by red lines, with solid lines denoting suburban highways and dotted lines indicating urban highways, which will be converted to primary city roads in the counterfactual exercise.

denoting suburban highways and dotted lines indicating urban highways.

The geographic centroid of each census tract is identified from its geometric shape and is used to compute travel routes. I employ a routing machine based on OpenStreetMap to compute optimal travel routes that minimize the travel time from the centroid of the origin census tract to the centroid of the destination census tract. Route computation takes the travel speed on each road segment as input and generates the geometric shape, travel time, and travel distance of the corresponding routes, using Dijkstra's algorithm. I use driving speed data from Uber Movement (discussed in Subsection 2.3) as input for Seattle MSA. For other MSAs, as Uber Movement data is not available, I use the default travel speeds—the speed limits—to compute travel routes.

Travel time and distance are used directly in the empirical analysis. Additionally, using the geometry of highways and travel routes, I compute the interactions of travel routes with highways and classify three types of routes by the overlapping length. Figure 2 illustrates an example of each route type. The figure highlights four census tracts in downtown Seattle, with black lines representing highways. There are three routes from one origin to three different destinations. The first type, the blue one, has no interactions with highways. The other two types interact with highways. I distinguish them by the length of the overlapping segments. The second type, defined as **using** highways, overlaps with highways for at least one mile, such as the green route.[15] The third type, such as the red one, is defined as **crossing** highways. There are two cases within this type. One is that the route overpasses a highway. The other case is that the route uses a highway for a short distance in order to cross the highway[16]. If there were no highways with limited entry and exit, the route would have gone straight and avoided the detour. So the highways effectively cut and elongate the route. If a route interacts with multiple highways, its type is defined by the interaction with the longest overlapping distance.

2.3 Travel speed from Uber Movement

I generate the weighted mean travel speeds, combining data from Uber Movement in 2019 and the 2017 National Household Travel Survey (NHTS), and use them in route computation for the Seattle MSA. Uber Movement publishes the average travel speed on specific road segments for each hour of the day. The speed data is collected and estimated from billions of Uber rides. Figure A.4 in Appendix A.2 shows the hourly average travel speeds by road type and on major highways. I additionally validate the speed data by comparing it to two other sources: the speed data calculated based on trips in Google Maps in Akbar et al. (2023) and the summarized vehicle speeds for specific state highways published by the Washington State Department of Transportation (WSDOT). See Appendix A.2 for detailed discussion.

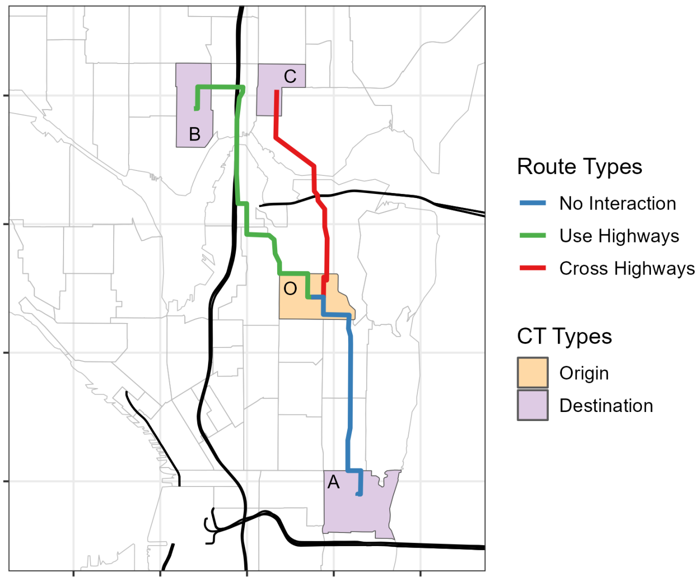
To incorporate the variation in the probability of taking trips throughout the day, I calculate the share of consumption and work trips at different hours of the day from the trip-level data in the NHTS (2017), which is shown by Figure A.2 in Appendix A.2. The figures show that commuting shares are significantly higher at 8 a.m. and 5 p.m., which are morning and evening rush hours, and consumption trip shares are high during usual day hours. Using these shares as weights, along with the hourly speed from Uber Movement, I calculate the weighted mean travel speeds on each road segment separately for consumption travel and commuting.

An advantage to using the weighted mean speeds in route computation, compared to the default speed limit data in OSM, is that the speeds reflect the average traffic conditions, especially the degree of congestion on different roads. Figure A.3 in Appendix A.2 shows this point by comparing the two speed variables. Therefore, using weighted mean speeds allows me to incorporate the impacts of traffic conditions on route choices and computed travel times, helping control for highway impacts on consumer choices beyond potential barrier effects in the empirical analysis. For example, one might think that highways are usually congested, making consumers dislike interacting with them during travel. First, in Figure A.3, I show that the primary roads are as congested as the highways. Thus, congestion is less

[15] Another case of the second type occurs when the overlap is shorter than one mile but accounts for more than 65% of the total route distance.

[16] The criteria for this type is: 1) the route overlaps with highways for shorter than one mile; 2) the overlapping distance is less than 35% of the total route distance; and 3) the origin and destination are on different sides of the highway.

Figure 2: Examples of Different Types of Travel Routes by Highway Interactions



Note: This figure shows examples of three route types, classified by interactions with highways. The census tracts on the map are part of the Seattle city. The black lines denote the highways. The three routes originate from one census tract (depicted in yellow and labeled as "O") and connect to three different destination census tracts (depicted in purple and labeled as "A", "B", "C"), demonstrating a variety of travel routes within the city.

likely to be the main reason that consumers dislike highway interaction. Second, the more congested a highway segment is, as reflected in the mean speed data, the less likely it is chosen to be part of the shortest route. The computed travel time will reflect the level of congestion for all the chosen roads in the shortest route. Therefore, the barrier or conduit effects are estimated on top of the impact of traffic conditions on consumer's travel behavior.[17]

However, the coverage of roads in Uber Movement is not perfect. 24% of all road segments in Seattle have valid speed information in the Uber data.[18] For the missing Uber data, I make predictions using the information on the speed limit from the OSM database. Appendix B explains the process in detail. To summarize, I establish a flexible statistical relationship between the mean speeds from Uber and the corresponding speed limits using the sample with valid Uber data. I assume this relationship holds for the sample with missing Uber data and use the speed limit variable to predict the missing data. Table B.1 reports an adequate fit of the model, with an R^2 of 0.58. Figure B.1 shows that the predicted speeds are, on average, lower and not too different from the speed limit.

[17] As shown in Section 3, this approach does not capture time-varying route choices due to changing traffic conditions. Ideally, one would model route selection endogenously by time of the trip. However, such information is not reported in the smartphone data. Other data sources, such as NHTS (2017) or roadway sensors, lack the granularity or representativeness needed. I therefore use weighted average speeds as an approximation for the typical conditions across all hours, acknowledging that this simplification may smooth over time-specific route heterogeneity.

[18] The coverage appears to be low because thousands of small residential roads have missing Uber speed data. All the highways and primary roads in Seattle and Bellevue areas have valid Uber data.

3 Discrete Choice Framework

In this section, I introduce a demand model of travelers' decisions on consumption trips, which informs the gravity regression in the following sections. In this partial equilibrium model, travelers take the spatial distribution of POIs, home locations, and workplaces as given. This enables me to focus on the impact of highways on consumer behavior. In Section 6, I extend the model to incorporate the spatial relocation of POIs and embed the consumer travel decisions in a general equilibrium model of home–workplace choices for welfare analysis.

3.1 The economic environment

There are J locations in the economy, denoted by i (for origin) and j (for destination). Each location j is endowed with N_{Rj} travelers and n_j POIs. Within each origin tract, travelers are assumed to be identical in their preferences over POIs. Demographic variables such as race and income reflect tract-level characteristics and capture spatial variation in preferences across locations. The number of POIs in each location is held fixed and exogenous to the consumers in this section. A POI is denoted by ω. A traveler derives her utility from visiting a POI to consume the goods and services it provides and decides which POI to visit to maximize her utility.

3.2 Traveler's problem

A traveler residing in location i makes a discrete choice regarding which POIs to visit to maximize her utility. She has an outside option of not visiting any POI and obtaining utility U_{iH}. The outside option includes the traveler's activities that occurred in home neighborhood, and, thus, is not captured by the visits to specific POIs in the smartphone data, such as staying at home, visiting neighbors, and going for a walk on the streets. I treat the outside option as fixed in this section to focus on trip choices. In Section 6, I endogenize it to examine the welfare effects of counterfactual highways.

The utility of visiting a POI ω in location j comprises two parts:

$$U_{i\omega} = V_{ij} + \varepsilon_{i\omega}, \tag{1}$$

where V_{ij} is the deterministic part observed by the researcher and $\varepsilon_{i\omega(j)}$ is the unobserved stochastic part. I parameterize the deterministic utility as

$$V_{ij} = d_{ij} + \gamma_4 \log \text{Race}_{ij} + \gamma_5 \log \text{Income}_{ij} + \text{POI}_j + \text{H}_i; \tag{2}$$

$$d_{ij} \equiv \gamma_1 \log \tau_{ij} + \gamma_2 \boldsymbol{D}_{ij}^{\text{crossHW}} + \gamma_3 \boldsymbol{D}_{ij}^{\text{useHW}}. \tag{3}$$

where d_{ij} is travel cost, measured by τ_{ij}, the access from location i to j, and the potential effects if the travel route crosses or uses highways. Specifically, I use the travel time of the optimal route between i and j to represent τ_{ij} in the structural estimation and the counterfactual analysis. Since τ_{ij} enters the indirect utility function (2) as part of the travel cost, it is natural to assume that travelers perceive cost in terms of their time, which could otherwise be spent on leisure (yielding utility) or work (yielding income). In some specifications, however, I measure τ_{ij} using travel distance, instead of travel time. As shown in Section 5, this alternative highlights the role of high travel speed, which is a key benefit of using highways. $\mathbf{D}_{ij}^{\text{useHW}}$ and $\mathbf{D}_{ij}^{\text{crossHW}}$ are both dummy variables, indicating route types, as shown in Figure 2.[19] These two types of interaction have distinct economic implications: using a highway facilitates faster travel and reduces travel time, whereas crossing a highway may elongate travel time by inducing detours. I investigate these effects separately, while also generating a combined dummy variable $\mathbf{D}_{ij}^{\text{HW}}$ to measure the mean effects of interaction with highways in any manner.

Race_{ij} denotes the racial frictions that may affect the appeal of j to i. It is measured by the Euclidean distance between the vectors of racial composition in the origin and destination census tract, which is defined in the same was as the dissimilarity index in Davis et al. (2019).[20] Income_{ij} reflects the income difference between i and j. It is measured by the absolute percent difference of the median income between i and j, also the same as in Davis et al. (2019).[21] Assuming local income levels proxy for the price level of local consumables, Income_{ij} captures preference matching between the income level of i and the price and quality of POIs in j. Finally, POI_j is the POI-location fixed effect, which captures the fixed attractiveness of location j, such as crime rate and natural amenities. H_i is the home-location fixed effect, which captures the common characteristics of travelers in location i, such as population, income level, and common preferences. The primary parameters of interest are γ_2 and γ_3, whose signs and magnitudes indicate the extent to which highways function as barriers (negative γ_2 and γ_3) or conduits (positive γ_2 and γ_3) for travel.

Note that the deterministic part contains only location-level and location-pair-level characteristics but not POI-level variables, while the unobserved idiosyncratic utility is specific to the traveler and POI. I assume the vector of unobserved utilities for traveler i, $\varepsilon_{ij} = \{\varepsilon_{i\omega};\ \forall \omega \in J_i\}$, is independent across i and has a joint type I extreme value distribution, with the cumulative distribution function being

$$F\left(\varepsilon_i\right) = \exp\left(-\sum_{\omega \in J_i} \exp\left(-\varepsilon_{i\omega} - \bar{\gamma}\right)\right), \tag{4}$$

where J_i denotes the choice set for travelers living in i, and $\bar{\gamma}$ is Euler's constant. This distribution yields a conditional-logit model of visits between locations (McFadden, 1978; Head and Mayer, 2004; Lee et al.,

[19] See Subsection 2.2 for explanations on route classification.

[20] Similar to Davis et al. (2019), I compute $\text{Race}_{ij} = \sum_g |\text{Share}_{g,i} - \text{Share}_{g,j}|$, where g denote racial group and $\text{Share}_{g,i}$ is the share of population belonging to the racial group g over the total population in census tract i.

[21] Specifically, $\text{Income}_{ij} = \frac{|\text{Income}_i - \text{Income}_j|}{\frac{1}{2}\left(\text{Income}_i + \text{Income}_j\right)}$, calculated using median income.

2021). Specifically, given the data and parameters $\boldsymbol{\gamma}$, the probability that a traveler living in location i visits location j for consumption purposes is

$$\text{Pr}_{ij} = \frac{\exp\left(V_{ij} + \ln n_j\right)}{\exp\left(U_{iH}\right) + \sum_{j' \in J_i} \exp\left(V_{ij'} + \ln n_{j'}\right)}. \tag{5}$$

The probability of choosing the outside option is

$$\text{Pr}_{iH} = \frac{\exp\left(U_{iH}\right)}{\exp\left(U_{iH}\right) + \sum_{j' \in J_i} \exp\left(V_{ij'} + \ln n_{j'}\right)} \tag{6}$$

Equation (5) shows that, for a traveler in i, the destination j has a higher probability of being visited if the deterministic value of visiting j is high or if there are more POIs in j. When n_j is large, it is more likely for the traveler to receive a high idiosyncratic shock for any POI in j, which makes j the best place to go. The inclusive utility from consumption trips taken by a consumer living in i is

$$\text{IU}_i = \ln\left(\exp\left(U_{iH}\right) + \sum_{j \in J} \exp\left(V_{ij} + \ln n_j\right)\right). \tag{7}$$

4 Gravity Estimation and Modifications

In this section, I discuss the methods used to estimate the gravity equation, using the consumption visit flows aggregated from the smartphone data. Subsection 4.1 presents the baseline regression derived from Equation (5) and explains the construction of variables. Subsection 4.2 introduces a series of modifications to the baseline specification. While not essential to the theoretical model, these modifications are found to be quantitatively important, and thus, determine the results used in the counterfactual analysis in Section 8.

4.1 Baseline estimation

Equation (5) is a gravity equation of visit flows as a function of bilateral frictions, origin fixed effects, and destination fixed effects. Rearranging it gives the following regression equation:

$$E\left(\text{Pr}_{ij}\right) = \exp\left(\gamma_1 \log \tau_{ij} + \gamma_2 \mathbf{D}_{ij}^{\text{crossHW}} + \gamma_3 \mathbf{D}_{ij}^{\text{useHW}} + \gamma_4 \log \text{Race}_{ij} + \gamma_5 \log \text{Inc}_{ij} + \text{D}_j + \text{O}_i\right), \tag{8}$$

where D_j and O_i are the structural fixed effects. I estimate Equation (8) using the Poisson Pseudo Maximum Likelihood (PPML) method. The main coefficients of interest are γ_2 and γ_3. Each location in the model is a census tract in the data.

Pr_{ij} is the share of consumer visits, calculated as the number of bilateral visits over the total number of choices made by the travelers in census tract i. Since choices involving the outside option are unobserved, I impose assumptions on the allocation of daily time slots to decide the total number of choices a traveler made in 2019. This assumption helps separately identify the home fixed effect H_i obtained in trips to POIs and the utility of the outside option U_{iH} and does not affect the key parameters of interest, γ_2 and γ_3, which are identified from variations in the probability of visiting different destinations based on route types. To see this, consider an increase in the number of time slots, given the observed visit data, this implies a higher share of choices allocated to the outside option, which in turn suggests a higher utility of staying at home relative to the home fixed effect H_i, with H_i being inferred from trips to POIs. Moreover, in the counterfactual exercise, the utility of the outside option adjusts in response to changes in counterfactual highway configurations, while home fixed effects remain constant. Thus, it is crucial to separately calibrate the two variables, as their values influence the magnitude of the welfare effects of counterfactual highways.

Specifically, I partition a day into time slots where a traveler chooses consumption trips or the outside option. I assume a consumer is given three time slots on weekdays and five time slots on weekends.[22] Using data on the number of unique devices in the smartphone dataset, along with the counts of weekdays and weekends in 2019, I obtain the total number of choices given to the sample consumers in each census tract. Pr_{ij} is determined by bilateral visits divided by the total number of choices. The above specification indicates that the share of choosing the outside option is 62% and a consumer is given 3.74 time slots on average per day. Appendix J investigates the sensitivity of the welfare gains with respect to the specification of the number of time slots.

For the fixed-effect variables on the right-hand side, $\mathrm{D}_j = \mathrm{POI}_j + \ln n_j$ is the destination fixed effect. $\mathrm{O}_i = \mathrm{H}_i - \ln \left(\exp\left(U_{iH}\right) + \sum_{j' \in J} \exp\left(V_{ij'} + \ln n_{j'}\right) \right)$ is the origin fixed effect.

4.2 Modifications

I propose three modifications to Equation (8), the baseline estimation, to address major concerns over the potential bias.

The first modification addresses the nonlinear elasticity of visits on travel time and the nonlinear effects of highways. As evident in Section 5, the time elasticity increases with the absolute value of travel distance. The same percentage increase in travel time leads to a greater decrease in visits when the travel time is already long. Given that a disproportionate number of long travel routes use highways, assuming a linear time elasticity biases the estimated γ_3 upwards, as $\mathbf{D}_{ij}^{\mathrm{useHW}}$ captures part of the effect of increasing elasticity. Moreover, the effect of highways is likely nonlinear. Especially, if there is a fixed part in the total cost of interaction with highways, while the benefits of using highways increase with travel distance. Therefore, I estimate the time elasticity γ_1 and the effects of highways γ_2, γ_3 in four different bins, defined by travel distance, to let the coefficients vary by the length of the trip.

[22] The assumption is based on the trip itinerary data in NHTS (2017). Specifically, the three time slots on weekdays are 1) before work, 2) after work and before dinner, 3) dinner and after dinner. The five time slots on weekends are 1) morning, 2) lunch, 3) early afternoon, 4) late afternoon, 5) dinner and after dinner.

Second, I estimate the effects of urban and suburban highways separately. Urban and suburban zones feature different densities, spatial distributions of residential and commercial clusters, and especially different impacts of highways on access to such clusters. For example, suburban areas, being sparse and predominantly driven through, may have dense commercial clusters built around highways to facilitate driving. Conversely, complaints from local communities about highways are often seen in high-density urban areas, highlighting congestion and limited access issues for local travelers. Therefore, urban and suburban highways may exhibit different impacts on travelers.

The third modification concerns the identification of highway effects in long trips in the sample. After splitting the sample into bins, my identification requires that there are adequate numbers of routes in each of the three types in each bin. However, according to the summary statistics by bins in Table A.3, for routes that are longer than 25 km, almost all routes interact with highways, making it impossible to identify the highway effects for the long routes. Therefore, I use the sample of routes shorter than 25 km, which covers 82% of the visits in the full sample. Restricting the sample in this way also ensures that the trips are more likely to be generated by the model in Section 3, rather than being driven by other types of travel, such as vacation, or by measurement errors.

5 Highway Effects on Consumption Travel

This section discusses the findings from the gravity regressions. Subsection 5.1 presents the average effects of highways, while Subsection 5.2 analyzes the distinct effects of urban and suburban highways across four distance bins. The modifications from Section 4.2 are introduced sequentially to highlight their contributions to the final interpretation. The preferred specification, which is presented in Subsection 5.2, incorporates all modifications and is used for the quantitative analysis in Section 8. Subsection 5.3 summarizes the robustness tests and additional investigations into the heterogeneous effects, which are detailed in Appendix C and D. In all the regressions, the standard errors are calculated using two-way clustering by origin (home) and destination (POIs).

5.1 Average effects of highways

Table 1 shows the results using PPML from both the baseline gravity regression discussed in Subsection 4.1 and the modified regression discussed in Subsection 4.2. The dependent variable used in all regressions is the share of consumption visits from origin to destination.

Column (1) shows the baseline estimation using the full sample of consumption travel. In column (2), I implement the third modification, retaining the routes that are shorter than 25 km.[23] The time elasticity

[23]The number of observations decreases by 194,224. It should be noted that each observation in the dataset is an origin–destination pair, along with the bilateral travel route, time, and interaction with highways. With the third modification, the 18% total visits that are dropped are distributed among the 194,224 bilateral routes. Remarkably, around 90% of the dropped long routes have zero visits.

decreases to 1.5, which is close to the estimates found in the literature on intracity mobility, such as Davis et al. (2019) and Miyauchi et al. (2021). The coefficient of $\mathbf{D}_{ij}^{\text{useHW}}$ shows that the probability decreases by 40% when the shortest route uses highways. This sizable negative effect appears counterintuitive given the high traffic volumes on highways. Comparing columns (2) and (3) shows that accounting for the upward-sloping time elasticity significantly reduces this bias, as discussed in Subsection 4.2.

Particularly, column (3) shows that, after correcting the bias stemming from linear time elasticity, the effect of using highways diminishes to 17% reduction in Pr_{ij}. This reluctance to use highways is not surprising. First, highway usage involves higher safety risks: according to the National Highway Traffic Safety Administration (NHTSA), 80% of the car crashes that involved fatalities in 2019 occurred on highways. In Washington state, the ratio is even higher at around 98%. Second, there is a vast amount of literature about the mental workload in driving and driving anxiety. The review paper, Hidalgo-Muñoz et al. (2023) points out that many studies found that complex urban highways are among the most demanding driving scenarios that will induce anxiety. Notably, a survey on driving anxiety finds that 26% of the respondents believe merging onto highways is one of the primary causes of anxiety. Additionally, interactions with highways often entail exposure to noise, emissions, unattractive city views, and sharing roads with trucks, which all contribute to their disamenities.

Column (4) shows the average effect of both types of interactions, which is an 17% decrease in the visiting probability. This effect is equivalent to an increase of travel time by 12%. Column (5) shows the significantly different effects of urban and suburban highways. Specifically, crossing urban highways is associated with a 24.9% decrease in visiting probability, and using them is associated with a 23.5% decrease. These quantitatively similar effects correspond to a substantial 18% increase, or 2.4 extra minutes, of travel time. In contrast, the coefficients of interaction with suburban highways are close to zero and insignificant.[24] As mentioned in Subsection 4.2, several factors contribute to the greater disamenity from crossings and using urban highways. Urban highways tend to be more complex, with frequent merging, denser traffic, and more variable designs, all of which are commonly associated with higher driving anxiety (more severe "freeway phobia"). Additionally, urban areas have more non-vehicle travelers (e.g., pedestrians and cyclists) and denser POI distributions, both of which make travelers more sensitive to barriers and more likely to choose destinations that avoid highway crossing.

The effects of racial and income disparities between pairs of locations remain stable across different specifications and align with expectations. Consumers are less likely to visit areas where local residents have significantly different income levels or belong to more dissimilar racial and ethnic groups, consistent with the findings of Davis et al. (2019).

To highlight the conduit role of highways, Columns (6) and (7) use travel distance rather than travel time to represent τ_{ij}. Since distance does not convey information on travel speed, the benefit of faster

[24]A Wald test confirms that the differences between the impacts of urban and suburban highways are statistically significant, with a p-value of 2.4×10^{-7}.

Table 1: Baseline and Modified Gravity Regression, PPML, Seattle MSA

Note:	Baseline		Modified			τ_{ij} = Distance	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log \tau_{ij}$	-1.72***	-1.53***					
	(0.029)	(0.030)					
$\log(\tau_{ij}) \times \mathbf{1}_{[0,\ 5\ \text{km}]}$			-1.02***	-1.02***	-1.00***	-0.975***	-0.952***
			(0.046)	(0.045)	(0.045)	(0.040)	(0.039)
$\log(\tau_{ij}) \times \mathbf{1}_{[5,\ 10\ \text{km}]}$			-1.16***	-1.16***	-1.14***	-1.10***	-1.09***
			(0.035)	(0.035)	(0.035)	(0.028)	(0.028)
$\log(\tau_{ij}) \times \mathbf{1}_{[10,\ 15\ \text{km}]}$			-1.31***	-1.31***	-1.30***	-1.25***	-1.24***
			(0.032)	(0.032)	(0.032)	(0.026)	(0.026)
$\log(\tau_{ij}) \times \mathbf{1}_{[15,\ 25\ \text{km}]}$			-1.42***	-1.42***	-1.40***	-1.35***	-1.33***
			(0.032)	(0.032)	(0.032)	(0.026)	(0.027)
$\mathbf{D}_{ij}^{\text{crossHW}}$	-0.109***	-0.206***	-0.180***			-0.198***	
	(0.037)	(0.034)	(0.031)			(0.032)	
$\mathbf{D}_{ij}^{\text{useHW}}$	-0.486***	-0.455***	-0.187***			0.036	
	(0.052)	(0.040)	(0.035)			(0.036)	
$\mathbf{D}_{ij}^{\text{HW}}$				-0.182***			
				(0.030)			
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Urban}}$					-0.287***		-0.293***
					(0.032)		(0.031)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Sub}}$					-0.031		-0.063
					(0.053)		(0.055)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}}$					-0.268***		-0.018
					(0.039)		(0.040)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Sub}}$					-0.009		0.147***
					(0.051)		(0.050)
$\log \text{Race}_{ij}$	-0.070***	-0.082***	-0.092***	-0.092***	-0.092***	-0.070***	-0.071***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\log \text{Inc}_{ij}$	-0.020***	-0.019***	-0.019***	-0.019***	-0.018***	-0.019***	-0.018***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Fixed Effects	Census tract of POI & Census tract of visitors home						
Observations	288,367	75,526	75,526	75,526	75,526	75,526	75,526
Pseudo R^2	0.338	0.224	0.226	0.226	0.227	0.227	0.227

Note: This table shows estimation results from the baseline and modified gravity regressions using PPML. The dependent variable used in all regressions is the share of visits from origin to destination, computed from the smartphone GPS data. Column (1) shows the baseline regression using the full sample. Columns (2) to (8) use the sample of intracity trips that are shorter than 25 km. Column (2) uses constant time elasticity specification. Columns (3) to (5) correct the bias in the estimated highway effects by controlling the nonlinear elasticity of the visiting probability on travel costs. They all indicate that interactions with highways have a negative impact on consumption travel. Column (5) shows a larger effect of urban highways. Access to the destination τ_{ij} is measured by travel time in columns (3) to (5), and by travel distance in columns (6) and (7). Columns (6) and (7) show that the advantage of higher travel speed on highways significantly mitigates the disadvantage of using highways. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

travel, which is enabled by highway use, is instead reflected in the coefficient of $\mathbf{D}_{ij}^{\text{useHW}}$. Comparing this coefficient to earlier specifications helps isolate the travel speed advantage associated with highway use.

Comparing column (6) to (3), it is evident that the impact of using highways shifts from a 17% drop in visiting probability to an insignificant 3% increase in visiting probability after I control travel distance instead of travel time. Comparing columns (7) to (5) indicates that this mitigation effect of higher travel speed is true for both urban and suburban highways. Given the same distance, using urban highways is associated with an insignificant 2% decrease in visiting probability, and using suburban highways indicates a significant 15% increase in the visiting probability. Travel speed plays a crucial role in explaining these findings. Uber speed data indicate that speeds on most suburban highways are higher than the speed limits, whereas primary suburban roads tend to be slower than their posted speed limits. As a result, conditional on distance, travelers prefer suburban highways due to the time savings they offer. However, this advantage does not extend to urban highways, which are more congested and serve higher traveler densities. Meanwhile, the effects of crossing highways are unaffected, as the higher speed afforded by highways does not confer an advantage to crossing them.

