Measuring the Value of Urban Consumption Amenities: A Time-Use Approach

Su, Yichen

Federal Reserve Bank of Dallas

7 March 2022

Measuring the Value of Urban Consumption Amenities: A Time-Use Approach

Yichen Su*

Federal Reserve Bank of Dallas

March 7, 2022

Abstract

Existing studies show that the rising spatial segregation between skill groups in the U.S. led to increasing inequality of amenity access. Access to consumption amenities, in particular, is often highlighted as an important driver of local amenity profile. However, quantifying the inequality of access to consumption amenities is often faced with two challenges. First, because consumption amenities, such as restaurants, often benefit residents living beyond the immediate vicinity of the amenities, researchers must account for how the amenity benefits diffuse through space. Second, to evaluate how much the access to consumption amenities contributes to the overall value of local amenity profiles, researchers must identify the proper aggregation weights. I present a model of amenity choice that provides the micro-foundation for accounting for spatial diffusion and aggregation weights. The model can be disciplined by the empirical patterns of people's time use interacting with the amenities. I demonstrate that correctly accounting for spatial diffusion and aggregation weights is important for accurately measuring the inequality of access to consumption amenities.

*Email: yichensu@outlook.com. The views in this paper are those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System. I thank Milena Almagro, participants at the AREUEA-ASSA conference, seminar participants at University of Houston, the editor, and two anonymous reviewers for their valuable comments.

1 Introduction

Over the past four decades, there has been a large increase in the geographic sorting by skill across cities and neighborhoods (Moretti (2013), Diamond (2016), Hoelzlein (2019), Couture and Handbury (2020), Couture et al. (2020), Su (2022)). The literature shows that the increased spatial segregation by skill widened the well-being inequality between skill groups on top of the already widening income inequality. A key reason behind spatial segregation's effect on inequality is that as high- and low-skilled people increasingly live in different locations, they are increasingly exposed to different levels of locally provisioned amenities.

Among the many different forms of amenities, *consumption* amenities have become increasingly regarded as an important component of the local amenity profile (Glaeser et al. (2000), Couture (2016), Almagro and Dominguez-Iino (2020)). Despite the recognition of the potential importance of consumption amenities, measuring the value of access to consumption amenities remains difficult and conceptually challenging. Typically, when researchers estimate the value of amenities with well-defined spatial delineation such as school districts, they can use a hedonic pricing model or a location choice model to determine the value of amenity provision by examining housing demand differentials across clearly marked borders (Oates (1969), Brueckner (1979), Yinger (1982), Epple (1987), Gyourko and Tracy (1989), Black (1999), Bayer et al. (2007), Albouy (2012)). While such methods may be suitable for evaluating amenities such as school districts, it may be difficult to use them to evaluate the value of access to *consumption amenities* due to the following challenges:

First, the value of consumption amenities often *diffuses spatially* beyond their immediate vicinities (Glaeser et al. (2016)), which means that residents living at a distance to the physical locations of the consumption amenities may also benefit from these amenities, though possibly to a lesser extent than residents living immediately next to these amenities. Take restaurants as an example. Because people often travel to a variety of different restaurants and not just the restaurants right next door, the value of a restaurant would likely diffuse to residents living beyond its immediate vicinity.[1] A simple count of amenity establishments either within the immediate neighborhood or in the metropolitan area as a whole will both likely create a distorted representation of the amenity provision available to residents. Moreover, the value of different types of amenities likely diffuse with *different* degrees of intensity. While residents may value a restaurant at a long distance, they may not value a gym located in the same distance if residents tend to use the gyms closest to

[1] According to the American Time Use Survey, the average trip time to or from restaurants is 20 minutes. Evidence of significant travel length to restaurants has also been shown in detail in Couture (2016) with the National Household Travel Survey.

them. Because of the varying intensity of spatial diffusion of consumption amenities, using a default fixed intensity of spatial diffusion to discount the value of amenities by distance will also likely create bias.[2]

The second challenge is that residents likely value access to different types of consumption amenities differently. For example, if residents eat at restaurants frequently but go to movie theaters much less frequently, they would likely not value the proximity to movie theaters as much as the proximity to restaurants. Hence, evaluating the value of consumption amenities requires appropriate *aggregation* weights to reflect residents' different valuations of different amenity types. Since there is a multitude of amenity types, researchers often lack enough spatial variation to directly identify how each type of amenity is valued under a typical hedonic approach. Moreover, if the provision of a specific type of consumption amenities is spatially correlated with the provision of other omitted consumption amenities or non-consumption amenities, a hedonic method could potentially overestimate the valuation of the type of consumption amenities in question due to the omitted variable bias.