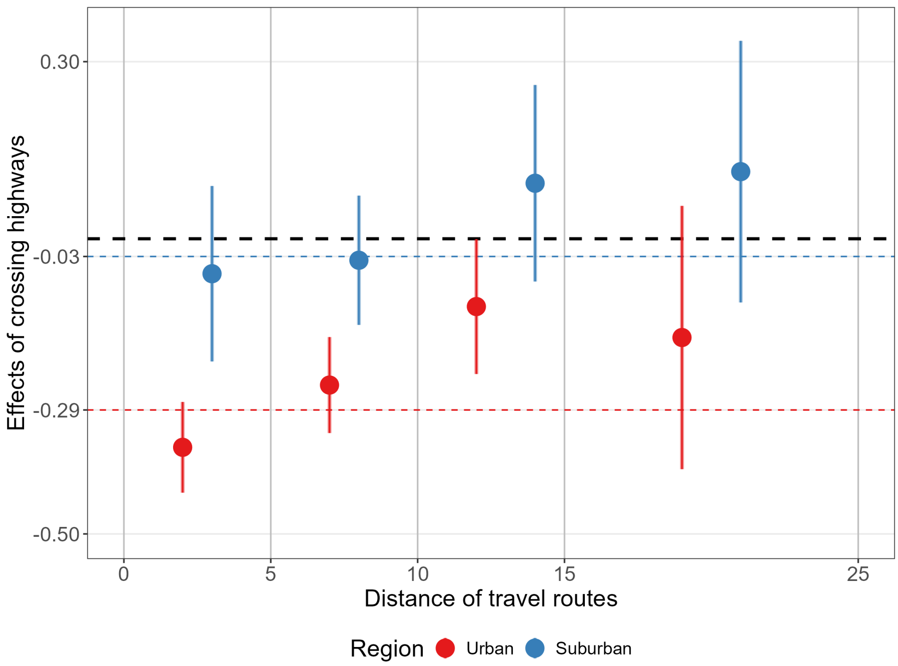
5.2 Urban and suburban highway effects by bin

In this subsection, I present the estimates of the impacts of urban and suburban highways separately in four distance bins, which is a breakdown of the estimates in column (5) of Table 1. Figure 3 illustrates the estimated effects of crossing and using highways, respectively. The dashed lines indicate the average effects as in column (5) of Table 1.

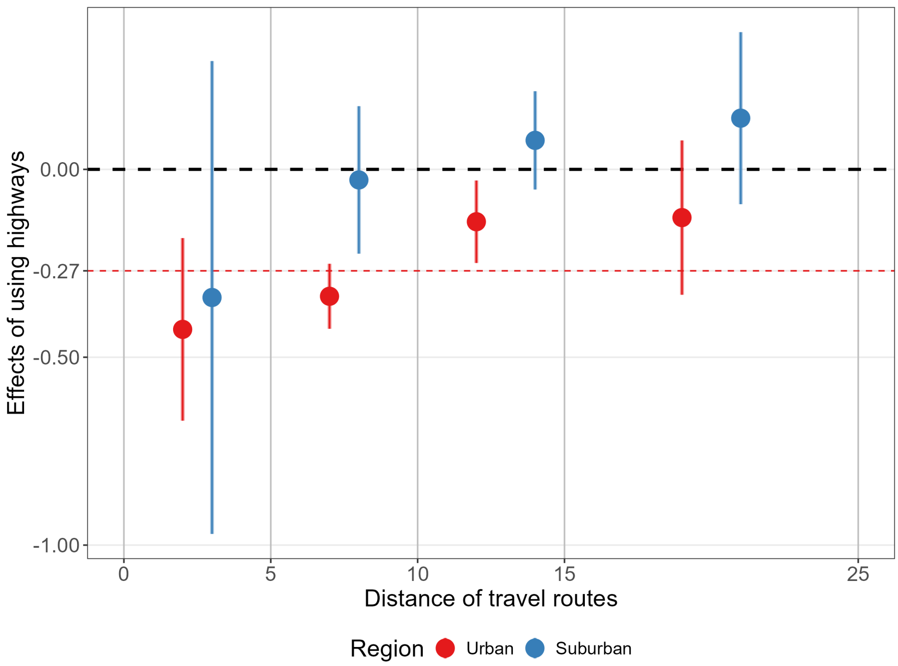
For both types of interactions, I find that the disamenity of interaction with urban highways decreases with the length of the travel routes. For the routes that are shorter than 10 km, which contain 71% of total visits, the disamenity is the most pronounced. The magnitude of the effect decreases with distance, becoming close to zero in the [10, 15 km] bin and remaining negative yet statistically indistinguishable from zero for longer trips. This decreasing disamenity (or increasing amenity) makes sense because part of the cost of interaction with highways aligns with the notion of a fixed cost, while the cost of travel time is a variable cost that increases with the length of the trip, and the benefits travelers obtain from using highways, namely the time saved from fast travel, also increases with trip length. Therefore, as trips become longer, travelers respond less to the fixed disutility of interaction with the highways and care more about the higher variable costs and benefits.

The second finding is that the disamenity of urban highways surpasses that of suburban highways in all the subsamples, with statistically significant differences in most of the sub-groups, as shown in Table D.6. The largest difference lies in the effect of crossing highways in the [0, 5 km] bin. Visiting probability decreases by 31% for crossing urban highways, compared to nearly zero for crossing suburban highways. For travelers on longer routes, interaction with suburban highways is even weakly preferred.

Figure 3: Highway Effects in 4 Distance Bins, PPML



(a) Effects of Crossing Highways



(b) Effects of Using Highways

Note: These two figures illustrate the nonlinear effects of urban and suburban highways in Seattle MSA. The sample is grouped into four bins based on the route distance, with cutoffs marked on the horizontal axis. Panel 3a displays the effects of crossing highways. Panel 3b shows the effects of using highways. For both types of interactions, the disamenities decrease with the route distance, turning positive for longer trips. Urban highways exert a larger disamenity than suburban highways.

This finding supports the second point in Subsection 4.2 and indicates that removing urban highways while maintaining suburban ones could yield benefits for local communities within the city.

These findings underscore that highways primarily disrupt travel within the nearest neighborhoods of the highest-density communities. This type of travel accounts for a sizable share of urban residents' time spent on various activities that generate utility—71% of all visits in the sample happen on routes that are shorter than 10 km, where urban highways create substantial disamenities. From a human-centered design perspective, the current configuration of urban highways suggests welfare losses due to a decline in quality of life, a point I further explore in Section 8.

Notably, these findings do not contradict but rather complement the existing literature on highways' benefits in facilitating longer-distance travel, particularly for urban–suburban and intercity trips. Instead, they highlight that the impact of highways varies depending on travel characteristics. Thus, while policymakers may prioritize global efficiency in highway design, they should also account for local consequences to minimize welfare losses and mitigate community resistance.

5.3 Robustness and heterogeneous effect

The findings in this section pass many robustness tests, which are discussed in detail in Appendix C. The locations of highways are not random, which can cause concerns that highways may be built in places with preexisting borders, worse amenities, lower-priced lands, etc., which leads to overestimated barrier effects. Therefore, in Subsection C.1, I use the planned highways in the *1947 Interstate Plan* as instruments and use control function approach to show that the causal effects are potentially larger than the baseline effects estimated by PPML.[25] Subsection C.2 additionally controls the administrative and geographical border effects and finds that the highway disamenities remain significant. Regarding potential concerns about the Uber Movement data, Subsection C.3 shows that the findings hold when I compute travel routes and interactions with highways with alternative assumptions on travel speed. Subsection C.4 shows that the disamenity of highways on consumption travel is not unique to Seattle but commonly exists in seven other big MSAs that cover a wide geographic span of the United States. Subsection C.5 shows that the findings are robust after controlling for the second best routes that do not interact with highways. Subsection C.6 shows that the findings are robust after considering preference matching between travelers and types of POIs. Subsection C.7 discusses the statistical significance of different effects of urban and suburban highways.

Additionally, Appendix D reports more heterogeneous effects of the disamenities of highways. These are all consistent with the main findings in this section and with the prior hypothesis. Concretely, Subsection D.1 shows that the disamenities are larger for travel within urban zones, and smaller for travel between urban and suburban zones. This is consistent with the findings of highways' impact on

[25]See Brinkman and Lin (2024) for details about the planned highway routes. My findings are also consistent with the findings using different estimation methods discussed in Brinkman and Lin (2024).

suburbanization in the literature, such as Baum-Snow (2007). Subsection D.2 shows that the estimated disamenities are significant and similar in visits to all groups of POIs, defined by NAICS codes in Table A.2. Subsection D.3 shows the disamenities for walking travelers in three cities. Subsection D.4 discusses heterogeneous preferences by income level. The conclusion of the investigation using three approaches is that preferences at different income levels are not strongly heterogeneous at the census tract level, and the findings in this section are robust. Subsection D.5 shows the stronger disamenity of detouring to cross a highway compared to using an overpass. Subsection D.6 shows that the disamenities of interaction with highways decrease with the fraction of the routes that are not highways.

6 A General Equilibrium Model of Urban Travel

To evaluate the welfare implications of counterfactual highways, in this section, I build a general equilibrium model with home–workplace choices, POI entry, and consumption travel choices. The model resembles Ahlfeldt et al. (2015) in terms of the characterization of commuting and includes the type of highway disamenity similar to the setting in Brinkman and Lin (2024). Relative to a standard model in the literature, I added two new mechanisms. First, amenity is endogenously pinned down by consumers' travel choices. Second, POIs could relocate following the changes in consumer travel behavior, generating agglomeration in consumption. I briefly introduce the basics of the model and focus on the novel mechanisms here. Appendix E describes the full model in detail.

6.1 Additional set-up

In addition to the environment in Subsection 3.1, I use k to denote the workplace. Each location i is endowed with land area L_i that may be split between residential and industrial uses. With a fixed land supply, land prices adjust based on demand, which is driven by both population and employment in a given location. This setup captures the impact of rigid supplies of residential housing and industrial capital, such as buildings and factories, on consumer welfare. The city is closed, with a fixed population $\boldsymbol{N}$, and thus, endogenous wages, land prices, and expected utility depending on the allocation of economic activities. Each traveler in i is also a worker. Workers are homogeneous.

A worker chooses a home–workplace pair to maximize utility. Workers' choices determine the commuting flows π_{ik}, the population in each location N_{Ri}, and the labor force in each location N_{Wk}. The worker's indirect utility consists of amenity B_i and land price q_i at home, wage w_k at workplace, commuting cost d_{ik}, and an idiosyncratic preference shock ν_{ik}. The commuting cost is

$$d_{ik} = \exp\left(\kappa_1 \log \tau_{ik} + \kappa_2 \mathbf{D}_{ik}^{\text{crossHW}} + \kappa_3 \mathbf{D}_{ik}^{\text{useHW}} + \kappa_4 \log \text{Race}_{ik}\right), \tag{9}$$

where τ_{ik} is a measure of access between place of residence i and workplace k. For the same reasons discussed in Subsection 3.2, I use travel time in the main estimation specification and use travel distance alternatively to reveal highway's conduit role.

Assuming ν_{ik} is drawn from a Fréchet distribution with shape parameter ε, the probability that a worker chooses to live in i and work in k is

$$\pi_{ik} = \frac{\left(\frac{w_k}{d_{ik}} B_i q_i^{(\beta-1)}\right)^{\varepsilon}}{\sum_{i'=1}^{I} \sum_{k'=1}^{I} \left(\frac{w_{k'}}{d_{i'k'}} B_{i'} q_{i'}^{(\beta-1)}\right)^{\varepsilon}}. \tag{10}$$

The worker's expected utility is equalized across locations and is given by

$$E\left[\bar{U}\right] = \Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right)\left[\sum_{i=1}^{I}\sum_{k=1}^{I}\left(\frac{w_k}{d_{ik}} B_i q_i^{(\beta-1)}\right)^{\varepsilon}\right]^{\frac{1}{\varepsilon}}, \tag{11}$$

where β is the consumption share of income.

6.2 Amenity

B_i captures the utility derived from non-work activities, which, in this model, are the leisure enjoyed in the home neighborhood and the utility obtained from all consumption visits to POIs. This means that B_i is fully pinned down by the travelers' choices and the consequent inclusive utility in Subsection 3.2. Therefore, in equilibrium,

$$B_i \equiv \mathrm{IU}_i = \ln\left(\underbrace{\exp\left(U_{iH}\right)}_{\text{Local amenity}} + \underbrace{\sum_{j\in J} \exp\left(V_{ij} + \ln n_j\right)}_{\text{Consumption trips to POIs}}\right). \tag{12}$$

The utility of staying in the home neighborhood, U_{iH}, is a function of the disamenity that highways generate for home places, such as noises and pollution. Following Brinkman and Lin (2024), I parameterize U_{iH} as

$$U_{iH} = \left(1 - b_{\mathrm{HW}} \exp\left(-\eta\delta_{i,HW}\right)\right) b_i, \tag{13}$$

where $\delta_{i,HW}$ is the distance from home i to the nearest highway and b_i is the fundamental amenity.

6.3 Locations of POIs

Consider the problem of a potential POI owner. She chooses a location j to set up a POI to maximize profit, with the outside option of not setting up a POI if profits fall below zero. Let μ_j be the profit per consumer at her POI and F_j be the fixed cost to set up a POI in j. The POI owner's problem is

$$\max_{j} \ \mathrm{Profit}_j = \mu_j M_j \xi_j - F_j, \tag{14}$$

where ξ_j is a revenue shifter and $M_j = \sum_i \Pr_{ij} N_{Ri} N^{\text{Choices}}$ is the market potential at location j, measured by the expected number of visits.

However, such a model is difficult to solve or compute, as the decision of one POI owner affects other POI owners through M_j. Additionally, the data required to estimate μ_j is not available and does not explicitly exist for non-commercial POIs. Therefore, I make two assumptions to derive a simple solution to n_j that is easy to estimate. First, I assume that F_j and μ_j are independent of location, i.e., $F_j = F$, $\mu_j = \mu$. Second, I assume that ξ_j follows an exponential distribution, so that $\log \xi_j$ follows Type-I Extreme Value distribution.

I show in Appendix F that, with the above assumptions,

$$E\left(n_j\right) = \frac{\exp\left(\gamma^{\text{POI}} \log M_j\right)}{1 + \sum_{j' \in J} \exp\left(\gamma^{\text{POI}} \log M_{j'}\right)} N^{\text{Potential POI}}, \tag{15}$$

where γ^{POI} is the supply elasticity.

7 Estimation and Calibration

In this section, I introduce the process of estimating and calibrating the model in Section 6. I additionally calibrate the consumer choice Equation (5), borrow other parameters from the literature, and estimate three equations using Seattle data. The three equations are the spatial distribution of POIs in Equation (15), the gravity equation on commuting flows in Equation (10), and the disamenity of highways in Equation (13). Appendix H illustrates the process of solving the model with a counterfactual highway system.

7.1 Calibrating the model

This subsection briefly introduces the calibration of the fundamentals in the model, which are used in later estimation.

I first borrow the values of three parameters from the literature, which are also the values used in Brinkman and Lin (2024). I set the consumption share to $\beta = 0.94$, the labor share in production to $\alpha = 0.97$, and the Frechet shape parameter to $\varepsilon = 3.8$. The location amenity B_i and productivity A_k are exactly identified up to a scale, using the data on residential population N_{Ri}, employment N_{Wk}, land area L_i, and commuting costs d_{ik}[26]. See Appendix G for details.

Three additional terms in Equation (5) need to be calibrated. First, POI_j is calculated from data on the number of POIs and the estimated destination fixed effect $\hat{D}_j$ as $\hat{\text{POI}}_j = \hat{D}_j - \log n_j$. Second, H_i is calculated from the calibrated location amenity and estimated origin fixed effect $\hat{\text{H}}_i = \hat{O}_i + B_i$[27]

[26] Subsection 7.3 discuss the estimation of commuting costs d_{ik}, which is independent of the parameters in this subsection.

[27] Recall that amenity is defined as the inclusive utility $B_i = \ln\left(\exp\left(U_{iH}\right) + \sum_{j \in J} \exp\left(V_{ij} + \ln n_j\right)\right)$.

Finally, the utility of staying at home in each location U_{iH} is obtained by numerically solving the system of equations $B_i = \ln\left(\exp\left(U_{iH}\right) + \sum_{j\in J}\exp\left(V_{ij} + \ln n_j\right)\right)$, where V_{ij} is a function of H_i and U_{iH} is the only unknown term.

7.2 Spatial distribution of POIs

Equation (15) can be re-written as

$$E\left(n_j\right) = \exp\left(\gamma^{\mathrm{POI}}\log M_j + \mathrm{SFE}\right), \tag{16}$$

where SFE stands for Supply-side Fixed Effect and

$$\mathrm{SFE} = \log N^{\text{Potential POI}} - \log\left(1 + \sum_{j'\in J}\exp\left(\gamma^{\mathrm{POI}}\log M_{j'}\right)\right). \tag{17}$$

Following the findings in Guimaraes et al. (2003), I estimate Equation (16) using PPML with the number of POIs and consumer visits in the data.[28] Figure 4 shows the relationship between n_j and M_j, where I put both axes into the log scale. Each dot in the figure represents a census tract. The simplified linear elasticity model fits the data well, with Pseudo R^2 equal to 0.7. The supply elasticity $\gamma^{\hat{\mathrm{POI}}} = 0.64$ and $\hat{\mathrm{SFE}} = -2.65$. Both estimates are statistically significant.

7.3 Gravity regression on commuting flows

Taking Equation (9) into Equation (10) yields

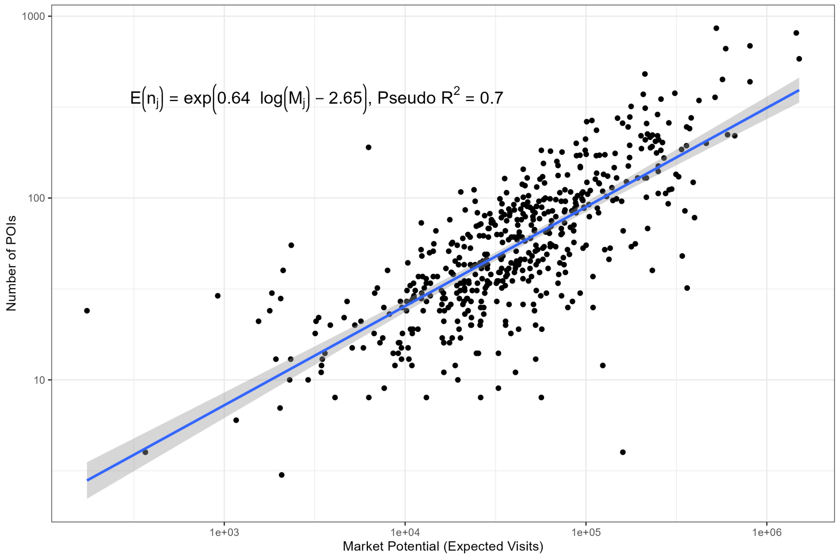
$$\pi_{ik} = \exp\left(-\varepsilon\kappa_1\log\tau_{ik} - \varepsilon\kappa_2\mathbf{D}_{ik}^{\text{crossHW}} - \varepsilon\kappa_3\mathbf{D}_{ik}^{\text{useHW}} - \varepsilon\kappa_4\log\mathrm{Race}_{ik} + \mathrm{R}_i + \mathrm{W}_k + \mathbb{C}\right), \tag{18}$$

where home fixed effects $\mathrm{R}_i = \varepsilon\log\left(B_i q_i^{(\beta-1)}\right)$, workplace fixed effects $\mathrm{W}_k = \varepsilon\log w_k$, constant term $\mathbb{C} = -\log\left(\sum_{i'=1}^{I}\sum_{k'=1}^{I}\left(\frac{w_{k'}}{d_{i'k'}}B_{i'}q_{i'}^{(\beta-1)}\right)^{\varepsilon}\right)$. I estimate Equation (18) using PPML with data on commuting flows, commuting time, the interaction between commuting routes and highways (only for routes that are shorter than 25 km), and the racial gap between home and workplace. For the same reasons discussed in Section 4.2, I estimate the commuting gravity equation flexibly, allowing for non-linear time elasticity and different effects of urban and suburban highways.

Table 2 presents the estimation results. The coefficient values in column (1) are used in the counterfactual exercises. Compared to consumption travel, commuting flows exhibit two distinct patterns. First, the time elasticity is smaller, especially for short trips. The elasticity for trips shorter than 25 km is approximately 0.6, significantly lower than the 1.5 elasticity observed for consumption travel, suggesting a larger geographic range of workplace choices. However, similar to consumption travel, elasticities

[28] See Appendix F for the equivalence between the PPML estimator and logit estimator in this case.

Figure 4: Number of POIs and Market Potential



Note: This figure illustrates the relationship between the number of POIs and the market potential of census tracts in the Seattle metro area. Both axes are scaled logarithmically. The supply model described in equation (16) fits the data well, yielding a Pseudo R^2 of 0.7.

increase with trip length. Once commuting distance exceeds 25km, the elasticity rises sharply to 1.5, leading to a steep decline in the number of commuters.[29] Second, commuting also involves disamenities from interactions with urban highways. Conditional on travel time, these effects are significantly negative but much smaller in magnitude than those for consumption travel, as shown in Table 1. Crossing or using highways reduces commuting flows by 8%, approximately one third of the impact observed for consumption travel. Intuitively, home and workplace choices are more constrained by the available options, compared to consumption destination choices. As a result, workers appear less sensitive to highway interactions in their commuting decisions compared to their consumption choices, as revealed by the preference-based estimation.

A major benefit of highways is their high speeds, which reduce travel time for a given distance. Thus, in column (2), I control the distance of the commuting routes. The insignificant coefficient of $\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}}$ indicates that the commuting routes that use urban highways are chosen with the same probability as a route of the same distance that does not interact with urban highways. In other words, the benefits of fast urban highways are mostly offset by the disamenity they generate for travelers. However, suburban highways are significantly preferred for their high speeds, indicated by the coefficient of $\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Sub}}$ in column (2). Workers are 12% more likely to choose a home–workplace pair that allows them to commute on highways rather than on non-highway roads.

[29]Most of the routes longer than 25 km connect different municipalities. The large elasticity for long commuting trips might be a result of workers preferring to live in the same municipality as their workplaces.

Table 2: Gravity Regression on Commuting

Dependent Variable:	π_{ik}	
Model:	(1) τ_{ij} = Time	(2) τ_{ij} = Distance
$\log(\tau_{ij}) \times \mathbf{1}_{[0,\ 5\ \text{km}]}$	-0.476***	-0.463***
	(0.040)	(0.036)
$\log(\tau_{ij}) \times \mathbf{1}_{[5,\ 10\ \text{km}]}$	-0.547***	-0.522***
	(0.030)	(0.024)
$\log(\tau_{ij}) \times \mathbf{1}_{[10,\ 15\ \text{km}]}$	-0.618***	-0.589***
	(0.027)	(0.021)
$\log(\tau_{ij}) \times \mathbf{1}_{[15,\ 25\ \text{km}]}$	-0.693***	-0.657***
	(0.027)	(0.021)
$\log(\tau_{ij}) \times \mathbf{1}_{[25,\ 50\ \text{km}]}$	-1.31***	-1.50***
	(0.100)	(0.084)
$\log(\tau_{ij}) \times \mathbf{1}_{[50,\ 75\ \text{km}]}$	-1.46***	-1.58***
	(0.089)	(0.073)
$\log(\tau_{ij}) \times \mathbf{1}_{[75,\ 125\ \text{km}]}$	-1.53***	-1.60***
	(0.087)	(0.071)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Urban}} \times \mathbf{1}_{[0,\ 25\ \text{km}]}$	-0.080***	-0.086***
	(0.022)	(0.021)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Sub}} \times \mathbf{1}_{[0,\ 25\ \text{km}]}$	-0.011	-0.030
	(0.029)	(0.029)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}} \times \mathbf{1}_{[0,\ 25\ \text{km}]}$	-0.091***	0.015
	(0.030)	(0.030)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Sub}} \times \mathbf{1}_{[0,\ 25\ \text{km}]}$	0.054	0.122***
	(0.038)	(0.038)
$\log \text{Race}_{ij} \times \mathbf{1}_{[0,\ 25\ \text{km}]}$	-0.069***	-0.060***
	(0.004)	(0.004)
$\log \text{Race}_{ij} \times \mathbf{1}_{[25,\ 120\ \text{km}]}$	-0.045***	-0.036***
	(0.013)	(0.012)
Fixed effects:		
Home	Yes	Yes
Workplace	Yes	Yes
Observations	288,369	288,369
Pseudo R^2	0.112	0.112

Note: This table shows the gravity regression as in Equation (18) using the commuting data. Time elasticity increases from 0.5 to 1.5 with the length of the trip. Disamenities of interaction with urban highways exist but are much lower than the disamenities estimated from consumption travel. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

7.4 Estimating highway disamenities

I estimate Equation (13) using nonlinear least squares to get the local disamenity of highways. The parameters $\{b_{\mathrm{HW}}, \eta\}$ are estimated as

$$\left\{\hat{b}_{HW}, \hat{\eta}\right\} = \underset{b_{\mathrm{HW}}, \eta}{\operatorname{argmin}} \sum_{i=1}^{I} \left(U_{iH} - \left(1 - b_{\mathrm{HW}} \exp\left(-\eta \delta_{i,HW}\right)\right)\right)^2. \tag{19}$$

I find $\hat{b}_{HW}$ =0.387 and $\hat{\eta}$ =0.132. The estimated value of $\hat{b}_{HW}$ indicates that the amenity value of living adjacent to a highway is 38.7% lower than that of a location infinitely far from highways. The spatial attenuation, governed by $\hat{\eta}$, implies that the disamenity effect decreases by half when moving 5 km away from a highway.[30].

8 Counterfactual Highway Systems

The significant impacts of urban highways on traveling motivate counterfactual exercises aimed at transforming them for welfare improvements. In this section, I investigate the welfare effects of two exercises that remove the disamenity of urban highways while preserving transportation accessibility across the metropolitan area. The first exercise simulates the effect of burying urban highways underground, inspired by existing projects like the *Big Dig* in Boston. The second exercise examines the effects of replacing urban highways with primary roads. This exercise is motivated by North American cities without downtown highways, such as Vancouver and San Francisco. This second scenario explicitly highlights the trade-off between high-speed travel and its associated disamenities.

8.1 Decomposing counterfactual welfare effects

For both exercises, I discuss the changes in consumer welfare, amenities, and equilibrium allocation of population and employment. In addition, I decompose the counterfactual shock into three parts based on their impacts on different activities in the model. These are 1) the impact on consumption travel through changes in travel cost, d_{ij}; 2) the impact on local amenity, U_{iH} through changes in distance to the nearest highways, $\delta_{i,\mathrm{HW}}$; 3) the impact on commuting through changes in commuting cost d_{ik}. The first two parts comprise the changes in amenity B_i in the model. I assess the contribution of each channel to the welfare effect. Welfare effects are measured by the changes in expected utility in Equation (11).

Another notable mechanism in the model is the agglomeration in consumption. As shown by Equations (5) and (15), changes in consumption trips due to a small shock to travel cost lead to the relocation

[30] My estimates of b_{HW} is close to that in Brinkman and Lin (2024). The spatial attenuation I find is weaker than that in Brinkman and Lin (2024), which is estimated from Chicago data. Unlike Chicago, Seattle is a non-monocentric city partly shaped by its natural geography, which imposes constraints on the location of highways and the distribution of population and employment.

of POIs, which further pushes consumer travel to move in the same direction. This reinforcing process affects migration, travel, and welfare through overall amenity B_i. To assess its importance, I also solve a restricted counterfactual equilibrium for each exercise, where the spatial distribution of POIs, represented by n_j, is exogenously given by the baseline economy and kept fixed in counterfactual. I further decompose the restricted counterfactual effects into the three components as discussed above.

8.2 Exercise 1: Burying urban highways

8.2.1 Exercise description

To implement the exercise, I change two variables in the model. First, I set the dummy variable representing crossing urban highways to zero for both commuting and consumption travel. Second, I change the distance to the nearest highway, $\delta_{i,\mathrm{HW}}$, for the *urban* locations to be the distance to the nearest *suburban* highways, as the noise and pollution generated by underground urban highways will not disseminate to nearby neighborhoods in counterfactual. Consequently, the average $\delta_{i,\mathrm{HW}}$ for urban census tracts increases from 1.7 km in the data to 7.3 km in the counterfactual economy. Note that the disamenity of using highways en route is retained, as the unpleasant experience and safety concerns associated with high-speed, limited-access travel remain.[31]

8.2.2 Welfare effects

Welfare effects and decomposition. Table 3 summarizes the welfare effects. Welfare increases by 10.2% in the counterfactual. Decomposing the gains into the three activities in the model, I show in Table 4 that the shock to consumption travel costs leads to a 2.6% welfare gain, or 25.4% of the total welfare gain. In contrast, the shock to commuting costs results in a 0.6% welfare gain. The smaller gain is due to the lower disamenity revealed by workers' commuting choices, as discussed in Section 7.3. Finally, the impact on local amenities contributes the most to welfare gain. This is because the share of choosing to stay in the home neighborhood (outside option) is 62%. The high spatial attenuation estimated from Equation (19) implies large amenity improvements for urban neighborhoods in the counterfactual economy: moving 5.6 km away from highways leads to a 33% increase in local amenity.

Amenities and relocation. While the expected utility is equalized everywhere, overall amenity B_i exhibits considerable variation in different locations, especially between urban and suburban areas. As shown in Table 4, overall amenity increases by 13%, with unevenly distributed effects across space: urban amenity increases by 80% while suburban amenity decreases by 42%. The disparity in amenity is an immediate result of the amenity improvement during travel within the urban area. In addition, better

[31] This approach assumes no additional disamenity associated with using tunnel highways relative to ground-level highways, as there is no direct evidence in the literature to quantify such differences. However, by intuition, tunnel highways may impose greater psychological or navigational burdens. In this sense, the welfare estimates reported here should be interpreted as an upper bound on the amenity gains in a counterfactual economy with tunneled urban highways.

quality of life within urban areas lead to relocation of POIs, population, and employment. In the closed city, suburban areas lose consumption amenities and population accordingly. As shown in Table 4, 23% of POIs, 21% of population and 11% of employment migrate from suburban areas to urban areas in the counterfactual.

The relocation of population and employment imply shifts in the demand for labor and land in different locations. Therefore, the wages and land prices adjust to reach the counterfactual equilibrium. Table 4 summarizes the changes in the price levels. I find that changes in wages are small as demand and supply for labor can adjust freely across locations, but land prices exhibit much larger responses with the shifted demand and fixed supply. Urban lands are 37% more expensive due to increased demand, which prevents production and residency from further concentrating in urban areas. In turn, suburban areas become much cheaper, compensating for its loss in amenity and employment opportunities.

Endogenous distribution of POIs. The disparate effects on amenities and relocation are partly due to the endogenous location of POIs. To see the strength of this mechanism, Table 3 and Table 4 also report the effects in the restricted counterfactual economy with fixed numbers of POIs in each location. Without the mechanism that generates consumption agglomeration, the welfare gain is lower by 3 percentage points. The gain from consumption travel is only 1.0%, much lower than the 2.6% gain in the unrestricted counterfactual and contributing much less to the overall welfare effect. Amenity improvement is also lower at 8%, with shrinks in both urban amenity improvement and suburban amenity reduction. For the degree of relocation, Table 4 shows that this mechanism contributes to the relocation of 9% of residents and 5% of jobs, which accounts for about 40% of the effects in the unrestricted counterfactual economy. To sum up, the consumption agglomeration driven by the endogenous relocation of POIs amplifies the overall welfare gain, urban amenity improvements, and suburban amenity deterioration.

8.2.3 Cost and benefits

According to ACS Briefs (2020), the median household income in the 2019 Seattle metro area is \$94,027. Using this median income and compensating variation method, the counterfactual shock is equivalent to an annual transfer of \$9,591 to each Seattle worker. Given the 186.4 lane miles of urban highways in the MSA, the 10.2% increase in income means each lane mile of buried highways brings \$63 million benefits in the counterfactual city.[32] Note that in the static model, this effect means each Seattle resident experiences utility equivalent to earning \$9,591 more in the counterfactual city. However, a realistic highway-burial project may have dynamic welfare implications, imposing various utility costs during construction while generating benefits mainly upon completion.

[32] The benefits are calculated as follows: According to the functional form in Equation (11), the 10.2% welfare gain is equivalent to a 10.2% increase in the wage rate in all locations. A 10.2% increase in median income equals \$9,591. With 1,226,836 commuters in the LODES data, the per-lane-mile benefit of \$63 million is calculated by dividing the total benefits, 1,226,836 $\times$ \$9,591, by the 186.4 total lane miles of urban highways. The same method is used for benefit calculation in the second exercise.

Despite the welfare gains, burying highways typically incurs substantial construction costs. For example, according to Greiman (2013), Boston's Central Artery/ Tunnel Project, known as the *Big Dig*, experienced sizable cost overruns, with expenses escalating from an initial estimate of $2.8 billion to approximately $14.8 billion, or $188 million per lane mile. Planning took nine years, followed by sixteen years of construction. Prolonged timelines also impose economic burdens on local communities, including traffic disruptions and reduced quality of life during construction.

WSDOT (2004) reports the Alaskan Way Viaduct Replacement Program as the most complex and expensive highway program to date, aimed at revitalizing downtown Seattle. It included tunnel construction, viaduct removal, and waterfront improvements in high-density areas, costing $3.35 billion or $223 million per lane mile—exceeding the *Big Dig* on a per-mile basis. Despite its high cost, local news, such as Trumm (2024), endorsed the project for improving pedestrian access, stimulating economic revitalization by attracting visitors and supporting local businesses, and thus, contributing to an overall improvement in urban quality of life.

8.3 Exercise 2: Replacing urban highways with primary roads

8.3.1 Exercise description

I implement the second exercise in two steps to change the features that are unique to urban highways and align them with primary roads:

Removing disamenities. First, I remove the effects on work and consumption travel by setting $\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Urb}}$ and $\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urb}}$ to 0.[33] Second, I change the counterfactual distance to the nearest highway for the urban census tracts, using the same methods as in the first counterfactual exercise.

Counterfactual travel time. I compute the counterfactual travel time between census tracts with a set of assumptions regarding travel speeds on counterfactual roads. First, by the design of the exercise, I assume the speed limits of the counterfactual roads are the same as those of primary roads, with a median and mode of 35 mph. Second, I assume that the overall traffic conditions of the MSA remain the same in the counterfactual. Traffic conditions are reflected by the deviation between actual travel speed and the speed limit for each road segment, as shown in Figure A.3. I assume this level of deviation remains the same for each urban highway segment.[34] I acknowledge that replacing urban highways may create additional congestion as travel speed declines nonlinearly with traffic volume and some traffic is directed from highways to primary roads. Thus, in Subsection 8.3.4, I investigate the welfare effects with different levels of increase in congestion.

[33] The disamenity of highways is identified by comparing routes that interact with highways to those that do not. Since most routes already involve primary roads, the estimated effect primarily reflects a comparison between highways and primary roads. Any disamenity associated with primary roads is implicitly retained in the counterfactual.

[34] For example, if an urban highway segment has an actual speed that is 80% of its speed limits, I assume its counterfactual travel speed is 80% of its counterfactual speed limit.

Table 3: Welfare Effects of Two Counterfactual Highway Systems

Exercise	Distribution of POIs	Welfare effects	Welfare Decomposition		
			Consumption Travel	Local Amenity	Work Travel
Burying Highways	Endogenous	10.2%	2.6%	7.0%	0.6%
		100%	25.4%	68.6%	6.0%
	Exogenous	7.0%	1.0%	5.6%	0.4%
		100%	14.3%	80.1%	5.7%
Replacing Highways	Endogenous	9.0%	6.5%	5.0%	-2.5%
		100%	72.3%	54.8%	-27.1%
	Exogenous	6.1%	1.7%	5.8%	-1.4%
		100%	27.4%	95.5%	-23.0%

Note: This table summarizes the welfare effects of two exercises that transform *urban* highways to eliminate disamenities estimated from the smartphone data and commuting data. The first exercise is burying urban highways underground. The second exercise is replacing urban highways with primary roads. For each exercise, I compute the counterfactual equilibrium with two model specifications—the spatial distribution of POIs is endogenously determined by the consumption visits or exogenously given by the data and kept fixed in the counterfactual. For each exercise and model specification, I decompose the counterfactual shock into three components to assess the contribution of different channels in the model. Each odd-numbered row reports the welfare effect for a given exercise and model specification. Each even-numbered row reports the share of the overall welfare effect attributable to each component, expressed as a percentage of the corresponding welfare total.

Table 4: Amenities Changes and Relocation in Counterfactual Economy

Exercise	Burying Highways		Replacing Highways	
Distribution of POIs	Endogenous	Exogenous	Endogenous	Exogenous
Change in amenities				
MSA	13%	8%	12%	8%
Urban areas	80%	46%	77%	45%
Suburban amenity	-42%	-23%	-41%	-22%
Relocation from urban to suburban areas				
% of total POIs	23%	0	23%	0
% of total population	21%	12%	20%	11%
% of total employment	11%	6%	11%	5%
Change in price levels				
MSA wage	1%		2%	
Urban wage	1%		1%	
Suburban wage	-2%		0%	
MSA land price	8%		6%	
Urban land price	37%		33%	
Suburban land price	-29%		-27%	

Note: This table lists the key statistics that summarize the responses of the economy to the counterfactual exercise. Aggregate amenity is measured by the sum of location amenity B_i times population N_{Ri}. Relocation of POIs is measured by the number of POIs that move from urban to suburban areas divided by the total number of POIs. Relocation of population and employment are measured in the same way. The endogenous distribution of POIs generates consumption agglomeration, which reinforces the migration of residents and jobs and the responses in amenities in counterfactual, compared to a counterfactual economy without relocation of POIs. Regional wages are calculated as wage bills divided by total employment. Regional land prices are calculated as land values over the total supply of land.

8.3.2 Welfare effects

Welfare effects and decomposition. As shown in Table 3, this exercise leads to a 9.0% increase in welfare. This gain, although at a substantial level, is smaller than that of the first exercise, because replacing highways with primary roads slows down both commuting and consumption travel. Due to increased travel time, I find partial welfare loss when decomposing the counterfactual effects.

The decomposition in Table 3 shows that the shock to consumption travel cost and consequent adjustments lead to a 6.5% welfare gain, or 72.3% of the total welfare gain. This is the primary source of gain for two reasons. First, the disamenities of highways revealed by consumption travel preferences are significant, so removing them yields a large gain. Second, consumption trips are short, at 10 minutes per trip on average, so the loss from slower travel speeds is small. On the contrary, the shock to commuting cost leads to a 2.5% welfare *loss*. This is due to the small impact of highway disamenities on commuting and the large increase in travel cost due to slower speeds, given that an average commuting trip is 23 minutes, much longer than a consumption trip. Nevertheless, the gain from reduced consumption travel costs outweighs the loss from increased commuting costs, resulting in net benefits for travelers. Meanwhile, the improvement in local amenities remains an important mechanism, for the same reasons discussed in the first exercise. Quantitatively, the 5.0% welfare gain from home amenity improvement is similar to that found in Brinkman and Lin (2024), despite using different sample cities.

Amenities and relocation. Table 4 shows that overall amenity increases by 12%, with a 77% increase in urban amenity and 41% decrease in suburban amenity. The initial improvement in urban amenity following the counterfactual highway system changes triggers a suburban-to-urban shift, leading to the relocation of 23% of POIs, 12% of population, and 11% of employment. This reallocation further amplifies the urban–suburban amenity disparity. As equilibrium population and employment adjust, wages and land prices respond accordingly, as presented in Table 4. With mobile labor in a closed city framework, wage levels remain largely unchanged. However, due to fixed land supply and shifts in amenities, urban land prices increase by 33%, while suburban land prices decrease by a comparable magnitude. The counterfactual equilibrium allocation and the underlying mechanisms driving these shifts closely resemble those in the first exercise.

Endogenous distribution of POIs. As discussed above, consumption agglomeration generated by trips to POIs and the endogenous location of POIs amplifies the welfare gain. Comparing the restricted counterfactual equilibrium with the unrestricted one, I show in Table 3 that this mechanism contributes to 2.9% welfare gain. The findings discussed for the first exercise also hold here: This mechanism mainly enhances the gain obtained through consumption travel channel. The 1.7% gain with exogenous POI distribution is much lower than that in the unrestricted counterfactual and contributes much less to overall welfare. For the contribution of consumption agglomeration on counterfactual economic allocation, Table 4 shows that this mechanism contributes to 9% resident migration and 6% relocation of employment, which is about half of the effects in the unrestricted counterfactual equilibrium.

8.3.3 Cost and benefits

Using the same data and method as in the first exercise , the 9.0% welfare gain is equivalent to a $8,462 transfer per capita, translating into a $56 million benefit per lane mile. As emphasized earlier, this static model estimates differences in welfare between the baseline and a counterfactual highway system, distinct from capitalized construction costs.

Beyond economic gains, the improved quality of life is a tangible benefit for urban travelers. Evidence from North American cities suggests that reducing intrusive roadways revitalizes communities and boosts local businesses. For instance, removing San Francisco's Embarcadero Freeway after the 1989 earthquake transformed the area into a thriving waterfront district, increasing property values and business activity (Chamings, 2021). Similarly, Vancouver's decision to forgo a downtown freeways preserved livability, urban density, and community stability (Woolley, 2016). These cases demonstrate the broader social and environmental benefits of urban highway transformations.

The cost of replacing elevated highways with surface roads is significantly lower. For example, according to WSDOT (2004), the most expensive highway project in Seattle MSA that only involves surface road construction, the I-405 Congestion Relief and Bus Rapid Transit Projects, has an estimated cost of $69 million per lane mile, less than one-fourth of the cost of a downtown tunnel project.

However, these cost estimates exclude temporary disruptions during construction, such as restricted traffic flow, increased noise and pollution, and temporary inconveniences for businesses. While not trivial, these transition costs are typically lower than the direct costs of construction. Surface-level road construction is also faster and less resource-intensive than tunneling projects (Congress for the New Urbanism (CNU), 2021), indicating the potential for surface-level highway replacements to deliver sizable economic and social benefits on shorter timelines.[35]

8.3.4 Incorporating congestion spillover

Another potential effect of replacing urban highways with lower-capacity primary roads is increased congestion. Reducing the physical capacity of roads can lead to disproportionately large declines in travel speeds. Additionally, with fixed demand for ll and reductions in road capacity, some traffic volume will be directed to primary roads, which are substitutes for highways. This may lead to additional congestion on all actual and counterfactual primary roads. The additional travel time due to congestion spillover may further push down the demand for travel. With exogenous roads and travel speed, my framework and

[35] For instance, San Francisco's Embarcadero Freeway was removed in just six months, with full revitalization achieved within a decade at a cost under $50 million.

data cannot measure the magnitude of endogenous congestion and consumers' travel response. However, I investigate this issue by examining the counterfactual equilibrium with different levels of congestion spillover.

To do this, I borrow the estimates from the literature. Bou Sleiman (2023) found a 17.5% reduction in travel speeds on the substitute roads following the shutdown of a road segment in Paris. Using her estimates, my counterfactual exercise, which decreases the median travel speed of affected roads from 53 mph to 31 mph, would lead to an 8% reduction in travel speeds on substitute roads. Therefore, I apply this 8% reduction to the counterfactual speeds I use in Subsection 8.3.1 for all actual and counterfactual primary roads in urban areas. I then compute travel time using the speeds with congestion spillovers. In addition, I examine the counterfactual results under weaker and stronger spillover effects by introducing an additional 4% or 12% reduction in speeds on primary roads. The intuition for weaker spillover is that congestion may prevent some consumers from traveling at all. The intuition for stronger spillover is that my counterfactual exercise is an extensive shock to Seattle's road supply, whereas Bou Sleiman (2023) studies the effect of a local road shutdown.

Figure 5 summarizes the welfare effects. Figure 5a shows the percentage change in expected utility at every level of congestion spillover. The welfare gains decline compared to the baseline case as the time costs of both consumption and work travel increase due to congestion. However, even with a strong spillover effect of 12% speed reduction, there is a 7.9% welfare gain.[36]

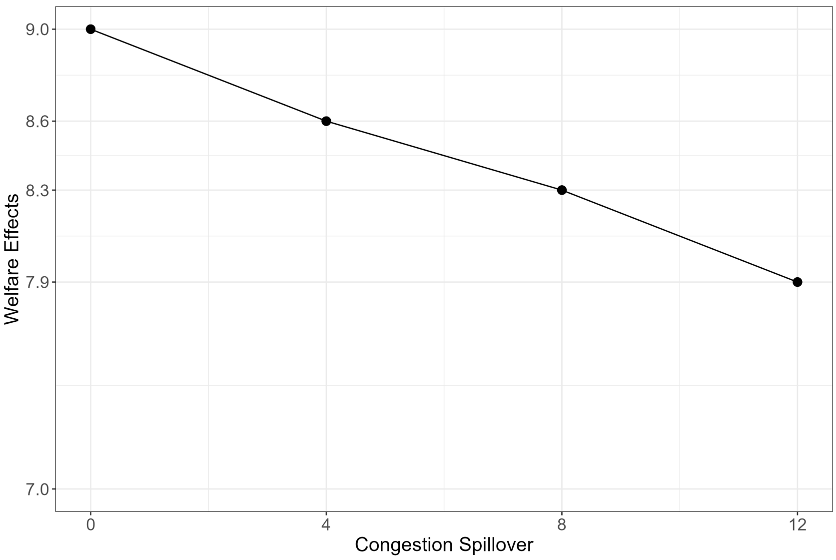
Figure 5b shows the decomposition of the welfare effects using the methods discussed above. While the gains from consumption travel decline and the losses from commuting rise with increased congestion, the gains consistently outweigh the losses at every level of spillover. Meanwhile, the gain from amenity improvement in the home neighborhood, which increases the utility of the outside option, remains at a substantial level of up to 7.1%. This mechanism is more important with worse congestion, indicating that more consumers choose to stay in home neighborhoods and benefit from improved local amenity when traffic becomes worse, effectively reducing the travel demand. The impact on consumption travel patterns shows a consistent phenomenon: In the counterfactual with the strongest spillover, compared to the counterfactual without spillover, total visits decline by 4%, and an average consumption trip in urban areas is 15% shorter, despite taking similar travel time.

9 Conclusion

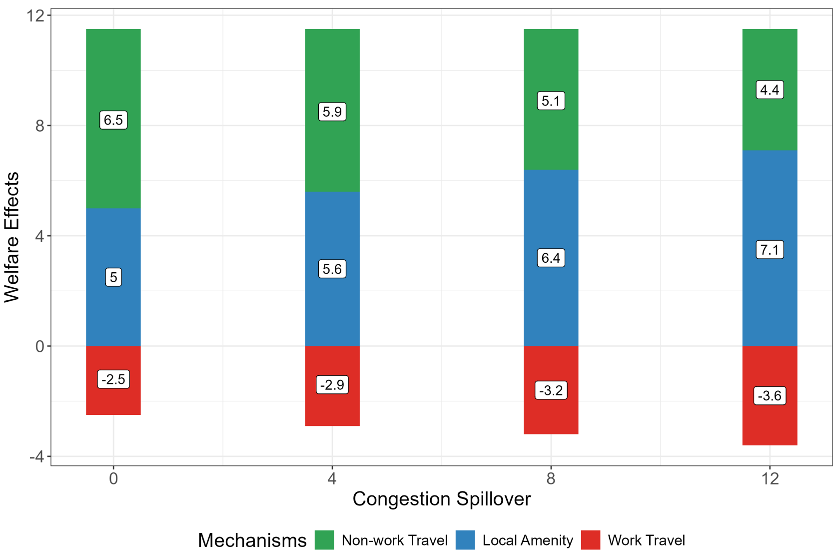
This paper examines the impacts of highways on both work and consumption travel within the Seattle metro area. Using smartphone GPS data and census data, I find that while highways can facilitate

[36]To test the robustness of these findings under extreme congestion, I simulate a counterfactual economy in which travel speeds on highways and primary roads fall by 40%—five times the baseline level of congestion spillover. After recomputing travel routes and solving for the counterfactual equilibrium, I find a welfare gain of 3.87%, indicating that benefits persist even under extremely severe congestion conditions.

Figure 5: Welfare Analysis with Congestion Spillover



(a) Welfare Effects



(b) Welfare Decomposition

Note: These two figures show the welfare effects of a counterfactual highway system where the urban highways are replaced with primary roads and spillover in congestion are applied to all primary roads. I adjust the speeds on counterfactual roads to match the speeds of actual primary roads and introduce 0%, 4%, 8%, and 12% reductions in speeds on all primary roads. Figure 5a indicates that welfare gain declines as congestion spillovers become stronger but is still at a substantial level of 7.9% with the strongest congestion spillover. The Y-axis is adjusted to reflect the small changes in welfare gain under congestion spillover. Figure 5b shows that the gains from increased utility from consumption trips consistently outweigh the losses from higher work trip costs at every level of congestion spillover.

faster travel, they also impose significant frictions on consumer movement within cities. The results suggest that *urban* highways primarily act as barriers to intracity travel, while *suburban* highways weakly function as conduits. Notably, the most pronounced discouragement of intracity travel is found for short, consumption trips within dense urban areas. These findings align with recent public debates about urban highways and substantiate some concerns raised by local residents during past "Freeway Revolts", suggesting highways' role in shaping local travel patterns in ways that may undermine urban welfare.

To further evaluate welfare, I develop a quantitative urban model that incorporates commuting decisions, consumption travel choices, and endogenous amenities. This general equilibrium model allows for a comprehensive evaluation of two counterfactual scenarios: burying urban highways underground and replacing them with primary surface roads. Both scenarios indicate substantial economic gains, yet they also yield heterogeneous effects. Specifically, these interventions improve accessibility within urban areas, attract population inflows, and stimulate consumption, especially through the reinforcement of consumers' and POI owners' behaviors. However, they also lead to higher land prices in central areas and a decline in suburban amenities due to shifts in activity centers. The relocation of economic activities in response to improved urban connectivity underscores the importance of accounting for general equilibrium effects in urban infrastructure planning and highlights regional winners and losers of such policies.

The counterfactual analysis partially aligns with theories of urban streets as places of social and economic exchange in Jacobs (1961). Without the physical barriers created by highways, city centers would thrive, attracting more POIs and people engaged in social and consumption activities. Nevertheless, the study's focus on intracity travel potentially undervalues highways' broader economic contributions, such as those to freight transport and intercity connectivity. Overall, my findings suggest the need for a nuanced approach to urban highway design, which carefully considers the interplay between regional mobility, local accessibility, and urban land use. While highways serve as vital transportation links, their placement and design can significantly influence the structure of cities and the quality of urban life.

References

ACS Briefs (2020). Household income: 2019. Technical Report ACSBR/20-03, U.S. Census Bureau.

Agarwal, S., Jensen, J. B., and Monte, F. (2020). Consumer mobility and the local structure of consumption industries. Technical report, National Bureau of Economic Research.

Ahlfeldt, G. M., Bald, F., Roth, D., and Seidel, T. (2021). Quality of life in a dynamic spatial model. Technical report.

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The economics of density: Evidence from the berlin wall. *Econometrica*, 83(6):2127–2189.

Akbar, P. A., Couture, V., Duranton, G., and Storeygard, A. (2023). The fast, the slow, and the congested: Urban transportation in rich and poor countries. Technical report, National Bureau of Economic Research.

Allen, T. and Arkolakis, C. (2014). Trade and the topography of the spatial economy. *The Quarterly Journal of Economics*, 129(3):1085–1140.

Allen, T. and Arkolakis, C. (2022). The welfare effects of transportation infrastructure improvements. *The Review of Economic Studies*, 89(6):2911–2957.

Almagro, M. and Domínguez-Iino, T. (2024). Location sorting and endogenous amenities: Evidence from amsterdam.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Argerious, N. B. (2021). Seattleites concerned over condition of interstate 5, a poll shows. *The Urbanist*.

Athey, S., Ferguson, B. A., Gentzkow, M., and Schmidt, T. (2020). Experienced segregation. Technical report, National Bureau of Economic Research.

Bagagli, S. (2024). The (express)way to segregation: Evidence from chicago. Technical report, Harvard University.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The quarterly journal of economics*, 122(2):775–805.

Black, L. (2019). Lid i-5 or get rid of i-5? a look at two plans that would totally change the city. *The Stranger*.

Black, L. (2020). Hiding a highway. *The Stranger*.

Bou Sleiman, L. (2023). Displacing congestion: Evidence from paris. Technical report, CEPREMAP.

Brinkman, J. and Lin, J. (2024). Freeway revolts! the quality of life effects of highways. *Review of Economics and Statistics*, 106(5):1268–1284.

Cao, Y., Chevalier, J. A., Handbury, J., Parsley, H., and Williams, K. R. (2024). Distributional impacts of the changing retail landscape.

Chamings, A. (2021). 'a monstrous mistake': Remembering the ugliest thing san francisco ever built. *SFGate*.

Chen, M. K. and Pope, D. G. (2020). Geographic mobility in america: Evidence from cell phone data. Technical report, National Bureau of Economic Research.

Congress for the New Urbanism (CNU) (2021). Case studies in urban freeway removal. Accessed: March 6, 2025.

Cook, C. (2023). Heterogeneous preferences for neighborhood amenities: Evidence from gps data. *Available at SSRN 4212524*.

Couture, V. (2016). Valuing the consumption benefits of urban density. Technical report, University of British Columbia.

Davis, D. R., Dingel, J. I., Monras, J., and Morales, E. (2019). How segregated is urban consumption? *Journal of Political Economy*, 127(4):1684–1738.

Dingel, J. I. and Tintelnot, F. (2023). Spatial economics for granular settings. Technical report, National Bureau of Economic Research.

Duranton, G. and Turner, M. A. (2012). Urban growth and transportation. *Review of Economic Studies*, 79(4):1407–1440.

Glaeser, E. L., Kolko, J., and Saiz, A. (2001). Consumer city. *Journal of economic geography*, 1(1):27–50.

Greiman, V. A. (2013). *Megaproject management: Lessons on risk and project management from the Big Dig*. John Wiley & Sons.

Guimaraes, P., Figueirdo, O., and Woodward, D. (2003). A tractable approach to the firm location decision problem. *Review of Economics and Statistics*, 85(1):201–204.

Hall, J. D. (2018). Pareto improvements from lexus lanes: The effects of pricing a portion of the lanes on congested highways. *Journal of Public Economics*, 158:113–125.

Handbury, J. (2021). Are poor cities cheap for everyone? non-homotheticity and the cost of living across us cities. *Econometrica*, 89(6):2679–2715.

Handbury, J. and Weinstein, D. E. (2015). Goods prices and availability in cities. *The Review of Economic Studies*, 82(1):258–296.

Hausman, N., Samuels, P., Cohen, M. C., and Sasson, R. (2023). Urban pull: The roles of amenities and employment. *Available at SSRN 3670974*.

Head, K. and Mayer, T. (2004). Market potential and the location of japanese investment in the european union. *Review of Economics and Statistics*, 86(4):959–972.

Hidalgo-Muñoz, A. R., Jallais, C., Evennou, M., and Fort, A. (2023). Driving anxiety and anxiolytics while driving: Their impacts on behaviour and cognition behind the wheel. *Heliyon*.

Jacobs, J. (1961). *The Death and Life of Great American Cities*. Random House, New York.

Lee, K. H. and Tan, B. J. (2023). Urban transit infrastructure and inequality. Technical report.

Lee, S., Lee, S. H., and Lin, J. (2021). The well-being of nations: estimating welfare from international migration. *International Economic Review*, 62(3):1111–1130.

Massenkoff, M. and Wilmers, N. (2023). Rubbing shoulders: Class segregation in daily activities. *Available at SSRN 4516850*.

McCormick, K. (2020). Deconstruction ahead. how urban highway removal is changing our cities? *Lincoln Institute*.

McFadden, D. (1978). Modelling the choice of residential location. In Karlquist, A., Lundqvist, L., Snickars, F., and Weibull, J., editors, *Spatial Interaction Theory and Residential Location*, pages 75–96. North-Holland, Amsterdam.

Millsap, A. A. (2019). Is it time to take highways out of cities? *Forbes*.

Miyauchi, Y., Nakajima, K., and Redding, S. J. (2021). The economics of spatial mobility: Theory and evidence using smartphone data. Technical report, National Bureau of Economic Research.

Mohl, R. A. (2004). Stop the road: Freeway revolts in american cities. *Journal of Urban History*, 30(5):674–706.

Mohl, R. A. (2008). The interstates and the cities: the us department of transportation and the freeway revolt, 1966–1973. *Journal of Policy History*, 20(2):193–226.

Monte, F., Redding, S. J., and Rossi-Hansberg, E. (2018). Commuting, migration, and local employment elasticities. *American Economic Review*, 108(12):3855–90.

NHTS (2017). 2017 national household travel survey. https://nhts.ornl.gov.

Redding, S. J. (2023). Quantitative urban models: from theory to data. *Journal of Economic Perspectives*, 37(2):75–98.

Severen, C. (2023). Commuting, labor, and housing market effects of mass transportation: Welfare and identification. *Review of Economics and Statistics*, 105(5):1073–1091.