In my paper, I overcome both challenges simultaneously by taking an alternative approach. I study people's usage of time interacting with different types of amenities and use the patterns of their time-use to recover the intensity of spatial diffusion and aggregation weights using an amenity choice model. I demonstrate that correctly accounting for the intensity spatial diffusion and aggregation weights turns out to be important when measuring the unequal access to consumption amenities by different skill groups.

I first motivate my approach by documenting how people spend their time interacting with each type of amenity venue.[3] I argue that people's observed time-use patterns around amenities reveal how they value these amenities. First, I find that the travel time to and from amenities is often very short for visiting certain amenities like gyms but often longer for visiting other amenities like restaurants. The difference in travel time suggests that amenities like gyms are only valued by residents living nearby, while other amenities like restaurants are valued by residents over a broader area. I argue that the different degrees of intensity of spatial diffusion of amenity benefits can be explained partly by the different degrees of substitutability between venues within each amenity type. For example, gyms tend to serve a well-defined function and thus are largely substitutable with one another. Thus, residents are likely to choose the gyms with the lowest cost of visits, namely the gyms with the shortest travel time. In contrast, the variety and styles of restaurants can be much

[2]Hoelzlein (2019) and Almagro and Dominguez-Iino (2020) account for the spatial diffusion of amenities over distance. However, both papers assume a fixed parameter that governs the strength of the spatial diffusion.

[3]In a related study, Murphy (2018) uses time-use data to show that residents living in dense locations spend less time on home production.

more idiosyncratic. As a result, restaurants may be less substitutable with one another than gyms. Thus, residents may be less sensitive to the travel time to restaurants.

I also find that people visit some amenities much more frequently than other amenities. The heterogeneity in the frequencies of visits, by revealed preference, suggests that convenient spatial access to certain types of amenities is valued more than other types of amenities. For example, a higher frequency of visits to restaurants compared to a lower frequency of visits to museums means an increase in restaurant varieties nearby, and the resulting reduction in travel time to restaurants will likely improve residents' welfare more than a comparable improvement of access to museums amenities.[4] The frequency of visits, therefore, informs me about the welfare aggregation weights for each amenity type.

Motivated by the patterns of time-use, I construct a model of amenity choice which allows residents living at each location to choose a bundle of visits to amenities available to them within the same MSA based on their tastes for each type of amenities, the elasticities of substitution between amenity establishments, and the cost of visits to the establishments (including the opportunity cost of travel time, the monetary cost of visits, and the opportunity cost of time spent at destinations).[5] Importantly, by allowing the elasticities of substitution for visiting different establishments to differ across amenity types, the model can reproduce the different intensities of spatial diffusion. By allowing different tastes for different amenities, the model reproduces the different frequency of visits to different types of amenity venues and provides a theoretical basis for welfare aggregation weights.

I estimate the elasticities of substitution by matching the model-predicted moments of log travel time and the observed moments. Once I estimate the elasticities of substitution, I estimate the taste parameters for all the amenity types using the frequency of visits to each type of amenities.

Equipped with the parameterized model, I show that the average high- and low-skilled residents do have substantially unequal access to consumption amenities due to spatial segregation. The differential access to consumption amenities contributes to an access inequality in 2000 equivalent of 2.8% of the observed real income gap in the same year. Further spa-

[4]Another way to think about the intuition is to think in terms of cost accounting. Having better spatial access to restaurants implies saving on travel costs on the average trip to a restaurant and having a better variety of restaurants to choose from for each restaurant trip. If people visit restaurants fairly frequently, then the benefit from a better provision of restaurant amenities would benefit people at a much higher frequency. In contrast, a low frequency of visits to museums implies that whatever benefits derived from a better provision of museums amenities would benefit the people less frequently.