Trumm, D. (2024). Seattle waterfront park project finally enters its home stretch. *The Urbanist*.

Tsivanidis, N. (2023). Evaluating the impact of urban transit infrastructure: Evidence from bogota's transmilenio. *University of California, Berkeley*.

Weiwu, L. (2024). Unequal access: Racial segregation and the distributional impacts of interstate highways in cities. Technical report, Massachusetts Institute of Technology.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, 50(2):420–445.

Woolley, F. (2016). How vancouver escaped the freeway curse. *Worthwhile Canadian Initiative*.

WSDOT (2004). Highway construction costs.are wsdot's highway construction costs in line with national experience? Technical report, Washington State Department of Transportation.

Appendix

A Data Description

This section shows more details and summary statistics of the data used in the paper.

A.1 Demographics and travel patterns in Seattle MSA

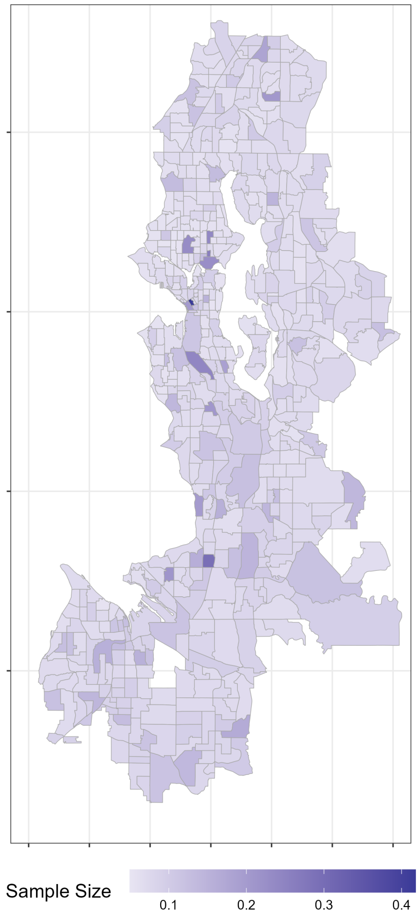
Table A.1 reports the summary statistics in different areas in Seattle MSA, which gives an outlook of the demographics and travel patterns. I define the municipalities of Seattle, Tacoma, and Bellevue, and their surrounding neighborhoods as urban zones and the rest of the places as suburban zones. Figure 1 gives a visualization of each area. The full sample used in the baseline regression includes more than 46 million visits to over 30 thousand POIs. The urban and suburban zones are similar in terms of the number of census tracts, sample population, average income level, total number of visits, and the number of POIs. The sample size in each census tract, measured by the total number of smartphone devices over population, is 12% on average and is also balanced across space, as shown in Figure A.1. Especially, the sample sizes in urban and suburban areas are similar, ensuring that the different effects of urban and suburban highways are not driven by sample selection.

Table A.2 reports the summary of POIs in my sample, grouped by type and industry. POIs that mainly provide amenities for local travelers are selected into the sample, whereas POIs related to manufacturing and workplaces are dropped. I use the classification in Cook (2023) and group the POIs into four types—Restaurants, Shops, Services, and Entertainment—by their NAICS codes. This classification is relevant in the investigation in Appendix C and D. In each type, I list the industries to which the POIs belong. As Table A.2 shows, the number of POIs and visits varies largely across industries.

The data published by SafeGraph does not provide location information for individual GPS pings or devices, so I am unable to observe trip chains, which are trips involving multiple stops at different POIs. As a result, I assume that all consumption trips originate from home. To see the strength of this assumption, Cook (2023) reports that, in a smaller sample of smartphone data across the United States, 79% of trips consist of a single stop, a share that remains high regardless of device coverage or the income level of the device holder. Additionally, defining trip chains accurately is challenging due to the limited GPS coverage in the sample and the high computational cost. To see the bias in welfare effects due to this assumption, Miyauchi et al. (2021), studying trip chains with smartphone GPS data from Japan, find that a model without trip chains—assuming a single consumption location from home—captures 81% of the total welfare effect of a model that incorporates trip chains.

Additionally, I use individual trip data from the 2017 National Household Travel Survey (NHTS) in several parts of the analysis. Based on the mode of transportation, I find that 88.7% of all trips are

Figure A.1: Sample Size across Census Tract



Note: This figure shows the sample size, measured by the total number of smartphone devices over population at the census tract level. The sample is balanced across locations, with an average share of 12%. The variance of sample size across locations is low, with only a few places that have higher shares at around 40%.

taken on roadways, including by private vehicle, taxi, rental car, or bus. This highlights the central role of roads in shaping welfare and quality of life, which are key research questions of this paper. To show the significance of intracity consumption travel, I first filter for trips that occur entirely within a metropolitan area and are not homecoming trips, based on their origin and destination. Then, using the reported trip purposes, I define consumption trips as those not related to work, medical services, transporting someone, or other reasons. The remaining consumption-related trips account for 80% of all non-homecoming trips within cities.

Figure A.2 shows the share of work and consumption (non-work) trips in each hour of the day, calculated based on the purpose and time of the trips. Most of the non-work trips happen from 8 a.m. to 6 p.m.. Most of the work trips occur during morning and evening rush hours. I use these shares as weights in the calculation of mean speeds on road segments, averaging over the hourly speed in Uber Movement, as discussed in the next section.

Table A.1: Summary Statistics for Areas in Seattle MSA

Regions	All region	All Urban	Urban Areas: Seattle	Urban Areas: Tacoma	Urban Areas: Bellevue	Suburbs
From *Census*						
# Census Tracts	511	258	150	60	48	253
Commuters (1,000)	1227	594	370	109	115	633
Mean Income ($1,000)	94.6	98.1	99.3	65.3	135.5	91.0
Median Income ($1,000)	92.1	96.6	97.2	62.4	130.5	85.5
From *SafeGraph*						
Total Visits (1,000,000)	46.0	21.9	12.2	4.9	4.8	24.1
# POI (1,000)	30.5	17.6	10.3	3.5	3.8	12.9
From *OpenStreetMap*						
Mean Travel Time (min)	9.7	8.6	8.5	8.4	9.0	10.5
Mean Travel Distance (km)	7.9	7.0	6.8	6.6	7.7	8.8
% Crossing Highway Routes	25.7	25.3	22.9	40.1	20.9	26.2
% Using Highway Routes	57.0	57.9	60.0	42.9	64.4	55.9
% No Interaction Routes	17.3	16.8	17.1	17.0	14.7	17.9

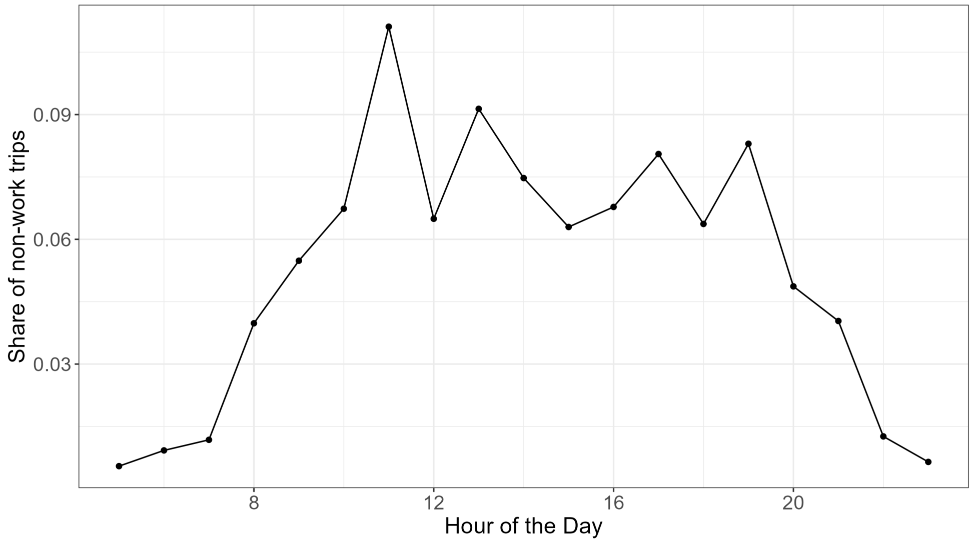
Note: This table shows the summary statistics by areas in Seattle MSA from three data sources.

Table A.2: Summary Statistics of POIs, by Type and Industry

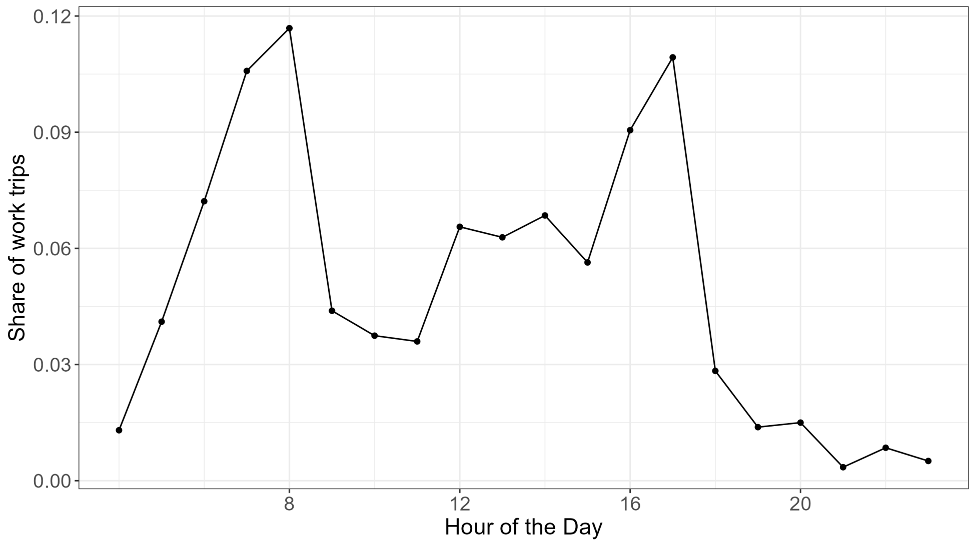
Types	NAICS group in Fig D.3	NAICS 3-digit sub-group	# POIs	# Visits
Restaurants	72 Restaurants	722 Food Services and Drinking Places	9,590	15,716,775
Shops	44 Grocery, Pharmacy	441 Motor Vehicle and Parts Dealers	1,012	986,217
		442 Furniture and Home Furnishings Stores	522	515,945
		443 Electronics and Appliance Stores	315	290,805
		444 Building Material, Garden Equipment and Supplies Dealers	437	740,322
		445 Food and Beverage Stores	1,327	2,528,903
		446 Health and Personal Care Stores	635	1,489,468
		448 Clothing and Clothing Accessories Stores	747	1,035,472
	45 Other Retails	451 Sporting Goods, Hobby, Musical Instrument, and Book Stores	867	1,576,874
		452 General Merchandise Stores	216	2,250,198
		453 Miscellaneous Store Retailers	1,252	2,537,746
Services	52 Finance, Insurance	522 Credit Intermediation and Related Activities	302	117,290
		523 Securities and Other Financial Investments	115	32,729
	54 Professional Services	541 Professional, Scientific, and Technical Services	325	126,635
	62 Healthcare Services	621 Ambulatory Health Care Services	3,462	1,890,915
		623 Nursing and Residential Care Facilities	451	361,754
		624 Social Assistance	754	891,686
	81 Other Services	811 Repair and Maintenance	1,027	448,708
		812 Personal and Laundry Services	1,332	697,811
		813 Religious, Grantmaking, Civic, Similar Organizations	2,115	1,394,272
Entertainment	71 Arts, Entertainment	711 Performing Arts, Spectator Sports, and Related Industries	110	467,013
		712 Museums, Historical Sites, and Similar Institutions	1,684	5,016,079
		713 Amusement, Gambling, and Recreation Industries	1,931	4,502,969
Total			30,528	46,016,586

Note: This table shows the number of POIs and number of consumption visits in different types and industries of POIs.

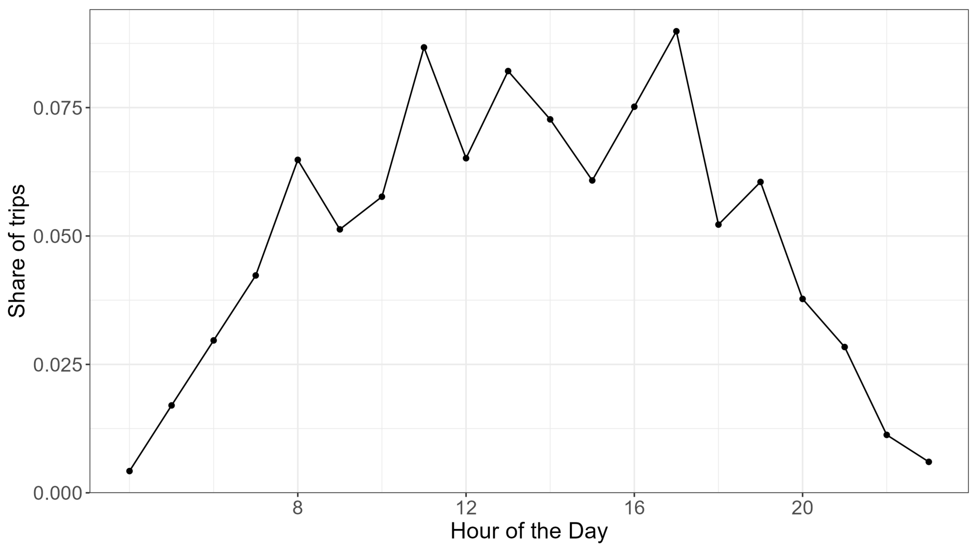
Figure A.2: Hourly Share of Trips, Seattle MSA, NHTS



(a) Share of Non-work Trips



(b) Share of Work Trips



(c) Share of All Trips

Note: These figures show the share of non-work and work trips in each hour of the day in the Seattle MSA, computed using the starting time of trips from NHTS.

A.2 Travel routes and speeds

Travel routes are computed as the path that minimizes travel time, based on the road network in OpenStreetMap. The default speed assumption in OpenStreetMap is the speed limit. To incorporate the impact of actual traffic conditions on route choices and travel time, I use mean travel speeds in route computation, which are calculated using data from Uber Movement and NHTS. Figure A.4 shows the hourly average travel speed on different types of roads and on popular highways. Speed at 5 p.m., marked by the vertical line, is usually the lowest speed throughout the day, reflecting congestion during the evening rush hour. To additionally validate the data from Uber Movement, I compare it to the speed data from the other two sources. First, I compare the hourly speeds from Uber and the data published by Akbar et al. (2023), with the latter one obtained from trips simulated on Google Maps.[37] The average travel speeds are similar: 37.52 mph from Akbar et al. (2023) and 39.41 mph from Uber Movement. Figure A.5 shows that the two data sources provide similar variations of vehicle speeds across different hours of the day, as well as similar levels of speeds from 7 a.m. to 8 p.m.. Congestion is captured by both sources, indicated by the lower speeds during morning and evening rush hours. Second, the Washington State Department of Transportation (WSDOT) publishes summarized vehicle speeds for specific state highways, which are estimated by data collected from the permanently installed traffic recorders. The data shows that the average travel speed on state highways in Seattle in 2019 is 58.16 mph. I find that the average speed on highways calculated from Uber Movement is 56.41 mph, which is very close to the average speed from WSDOT data.

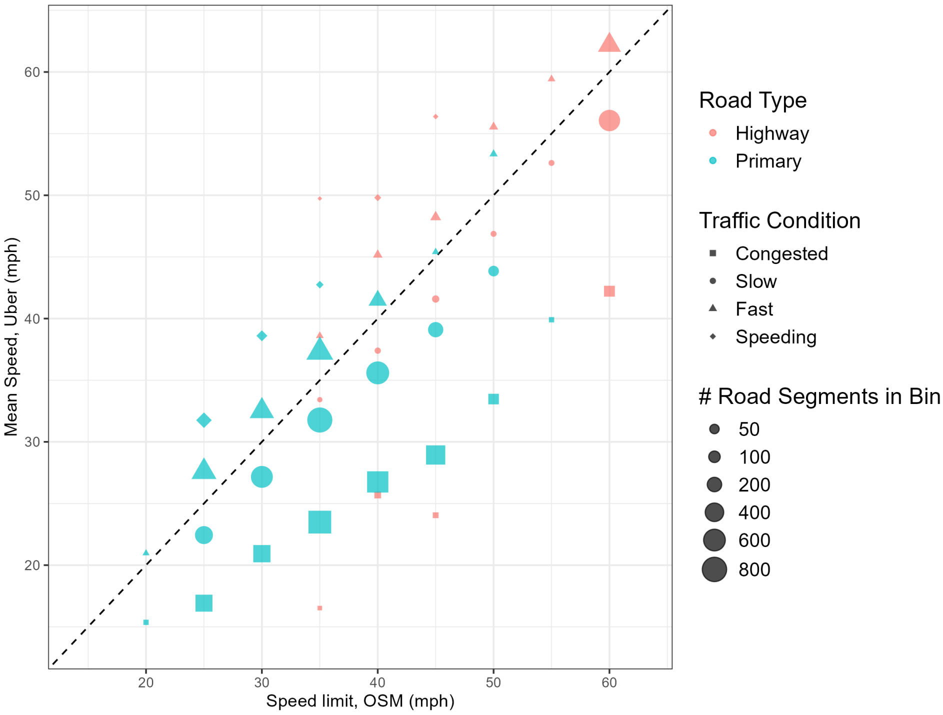
Figure A.3 shows the traffic conditions reflected in the Uber Movement data. It is a bin-scatter plot showing the relationship between the weighted mean speed and the speed limit for road segments that are highways or primary roads[38], the most commonly used roads in the city. To draw Figure A.3, I first group the road segments by type and the speed limit. For each group of roads, I define 4 bins that represent different traffic conditions, based on the ratio between the speed from Uber and the speed limit. The shape of the marker indicates the traffic conditions. The size of the marker indicates the number of road segments in the bin, reflecting the density of roads at each level of traffic condition. Congestion is captured in the Uber speed as shown by the large number of roads in the slow and congested group. Most highways have speeds above 40 mph, which is significantly higher than the speeds on primary roads.

Figure A.6 visualizes congestion reflected by the Uber data on a map of Seattle MSA. Each shape (in gray) on the map is a municipality. I show all the highways (in light blue) and primary city roads (in light yellow) with valid speed data in Uber Movement. I highlight the congested road segment in each type, shown by the legend. The line segments in dark purple show the road segments of highways with mean speeds below 50 mph, compared to the usual speed limit of 60 mph. These congested roads

[37] The two sources differ mainly in the sample of trips. Uber does not publish the technical procedure for speed estimation, so I cannot discuss the differences in methodology.

[38] I use the definition of primary roads in the OSM database, which is the fastest type of surface roads with open access.

Figure A.3: Weighted Mean Speed (Uber) and Speed Limit



Note: This figure is a bin-scatter plot between the weighted mean speed, calculated from Uber and NHTS, and the corresponding speed limit for road segments that are highways or primary city roads. I group the road segments by the speed limit. For each group of roads, I define 4 bins, based on the ratio between speed from Uber and the speed limit, to represent traffic conditions. The shape of the marker indicates the traffic conditions. The size of the marker indicates the number of road segments in the bin. The dashed black line is the 45-degree line. Congestion is incorporated in the mean speed because of the large number of roads in the slow and congested group. The majority of highways have speeds above 40 mph, which is significantly higher than the speeds on primary roads, which are mainly between 20 to 40 mph.

are 32% of all highway road segments and are located in downtown Seattle, major intersections, and merging points in the highway system. Similarly, the line segments in dark orange show the primary road segments with mean speeds below 25 mph, compared to the usual speed limit of 35 mph. The slow primary roads are 25% of all primary road segments and are especially concentrated in downtown Seattle.

The identification method in the paper requires that there are an adequate amount of routes in each route type defined in Subsection 3.2. As I split the data into sub-samples to find heterogeneous effects, a concern is that there are not enough routes of each type in each bin to enable the identification. Thus, I report in Table A.3 the share of routes of the three types and the cumulative share of visits and observations (origin-destination pairs) in ten sub-samples, grouped by the distance of the travel route. For the routes that are longer than 25km (in the sixth bin and beyond), almost all of the routes use highways, which makes it impossible to identify the disamenity of highways for the travelers on these routes. Therefore, in the regression and welfare evaluation, I use the sample of origin–destination pairs that are shorter than 25km and combine the fourth and fifth bin, as shown in Section 5. This sub-sample covers 82% of all the visits in the whole sample, which captures the majority of the welfare impacts,

Table A.3: Summary Statistics by Bin

Bin	Route Distance	Cumulative % of Observations	Cumulative % of Visits	% of route by type Cross	Use	NoInt
1	[0, 5 km]	2.3	35.3	25.9	2.6	71.5
2	[5, 10 km]	7.1	57.5	40.5	25	34.5
3	[10, 15 km]	12.8	68.9	29.9	56	14.1
4	[15, 20 km]	19.2	76	23.9	70.9	5.2
5	[20, 25 km]	26.2	81.7	14.8	84.2	1.0
6	[25, 30 km]	33.6	86.3	6.6	93.4	0
7	[30, 40 km]	49	92.6	2.5	97.5	0
8	[40, 50 km]	63.6	96.4	0.7	99.3	0
9	[50, 60 km]	75	98	0.1	99.9	0
10	[60, 125 km]	100	100	0	100	0

Note: This table shows the summary statistics of routes in ten groups of bins. The bins are determined by the length of the routes in kilometers, shown by Column Range. In each bin, I show the percentage of routes by type, which is defined by their interaction with highways, namely, crossing a highway, using a highways, or no interaction with a highway.

albeit accounting for 26% of all the origin–destination pairs.

B Predicting Travel Speed

24% of total road segments in the OSM database have a valid weighted mean speed from Uber. For the roads where the Uber data is missing, I make predictions using the speed limits available in OSM. To do so, I first estimate the relationship between the available weighted mean speed and the speed limit[39] using the following equation:

$$V_r = \sum_{\theta} \gamma_{1,\theta} \text{Vlim}_{r\in\theta} + \gamma_{2,\theta=\text{Highway}} \text{Vlim}^2_{r\in\theta} + \text{FE}_\theta + D_{\text{Urban}} + \varepsilon_r, \tag{20}$$

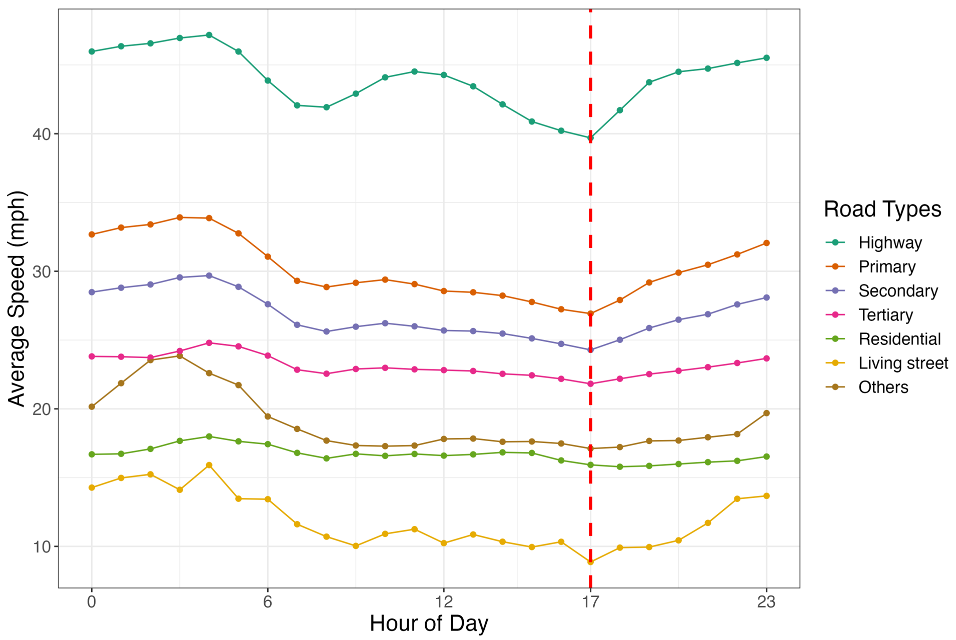
where r denotes a road segment, θ denotes road types, V represents weighted mean travel speed, $Vlim$ represents speed limit. $\gamma_{1,\theta}$ measures the type-specific linear relationship between weighted mean speed and speed limit. $\gamma_{2,\theta=\text{Highway}}$ captures the potential nonlinear relationship for highways. And I allow each road type to have a separate intercept, which is captured by the type fixed effect FE_θ. Finally, a dummy variable for urban zones is added to capture different travel preferences related to urban density.

Table B.1 shows the estimation result of Equation (20). The relationship for highways exhibits pronounced nonlinearity. The coefficients are statistically significant for urban and suburban highways. Coefficients for other types of roads are between 0.4 and 0.8, some of which are significant. The estimation yields an R^2 of 0.58. The racial of root mean square error (RMSE) to the mean value of the dependent variable is 0.23.

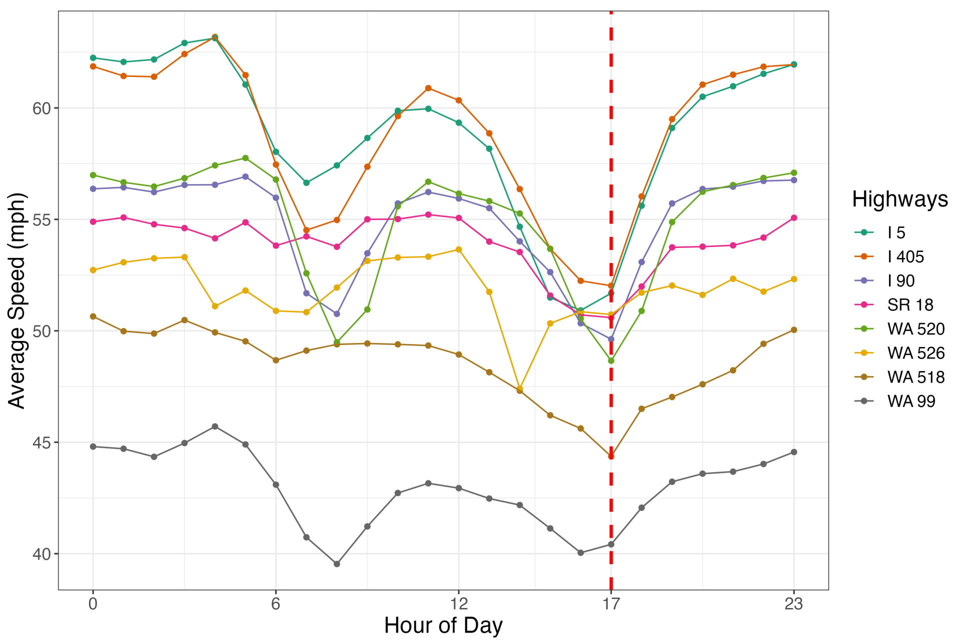
I thus use the coefficient values in Table B.1 and data on speed limits to predict the missing values of

[39] For missing values in speed limits, I replace with the type-specific mean value of the available speed limits.

Figure A.4: Hourly Average Speeds from Uber Movement, Seattle MSA



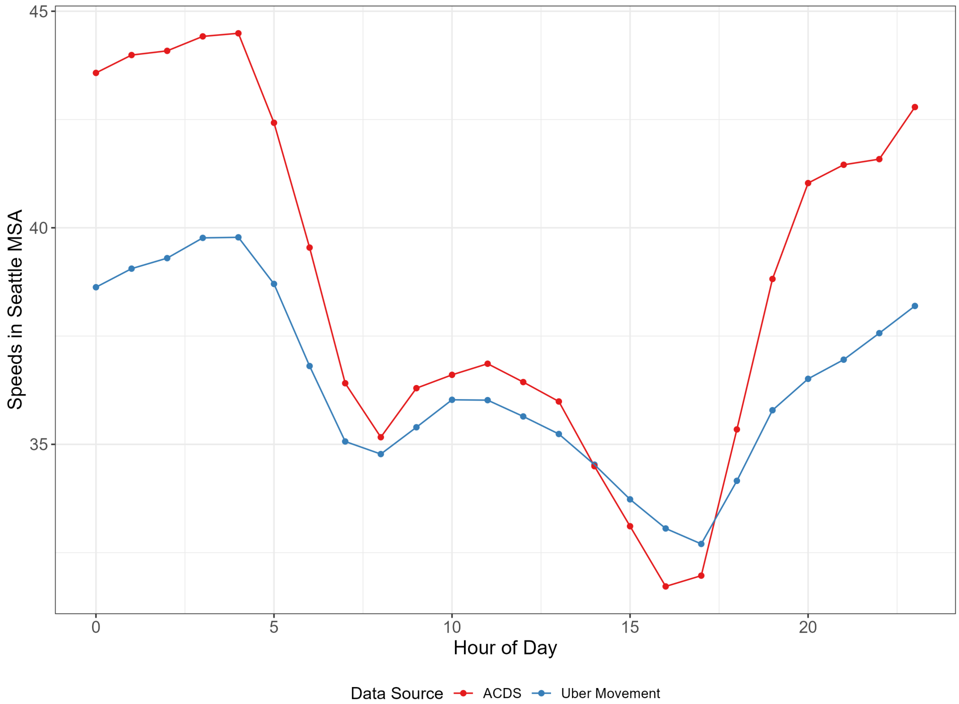
(a) Speed by Road Types



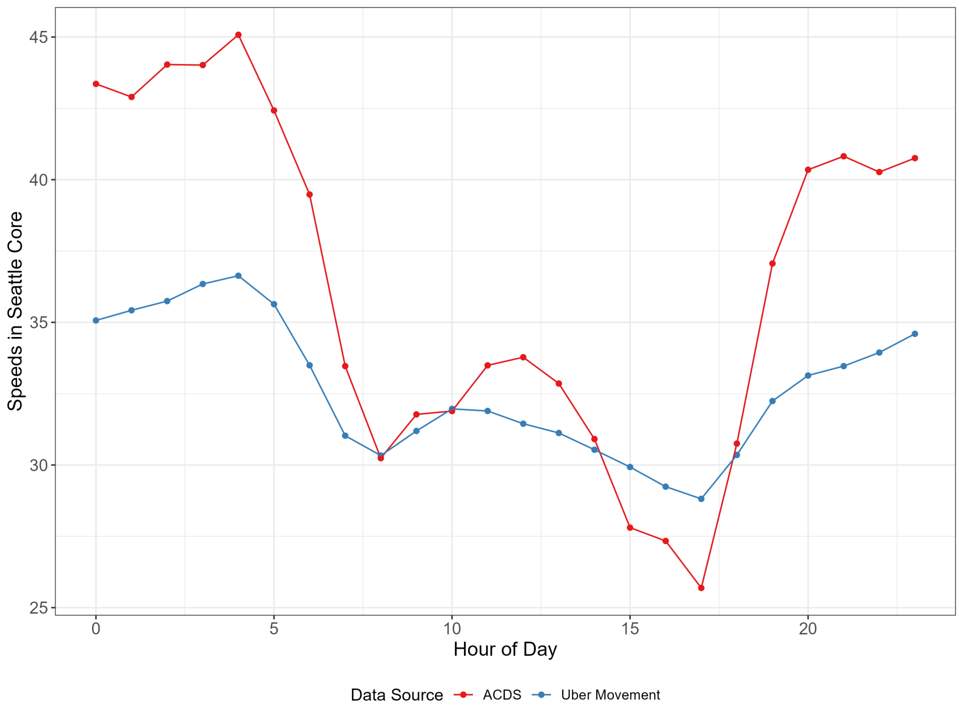
(b) Speed on Highways

Note: These two figures display the hourly average travel speeds on various types of city roads, computed with the speed data from Uber Movement. Panel A.4a shows the hourly speeds across seven types of roads. Panel A.4b shows the hourly speeds on eight heavily-used highways. The lowest average travel speed throughout the day occurs during the 5 p.m. rush hour, which is used to assess the robustness of the empirical findings regarding congestion.

Figure A.5: Hourly Average Speeds from Uber Movement and Akbar et al. (2023)



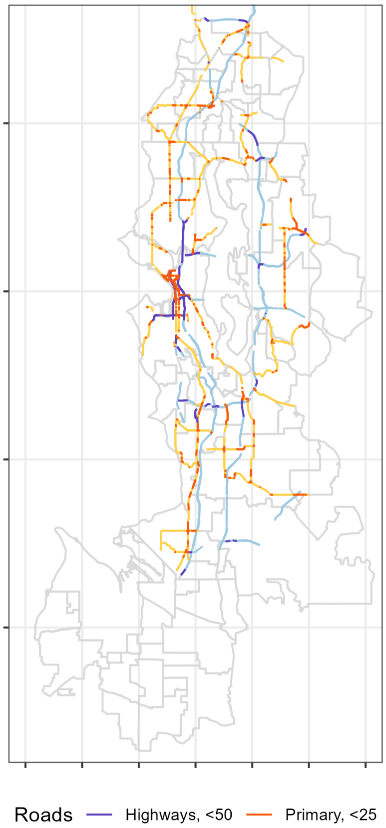
(a) Speeds in Seattle MSA



(b) Speeds in Seattle Core

Note: These two figures compare the average hourly speeds in Seattle from two data sources: *Uber Movement* and the data published by Akbar et al. (2023). The two data sources provide similar variations of speeds throughout the day. The level of speeds during usual day hours (7 a.m. to 8 p.m.) are also similar. This shows the validity of the Uber Movement's data.

Figure A.6: Map of Congested Highways and Primary Roads



Note: This figure shows the road segments covered by Uber Movement data. The lines in lighter blue are highways. The lines in lighter yellow are primary roads. The darker colors mark the congested road segments in each type. The road segments in dark purple are the highways that are, on average, slower than 50mph, which are 32% of all highways. The roads in dark orange are the primary roads that are, on average, slower than 25mph, which are 25% of all primary roads. For both types, the congested roads are the major roads in the city of Seattle, especially downtown Seattle, and big intersections and merging. Traffic conditions on suburban highways are better than on suburban primary roads.

Table B.1: Weighted Mean Speed (Uber) and Speed Limits (OSM)

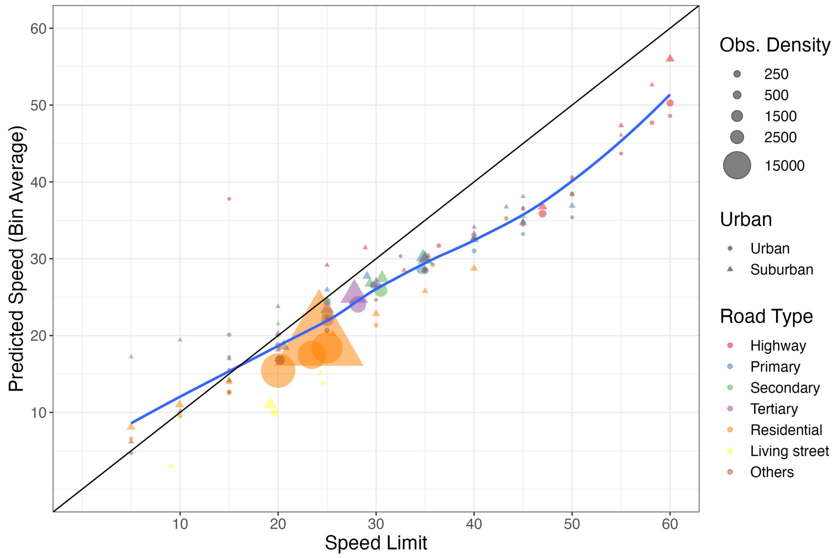
Dependent Variable:	Mean Speed Uber
Speed limits $\times \mathbf{1}_{\text{Urban Highway}}$	-1.67**
	(0.049)
Speed limits^2 $\times \mathbf{1}_{\text{Urban Highway}}$	0.026**
	(0.0005)
Speed limits $\times \mathbf{1}_{\text{Suburban Highway}}$	-1.98**
	(0.036)
Speed limits^2 $\times \mathbf{1}_{\text{Suburban Highway}}$	0.032***
	(0.0004)
Speed limits $\times \mathbf{1}_{\text{Primary}}$	0.437**
	(0.029)
Speed limits $\times \mathbf{1}_{\text{Secondary}}$	0.561*
	(0.045)
Speed limits $\times \mathbf{1}_{\text{Tertiary}}$	0.649
	(0.108)
Speed limits $\times \mathbf{1}_{\text{Residential}}$	0.590*
	(0.068)
Speed limits $\times \mathbf{1}_{\text{Others}}$	0.798*
	(0.116)
Fixed effects	Type & D_{Urban}
Observations	64,484
R^2	0.579
RMSE	5.7
Clustered SE	Type & Urban

Note: This table shows the regression results of equation (20). The dependent variable is the mean speed of from Uber Movement road segments in Seattle MSA. I fit the Uber data with data on speed limits, assuming each type of roads has a different slope and intercept. I also allow for a quadratic relationship for highways and a dummy variable for whether the road is in urban or suburban area. Speed limit fits the Uber speed well, with an R^2 of 0.579. The equation is used to predict mean speeds for the roads with missing Uber data.

Uber speeds, assuming the estimated relationship is the same for the sample with missing Uber speeds. Figure B.1 is a bin-scatter plot between the predicted speeds and speed limits, where I show the road type, road location, and number of road segments in each bin. Most of the predicted values are close to and under the forty-five degree line, which is consistent with Table B.1[40]. I then combine the weighted mean Uber speeds and the predicted values for missing Uber speeds to construct a full sample of travel speed for all roads in Seattle MSA. I then match the speeds to road segments in the OSM database and compute the travel route, time, and distance that minimize travel time.

[40]Most of the roads with missing Uber data are the rarely used residential and tertiary roads, which have a small weight in the travel routes.

Figure B.1: Predicted Speed vs Speed Limits



Note: This figure shows the relationship between the predicted speed values for the sample with missing Uber speeds and the data on speed limits. I group the road segments into bins and calculate the mean value of the predicted speed on each road. Each marker in the figure represents a cluster. The color indicates the type of roads in the cluster. The marker size represents the number of road segments in the cluster. The shape indicates whether the roads are in urban or suburban zones. The black line is a forty-five degree line. The blue line is the fitted nonlinear relationship.

C Robustness

C.1 Identification using control functions

In Section 4, I use route type to identify the disamenity of highways, conditional on fixed effects and many control variables. However, the allocation of highways in cities is far from random and locations have different levels of exposure to highways. In fact, the *Freeway Revolts* in Seattle had successfully changed the location of some highway routes in order to protect green space and avoid cutting vital neighborhoods (Mohl, 2004, 2008; Brinkman and Lin, 2024). Thus, the identification may be biased due to omitted variables in the generation of highway locations.

To address the endogeneity of highway locations, I use the planned routes in the 1947 highway plan (digitized by Brinkman and Lin (2024)) as instruments for the actual highways. As discussed in Brinkman and Lin (2024), the planned routes are drawn independently from the economic and demographic conditions of the cities. Figure C.1 shows the planned and actual highway routes in Seattle MSA. The planned routes are spatially correlated with the actual highways in the center of the three core municipalities and one of the two suburban highways that link Bellevue and Tacoma. While the planned routes are abstracted from the details and natural geography of Seattle, indicating its exogeneity. The instruments are defined as follows: $\mathbf{D}_{ij}^{\text{HW-IV}}$ is a dummy variable that equals one if the travel route interacts with the planned highways.[41] $\mathbf{D}_{ij}^{\text{crossHW-IV}}$ is a dummy variable that equals one if the travel route interacts with

[41] Technically, this is determined by the spatial overlap between the geometry of the travel routes and the planned highway segments. To implement this, I created a 15–meter buffer around the planned highway shapefiles before computing overlap,

the planned highways and crosses the actual highways. $\mathbf{D}_{ij}^{\text{useHW-IV}}$ is a dummy variable that equals one if the travel route interacts with the planned highways and uses the actual highways.

I use the control function method[42] since Equation 8 is a nonlinear gravity equation. Moreover, I use probit regression in the first stage for the binary nature of the dummy variables of interactions with highways. One might be concerned that probit regression renders the first stage a forbidden regression. Specifically, if the probit model at the first stage is misspecified, the second stage estimation will be inconsistent, as pointed out by Wooldridge (2015). However, Angrist and Pischke (2009) suggest that while it's hard to verify the specification of first-stage nonlinear models, the expectation produced by the first-stage nonlinear model can be used as an instrument. I report estimates from both methods in Table C.1.

Column (1) to (3) in Table C.1 show the gravity regressions of the disamenity of interaction with highways, where I use $\mathbf{D}_{ij}^{\text{HW-IV}}$ as an instrument for $\mathbf{D}_{ij}^{\text{HW}}$. Columns (4) to (6) in Table C.1 show the estimated disamenity of crossing and using highways separately, where I use $\mathbf{D}_{ij}^{\text{crossHW-IV}}$ and $\mathbf{D}_{ij}^{\text{useHW-IV}}$ as instruments for $\mathbf{D}_{ij}^{\text{crossHW}}$ and $\mathbf{D}_{ij}^{\text{useHW}}$. Column (1) and (4) are the baseline gravity regression using PPML, identical to Table 1. In Columns (2) and (5), I add $\hat{\xi}_{ij}^{\text{HW, probit}}$, the residual from a probit regression in the first stage, as a control variable. The corresponding first-stage regressions are reported in columns (1), (3), and (5) in Table C.2. In Columns (3) and (6), I use $\hat{\xi}_{ij}^{\text{HW, probit-as-IV}}$, the residual from first stage regressions of the endogenous term on the expectation of corresponding probit models, as additional control variable. The corresponding first-stage regressions are reported in columns (2), (4), and (6) in Table C.2.

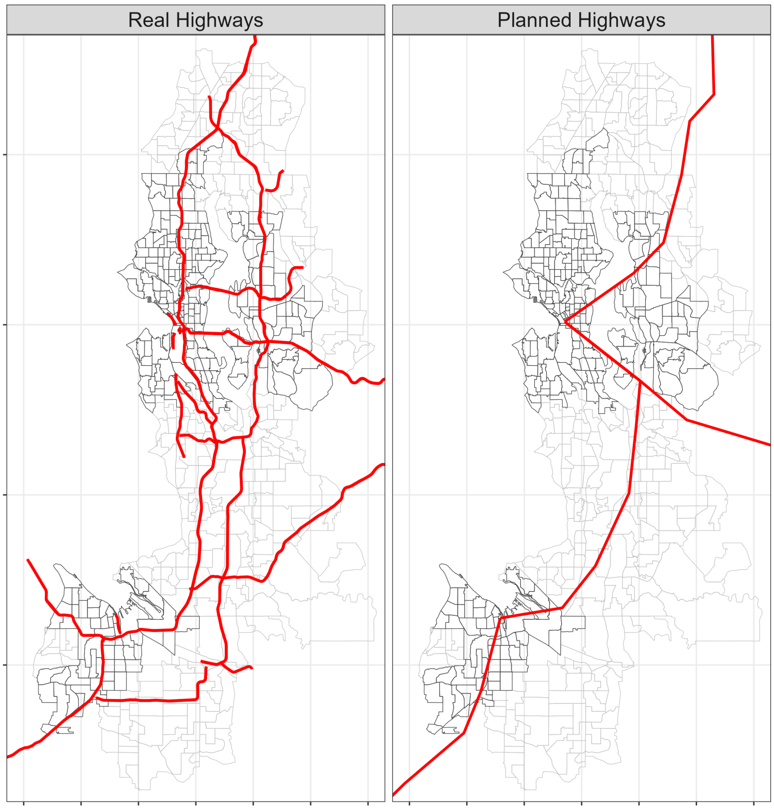
For the effects of $\mathbf{D}_{ij}^{\text{HW}}$, columns (2) and (3) show a much stronger disamenity of highways than in the baseline regression. The decline in consumption visits is twice as big as the baseline PPML level and is significant. First stage regression in column (1) of Table C.2 also shows a strong correlation between $\mathbf{D}_{ij}^{\text{HW}}$ and the instrument $\mathbf{D}_{ij}^{\text{HW-IV}}$. The results in columns (2) and (3) are similar. And when I use $E_{\text{probit}}\mathbf{D}_{ij}^{\text{HW}}$, the expectation of the probit model in column (1) of Table C.2, as the instrument and plug it in the first stage regression in column (2), I find the coefficient of $E_{\text{probit}}\mathbf{D}_{ij}^{\text{HW}}$ is significant and close to one, with the coefficient of all other control variables close to zero. These all indicate that the probit model fits $\mathbf{D}_{ij}^{\text{HW}}$ well and estimations in Table C.1 are less likely to be corrupted by misspecification problem. The findings are similar when I estimate the effects of crossing and using highways separately. The regression in column (5), where I use probit regression in the first stage, shows stronger disamenity for both types of interaction. And using the probit-expectation as IV, I find even larger disamenity in column (6). The first stage regressions, column (3) to (6) in Table C.2 shows a good fit for $\mathbf{D}_{ij}^{\text{useHW-IV}}$ but an unideal fir for $\mathbf{D}_{ij}^{\text{crossHW-IV}}$.

A key takeaway from Table C.1 is that the identification using the control function method shows

ensuring a more accurate capture of potential interactions had the highways been constructed.

[42]See Wooldridge (2015) for a review of the control function method.

Figure C.1: Planned Highway in 1947 Yellow Book vs Real Highway in Seattle MSA



Note: The red lines show the real and planned highways in Seattle MSA. Each shape is a census tract. The urban areas are drawn in black and the suburban areas in light gray. The planned highways overlap with the real highways in the center of Seattle and Tacoma, the connection between Seattle and Bellevue, and the suburban highways that connect Tacoma and Bellevue. The real highways are longer and more complicated than the planned highways.

Table C.1: PPML with Control Function, 2nd Stage

Model:	(1)	(2)	(3)	(4)	(5)	(6)
1st Stage:	NA	probit	probit-as-IV	NA	probit	probit-as-IV
$\log \text{Time}_{ij} \times \mathbf{1}_{[0,\ 5\ \text{km}]}$	-1.02***	-0.970***	-0.968***	-1.02***	-1.01***	-0.995***
	(0.045)	(0.046)	(0.046)	(0.046)	(0.051)	(0.058)
$\log \text{Time}_{ij} \times \mathbf{1}_{[5,\ 10\ \text{km}]}$	-1.16***	-1.07***	-1.07***	-1.16***	-1.13***	-1.11***
	(0.035)	(0.039)	(0.039)	(0.035)	(0.043)	(0.055)
$\log \text{Time}_{ij} \times \mathbf{1}_{[10,\ 15\ \text{km}]}$	-1.31***	-1.21***	-1.21***	-1.31***	-1.28***	-1.26***
	(0.032)	(0.038)	(0.038)	(0.032)	(0.040)	(0.054)
$\log \text{Time}_{ij} \times \mathbf{1}_{[15,\ 25\ \text{km}]}$	-1.42***	-1.32***	-1.32***	-1.42***	-1.39***	-1.37***
	(0.032)	(0.038)	(0.038)	(0.032)	(0.039)	(0.054)
$\mathbf{D}_{ij}^{\text{HW}}$	-0.182***	-0.430***	-0.422***			
	(0.030)	(0.068)	(0.066)			
$\hat{\xi}_{ij}^{\text{HW, probit}}$		0.290***				
		(0.068)				
$\hat{\xi}_{ij}^{\text{HW, probit-as-IV}}$			0.282***			
			(0.066)			
$\mathbf{D}_{ij}^{\text{crossHW}}$				-0.180***	-0.253***	-0.320***
				(0.031)	(0.062)	(0.106)
$\hat{\xi}_{ij}^{\text{crossHW, probit}}$					0.078	
					(0.064)	
$\hat{\xi}_{ij}^{\text{crossHW, probit-as-IV}}$						0.144
						(0.112)
$\mathbf{D}_{ij}^{\text{useHW}}$				-0.187***	-0.223***	-0.301***
				(0.035)	(0.060)	(0.105)
$\hat{\xi}_{ij}^{\text{useHW, probit}}$					-0.006	
					(0.062)	
$\hat{\xi}_{ij}^{\text{useHW, probit-as-IV}}$						0.072
						(0.108)
$\log \text{Race}_{ij}$	-0.092***	-0.094***	-0.092***	-0.092***	-0.094***	-0.093***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\log \text{Income}_{ij}$	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**
	(0.007)	(0.008)	(0.008)	(0.007)	(0.009)	(0.009)
Fixed Effects:	Census Tract of Origin & Destination					
Observations	75,526	75,526	75,526	75,526	75,526	75,526
Pseudo R^2	0.226	0.226	0.226	0.226	0.226	0.226

Note: This table shows the gravity regression using the control function method for causal identification. Columns (1) to (3) show regression with one endogenous variable, which is interaction with highways. Columns (4) to (6) show regression with two endogenous variables, which are crossing and using highways. Columns (1) and (4) show the baseline PPML regression, same as in Table 1. In columns (2) and (5), I add the residual from a probit regression in the first stage. In columns (3) and (6), I use the fitted value of a probit regression in the first stage as the instrument and add the residual from the regressions from columns (2), (4), and (6) in Table C.2. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

Table C.2: First Stage, probit & probit-expectation-as-IV

Dependent Variables:	$\mathbf{D}_{ij}^{\text{HW}}$		$\mathbf{D}_{ij}^{\text{crossHW}}$		$\mathbf{D}_{ij}^{\text{useHW}}$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Function	probit	OLS	probit	OLS	probit	OLS
$\log \text{Time}_{ij} \times \mathbf{1}_{[0,\ 5\ \text{km}]}$	1.21***	0.008	1.76***	0.090***	-1.20***	0.002
	(0.151)	(0.016)	(0.129)	(0.022)	(0.354)	(0.018)
$\log \text{Time}_{ij} \times \mathbf{1}_{[5,\ 10\ \text{km}]}$	1.51***	5.35×10^{-5}	1.51***	0.154***	0.163	-0.013
	(0.127)	(0.014)	(0.112)	(0.021)	(0.247)	(0.013)
$\log \text{Time}_{ij} \times \mathbf{1}_{[10,\ 15\ \text{km}]}$	1.66***	-0.003	1.20***	0.183***	0.699***	-0.019
	(0.119)	(0.013)	(0.095)	(0.019)	(0.233)	(0.012)
$\log \text{Time}_{ij} \times \mathbf{1}_{[15,\ 25\ \text{km}]}$	1.87***	-0.003	0.972***	0.190***	0.973***	-0.019*
	(0.127)	(0.012)	(0.086)	(0.018)	(0.245)	(0.011)
$\mathbf{D}_{ij}^{\text{HW-IV}}$	1.43***					
	(0.183)					
$E_{\text{probit}}\mathbf{D}_{ij}^{\text{HW}}$		1.03***				
		(0.030)				
$\mathbf{D}_{ij}^{\text{crossHW-IV}}$			2.09***		-8.46***	
			(0.154)		(0.368)	
$\mathbf{D}_{ij}^{\text{useHW-IV}}$			-1.78***		3.43***	
			(0.132)		(0.327)	
$E_{\text{probit}}\mathbf{D}_{ij}^{\text{crossHW}}$				0.505***		0.070***
				(0.042)		(0.018)
$E_{\text{probit}}\mathbf{D}_{ij}^{\text{useHW}}$				-0.586***		1.09***
				(0.036)		(0.021)
$\log \text{Race}_{ij}$	0.111***	-0.001	0.055***	0.006***	0.027	-0.001
	(0.020)	(0.002)	(0.013)	(0.002)	(0.018)	(0.002)
$\log \text{Income}_{ij}$	-0.026*	0.0003	-0.036***	-0.001	0.037**	0.0003
	(0.015)	(0.002)	(0.011)	(0.002)	(0.015)	(0.002)
Fixed Effects:	Census Tract of Origin & Destination					
Observations	75,526	75,526	75,526	75,526	75,526	75,526
R^2		0.572		0.510		0.756
F-test		97.4		65.8		196.0

Note: This table shows the results of the first stage regressions associated with the control function regression in Table C.1. Columns (1), (3), and (5) use probit function to fit the independent variables to the endogenous variable. Columns (2), (4), and (6) use the fitted value from the previous probit regression, instead of the exogenous variable, as the instrument. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

larger causal effects of the disamenity of interaction with highways. However, I use the coefficients of the baseline PPML regression in counterfactual exercises for the following reasons. First, after breaking down the interaction with highways to crossing and using highways and further to urban and suburban highways for different groups of routes, it is hard to generate valid instruments for the increasing numbers of potentially endogenous variables. Since the planned routes are not real roads, it is impossible to generate variables on crossing or using the planned routes without imposing strong assumptions. And any assumptions made would be hard to validate. However, the different effects between urban and suburban highways and the nonlinear effects in terms of trip distance are key findings in this paper. It's hard to capture accurate variations in the causal effects without good instruments. Second, the causal effects are larger than the PPML estimate, which means that using the coefficient of PPMl regressions would give a lower bound of the welfare effects of removing the disamenities. Third, the instrument, planned routes, are correlated with part of the actual highways that are mostly in urban cores, which means the instrument might capture the local effects of the disamenity of the highways in the urban cores. However, the counterfactual exercise is a policy change applied to all actual highways in urban municipalities. I therefore use the baseline estimation, which shows the effects of all actual highways.

C.2 Border Effects

One might be concerned that the highway effects unintentionally capture the effects of other barriers to consumption travel. In this subsection, I investigate the effects of two types of borders on consumption trip choices: administrative borders and geographical borders. Table C.3 reports the results of gravity regressions controlling for other potential borders. In column (2), I add a dummy variable $\mathbf{D}_{ij}^{\text{Municipal Border}}$, which equals one if the municipality of trip origin differs from that of the destination. The coefficient indicates that crossing a municipal border is associated with a 21% reduction in visiting probability. However, compared to column (1), the effects of highway interactions change little with the inclusion of municipal border effects.

Another border is natural geographical barriers, such as rivers. To assess the effects of natural borders, I focus on the city of Seattle, which has a unique geographical feature of being divided by the Lake Washington, Ship Canal, and the Duwamish River. I divide the city of Seattle into three parts, based on the location of the rivers, and create a border dummy variable that equals one if the origin and destination of the trip are in different parts of the city. This variable captures the potential effects of crossing all highway and non-highway bridges. Column (3) of Table C.3 shows the baseline results using data on travel within the Seattle municipality. The effects of highway interactions are significantly negative and quantitatively larger than those found in the MSA data. In column (4), after adding the border dummy, I find that crossing a natural border is associated with a 13% decline in visiting probability. However, the highway effects remain large and significant, with little change after adding

Table C.3: Gravity Regression on Consumption Travel, Border Effects

Sample:	Seattle MSA		City of Seattle	
Model:	(1) Baseline	(2) Border	(3) Baseline	(4) Border
$\log \tau_{ij} \times \mathbf{1}_{[0,\ 5\ \text{km}]}$	-1.00***	-0.988***	-1.20***	-1.19***
	(0.045)	(0.046)	(0.051)	(0.051)
$\log \tau_{ij} \times \mathbf{1}_{[5,\ 10\ \text{km}]}$	-1.14***	-1.10***	-1.33***	-1.30***
	(0.035)	(0.038)	(0.045)	(0.048)
$\log \tau_{ij} \times \mathbf{1}_{[10,\ 15\ \text{km}]}$	-1.30***	-1.24***	-1.43***	-1.38***
	(0.032)	(0.036)	(0.043)	(0.046)
$\log \tau_{ij} \times \mathbf{1}_{[15,\ 25\ \text{km}]}$	-1.40***	-1.35***	-1.52***	-1.47***
	(0.032)	(0.036)	(0.042)	(0.046)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Urban}}$	-0.287***	-0.301***	-0.328***	-0.335***
	(0.032)	(0.032)	(0.044)	(0.044)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Sub}}$	-0.031	-0.053		
	(0.053)	(0.053)		
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}}$	-0.268***	-0.294***	-0.307***	-0.330***
	(0.039)	(0.039)	(0.051)	(0.052)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Sub}}$	-0.009	-0.033		
	(0.051)	(0.051)		
$\mathbf{D}_{ij}^{\text{Municipal Border}}$		-0.232***		
		(0.048)		
$\mathbf{D}_{ij}^{\text{Geographical Border}}$				-0.142***
				(0.053)
$\log \text{Race}_{ij}$	-0.092***	-0.087***	-0.114***	-0.116***
	(0.004)	(0.004)	(0.006)	(0.006)
$\log \text{Inc}_{ij}$	-0.018***	-0.016**	0.006	0.008
	(0.006)	(0.007)	(0.009)	(0.010)
Fixed Effects	Census tract of POI & visitor's home			
Observations	75,526	75,526	21,655	21,655
Pseudo R^2	0.227	0.227	0.193	0.193

Note: This table shows the robustness of the highway effects, controlling for the potential effects of municipal and geographical borders. Columns (1) and (2) use the data on consumption travel within the Seattle MSA. Columns (3) and (4) use the subsample of travel within the Seattle municipality. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

the border effect. Therefore, the disamenities of highways are robust to the inclusion of other border effects. Since the economic and policy implications of these border effects are unclear and adding them does not improve the model fit, I will not incorporate border effects in the counterfactual analysis.