[5]In this paper, I consider the term "preferences" or "taste" in a reduced-form sense. I do not further micro-found the tastes for amenities. It may be the case that the "taste" for car repair shops arises less from a genuine desire to visit them for leisure than a need to fulfill an errand. The "taste" of car repair shops represents the marginal utility value of the provision of car repair shops, regardless of whether such value arises for leisure or errands. I use the word "taste" to denote the valuation of accessing amenities broadly.

tial sorting of residents and consumption amenities from 2000 to 2010 led to a widening of access inequality of equivalent to 2% of the concurrent increase in the observed real income gap. However, the widening access inequality to consumption amenities contributes only a fraction (4%-16%) of the increase in amenity inequality estimated in prior papers which analyze spatial sorting and the resulting divergence of access to amenities in general. The contrasting results stem from the fact that my analysis focuses exclusively on the access to *consumption amenities*, while other local amenities, such as neighborhood safety, aesthetic value, clean air and water, job market, and public goods such as school quality and infrastructures, are accounted for implicitly if not explicitly in most papers that study spatial sorting and amenities. The comparison of the estimates suggests that while the widening access inequality to consumption amenities is a substantial contributor behind the increasing well-being inequality, the differential exposure and access to other *non-consumption* amenities likely plays a more important role in driving up inequality than the unequal access to consumption amenities alone.

Lastly, I demonstrate that correctly accounting for both *spatial diffusion* and *aggregation* is important for accurately measuring the access to consumption amenities and access inequality. Assuming the amenity value does not diffuse beyond the amenity establishments' closest neighboring residents could lead to an underestimation of the access inequality. The bias is partly driven by the fact that many high-skilled residents in the U.S. live in low-density developments, whose access to amenities often requires a moderate travel time. Not allowing for spatial diffusion in the welfare framework could lead to a severe downward bias for the welfare of residents living close to but not right next to a large variety of amenities. In contrast, assuming that amenity value diffuses over too broad an area could lead to an overestimation of access inequality. The result is partly driven by the fact that a higher number of amenities are concentrated near high-income neighborhoods and MSAs. The abundance of amenity establishments in high-income neighborhoods and MSAs could inflate high-skilled residents' access to amenities with actual weak spatial diffusion (such as gyms). And vice versa, around low-income neighborhoods or MSAs, the scarcity of amenity establishments could lead to an undervaluation of low-skilled residents' access to these amenities. This could lead to an upward bias for measuring access inequality. Finally, I show that analyzing a hedonic model with the focus on only a few selected amenity types could lead to incorrect estimates of the aggregation weights, which may lead to bias in assess the role of consumption amenities in driving up welfare inequality.

Part of the model introduced in this paper is based on work done by Couture (2016), who uses observed trip time distribution to assess the value of restaurants using the NHTS data. My model features a similar treatment of amenity varieties, and I use a similar method to back out the parameters of elasticities of substitution as in Couture (2016). But in my paper, instead of focusing on just restaurants, which is only one of the many amenity types, I expand the scope of analysis by looking at 16 different types of amenities. I demonstrate that the nature of valuation differs tremendously across amenities. I show that the differential lengths of time spent at each amenity, the frequencies of visits, and differential monetary costs of visits all contribute to the differential intensity of spatial diffusion and the aggregation weights for different types of amenities. However, due to the lack of precise geocode in the time-use data, I must rely on much coarser geography than Couture does, which requires me to make some stronger assumptions about the geography of preferences. Related to my work, Agarwal et al. (2018) study the geographic patterns of consumption activities using highly detailed credit card transaction data. They find that expenditure declines with distance from home, especially in sectors highly frequented by customers. A key aspect of their analysis is to explore the relationship between the storability of the products and the geographic spending patterns of the consumers. A more recent paper by Miyauchi et al. (2021) uses high-frequency and high-resolution smartphone data in Japan to study non-commuting trip choices and show that access to consumption amenities contributes to spatial differences in the value of lands and the value of transportation investments. Their findings corroborate the importance of accounting for the access to consumption amenities in analyzing residents' well-being across locations. But distinct from their study, the goal of my paper is to evaluate the importance of correctly accounting for differential spatial diffusion and aggregation weights in measuring amenity access and access inequality.

The rest of the paper is organized as the following: Section 2 shows the time-use patterns involving amenities. Section 3 describes the model framework. Section 4 discusses the identification strategies for key parameters. Section 5 discusses data and estimation. Section 6 evaluates the value of access to consumption amenities using the estimated model. Section 7 discusses potential caveats. Section 8 concludes.

2 Amenity Time-Use Patterns

First, I use the American Time Use Survey (ATUS) (2003-2015) to document the travel time, frequency of visits, and the duration of visits involving each type of amenity. The ATUS program is conducted by the Census Bureau for the Bureau of Labor Statistics. It provides data on how and where Americans spend their time on different activities, such as work, travel, and eating. The ATUS provides a highly detailed activity code and locations in which these activities occur, which allows me to create a crosswalk between the ATUS time-use segment and amenity types.[6]

I categorize amenity activities into 16 categories: *restaurant and bar, takeout (food), grocery shopping, non-grocery shopping, gym, medical facility, laundry shop, post office, bank, worship, car repair, personal care, movie, museum, performance arts, and sports event.* I match activity types in the ATUS data into each of the 16 amenity categories. The details of the matching are in appendix A.[7]

2.1 Travel Time

In Figure 1, I show the average one-way travel time to or from each type of the 16 amenities. There is a considerable degree of heterogeneity in travel times for different activities. For example, the mean travel time to restaurants is 20.07 minutes, whereas the travel time to gyms is only 11.64 minutes.[8]

The differential travel patterns suggest that people likely visit restaurants that are far from their homes but may simply only visit gyms that are close to them. The differential sensitivity to distance could be rationalized if people's elasticity of substitution among restaurants is lower than the elasticity of substitution among gyms. In other words, residents may greatly value the variety of restaurants but may not value the variety of gyms as much. This makes sense because gyms tend to be highly functional and relatively homogeneous across facilities, while restaurants tend to be more differentiated due to the variation in cuisines and services.

The differential valuation of variety for different types of amenities implies that the benefits from the amenities would diffuse spatially with different degrees of intensity for different types of amenities. Since people are less sensitive to the cost of travel when they visit restaurants, a restaurant in a neighborhood would likely benefit residents over a broad area. In contrast, a gym may likely only benefit residents living in the immediate vicinity because people tend to use gyms closest to them.

To confirm that the difference in travel times for different amenities is not driven by different degrees of sparsity of different amenities, I plot travel time to each amenity establishment against the rank of establishments by travel time in Figure 2. I do so for four types of amenities, restaurants, post offices, gyms, museums, for the purpose of demonstration. The red line represents the average travel time to restaurants reported in the data. For

[6] I discuss all the other datasets I use in the paper in section 5.

[7] For external validation, I also bring in the National Household Travel Survey (NHTS) data and the SafeGraph data to do a few comparison exercises with the time-use statistics from the ATUS data. See appendix section D for detail.

[8] Different from Couture (2016), restaurant and bar activities here exclude picking up food (takeout).

restaurants, on average, the closest restaurants are about 8 minutes away.[9] But the average trip time is about 20 minutes. There are, on average, 300 restaurants that are closer than the restaurant 20 minutes away. In contrast, the closest gym is about as far as the closest restaurant, but the average travel time reported in the ATUS is only slightly above 10 minutes, much shorter than the average travel time to restaurants.

2.2 Frequency of Visits

Figure 3 shows that the frequencies of visits per month to different types of amenities are extremely uneven. People on average visit restaurants or go shopping at very high frequencies but go to cultural sites such as museums at much lower frequencies.[10] The difference in the frequency of visits across amenity types implies that any welfare gains from travel time savings or the increased varieties due to better spatial access to a certain type of amenities should likely be large if residents visit that type of amenities very frequently, and the welfare gains from similarly better spatial access to another type of amenities should likely be smaller if they visit that type of amenities less frequently. To demonstrate why more intuitively, let's think through the examples of restaurants and museums. Having better spatial access to restaurants implies saving on travel costs on the average trip to a restaurant and having better varieties of restaurants to choose from for each restaurant trip. If people visit restaurants frequently, such better provision of restaurant amenities would benefit people at a much higher frequency and thus should yield greater welfare benefit in total. In contrast, a low frequency of visits to museums implies that a similarly better provision of museum amenities would benefit people less frequently and thus less in total.[11] Thus, intuitively, the different frequency of visits by amenity type will be an important input for constructing the aggregation weights for welfare calculation, which will be discussed in detail in the model section.

Besides the vast variation across amenity types, I also find striking heterogeneity in the

[9] Since I use Zip Code level geocode for business establishment and travel time is only as detailed as down to the Zip Code level, the distance to the closest restaurants may be overestimated. With more precise data, Couture (2016) reports 5.5 minutes as the average travel time to the closest restaurant.