C.3 Travel routes in alternative speed assumptions

This subsection examines how assumptions about travel speed affect the estimated disamenity effects of highways. I compare two alternatives to the main specification using weighted mean speeds: one based on posted speed limits (the default in OSM) and one using speeds at 5 p.m. from Uber Movement to simulate peak-hour congestion.

First, the travel speeds of 76% of the roads in Seattle MSA are predicted using a statistical model in Section B. To assess how much the estimated travel speeds from Uber affect the main findings, I recompute travel routes using the speed limits and update the dummy variables on route types. This approach does not reflect actual travel behavior, particularly differences in congestion and driving patterns between urban and suburban areas. As discussed below, these differences constitute a key mechanism contributing to the heterogeneous conduit effects of urban and suburban highways. Columns (1) to (3) in Table C.4 show the corresponding regression results.

Second, the impact of congestion might be more severe than what the NHTS and Uber Movement data can capture: Uber trips are typically shorter or extremely long and less likely to occur during peak hours. Compared to representative travelers, Uber drivers have stronger incentives to avoid congested highways by deviating to arterial roads. To see an extreme case where the impact of congestion on travel is the largest, I compute the travel routes using the speed at 5 p.m. in the Uber Movement data. Columns (4) to (6) in Table C.4 show the regression results using travel routes at 5-pm speed.

Several patterns remain consistent across specifications. First, columns (1) and (4) show that interaction with highways is associated with 19%∼20% reduction in visiting probability; second, columns (2) and (5) show that the impact of either type of interaction, crossing or using highways, is similar in scale; third, column (6) shows that the disamenities mainly come from interactions with urban highways and suburban highways have little impact. In this specification, the barrier effects of urban highways appear larger than in the baseline, consistent with the expectation that rush hour congestion overstates average daily conditions.

The only notable deviation from the baseline findings appears in Column (3), where suburban highways show a significant disamenity. This stems from the use of posted speed limits, which understate the conduit role of suburban highways and overstate the barrier effect of urban highways. As reflected in the Uber data, consumers often face heavier congestion on urban highways and typically travel faster than the speed limit on suburban highways. Because the posted-speed approach fails to account for these differences, it introduces measurement error in travel time. This result highlights the importance

Table C.4: Gravity Regression Using Alternative Speed Assumptions, Seattle MSA

Speed assumptions:	Speed limits			Speed at 5pm, Uber Movement		
D.V.: $\Pr_{ij}$	(1)	(2)	(3)	(4)	(5)	(6)
$\log \tau_{ij} \times [0,\ 5\text{ km}]$	-1.09***	-1.09***	-1.08***	-0.916***	-0.918***	-0.893***
	(0.045)	(0.045)	(0.044)	(0.066)	(0.066)	(0.065)
$\log \tau_{ij} \times [5,\ 10\text{ km}]$	-1.21***	-1.21***	-1.21***	-1.06***	-1.06***	-1.04***
	(0.036)	(0.036)	(0.035)	(0.052)	(0.052)	(0.052)
$\log \tau_{ij} \times [10,\ 15\text{ km}]$	-1.37***	-1.37***	-1.36***	-1.21***	-1.21***	-1.19***
	(0.033)	(0.034)	(0.034)	(0.048)	(0.049)	(0.049)
$\log \tau_{ij} \times [15,\ 25\text{ km}]$	-1.52***	-1.51***	-1.50***	-1.32***	-1.32***	-1.31***
	(0.032)	(0.033)	(0.033)	(0.046)	(0.047)	(0.047)
$\mathbf{D}_{ij}^{\text{HW}}$	-0.205***			-0.229***		
	(0.032)			(0.038)		
$\mathbf{D}_{ij}^{\text{crossHW}}$		-0.194***			-0.224***	
		(0.033)			(0.037)	
$\mathbf{D}_{ij}^{\text{useHW}}$		-0.241***			-0.247***	
		(0.039)			(0.047)	
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Urban}}$			-0.219***			-0.329***
			(0.039)			(0.041)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Sub}}$			-0.159***			-0.052
			(0.045)			(0.056)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}}$			-0.270***			-0.314***
			(0.045)			(0.052)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Sub}}$			-0.177***			-0.082
			(0.043)			(0.052)
$\log \text{Race}_{ij}$	-0.075***	-0.075***	-0.076***	-0.094***	-0.094***	-0.095***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$\log \text{Inc}_{ij}$	-0.008	-0.008	-0.007	-0.020**	-0.020**	-0.018**
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Fixed Effects	Census tract of POI & Census tract of visitors home					
Observations	79,873	79,873	79,873	69,124	69,124	69,124
Pseudo R^2	0.159	0.160	0.160	0.155	0.155	0.156

Note: This table provides evidence for the robustness of the gravity estimation results using two alternative assumptions on travel speeds. Columns (1) to (3) show the results using the travel routes computed at the speed limits. Columns (4) to (6) show the results using the travel routes computed at travel speed at 5 pm from Uber Movement data. The estimated time elasticity and highway effects are similar to the baseline estimates in Table 1. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

of using observed traffic speeds, such as those from Uber, to better capture effective travel conditions and accurately estimate the heterogeneity in highway impacts.

C.4 Highway effects in other MSAs

The findings in Section 5 are obtained from data in the Seattle MSA. To ascertain that the highway effects are not unique to Seattle, I apply the analysis using the same datasets from seven other major MSAs across the U.S.[43] Figure C.2 illustrates the highway effects in these eight MSAs as well as a pooled sample (combining data from all MSAs), estimated using the specification in column (3) and (7) of Table 1. Since the speed data from Uber Movement is only available for Seattle MSA, I use the travel routes computed by speed limits in all sample cities for consistency.

The estimated coefficients of crossing highways in Figure C.2a range between -0.12 in SF and -0.23 in NYC, with an average of -0.21 for the pooled sample. Measuring access with travel distance does not affect the estimated crossing-highway disamenity. Figure C.2b compares the effects of using highways conditional on travel time (same as column (3) of Table 1) and conditional on travel distance (same as column (7) of Table 1). The coefficient conditional on time is -0.24 for the pooled sample, close to the effects observed in Seattle. Controlling for travel distance reveals the speed advantage of highways and mitigates the using-highway disamenity in all MSAs. This is visually evident in the higher (less negative) blue dots compared to red dots in each city, indicating a weaker disamenity when faster speed on highways is not absorbed by the travel time measure. Therefore, the conclusions drawn in Subsection 5.1 apply to other MSAs.

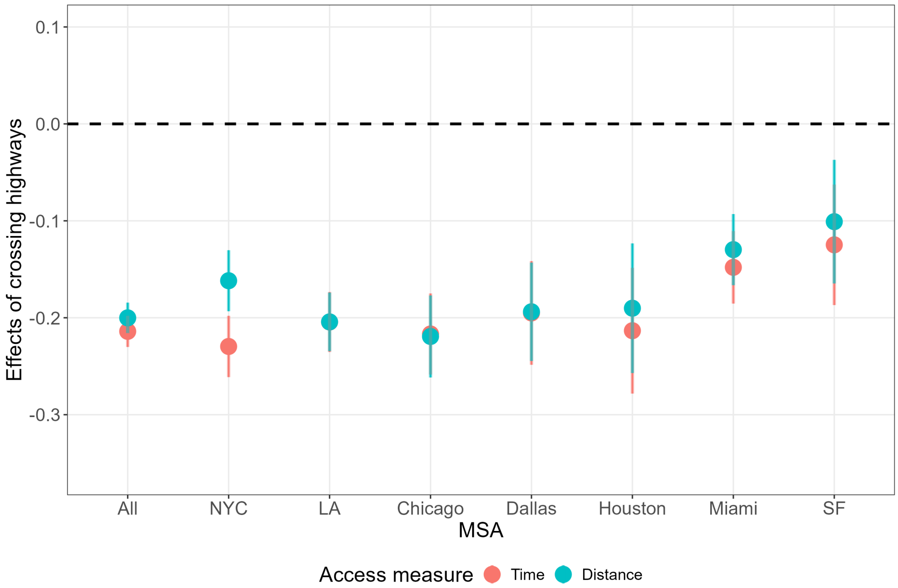
C.5 Second best route

An ideal way to model consumers' choices would be to let them choose both POIs and travel routes, denoted by the tuple (j, d_{ij}). However, this is infeasible, as I only observe visits at POIs and not the actual routes taken. By using travel time and distance of the shortest route in the gravity regression, I implicitly assume that consumers take these travel routes that minimize travel time when choosing destinations. As Table 1 shows significant disamenities associated with urban highways, and I assume consumers know such disamenities, a concern arises from the possibility that travelers may entirely avoid highways when selecting their routes, even when a highway route is theoretically faster. In this case, the shortest computed route may not reflect actual consumer behavior, resulting in inconsistency between my model and the data and introducing potential bias into the estimation of highway effects.

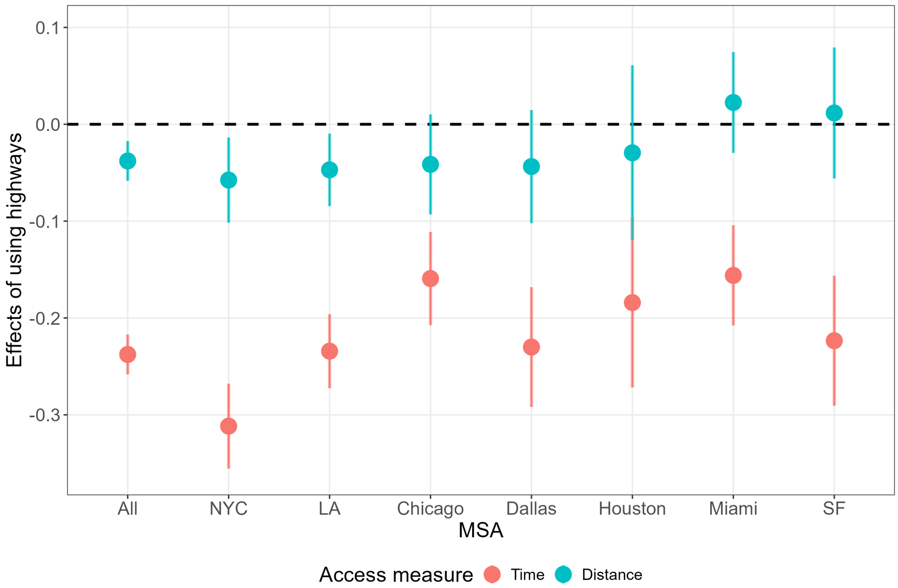
To determine the extent of this inconsistency, I define a "second-best" route as the shortest feasible route that avoids interaction with highways. In practice, I compute these routes by assigning a travel speed of 25 mph to all highway segments, which is significantly lower than the typical speed on primary

[43]The samples are New York City (NYC), Los Angeles (LA), Chicago, San Francisco (SF), Dallas, Houston, and Miami.

Figure C.2: Effects of Highways in Eight MSAs



(a) Effects of Crossing Highways



(b) Effects of Using Highways

Note: These two figures illustrate the effects of highways for 8 city samples as well as a pooled sample of the data on all eight cities. The coefficients are estimated using the specification in columns (3) and (6) in Table 1. Both figures show robust disamenities associated with crossing and using highways in different cities. Highways' benefit of higher travel speeds mitigates the disamenity of using highways (in panel C.2b) but does not affect the disamenity of crossing highways (in panel C.2a). The standard errors are calculated using two-way clustering by origin (home) and destination (POIs).

and secondary roads, so that the routing algorithm substitutes highways with alternative roads wherever possible.[44] I then compare the travel time of these highway-free routes with that of the optimal highway-involving routes to assess the feasibility of avoiding highways and the additional travel time such avoidance would entail.

Empirically, this theoretical inconsistency does not pose a practical problem in the Seattle context. First, because Seattle highways are arranged in a grid-like structure, second-best routes do not exist for routes that cross highways. Only routes that use highways, which constitute 57% of the sample, can have potential second-best alternatives. Second, among these using-highway routes, 22% lack viable second-best routes, for which the computed second-best routes still use highways, and another 69% have second-best routes that still involve crossing highways, leaving travelers with one form of highway disamenity. Only the remaining 9% of these cases (5% of the full sample) provide true highway-free alternatives. Even within this small subset, highway avoidance incurs an average travel time penalty exceeding 16%. Thus, it is unlikely that many consumers actively consider or ultimately choose second-best routes to avoid highways when selecting destinations.

Nonetheless, consumers' willingness to visit POIs may still be affected by the quality or existence of a highway-free alternative, particularly in terms of the additional travel time it requires. To investigate this, I define a dummy variable, $\mathbf{D}_{ij}^{\text{2nd}}$, which equals 1 if the "time penalty" imposed by the second-best alternative—the ratio of the second-best route's travel time to that of the shortest route—is less than 18%, the threshold estimated in the baseline regression in Section 5.1, and 0 otherwise. Note that a majority of the sample (79.2% of routes) do *not* have valid alternatives, as discussed earlier. For these routes, $\mathbf{D}_{ij}^{\text{2nd}}$ equals 0, reflecting an effectively infinite time penalty.[45] The hypothesis is that when $\mathbf{D}_{ij}^{\text{2nd}} = 1$, consumers should be less sensitive to highway disamenities that reduce the indirect utility of visiting a destination, as they have access to viable alternative routes. Therefore, I include an interaction term between the using-highway dummies and $\mathbf{D}_{ij}^{\text{2nd}}$ in the gravity regression, expecting a positive coefficient.[46]

Column (2) of Table C.5 presents the regression result with the interaction terms. Compared to the baseline estimates in column (1), the coefficients for highway interactions remain similar, and the coefficients for $\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}} \times \mathbf{D}_{ij}^{\text{2nd}}$ and $\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Suburban}} \times \mathbf{D}_{ij}^{\text{2nd}}$ are positive, as hypothesized. However, the coefficients for these interaction terms are poorly identified, exhibiting large standard errors, and are

[44] This assumption ensures that highways are avoided in favor of primary and secondary roads. Compared to assigning a speed of zero to highways, this approach preserves the integrity of the road network across the metropolitan area and enables robust and efficient route computation without generating invalid values. If, under this assumption, a route still requires highway usage, I classify it as lacking a viable second-best (highway-free) alternative.

[45] Specifically, there are two types of routes with $\mathbf{D}_{ij}^{\text{2nd}} = 1$: first, routes that do not interact with highways and thus serve as their own good alternative (15.8% of the full sample); second, using-highway routes that have truly good alternatives with a time penalty below the threshold (3.2% of the sample). In contrast, for routes with $\mathbf{D}_{ij}^{\text{2nd}} = 0$, the second-best alternatives either involve time penalties above 18% (1.8% of the sample) or do not exist at all (79.2% of the sample).

[46] I also test alternative thresholds for $\mathbf{D}_{ij}^{\text{2nd}}$ (10% and 20% time penalty) and find same results. Because so few routes have valid second-best alternatives (only 5% of the full sample), the composition of the subsample with truly good alternatives remains largely unchanged across different thresholds.

smaller in magnitude than the main effects. This might be a result of limited variation: only 3.2% of the full sample has valid second-best routes with sufficiently low time penalties, which limits the model's ability to detect responses in consumers' choices. Another possible explanation is that consumers may not actively consider or respond to alternative routes when selecting destinations, as even when $\mathbf{D}_{ij}^{2\text{nd}} = 1$, the combined effect of $\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}}$ remains negative. In either case, the theoretical concern regarding highway-free alternatives does not appear to compromise the robustness of the estimated highway disamenities.

C.6 Correlated preferences

The model assumes the idiosyncratic preference shock is i.i.d. for a traveler to each POI. In reality, residents in one location may have specific preferences for certain groups of POIs. For example, consumers living near Discovery Park may prefer open green spaces, while consumers living downtown may favor dense supplies of restaurants and shops over parks and playgrounds.

To address this issue, I assume that if a traveler resides in one census tract, it implies that the traveler weakly prefers the combination of POIs in that place. Then the dissimilarity between the combination of POIs in the traveler's home census tract and that in the destination census tract reflects the extent of the traveler's likes and dislikes towards the destination POIs.

To measure the dissimilarity in the combination of POIs between origin and destination, I rely on the method that Cook (2023) uses to categorize the POIs into four groups: restaurant, shop, service, and entertainment. I calculate the share of POIs in each group in every census tract and measure the dissimilarity in POIs as

$$\text{Diff}^{\text{Amenity}} = \sqrt{\sum_g \left(\text{Share}_i^g - \text{Share}_j^g\right)^2}, \text{ for } g = \{\text{Restaurant, Shop, Service, Entertainment}\}. \tag{21}$$

The above dissimilarity index is then controlled in the regression in addition to the variables in Section 5. Table C.5 reports the results. I put the baseline regression in Table 1 in column (1) for reference. Column (2) controls the log of $\text{Diff}^{\text{Amenity}}$ and column (3) controls the log of four terms in the function of $\text{Diff}^{\text{Amenity}}$. For example, $\text{Diff}^{\text{Shop}} = \left(\text{Share}_i^{\text{Shop}} - \text{Share}_j^{\text{Shop}}\right)^2$. Both the dissimilarity in overall amenity and in POIs of any type do not affect the baseline findings. The negative effect of dissimilarity in amenities indicates that consumers do prefer places that provide consumption benefits similar to their homes. However, this statistically significant effect is mainly driven by preferences for entertainment places, shown by column (5)

Table C.5: Robustness: Second-best Routes, Correlated Preference

Model:	Baseline (1)	Second-best route (2)	Correlated preference (3)	(4)
$\log \text{Time}_{ij} \times \mathbf{1}_{[0,\ 5\ \text{km}]}$	-1.00***	-1.00***	-0.997***	-0.998***
	(0.045)	(0.045)	(0.045)	(0.045)
$\log \text{Time}_{ij} \times \mathbf{1}_{[5,\ 10\ \text{km}]}$	-1.14***	-1.14***	-1.14***	-1.14***
	(0.035)	(0.035)	(0.035)	(0.035)
$\log \text{Time}_{ij} \times \mathbf{1}_{[10,\ 15\ \text{km}]}$	-1.30***	-1.30***	-1.30***	-1.30***
	(0.032)	(0.032)	(0.032)	(0.032)
$\log \text{Time}_{ij} \times \mathbf{1}_{[15,\ 25\ \text{km}]}$	-1.40***	-1.40***	-1.41***	-1.41***
	(0.032)	(0.032)	(0.032)	(0.032)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Urban}}$	-0.287***	-0.199**	-0.286***	-0.286***
	(0.032)	(0.085)	(0.032)	(0.032)
$\mathbf{D}_{ij}^{\text{crossHW}}\mathbf{D}_{ij}^{\text{Suburban}}$	-0.031	0.050	-0.029	-0.030
	(0.053)	(0.085)	(0.053)	(0.053)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}}$	-0.268***	-0.192**	-0.267***	-0.266***
	(0.039)	(0.085)	(0.039)	(0.039)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Suburban}}$	-0.009	0.064	-0.007	-0.008
	(0.051)	(0.091)	(0.051)	(0.051)
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}} \times \mathbf{D}_{ij}^{\text{2nd}}$		0.136		
		(0.112)		
$\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Suburban}} \times \mathbf{D}_{ij}^{\text{2nd}}$		0.079		
		(0.105)		
$\mathbf{D}_{ij}^{\text{2nd}}$		0.094		
		(0.077)		
$\log \text{Diff}^{\text{Amenity}}$				-0.020***
				(0.007)
$\log \text{Diff}^{\text{Restaurant}}$				-0.005*
				(0.003)
$\log \text{Diff}^{\text{Shop}}$				-0.002
				(0.003)
$\log \text{Diff}^{\text{Service}}$				0.001
				(0.002)
$\log \text{Diff}^{\text{Entertainment}}$				-0.008***
				(0.003)
$\log \text{Race}_{ij}$	-0.092***	-0.092***	-0.064***	-0.078***
	(0.004)	(0.004)	(0.011)	(0.008)
$\log \text{Inc}_{ij}$	-0.018***	-0.018**	-0.017**	-0.017**
	(0.006)	(0.007)	(0.007)	(0.007)
Fixed Effects	Home & POI census tract			
Observations	75,526	75,526	75,526	75,526
Pseudo R^2	0.227	0.226	0.227	0.227

Note: This table reports gravity regressions controlling for potential impacts from "second-best" routes and correlated preferences by home location. τ_{ij} is measured by the travel time of the shortest path. Column (1) shows the baseline estimates from column (3) of Table 1. Column (2) investigates highway disamenities while accounting for alternative routes, by including interaction terms between using-highways indicators and a dummy variable on the existence of a good second-best alternative. The estimated coefficients suggest that consumers are more likely to visit destinations connected by highways when there are good alternative routes that allow them to avoid highways, but these effects are highly insignificant. Columns (3) and (4) further control for the differences in the combination of amenities between the origin and destination locations, demonstrating the robustness of the baseline estimates for highway disamenities. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

C.7 Significance of urban/suburban heterogeneity

Table D.6 reports the p-values from Wald tests of the null hypothesis that the coefficients on urban and suburban highways are equal within each distance bin. Most sub-groups show statistically significant differences between the impacts of urban and suburban highways, as indicated by small p-values. One exception occurs for travelers in the [0, 5 km] bin, where using-suburban-highway-effect exhibits large standard errors due to a small treatment group in this bin.

The differences between urban and suburban highways' effects, especially in the latter two bins, are more significant as shown by Table D.6 than what visual inspection of marginal confidence intervals alone would suggest in Figure 3. This is because the estimates are highly positively correlated: in the data, each travel route either uses an urban highway, a suburban highway, or neither. As a result, the two indicators are mutually exclusive and economically linked, leading to a strong positive covariance between their coefficient estimates, and thus, a small p-value.

D Heterogeneous Effects

D.1 Urban and suburban travelers

Baum-Snow (2007) finds that highways contribute significantly to the suburbanization trend in cities, because highways reduce the commuting cost between suburban residences and urban workplaces. One expectation following this finding is that urban and suburban consumption travelers might respond differently to the disamenity of highways. Suburban travelers might care less about interaction with highways because they can not avoid the interactions in commuting. Suburban highways are faster and connect urban–suburban locations more efficiently. But for urban travelers, if their commuting routes do not involve highways, interaction with highways for consumption purposes may be a higher marginal cost for them.

To tease out the heterogeneous effects, I further split the sample of routes that interact with urban highways into three sub-samples: the routes between urban home places to urban POIs, the routes between suburban home places to urban POIs, and the routes between urban home places to suburban POIs. I then run the gravity regressions separately for the three sub-samples. The results are reported in Table D.7.

Comparing the coefficients of $\mathbf{D}_{ij}^{\text{useHW}}\mathbf{D}_{ij}^{\text{Urban}}$ across the sub-samples, the disamenity of using highways are mainly found for consumers traveling within the urban zones, which is urban travelers visiting urban POIs. The consumers who travel between urban and suburban places are indifferent between using highways or not. Especially, the effect on suburban travelers' trips to urban POIs is close to zero, which is consistent with Baum-Snow (2007)'s finding on suburbanization and inferred effects on commuting (also in Brinkman and Lin (2024)). The disamenity of crossing highways is also the largest for urban travelers's

Table D.6: Wald Test p-values for Urban vs. Suburban Highway Effects

Bin	[0, 5 km]	[5, 10 km]	[10, 15 km]	[15, 25 km]
Crossing highways	0.000	0.001	0.008	0.001
Using highways	0.528	0.000	0.003	0.002

Note: This table reports the p-values from Wald tests of the null hypothesis that the coefficients on urban and suburban highways are equal within each distance bin. A small p-value indicates statistically significant differences between the effects associated with urban and suburban highways. Note that in the latter two bins, the difference is significant despite overlapping confidence intervals shown in Figure 3. This is due to high positive covariance between the estimates, which reduces the standard error of their difference.

trips to urban POIs, which is reasonable given the residential and commercial density of urban zones and the physical barriers created by highways. The disamenity of crossing highways on travel between urban and suburban places is also big, confirming the role of highways as physical barriers.

Table D.7: Heterogeneous Effects for (Sub)Urban

Dependent Variable:	Visiting probability		
Sample:	Urban→Urban	Suburban→Urban	Urban→Suburban
Model:	(1)	(2)	(3)
$\log \text{Time}_{ij} \times \mathbf{1}_{[0,\ 5\ \text{km}]}$	-1.08***	-1.23***	-1.39***
	(0.050)	(0.115)	(0.125)
$\log \text{Time}_{ij} \times \mathbf{1}_{[5,\ 10\ \text{km}]}$	-1.19***	-1.39***	-1.45***
	(0.043)	(0.096)	(0.106)
$\log \text{Time}_{ij} \times \mathbf{1}_{[10,\ 15\ \text{km}]}$	-1.32***	-1.52***	-1.55***
	(0.043)	(0.094)	(0.096)
$\log \text{Time}_{ij} \times \mathbf{1}_{[15,\ 25\ \text{km}]}$	-1.44***	-1.60***	-1.64***
	(0.048)	(0.096)	(0.094)
$\mathbf{D}_{ij}^{\text{crossHW}}$	-0.214***	-0.149**	-0.195***
	(0.041)	(0.059)	(0.054)
$\mathbf{D}_{ij}^{\text{useHW}}$	-0.244***	-0.029	-0.125**
	(0.060)	(0.062)	(0.062)
$\log \text{Race}_{ij}$	-0.108***	-0.044***	-0.031**
	(0.006)	(0.011)	(0.014)
$\log \text{Inc}_{ij}$	-0.006	-0.010	-0.029*
	(0.009)	(0.012)	(0.016)
Fixed Effects	Home & POI census tract		
Observations	28,344	13,187	13,617

Note: This table shows the heterogeneous effects for urban and suburban travelers. I split the sample into three groups and run the gravity regression for each subsample. Column (1) uses the visits from urban origin to urban destination. Column (2) uses the visits from suburban origins to urban destinations. Column (3) uses the visits from urban origin to suburban destination. Two heterogeneous effects are found: first, crossing highways is a disamenity for all travelers and is especially undesired for urban travelers; second, using highways is only a disamenity for traveling within the urban area. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

D.2 Effects by industry

The empirical analysis in the paper uses data on visits to all the POIs that belong to the NAICS subgroups listed in Table A.2. However, POIs in different industries (defined by two-digit NAICS codes) might have different levels of substitution. For POIs substitutable to each other, such as franchised restaurants and grocery stores, consumers might be more sensitive to the cost generated by travel time and by interaction with highways. In this section, I aggregate the POI-level visits to census-tract-level visits to POIs that belong to different industries, and use the specification of column (3) in Table 1 to estimate time elasticities and effects of highways by industry.

Table D.9 shows the estimated time elasticities by industry across four distance bins. Notably, short-distance travelers show very little difference in sensitivity across industries. For longer-distance travel (10-25 km), consumers are more sensitive to time costs when visiting POIs that are generally viewed as more substitutable, such as restaurants, grocery stores, and pharmacies, and are less sensitive when visiting personalized or professional services and entertainment venues, where substitution is more limited. Overall, the elasticity estimates are in a relatively narrow range, suggesting broadly similar substitution patterns across industries.