[10] Agarwal et al. (2018) produce a similar set of statistics of the frequency of visits from credit card transactions. They also find that the frequency of visits to venues like food stores or restaurants tends to be very high. Their documented frequency is divided by a rather different set of categories, making it somewhat difficult to do a straightforward comparison.

[11] Some may argue that even though visits to museums are typically less frequent than restaurants, the lower frequency of visiting museums does not necessarily imply that the museum activities are less valuable to people than restaurants. In my paper, I do not intend to measure the value of museums, *per se*, vis-a-vis the value of restaurants, *per se*. The goal of this paper is to understand the value of spatial *access* to amenities such as museums vis-a-vis restaurants. Even in the case that people greatly gain from the intrinsic value of museums, they may not value the convenient access to museums as much as they value the access to restaurants if they do not visit museums as often as they visit restaurants.

frequency of visits to each amenity type across education and age groups. In Figure 4 a) b) c), I dissect the survey respondents into four demographic groups: people younger than 40 years of age with or without college degrees and people older than or at 40 years of age with or without college degrees, and then present the frequencies of visits for each of these demographic groups.

Residents with college degrees visit restaurants much more frequently than people without college degrees, and within each education group, younger residents visit restaurants slightly more frequently. Residents with college degrees go to the gyms much more frequently than residents without college degrees do. Within each education group, younger residents visit gyms more frequently. In contrast, the frequency of visits to other amenities such as medical facilities, banks, post offices, and places of worship differ more by age, where older people visit these amenities much more frequently than younger people do. The frequency of visits to museums and performing art venues seem to differ mainly by education group. The strong heterogeneity suggests that the aggregation weight for each specific type of amenities is likely to differ by group.

2.3 Duration of Visits

In addition, Figure 5 shows the mean duration (in minutes) that people spend in venues of each amenity type. Note that the duration of visiting each type of amenity is also highly uneven across amenities. Recreational activities such as going to the movies, museums, performing arts, and sports events take longer than two hours on average, whereas errands like going to the post offices and banks tend to take only a fraction of the time.[12]

The unevenness of the lengths of visits has two implications. First, the cost of visiting each type of amenities may be very different. Going to the museums or watching a performance may be a much costlier event than running errands at the banks. Therefore, if people choose to visit a certain type of amenities frequently even though visiting them is typically costly, that would suggest that they value such amenities greatly. Secondly, the heterogeneity in the length of visits means that the same absolute length of travel time may differ as a percentage of total time spent associated with each type of amenities. For example, when one decides to go to a museum, the length of visits is around two hours. Driving 30 minutes is a relatively small fraction of the overall cost of visiting the museum. On the other hand, visiting the post office takes less than 10 minutes. Driving 30 minutes to do an errand that itself lasts shorter than 10 minutes is very costly percentage-wise. Therefore, a long duration of visits could imply that residents are less sensitive to the traveling time, thus leading to wide spatial

[12] The duration of activities does not seem to be very different across demographic groups (education and age) in all amenity categories except laundry shops.

diffusion of amenity value, whereas a short duration of visits could imply that residents are more sensitive to traveling time, leading to a more confined spatial diffusion of amenity value.

3 Model Framework

Motivated by the time-use patterns, I construct a model framework to rationalize the way people spend time interacting with the consumption amenities. The model is set up in such a way that I can directly link its key features such as the spatial diffusion of amenity value and welfare aggregation to empirically observable time-use patterns.

3.1 Setup

I allow each resident i to choose bundles of visit frequencies to amenity establishments to maximize utility, from a choice set that consists of all amenity establishments located within the MSA that she lives in. The resident has a Cobb-Douglas utility function over the visits to K composite amenity good X_k and a numeraire consumption good x_0. Each composite good X_k is defined as a CES aggregation of visits to each amenity establishments j, x_{kj}. θ_k is the Cobb-Douglas taste parameter for each composite amenity good k. The composite good X_k is the pre-weight utility gained from the bundle of visits $(x_{k1}, x_{k2}, ..., x_{kJ_k})$. $\sigma_k = 1/\left(1 - \rho_k\right)$ is the elasticity of substitution within each amenity type. This multi-level utility framework is similar to Broda and Weinstein (2006, 2010), Couture (2016), Handbury (2019), Jaravel (2019), and Almagro and Dominguez-Iino (2020):

$$x_0^{\theta_0} \prod_k X_k^{\theta_k}, \text{ where } k = 1, ..., K$$

$$X_k = \left(\sum_{j=1}^{J_k} x_{kj}^{\rho_k} \right)^{1/\rho_k}.$$

Each time resident i visits an amenity establishment j, she has to pay a monetary cost of visits or a service price $\bar{p}_k$ specific to type k.[13] Visiting amenities also requires time inputs: 1. time spent at the establishments h_k,[14] 2. time spent traveling to and from the establishments t_{ij}. γ is the opportunity cost of the resident's time in terms of foregone

[13] Different types of amenity establishments incur different monetary cost of visits. $\bar{p}_k$ is intended to capture that difference. I abstract away from within-type heterogeneity of service price. For example, regarding restaurant amenities, I assume that restaurant service costs the same across all restaurants.

[14] h_k is the time typically spent at amenity type k. For example, a typical visit to the bank is shorter than a typical visit to a restaurant due to the nature of the activities involved in these visits.

earnings or the earning equivalent of the foregone utility of staying at home.[15] Thus, the resident is subject to the following budget constraint:

$$x_0 + \sum_{k=1}^{K} \sum_{j=1}^{J_k} x_{kj} \bar{p}_k = I - \sum_{k=1}^{K} \sum_{j=1}^{J_k} x_{kj} \gamma \left(h_k + t_{ij} \right).$$

The resident has a realizable source of income I. Her time spent on activities related to amenities dips into her earnings potential, at the rate of γ, which is the opportunity cost of each unit of her time. The income net of the total foregone opportunity cost of time is used to purchase services at each amenity establishment at prices $\bar{p}_k$.

I can rewrite the budget constraint by moving the terms of opportunity cost of visiting amenity establishment to the left-hand side:

$$x_0 + \sum_{k=1}^{K} \sum_{j=1}^{J_k} x_{kj} \left(\bar{p}_k + \gamma \left(h_k + t_{ij} \right) \right) = I.$$

Now the budget constraint becomes similar to a standard budget equation, with the cost of visiting each amenity establishment being $p_{ikj} = \bar{p}_k + \gamma \left(h_k + t_{ij} \right)$.[16]

The utility-maximization problem can be completed in two sequential steps: 1. solve the cost-minimization problem for each the composite consumption of each amenity type k and compute the price indexes P_{ik} for each X_k; 2. given the price indexes, maximize the Cobb-Douglas utility at the upper level.[17]

[15] For people with fixed hours of work, saving time on visits to amenities do not increase the amount of time used in marketable work hours. But instead, the saved time would be devoted to home leisure (including home production). If people value leisure, the extra time would increase utility. γ would capture the dollar value of utility gain in home leisure.

[16] Another caveat of the model is the Cobb-Douglas functional form assumption. Essentially, I assume households devote a certain fixed fraction of their resources toward the consumption of each type of amenities. Here, I assume that the taste for each type of amenities is exogenous to the model. One implication of such an assumption is that different types of amenities are assumed to be neither substitutes nor complements. One situation in which this assumption may be problematic is if there is an increasing number of restaurants in the surrounding area, then the demand for grocery services may go down. In this case, increasing access to grocery stores could be less valuable in a place with lots of restaurants. Alternatively, if people tend to do grocery shopping on the same trip as going to restaurants, then restaurants and grocery stores may be complements. In this case, access to grocery stores may be more valuable in a place with lots of restaurants. Under the assumption of Cobb-Douglas, I am assuming that the price index of each type of amenities depends only on the choice set of the amenity establishments of its own type.

[17] I discuss the cost-minimization and the utility-maximization problem in appendix B.