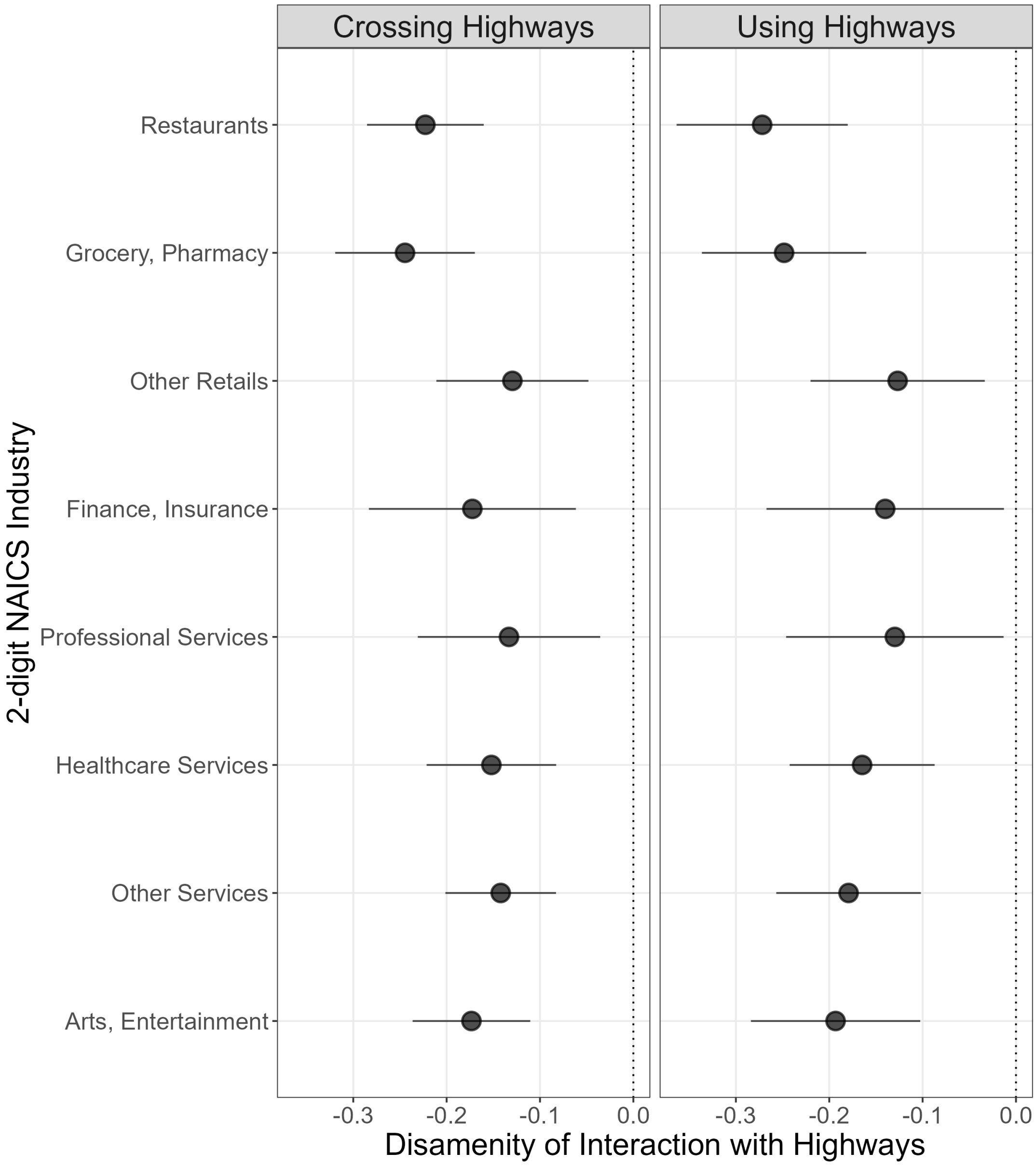
Similar pattern is shown in Figure D.3, which depicts the coefficients of $\mathbf{D}_{ij}^{\text{crossHW}}$ and $\mathbf{D}_{ij}^{\text{useHW}}$, as well as the confidence intervals. It is evident that the disamenities are revealed from visits to every group of POIs. The magnitude of the effects is in a small range between -0.27 and -0.13. The estimated effects are larger for more substitutable POIs, such as restaurants and grocery stores, and are smaller for less substitutable POIs, such as financial and professional services. However, such correlations are noisy and not statistically significant. And since the effects are similar in magnitude, to keep the regressions simple and neat, I combine all the visits in the main body of the paper.

D.3 Non-vehicle travelers

The data on visits contains walking and cycling visitors, although I do not observe the travel model. This subsection examines the effects on the visits that are more likely done by non-vehicle visitors. I obtain the map for walking from OSM and compute the walking time and whether or not the route crosses a highway. Table D.8 shows the regression using the sample of walking routes that are shorter than 5km[47] in Seattle, San Francisco, and New York. The disamenity of crossing highways in Seattle is large and similar to the overall impact found in Table 1. The disamenity in San Francisco is much lower, which is correlated with the fact that highways in downtown San Francisco are surface roads that have more convenient and safer intersections for pedestrians to use. New York also has fewer highways downtown, but, despite its high-density downtown and reputation for high-quality amenities for non-vehicle travelers, short-trip walkers still respond to crossing highways with 17% less visiting probability.

[47] I implicitly assume that walkers can not or do not want to walk along highways and the visitors are more likely to walk within 5km and more likely to drive beyond 5km walking-distance.

Figure D.3: Disamenities of Highways by 2-digit NAICS Industry



Note: This figure shows the disamenity of crossing and using highways for visits to different industries of POIs. The industry is defined by the 2-digit NAICS codes, with an abbreviation for each industry listed vertically. The horizontal axis shows the coefficient values of $\mathbf{D}_{ij}^{\mathrm{crossHW}}$ and $\mathbf{D}_{ij}^{\mathrm{useHW}}$. Disamenities exist for trips in all industries. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs).

Table D.8: Disamenities for Non-vehicle Travelers

MSA:	(1) Seattle	(2) SF	(3) NYC
log Time$_{ij}$	-0.991***	-1.03***	-1.36***
	(0.035)	(0.022)	(0.012)
$\mathbf{D}_{ij}^{\text{crossHW}}$	-0.232***	-0.144***	-0.187***
	(0.055)	(0.028)	(0.018)
log Race$_{ij}$	-0.083***	-0.077***	-0.117***
	(0.003)	(0.002)	(0.002)
log Inc$_{ij}$	-0.020*	-0.048***	-0.027***
	(0.011)	(0.009)	(0.004)
Fixed Effects:	Home & POI CT		
Observations	6,244	18,336	260,978
Pseudo R^2	0.171	0.172	0.163

Note: This table shows the gravity regression for visits where the route distance is shorter than 5 km in three different cities, where non-vehicle traveling and face-to-face interactions are considered frequent and important. The routes are computed with a map with walking paths. I assume the travelers on these routes take the non-vehicle mode of travel, so they cannot use the highways. Crossing highways reduces travel for all sample cities. The effects are larger for the baseline effects for the whole-city sample in Figure C.2. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

Table D.9: Time Elasticity by POIs Industry

Bin	[0, 5 km]	[5, 10 km]	[10, 15 km]	[15, 25 km]
Industry (2-digit NAICS code):				
Grocery, Pharmacy	-1.10***(0.057)	-1.30***(0.046)	-1.46***(0.042)	-1.56***(0.040)
Other Retails	-1.04***(0.067)	-1.15***(0.053)	-1.31***(0.048)	-1.44***(0.047)
Finance, Insurance	-0.95***(0.083)	-1.11***(0.064)	-1.26***(0.062)	-1.30***(0.060)
Professional Services	-1.16***(0.095)	-1.25***(0.071)	-1.31***(0.064)	-1.40***(0.059)
Healthcare Services	-1.00***(0.067)	-1.08***(0.055)	-1.19***(0.049)	-1.30***(0.045)
Arts, Entertainment	-0.96***(0.056)	-1.05***(0.044)	-1.17***(0.043)	-1.27***(0.041)
Restaurants	-1.19***(0.048)	-1.30***(0.037)	-1.44***(0.033)	-1.53***(0.037)
Other Services	-0.95***(0.056)	-1.07***(0.043)	-1.20***(0.038)	-1.28***(0.037)

This table reports consumers' time elasticity of travel across four distance bins, estimated separately using gravity regressions on visits to POIs in different industries. Industries are classified by two-digit NAICS codes. A larger (more negative) elasticity implies stronger substitutability between POIs within that industry. That is, consumers are more sensitive to travel time when choosing between similar POIs. The results show that elasticities are similar in magnitude across industries, suggesting comparable substitution patterns.

D.4 Heterogeneity by income level

Since the purpose of the trips is consumption, and consumption at most of the POIs (except for public places, such as parks and libraries) incurs monetary expenses, the income level of visitors and the price level of the POIs are important for the destination choices. While the origin and destination fixed effects control the income and price level at the census tract level, one might think that the visitors' preferences are correlated with income levels.

I use multiple strategies to control and investigate the heterogeneous preferences by income level.

First, all the regressions in the paper control $\log \text{Inc}_{ij}$, the percentage difference in the median income between the origin and destination locations. I assume that the median income is also a proxy variable for the level of price and quality of POIs in a location. Then $\log \text{Inc}_{ij}$ controls that preference matching between the income of consumers and the price and quality of destination POIs.

Second, Cook (2023) provides a thorough study on the heterogeneous preferences by income for local amenities using data on smartphone GPS and a discrete choice model on destination choices similar to this paper. The main finding is that rich consumers' preference for neighborhoods' overall level of amenities is highly correlated with the preference for poor consumers', with an average correlation of 0.9[48]. Instead, the density of POIs is important for consumers at all income levels. In other words, high- and low-income consumers visit similar places where there are sufficient numbers and varieties of POIs that appeal to both types of consumers.

Finally, columns (2) and (3) in Table D.10 show results for additional investigations, using the methods in Cook (2023). The hypothesis is that consumers at different income levels may have heterogeneous preferences for certain types of POIs. For example, wealthy consumers may prefer places with more theaters, concert halls, and fancy clubs, while lower-income consumers may prefer places with more stores with essential goods and services. So I use the categorization in Cook (2023) and put the POIs into four groups: restaurant, shop, service, and entertainment. I calculate the share of POIs in each group in every census tract and add the interaction terms between these shares and the median income of the origin census tract. The interaction terms control the potential heterogeneous preferences mentioned above.

Column (2) shows that the disamenities of highways are robust after adding the interaction terms. And the interaction terms are weekly or not significant. The signs are consistent with expectations: wealthier consumers weekly prefer places with more entertainment and services POIs and fewer shops. Additionally, I add the interaction terms between median income and $\mathbf{D}_{ij}^{\text{crossHW}}$, $\mathbf{D}_{ij}^{\text{useHW}}$ to investigate potential heterogeneous disamenities of highways on consumers with different income. The result in column (3) shows that the coefficients of the interaction terms are small and insignificant, suggesting that the level of highway disamenities is similar to consumers at all income levels. And the disamenities, the coefficients of $\mathbf{D}_{ij}^{\text{crossHW}}$ and $\mathbf{D}_{ij}^{\text{useHW}}$, are robust.

In conclusion, the disamenities of highways on consumers are robust with the inclusion of heterogeneous preferences. The degree of heterogeneous preferences is not strong at the census tract level.

D.5 Overpassing vs. detour

Crossing a highway refers to two cases in reality, depending on the structure of the road network. One is traveling on a road that runs over or under a highway. The second is using a highway for a short distance

[48] Concretely, the findings in Cook (2023) are that the preferences at the neighborhood level is highly correlated, and conditional on one neighborhood, the preference over specific POIs could be heterogeneous by income level and the degree of heterogeneity vary by types of POIs. Since the locations in my model and data are census tracts, the findings indicate that the heterogeneous preferences for destination locations are not strong in my setting.

Table D.10: Heterogeneous Effects in Income and Non-Highway Exposure

Model:	Baseline (1)	Heterogeneous Preferences by Income (2)	(3)	Non-Highway Exposure (4)
$\log \text{Time}_{ij} \times [0,\ 5\text{ km}]$	-1.02***	-1.02***	-1.02***	-0.406***
	(0.046)	(0.045)	(0.045)	(0.101)
$\log \text{Time}_{ij} \times [5,\ 10\text{ km}]$	-1.16***	-1.16***	-1.16***	-0.517***
	(0.035)	(0.035)	(0.035)	(0.099)
$\log \text{Time}_{ij} \times [10,\ 15\text{ km}]$	-1.31***	-1.31***	-1.31***	-0.680***
	(0.032)	(0.032)	(0.032)	(0.098)
$\log \text{Time}_{ij} \times [15,\ 25\text{ km}]$	-1.42***	-1.42***	-1.42***	-0.826***
	(0.032)	(0.032)	(0.032)	(0.095)
$\mathbf{D}_{ij}^{\text{crossHW}}$	-0.180***	-0.177***	-0.206***	-1.14***
	(0.031)	(0.031)	(0.039)	(0.353)
$\mathbf{D}_{ij}^{\text{useHW}}$	-0.187***	-0.181***	-0.177***	-3.31***
	(0.035)	(0.035)	(0.045)	(0.531)
$\log \text{Race}_{ij}$	-0.092***	-0.091***	-0.091***	-0.076***
	(0.004)	(0.004)	(0.004)	(0.004)
$\log \text{Inc}_{ij}$	-0.019***	-0.037	-0.033	-0.018***
	(0.007)	(0.046)	(0.046)	(0.007)
$\log \text{Inc}_i \times \text{Share}^{\text{Restaurant}}$		-0.058	-0.061	
		(0.060)	(0.060)	
$\log \text{Inc}_i \times \text{Share}^{\text{Shop}}$		-0.247**	-0.249**	
		(0.099)	(0.101)	
$\log \text{Inc}_i \times \text{Share}^{\text{Service}}$		0.071	0.067	
		(0.070)	(0.070)	
$\log \text{Inc}_i \times \text{Share}^{\text{Entertainment}}$		-0.309***	-0.313***	
		(0.109)	(0.108)	
$\log \text{Inc}_i \times \mathbf{D}_{ij}^{\text{crossHW}}$			-0.018	
			(0.013)	
$\log \text{Inc}_i \times \mathbf{D}_{ij}^{\text{useHW}}$			0.004	
			(0.014)	
$\log \text{Distance}_{ij}^{\text{Non Highway}}$				-0.618***
				(0.091)
$\log \text{Distance}_{ij}^{\text{Non Highway}} \times \mathbf{D}_{ij}^{\text{crossHW}}$				0.109***
				(0.041)
$\log \text{Distance}_{ij}^{\text{Non Highway}} \times \mathbf{D}_{ij}^{\text{useHW}}$				0.340***
				(0.059)
Fixed Effects	Census tract of POI & visitors home			
Observations	75,526	75,526	75,526	75,526
Pseudo R^2	0.226	0.227	0.227	0.302

Note: This table provides evidence for various heterogeneous effects of highways. Column (1) shows the baseline effects, which are the same as in Table 1. Columns (2) and (3) show that there is little heterogeneity in the preference of consumers at different income levels, which is discussed in Subsection D.4. Column (4) shows that the longer consumers travel on non-highways, the less they care about highway disamenities, which is discussed in Subsection D.6. The standard errors are calculated using two-way clustering by origin (home) and destination (POIs). Significant Codes: ***: 0.01, **: 0.05, *: 0.1.

Table D.11: Heterogeneous Effects in Overpass and Detour

Speed assumptions: Model:	Weighted mean (1)	Speed limits (2)	Speed at 5pm, Uber (3)
$\log \text{Time}_{ij} \times [0,\ 5\text{ km}]$	-1.02***	-1.09***	-0.915***
	(0.046)	(0.044)	(0.066)
$\log \text{Time}_{ij} \times [5,\ 10\text{ km}]$	-1.16***	-1.21***	-1.06***
	(0.035)	(0.036)	(0.052)
$\log \text{Time}_{ij} \times [10,\ 15\text{ km}]$	-1.31***	-1.36***	-1.20***
	(0.032)	(0.034)	(0.049)
$\log \text{Time}_{ij} \times [15,\ 25\text{ km}]$	-1.42***	-1.50***	-1.31***
	(0.032)	(0.033)	(0.046)
$\mathbf{D}_{ij}^{\text{crossHW, overpassing}}$	-0.161***	-0.152***	-0.155***
	(0.034)	(0.031)	(0.041)
$\mathbf{D}_{ij}^{\text{crossHW, detour}}$	-0.224***	-0.253***	-0.308***
	(0.035)	(0.042)	(0.039)
$\mathbf{D}_{ij}^{\text{useHW}}$	-0.191***	-0.248***	-0.257***
	(0.035)	(0.039)	(0.047)
$\log \text{Race}_{ij}$	-0.092***	-0.076***	-0.095***
	(0.004)	(0.004)	(0.004)
$\log \text{Inc}_{ij}$	-0.018***	-0.008	-0.020**
	(0.007)	(0.007)	(0.008)
Fixed Effects	Census tract of POI & visitors home		
Observations	75,526	79,873	69,124
Pseudo R^2	0.226	0.160	0.156

Note: This table distinguishes between two types of crossing highways: overpassing and detouring, based on the length of spatial overlap with the highways. An overpass is defined as a crossing where the interaction distance is less than 150 meters; a detour is defined otherwise. The results show that detours have systematically larger negative effects on consumer visits than overpasses, conditional on travel time and across all speed assumptions.

to cross the highway. In the second case, highways effectively cut and elongate the route, because if there were no highways with limited entry and exit, the route would have been more efficient and avoided the detour. It is reasonable to conjecture that a detour is associated with higher disamenities than using an overpass, even after controlling for travel time, because it requires higher mental costs to enter and exit highways. So I distinguish the two types of crossings by the length of the interacted part: For a route that crosses highways, an overpass has an interaction distance below 150 meters; otherwise, it is a detour.

Table D.11 shows the heterogeneous effects of overpassing highways and taking a detour, which is robust across different assumptions of travel speed. Column (1) uses the baseline speed assumption and shows that the negative impact of taking a detour to cross a highway is 40% larger than the effects of using an overpass, which indicates that consumers react to the additional risks and mental efforts required to navigate entering and exiting a highway. Under the assumption without information on real traffic conditions in column (2) and the assumption with the worst congestion in column (3), the impact of taking a detour is systematically larger than overpassing a highway, which shows the robustness of this pattern. However, since the policy implication of distinguishing between overpasses and detours is unclear, I will only use the effect of crossing highways in the counterfactual analysis.

D.6 Non-Highway Exposure Effects

Another hypothesis is that the effects are heterogeneous over the portion of routes that are not highways. As mentioned, the cost of interaction with highways aligns with the notion of a fixed cost. Conditional on interaction with highways, the longer the consumers travel on non-highway roads, the higher variable costs they spend that are not associated with highways, and thus the less they may care about the fixed cost of interaction with highways. To investigate this, I add interaction terms between $\text{Distance}_{ij}^{\text{Non Highway}}$, the distance of the routes that are not highways, and $\mathbf{D}_{ij}^{\text{crossHW}}$, $\mathbf{D}_{ij}^{\text{useHW}}$ and report the regression results in column (4) of Table D.10. The positive and significant coefficients of $\log \text{Distance}_{ij}^{\text{Non Highway}} \times \mathbf{D}_{ij}^{\text{crossHW}}$ and $\log \text{Distance}_{ij}^{\text{Non Highway}} \times \mathbf{D}_{ij}^{\text{useHW}}$ indicate that the longer distance consumers travel on non-highway roads, the less they will respond to the disamenities of highways, which is consistent with the hypothesis[49].

E Full Description of General Equilibrium Model

This section describes the full general equilibrium model of commuting and consumption travel, encompassing the modules in Section 3 and 6

E.1 The economic environment

There are J locations in the economy, denoted by i (for home location), k (for workplace), and j (for destination of a consumption trip). Each location i is endowed with land area L_i that may be split between residential and industrial uses. Land supply is fixed, and thus, land prices adjust based on demand, which is driven by both population and employment in a given location. The city is closed, with a fixed population $\boldsymbol{N}$, and thus, an endogenous expected utility. A representative worker chooses a home–workplace pair to maximize utility. Workers' choices determine the commuting pattern, the population in each location N_{Ri}, and the labor force in each location N_{Wk}. A worker is also a consumer who derives utility by traveling to POIs in different destinations. The free migration and traveling of workers ensures that the expected utility is equalized between locations. Observing consumers' travel behavior, potential POI owners choose to enter a location and set up a POI to maximize utility. POI owners' decisions determine the number of POIs in each location, n_i.

[49] Additionally, the mean value of $\text{Distance}_{ij}^{\text{Non Highway}}$ is 9. Taking this value to column (4) indicates that the mean disamenity of crossing highways is -0.152 and the mean disamenity of using highways is -0.268, which are close to the baseline results in column (1).

E.2 Worker's location choices

Workers derive utility from consumption c, land l, and neighborhood amenities B. Each worker receives an idiosyncratic preference shock ν_{ik} for a given home–workplace pair $\{i,k\}$. The utility of living in i and working in k is

$$U_{ik}\left(c_i,l_i\right)=\nu_{ik}B_i\left(\frac{c_i}{\beta}\right)^{\beta}\left(\frac{l_i}{1-\beta}\right)^{1-\beta}, \tag{22}$$

where β is the consumption share of income. The commuting cost is

$$d_{ik}=\exp\left(\kappa_1\log\tau_{ik}+\kappa_2\mathbf{D}_{ik}^{\text{crossHW}}+\kappa_3\mathbf{D}_{ik}^{\text{useHW}}+\kappa_4\log\text{Race}_{ik}\right), \tag{23}$$

where τ_{ik} is a measure of access between place of residence i and workplace k. Workers earn a wage net of commuting costs $\frac{w_k}{d_{ik}}$. The workers' budget constraint is then $\frac{w_k}{d_{ik}}=l_iq_i+c_i$, where q_i is the price of land at place of residence i.[50] Maximizing utility conditional on wages and rents yields indirect utility for each commuting pair

$$V_{ik}\left(w_k,q_j\right)=\nu_{ik}\frac{w_k}{d_{ik}}B_iq_i^{(\beta-1)}. \tag{24}$$

Assuming ν_{ik} is drawn from a Fréchet distribution with shape parameter ε, the probability that a worker chooses to live in i and work in k is

$$\pi_{ik}=\frac{\left(\frac{w_k}{d_{ik}}B_iq_i^{(\beta-1)}\right)^{\varepsilon}}{\sum_{i'=1}^{I}\sum_{k'=1}^{I}\left(\frac{w_{k'}}{d_{i'k'}}B_{i'}q_{i'}^{(\beta-1)}\right)^{\varepsilon}}. \tag{25}$$

Note that the share of population in a location is $\frac{N_{Ri}}{\boldsymbol{N}}=\sum_{k=1}^{I}\pi_{ik}$. According to Equation (10), that is

$$\frac{N_{Ri}}{\boldsymbol{N}}=\left(B_iq_i^{(\beta-1)}\right)^{\varepsilon}\frac{\sum_{k=1}^{I}\left(\frac{w_k}{d_{ik}}\right)^{\varepsilon}}{\sum_{i'=1}^{I}\sum_{k'=1}^{I}\left(\frac{w_{k'}}{d_{i'k'}}B_{i'}q_{i'}^{(\beta-1)}\right)^{\varepsilon}}, \tag{26}$$

where N_{Ri} is the measure of workers residing in i. Equation (26) indicates that a worker is more likely to reside in location i that offers higher amenity value B_i and lower land price q_i. Given the fixed land supply, a population inflow into location i drives up q_i, reducing the incentive to migrate to i and limiting further concentration of workers in the location.

The probability that a worker commutes to k conditional on living in i is

$$\pi_{ik|i}=\frac{\left(\frac{w_k}{d_{ik}}\right)^{\varepsilon}}{\sum_{k'=1}^{I}\left(\frac{w_{k'}}{d_{i'k'}}\right)^{\varepsilon}}. \tag{27}$$

[50] The price of the consumption good is normalized to 1.

This implies the commuting market clearing condition.

$$N_{Wk} = \sum_{i=1}^{I} \left[\frac{\left(\frac{w_k}{d_{ik}}\right)^{\varepsilon}}{\sum_{k'=1}^{I} \left(\frac{w_{k'}}{d_{i'k'}}\right)^{\varepsilon}} N_{Ri} \right], \tag{28}$$

where N_{Wk} is the measure of workers working in k. Total residential land consumption in a location is the sum of land demand by all workers choosing to live in that location.

$$L_{Ri} = (1-\beta) \frac{N_{Ri}}{q_i} \sum_{k=1}^{I} \pi_{ik|i} \frac{w_k}{d_{ik}}. \tag{29}$$

The expected utility is equalized across locations and is given by

$$E\left[\bar{U}\right] = \Gamma \left(\frac{\varepsilon - 1}{\varepsilon}\right) \left[\sum_{i=1}^{I} \sum_{k=1}^{I} \left(\frac{w_k}{d_{ik}} B_i q_i^{(\beta-1)} \right)^{\varepsilon} \right]^{\frac{1}{\varepsilon}}. \tag{30}$$

E.3 Consumer choices, amenities, and POIs

After deciding on the home and workplace, a consumer chooses to visit a POI in destination j to maximize utility. She has an outside option of not visiting any POI and obtaining utility U_{iH}. The utility of a trip depends on the travel cost, consumer's characteristics, the value offered by the POI in j, and an idiosyncratic preference shock. The utility and consumer's choices are fully described in Subsection 3.2.

Consumption travel choices fully pin down location amenity, B_i, as explained in Subsection 6.2. The location choices of potential POI owners are also determined by consumer travel flows, as described in Subsection 6.3. With additional assumptions, the number of POIs in each location n_i is a monotonic function of the number of consumer visits to the location.

E.4 Production

At each location, a single homogeneous final good is produced under constant returns and perfect competition. The production function is

$$Y_k = A_k L_{Wk}^{1-\alpha} N_{Wk}^{\alpha}, \tag{31}$$

where A_k is total factor productivity, L_{Wk} is total land used for production, N_{Wk} is total employment, and α is the labor share in production. Profit maximization yields total industrial land use in each location is

$$L_{Wk} = \frac{1-\alpha}{\alpha} N_{Wk} \frac{w_k}{q_i}. \tag{32}$$

E.5 Equilibrium

Land area L_i, travel time τ_{ik}, and total population $\boldsymbol{N}$ are given by the data. Additionally, given values of parameters $\{\alpha, \beta, \varepsilon\}$ and location fundamentals $\{B_i, A_k\}$, equilibrium is a vector of prices $\{q_i, w_k\}$ and quantities of labor, land, and number of POIs $\{N_{Ri}, N_{Wk}, L_{Ri}, L_{Wk}, n_j\}$ such that:

1. Labor markets clear through workplace and commuting choices in Equation (28).
2. Total population is $\boldsymbol{N} = \sum_{i=1}^{I} N_{Ri}$.
3. Land markets clears through $L_{Ri} + L_{Wi} = L_i$, where L_{Ri} is given by Equation (29) and L_{Wi} is given by Equation (32).
4. The distribution of POIs given by Equation (15) is consistent with the visits generated by equilibrium residents N_{Ri}.

F Derivation

In this section, I first show how Equation (15) is generated from firm's problem (14). Then, I show that applying the findings in Guimaraes et al. (2003), the PPML estimator of Equation (15) is the same as the conditional logit estimator.

Assuming that the fixed cost F_j and the per-capita profit of serving a consumer is independent across locations, that is $F_j = F, \mu_j \equiv e_j - c_j = \mu$, the probability that a POI choose to enter j is

$$\mathrm{Pr}_j = \Pr\left(\text{Profit}_j > \text{Profit}_{j'},\ \forall j'\right) \tag{33}$$

$$= \Pr\left(\mu M_j \xi_j - F > \mu M_{j'} \xi_{j'} - F,\ \forall j'\right) \tag{34}$$

Adding F on both sides of the inequality, taking log, and multiplying both sides with a positive scalar α, Equation (34) becomes

$$\mathrm{Pr}_j = \Pr\left(\mu M_j \xi_j > \mu M_{j'} \xi_{j'},\ \forall j'\right) \tag{35}$$

$$= \Pr\left(\log M_j + \log \mu + \log \xi_j > \log M_{j'} + \log \mu + \log \xi_{j'},\ \forall j'\right) \tag{36}$$

$$= \Pr\left(\alpha \log M_j + \log \xi_j > \alpha \log M_{j'} + \log \xi_{j'},\ \forall j'\right) \tag{37}$$

Assuming $\log \xi_j$ ∼T1EV and considering that the POI owner has the outside option of not opening a POI and earns zero profits, Equation (37) yields Equation (15) where

$$\mathrm{Pr}_j = \frac{\exp\left(\alpha \log M_j\right)}{1 + \sum_{j' \in J} \exp\left(\alpha \log M_{j'}\right)}. \tag{38}$$

The expected number of POIs in j is

$$E(n_j) = N^{\text{Potential POI}} \times \Pr(\text{Profit}_j > \text{Profit}_{j'},\ \forall j' \neq j), \tag{39}$$

which delivers Equation 15 after inserting Equation 38.

Let n denote a POI owner and there are N number of them. The log likelihood function of conditional logit model (38) is

$$\log L_{\text{cl}} = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \text{Pr}_j = \sum_{j=1}^{J} n_j \text{Pr}_j, \tag{40}$$

where $d_{nj} = 1$ in case POI owner n chooses to enter location j and $d_{ij} = 0$ otherwise, n_j is the number of POIs located in location j.

Alternatively, let n_j be Poisson-distributed with

$$E(n_j) = \lambda_j = \exp(\alpha_0 + \alpha \log M_j). \tag{41}$$

The log-likelihood function of the above equation is

$$\log L_{\text{P}} = \sum_{j=1}^{J} (-\lambda_j + n_j \log \lambda_j - \log n_j!) \tag{42}$$

$$= \sum_{j=1}^{J} (-\exp(\alpha_0 + \alpha \log M_j) + n_j (\alpha_0 + \alpha \log M_j) - \log n_j!) \tag{43}$$

From the first order condition with respect to α_0, we have

$$\frac{\partial \log L_P}{\partial \alpha_0} = \sum_{j=1}^{J} (n_j - \exp(\alpha_0 + \alpha \log M_j)) = 0 \Longrightarrow \exp(\alpha_0) = \frac{N}{\sum_{j=1}^{J} \exp(\alpha \log M_j)}$$

Substituting α_0 back to Equation (43), we have

$$\log L_{\text{P}} = \sum_{j=1}^{J} \left(-\frac{N \exp(\alpha \log M_j)}{\sum_{j=1}^{J} \exp(\alpha \log M_j)} + n_j \left(\log N - \log \sum_{j=1}^{J} \exp(\alpha \log M_j) + \alpha \log M_j \right) - \log n_j! \right) \tag{44}$$

$$= -N + N \log N - \sum_{j=1}^{J} n_j \left(\log \sum_{j=1}^{J} \alpha \log M_j \right) + \sum_{j=1}^{J} n_j \alpha \log M_j - \sum_{j=1}^{J} \log n_j! \tag{45}$$

$$= \sum_{j=1}^{J} n_j \log \text{Pr}_j - N + N \log N - \sum_{j=1}^{J} \log n_j! \tag{46}$$

The first term in Equation (46) is $\log L_{\text{cl}}$ in Equation (40), and the remaining terms are all constants. Thus, the estimated α using both likelihood functions are the same.

G Calibrating Amenity B_i and Productivity A_k

This section shows the process of calibrating $\{B_i, A_k\}$ using the data on population, employment, and the estimates from the gravity regressions.

Wage at each location can be solved iteratively from Equation (28):

$$w_k = \left[\frac{1}{N_{Wk}} \sum_{i=1}^{I} \left(\frac{\left(\frac{1}{d_{ik}}\right)^{\varepsilon}}{\sum_{k'=1}^{I} \left(\frac{w_{k'}}{d_{i'k'}}\right)^{\varepsilon}} N_{Ri} \right) \right]^{-\frac{1}{\varepsilon}}. \tag{47}$$

Given wage, land price is determined by the demand of land by residents in Equation (29) and by firms in Equation (32) and land market clearing:

$$q_i = \frac{(1-\beta) N_{Ri} \sum_{k=1}^{I} \pi_{ik|i} \frac{w_k}{d_{ik}} + \frac{1-\alpha}{\alpha} N_{Wi} w_i}{L_i}. \tag{48}$$

Combining Equations (10), (11), and (27), amenity can be written as

$$B_i = \frac{E\left[\bar{U}\right]}{\Gamma\left(\frac{\varepsilon-1}{\varepsilon}\right)} \left[\frac{N_{Ri}}{N}\right]^{\frac{1}{\varepsilon}} q_i^{(1-\beta)} \left[\sum_{k'=1}^{I} \left(\frac{w_{k'}}{d_{i'k'}}\right)^{\varepsilon} \right]^{-\frac{1}{\varepsilon}}. \tag{49}$$

Productivity is pinned down by profit maximization and zero profit condition:

$$A_k = \left(\frac{w_k}{\alpha}\right)^{\alpha} \left(\frac{q_k}{1-\alpha}\right)^{1-\alpha}. \tag{50}$$

H Solving the Model in Counterfactual Economy

In this section, I introduce the process of solving the model in counterfactuals. In the counterfactual economy, I simulate policies that transform urban highways. This shifts three terms in the model: 1) the utility of visiting a POI, V_{ij}, through travel time τ_{ij} and highway dummies, 2) the utility of staying at home U_{iH} through distance to the nearest highway $\delta_{i,HW}$, 3) the commuting cost d_{ik} through travel time τ_{ij} and highway dummies. I use x^* to denote variables in counterfactual equilibrium and $x^0, x^1, \ldots$ to denote the endogenous variables in each iteration. Note that due to multiple sources of agglomeration forces, I cannot formally prove the existence and uniqueness of the equilibrium. However, the counterfactual equilibrium is solved iteratively, starting from the baseline equilibrium, to ensure consistency.

In the counterfactual economy, workers choose a location pair of home and workplace, with an expectation of the location amenity B_i. They observe the distribution of POIs and choose their consumption trips. The consequent number of consumption visits determines the POI owners' decision and thus, the distribution of POIs n_j, which, in turn, affects consumption travel. The distribution of POIs and consumer travel are consistent with each other in equilibrium. Finally, workers' expectations for the location amenity are consistent with the ex-post amenity, which is determined by consumer travel.

With an initial guess of location amenity, POI distribution, wage, and land price $\left\{B_i^0, n_i^0, w_i^0, q_i^0\right\}$, the algorithm solves the model iteratively. The commuting choices are

$$\pi_{ik}^0 = \frac{\left(\frac{w_k^0}{d_{ik}^*} B_i^0 \left(q_i^0\right)^{(\beta-1)}\right)^{\varepsilon}}{\sum_{i'=1}^{I} \sum_{k'=1}^{I} \left(\frac{w_{k'}^0}{d_{i'k'}^*} B_{i'}^0 \left(q_{i'}^0\right)^{(\beta-1)}\right)^{\varepsilon}}. \tag{51}$$

$$\pi_{ik|i}^0 = \frac{\left(\frac{w_k^0}{d_{ik}^*}\right)^{\varepsilon}}{\sum_{k'=1}^{I} \left(\frac{w_{k'}^0}{d_{i'k'}^*}\right)^{\varepsilon}}. \tag{52}$$

Residential population and employment are

$$N_{Ri}^0 = N \sum_{k=1}^{I} \pi_{ik}^0, \; N_{Wk}^0 = N \sum_{i=1}^{I} \pi_{ik}^0. \tag{53}$$

Residential land use is

$$L_{Ri}^0 = (1-\beta) \frac{N_{Ri}^0}{q_i^0} \sum_{k=1}^{I} \pi_{ik|i}^0 \frac{w_k^0}{d_{ik}^*}. \tag{54}$$

Commercial land use is

$$L_{Wk}^0 = \frac{1-\alpha}{\alpha} N_{Wk}^0 \frac{w_k^0}{q_i^0}. \tag{55}$$

Production is

$$Y_k^0 = A_k \left(L_{Wk}^0\right)^{1-\alpha} \left(N_{Wk}^0\right)^{\alpha}. \tag{56}$$

The updated wages and land prices are

$$w_k^1 = \frac{\alpha Y_k^0}{N_{Wk}^0}, \; q_k^1 = \frac{(1-\alpha) Y_k^0}{L_{Wk}^0}. \tag{57}$$

After the wage and land price converge conditional on $\left\{B_i^0, n_i^0\right\}$, I solve the consumption trip choices problem. The counterfactual choice probabilities are

$$\mathrm{Pr}_{ij}^0 = \frac{\exp\left(V_{ij}^* + \ln n_j^0\right)}{\exp\left(U_{iH}^*\right) + \sum_{j' \in J} \exp\left(V_{ij'}^* + \ln n_{j'}^0\right)}, \; \mathrm{Pr}_{iH}^0 = \frac{\exp\left(U_{iH}^*\right)}{\exp\left(U_{iH}^*\right) + \sum_{j' \in J} \exp\left(V_{ij'}^* + \ln n_{j'}^0\right)}. \tag{58}$$

Combing with the counterfactual population, the market potential is given by

$$M_j^0 = \sum_{i=1}^{I} N_{Ri}^0 \mathrm{Pr}_{ij}^0 C_{\mathrm{NW}}, \tag{59}$$

where C_{NW} is the number of choices given to a consumer. The updated POI distribution is

$$n_j^1 = \frac{\exp\left(\theta \log M_j^0\right)}{1 + \sum_{j' \in J} \exp\left(\theta \log M_j^0\right)} N^{\text{Potential POI}}. \tag{60}$$

The updated amenity is

$$B_i^1 = \ln\left(\exp\left(U_{iH}^*\right) + \sum_{j \in J} \exp\left(V_{ij}^* + \ln n_j^1\right)\right). \tag{61}$$

The algorithm then iterate the process using $\left\{B_i^1, n_i^1, w_i^1, q_i^1\right\}$ until they converge to $\{B_i^*, n_i^*, w_i^*, q_i^*\}$. The counterfactual amenity is computed in the same way as in Equation (11):

$$E^*\left[\bar{U}\right] = \Gamma\left(\frac{\varepsilon - 1}{\varepsilon}\right)\left[\sum_{i=1}^{I}\sum_{k=1}^{I}\left(\frac{w_k^*}{d_{ik}^*} B_i^* \left(q_i^*\right)^{(\beta-1)}\right)^{\varepsilon}\right]^{\frac{1}{\varepsilon}}. \tag{62}$$

I Additional Findings in Counterfactual

This section discuss more detailed findings in the counterfactual equilibrium with alternative highway systems, especially the equilibrium allocation at the census tract level.

I.1 Exercise 1: Burying urban highways

Neighborhood level effects. Patterns of changes at the neighborhood level are consistent with the urban–suburban disparity. Figure J.4 shows the changes in B_i at the census tract level. Figure J.4a reveals two patterns within the urban area: first, the neighborhoods that are closer to urban highways experience a greater increase in amenity in the counterfactual; second, amenity improvements mainly occur in the two largest municipalities, Seattle and Tacoma. The other urban area, Bellevue, does not gain because removing the crossing-highway disamenity does not affect a great number of travelers in Bellevue. While in Seattle, the dividing highway, Interstate-5, hinders much downtown traveling and leads to larger gains in counterfactual, echoing the complaints from the general public in Seattle. Changes in the distribution of POIs in Figure J.5a show consistent patterns: POIs mainly move to Seattle and Tacoma, with places that are closer to urban highways seeing a greater increase in POIs. Figure J.6 shows the percentage change in the population and employment in each census tract following the burying highway program. Urban areas, especially Seattle and Tacoma, experience substantial increases. The places closer to urban highways see larger increases in residents and jobs, which are consistent with the aggregated findings discussed in Subsection 8.2.

I.2 Exercise 2: Replacing urban highways with primary roads

Neighborhood level effects. Census tract level effects are consistent with the regional pattern. There is considerable variation in the changes in quality of life, as shown in Figure J.4b. The distribution of amenity changes closely resembles those found in the first exercise in Figure J.4a. This is because the two additional components in this exercise, relative to the previous one, counteract each other: the effects of removing using-highway disamenity are opposite to that of increases in travel time. Thus, the two patterns discussed in Subsection 8.2 hold: First, urban areas, especially Seattle and Tacoma, benefit from better amenities; second, the locations closer to actual urban highways see larger amenity improvements. Note that compared to the first exercise, Bellevue experiences greater amenity improvements due to the removal of using-highway disamenity, as more using-highway routes are used intensively there. Thus, more travelers benefit from the increased utility of consumption travel, and more POIs remain in Bellevue rather than relocating to Seattle, as shown in Figure J.5b. Amenities increase accordingly. The allocation of residents and workers at the census tract level also follows this pattern and are consistent with the aggregate regional level relocation. Figure J.7 shows the percentage change in the population and employment in each census tract, which exhibits similar patterns to Figure J.6.

J Robustness of Counterfactual Exercises

The counterfactual effects discussed in Section 8 are based on the specific assumption of dividing a day into time slots. In this section, I investigate the robustness of these effects under different partition specifications. I set an upper and a lower bound for the number of time slots within a day. Using the bounds of slots, I recalibrate the shares of consumption trips, estimate the corresponding parameters, and implement the same counterfactual exercises as in Section 8. Note that the estimated values of the parameters $\boldsymbol{\gamma}$ in Equation (8) are unaffected, as conditional on origin fixed effects, the share of visiting different locations Pr_{ij} is independent of the partition specifications. This specification mainly influence the calibrated home fixed effects H_i and associated utility of the outside option $U_{i,H}$

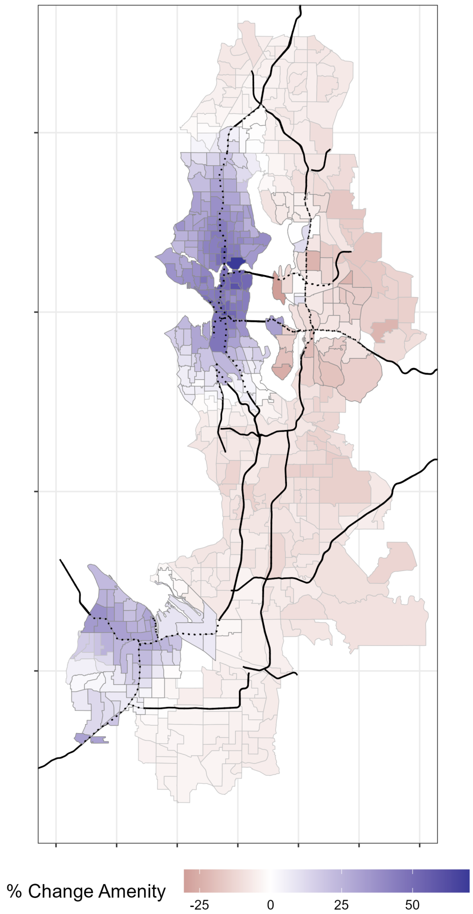
Upper Bound The upper bound of the time slots is obtained by partitioning a weekday into four slots[51] and a weekend into seven slots[52]. This means that the average number of choices per day for a consumer is 5.1, higher than the baseline value of 3.7. The higher number of choices and the fixed number of visits from the smartphone data imply that the share of choosing the outside option is 72%, higher than the 62% share generated by the baseline calibration.

Lower Bound The lower bound of the time slots is obtained by partitioning a weekday into two

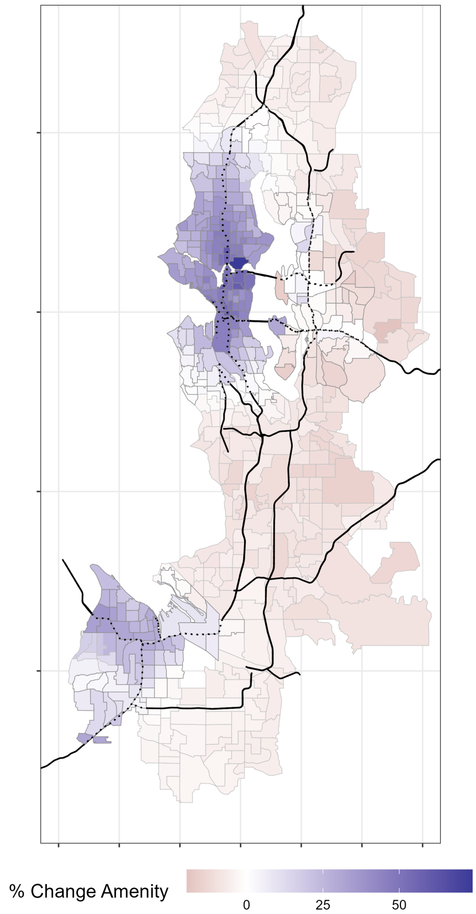
[51] The four weekday time slots are before work, between work and dinner, during dinner, and after dinner.

[52] The seven weekend time slots are early morning, late morning, lunch, early afternoon, late afternoon, during dinner, and after dinner.

Figure J.4: Changes in Amenity B_i in Counterfactual



(a) Exercise 1: Burying Highways



(b) Exercise 2: Replacing Highways

Note: These two figures show the changes in amenity B_i at the census tract level following two counterfactual exercises. The black lines are the highways, with dotted lines representing urban highways, which are modified by counterfactual exercise, and solid lines representing suburban highways, which are kept in the counterfactual economy. Note that the legends of the two figures are different.

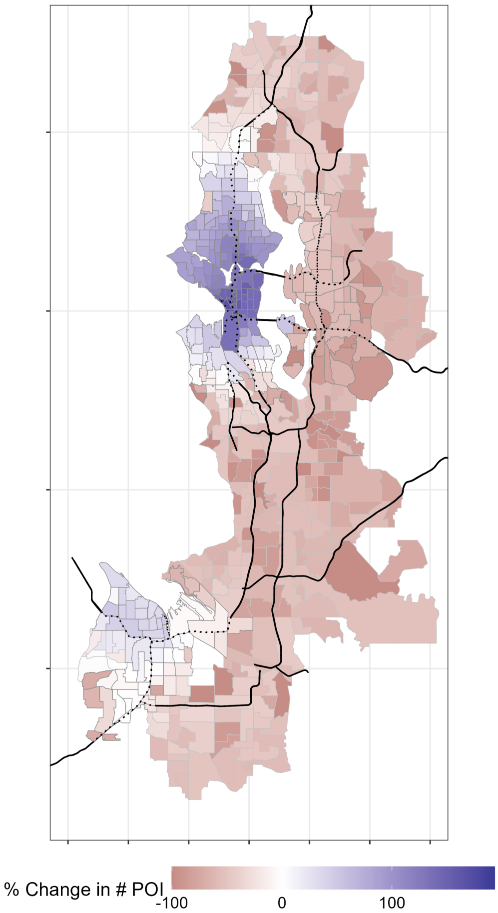
slots[53]. and a weekend into four slots[54] This means that the average number of choices per day is 2.7, and the share of choosing the outside option is 47%, both lower than the baseline level.

Table J.12 summarizes the welfare effects of two counterfactual exercises at the assumed bounds for the number of choices. The baseline welfare effects are duplicated from Table 3 for easier comparison. The welfare effects column provides the bounds of the welfare gain. When the assumption is adjusted, the welfare results remain consistently positive, with modest variations in magnitude. Specifically, reducing choice opportunities to the lower limits increases the estimated welfare gain by more than 2 percentage points for both counterfactual exercises. Conversely, increasing the assumed number of choices to the upper limits results in a marginal decrease of about 1 percentage point in welfare improvement.

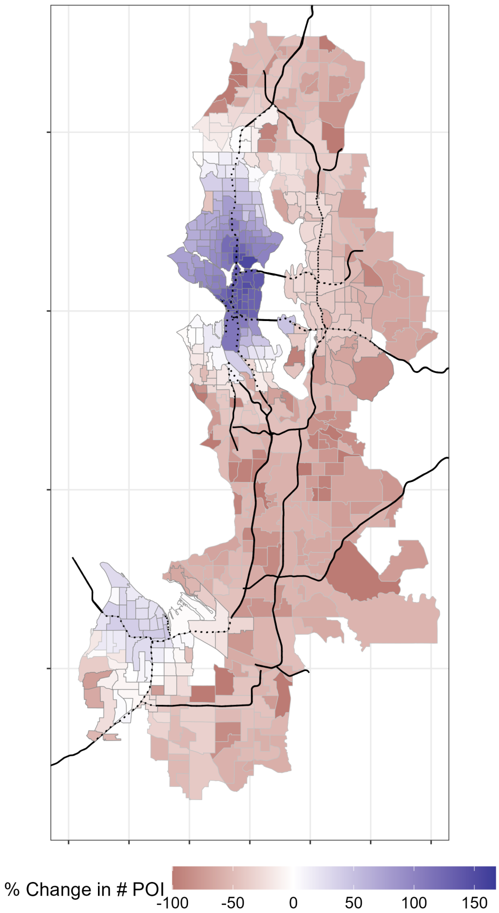
These variations occur because the assumed number of choice opportunities directly influences the

[53]The two weekday time slots are before work and after work.
[54]The four weekend time slots are morning, lunch, afternoon, and dinner.

Figure J.5: Changes in the number of POIs n_j in Counterfactual



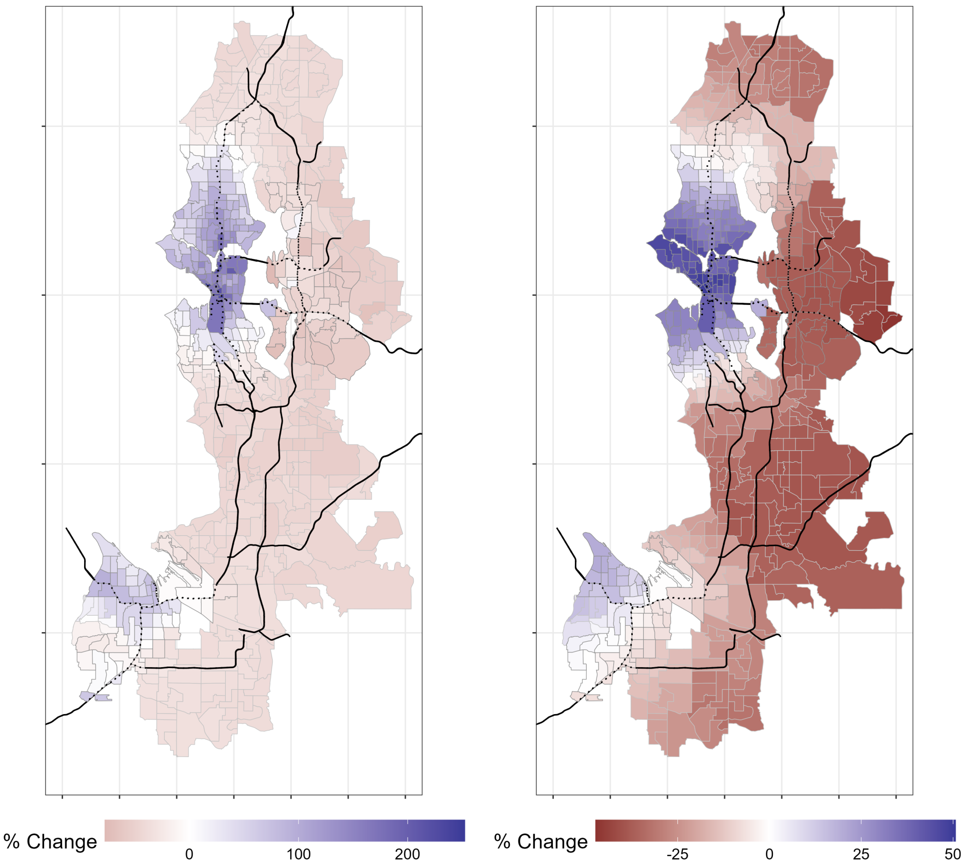
(a) Exercise 1: Burying Highways



(b) Exercise 2: Replacing Highways

Note: These two figures show the changes in the number of POIs. at the census tract level following two counterfactual exercises. The black lines are the highways, with dotted lines representing urban highways, which are modified by counterfactual exercise, and solid lines representing suburban highways, which are kept in the counterfactual economy. Note that the legends of the two figures are different.

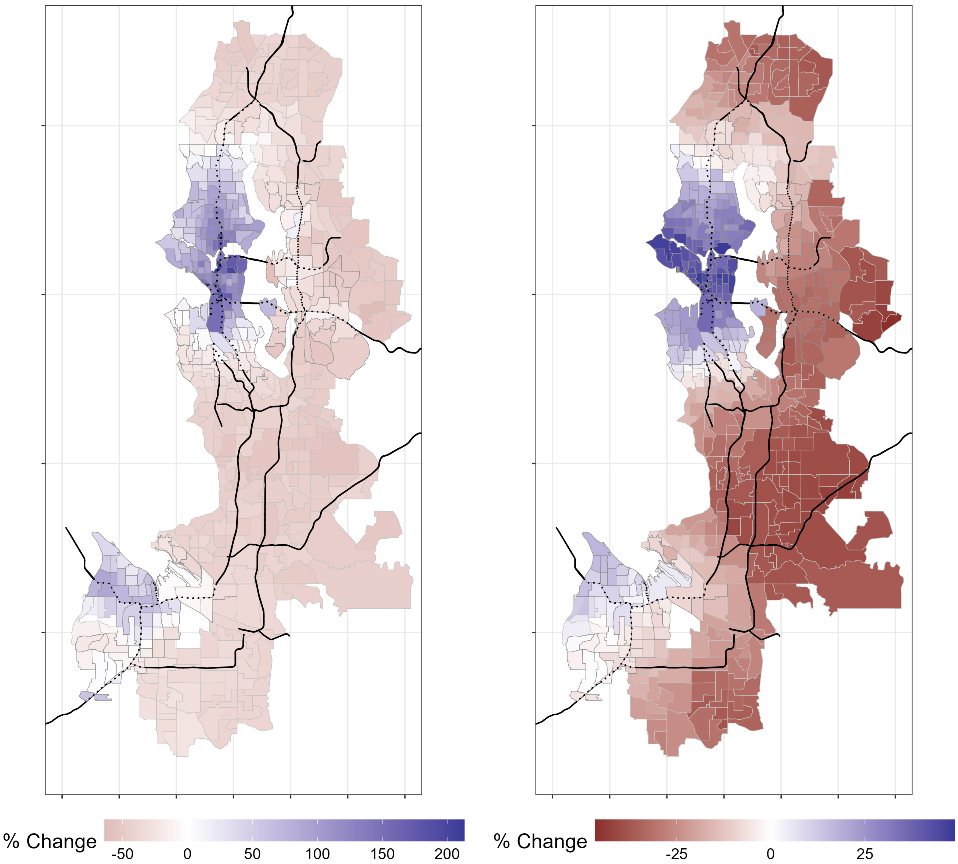
Figure J.6: Changes in Population and Employment, Burying Urban Highways



(a) Percentage Change in Population (b) Percentage Change in Employment

Note: These two figures show the changes in population and employment at the census tract level. The black lines are the highways, with dotted lines representing urban highways, which are buried in the counterfactual economy, and solid lines representing suburban highways, which are kept in the counterfactual economy. Note that the legends of the two figures are different. The effects of the counterfactual shock on the population are larger than those on employment.

Figure J.7: Changes in Population and Employment, Replacing Urban Highways



(a) Percentage Change in Population (b) Percentage Change in Employment

Note: These two figures show the changes in population and employment at the census tract level. The black lines are the highways, with dotted lines representing urban highways, which are replaced with primary roads in the counterfactual economy, and solid lines representing suburban highways, which are kept in the counterfactual economy. Note that the legends of the two figures are different. The effects of the counterfactual shock on the population are larger than those on employment.

calibration of the outside option's utility $U_{i,H}$ relative to the home fixed effects H_i. With fewer assumed choice opportunities, the calibrated value of the outside option decreases relative to home fixed effects, making travel to POIs relatively more attractive. Therefore, removing highway disamenities has larger general equilibrium effects by inducing larger increases in the number of POIs, population, and employment flowing into urban areas. The stronger agglomeration economy in terms of production, consumption, and social activities in the urban areas leads to higher welfare gains and a higher contribution of the consumption travel mechanism to the overall welfare gain, as reflected by the increasing weights of the first part in the welfare decomposition.

Nevertheless, these differences are quantitatively minor. Across all examined scenarios, the welfare gains from counterfactual highway modifications remain substantial. The relative contributions of the three mechanisms remain stable across these assumptions, enhancing the robustness of the findings about counterfactual welfare.

Table J.12: Welfare Effects Using Different Day Partition Specifications.

Policy	Choice Bound	Welfare Effect	Welfare Decomposition		
			Consumption Travel	Outside option	Work Travel
Burying Highways	Upper	8.9%	16.9%	76.4%	6.7%
	Baseline	10.2%	25.4%	68.6%	6.0%
	Lower	12.3%	30.1%	64.2%	5.7%
Replacing Highways	Upper	7.8%	64.1%	62.8%	-26.9%
	Baseline	9.0%	72.3%	54.8%	-27.1%
	Lower	11.1%	75.7%	51.4%	-27.1%

Note: This table presents the welfare effects and the weights of three mechanisms using different day partition specifications. I assume an upper bound and a lower bound for the time slots allocated to consumption activities in a day, then use these bounds to recalibrate the shares of consumption trips and calculate the bounds for welfare effects of the two counterfactual exercises with alternative highway systems. The baseline results are duplicated from Table 3 for easier comparison. Although the magnitude of the gain is affected by partition specification, the lower bound of the gain remains substantial, indicating a robust welfare effect.