3.2 Price Indexes

By solving the cost-minimization problem of a CES utility, I obtain the unit cost of the composite good facing resident i, which is the price index P_{ik}. The form of the price index is similar to the one derived in Couture (2016) in a logit framework analyzing the gain from the density of restaurants:

$$P_{ik} = \left(\sum_{j=1}^{J_k} \left(\bar{p}_k + \gamma \left(h_k + t_{ij} \right) \right)^{1-\sigma_k} \right)^{1/(1-\sigma_k)} .$$

One can consider the price index as the inverse of the indirect utility derived from type k amenity for agent i. The price index aggregates cost of visiting each amenity establishment p_{ikj}. The elasticity of substitution σ_k governs residents' willingness to substitute visits to costlier (farther) locations with visits to cheaper (closer) locations. One can consider it as an inverse of the taste for variety. If σ_k is small, she is willing to visit distant locations, which means the amenities at distant locations have a material welfare impact on her. If σ_k is large, she is then willing only to visit closer locations, which means that the amenities at distant locations would be relatively unimportant. Thus, amenities associated with larger σ_k would tend to have weaker diffusion of amenity benefit, whereas amenities associated with smaller σ_k would have farther diffusion of amenity benefit. I allow σ_k to vary across different types of amenities.

By rearrangement, we can re-write the price index P_{ik} as $J_k^{\frac{1}{1-\sigma_k}} \left(\frac{1}{J_k} \sum_{j=1}^{J_k} p_{ikj}^{1-\sigma_k} \right)^{1/(1-\sigma_k)}$. The first multiplicative term indicates that the price index will be smaller if J_k, the number of varieties resident i can choose from, increases, especially if σ_k is small. The second multiplicative term is the power mean of the cost of visits to all available establishments, which represents the average cost of visits to the establishments she chooses to visit.[18]

To provide intuition for how the price indexes capture the spatial access to amenities, let me use the example of restaurants. Assume a new restaurant is open near where resident i lives. How does the addition of the new restaurant affect the price index for restaurants that resident i faces? It does so in two ways: First, the new opening increases the number of restaurants (J_k) that she has access to, lowering the size of P_{ik}, especially if the resident has a strong taste for variety, namely σ_k is small. Second, since the newly opened restaurant is located near where she lives, it reduces her average cost of visits to restaurants she visits.

[18] Here are the two extreme cases with which I demonstrate the intuition of how the average cost of visits may depend on σ_k. If $\sigma_k \to 0$ (perfect complement), the average cost of visits approaches $\frac{\sum_j p_{ikj}}{J_k}$, which is the average cost of visits to all establishments. If $\sigma_k \to \infty$ (perfect substitute), the average cost of visits approaches $\min\{p_{k1}, p_{k2}, ..., p_{kJ_k}\}$, which is the price of visit to the establishment with the lowest price of visit. All other cases in which $\sigma_k > 0$ are somewhere between the two extreme cases.

Thus, the price index summarizes the access to amenities by capturing both the variety of amenity establishments available to the resident and her average cost of visits to the establishments she visits (Couture (2016)).

It is important to note that the cost of visit $p_{ikj} = \bar{p}_k + \gamma(h_k + t_{ij})$ consists of monetary service prices $\bar{p}_k$, time spent at destination h_k, and travel time to and from the visit t_{ij}. It is obvious that travel time t_{ij} should be an important component in the cost of visits p_{ikj}. However, unlike Couture (2016), I argue that the cost of the trip should also include the monetary service price $\bar{p}_k$ and duration of visits h_k besides travel time. The first reason is that people might exhibit different sensitivity to travel time t_{ij} depending on whether travel time is a small or a large fraction of the total cost of the trip. For example, if $\bar{p}_k$ or h_k are very small, say a bank errand or picking up takeout food, the cost of visiting a far-away branch of the bank or a takeout spot would be very high on a percentage term, and residents would likely be very sensitive to distance in those cases. On the other hand, if $\bar{p}_k$ and h_k are large, say a trip to a full-service restaurant for a dinner, the relative difference in the cost of visiting a place far away and the cost of visiting another place nearby would be small on a percentage term, and the resident would likely not be very sensitive to distance. Such difference in the sensitivity to distance would manifest itself even if σ_k were the same.[19] Without allowing $\bar{p}_k$ or h_k to differ across amenity types or removing them altogether from the cost of visits, I would not be able to capture such a difference in sensitivity.

Moreover, another reason to include monetary service prices $\bar{p}_k$ and duration of visits h_k is to ensure that the taste parameter θ_k is interpretable. For many of the amenity types such as restaurants, each visit typically involves spending a long duration of time, which many would consider enjoyable on its own. By including the duration of visits h_k in the total cost of visits, the parameter θ_k captures the share of total resources, including the opportunity cost of time, that people are willing to spend on visiting restaurants. If I omit the duration of visits at destinations, θ_k would lack a natural interpretation and will be much smaller for amenities like restaurants than if I account for the fact that people spend a long duration of time there.

[19] The travel time to restaurants tends to be much longer for a sit-down meal compared to the travel time to restaurants to pick up takeout (see Figure 4). In the baseline estimates, which I include all components in the cost of visits, the σ_k estimates turn out to be similar for restaurant and bar (full-service meals) vs. takeout, implying that the inherent taste for food variety does not differ by much across the two amenity types despite difference travel time distribution. See the estimates for σ_k for restaurant and bar vs. takeout in Table 2.

3.3 Aggregation

Given the price index of each amenity type k, the resident maximizes the upper-level Cobb-Douglas utility. The indirect utility can be written as follows:

$$V_i = \alpha + \ln(I) - \sum_{k=1}^{K} \theta_k \ln(P_{ik}). \tag{1}$$

θ_k are normalized such that $\sum_{k=1}^{K} \theta_k = 1 - \theta_0$, where θ_0 is the expenditure share on numeraire goods. θ_k represents the share of the residents' total resources, including time, that the residents are willing to spend on visiting amenity type k.[20]

The aggregate indirect utility from all amenities is a linear combination of negative log price indexes, weighted by Cobb-Douglas taste parameters θ_k. The lower the prices of obtaining each unit of composite amenity, the better off the resident becomes. But the size of the effect of the lower price indexes on welfare is governed by the taste parameters. Hence, θ_k would serve as the aggregation weights that map the price indexes to welfare.

4 Identification

In this section, I discuss how to identify and estimate the model's key parameters: **the elasticities of substitution** σ_k and **the taste parameters for amenities** θ_k for each type k.

4.1 Trip Choices

For each resident i, given her choice set, each value σ_k maps into a unique distribution of amenity choices. I derive the trip choice distribution by dividing the predicted visiting frequency for establishment j by the sum of predicted visits to all establishments. The probability that a given visit made by resident i to establishment j is thus given by the following equation:

$$\Pr(j|k,i) = \frac{p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{-\sigma_k}}. \tag{2}$$

[20] θ_k as the expenditure share should be interpreted broadly. Recall that the cost of a visit to each amenity establishment includes not only the monetary expenditure $\bar{p}_k$ but also the opportunity cost of time spent on the activities and on travel: $\gamma(h_k + t_{ij})$. Therefore, the opportunity cost of time spent on activity k counts as part of the expenditure on activity k. For example, despite the fact that visits to churches are free, each visit still incurs a substantial cost of time. Therefore, if the resident has a large θ_{worship}, she is willing to devote substantial resources to going to church in terms of both her foregone earnings and the earnings equivalent of her foregone utility at home.

The model-predicted distribution of establishment choice implies a travel time distribution.[21] Given the trip choice distribution and the travel time between the residents' homes and the establishments, I can compute the mean log travel time. The higher σ_k is, the more likely the resident would choose the closest establishment and thus travel a shorter distance, and vice versa. Thus, I can identify σ_k for each amenity type k by matching the model-predicted mean log travel time with the mean log travel time observed in the data.

4.2 Frequency of Visits

Once the sizes of σ_k is identified, the taste parameters θ_k can be identified by the frequencies of visits. The frequency of visits to establishment j of amenity type k can be written as the following:

$$x_{ikj} = \theta_k I \cdot \frac{p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{1-\sigma_k}}.$$

Summing over all visits for establishments of amenity type k, I can write the frequency of visits to all type k establishments $E\left(\sum_j x_{ikj}\right)$ as a linear function of θ_k:

$$E\left(\sum_j x_{ikj}\right) = \theta_k I \cdot E\left(\frac{\sum_j p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{1-\sigma_k}}\right).$$

I can then write the taste parameter θ_k as:

$$\theta_k = \frac{E\left(\sum_j x_{ikj}\right)}{I \cdot E\left(\frac{\sum_j p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{1-\sigma_k}}\right)}. \tag{3}$$

The size of θ_k is thus identified by the frequency of visits $E\left(\sum_j x_{ikj}\right)$ to amenity type k and the average price of visits $\frac{1}{E\left(\frac{\sum_j p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{1-\sigma_k}}\right)}$. If the price of visits to each amenity type k is identical, θ_k would be proportional to the frequency of visits. The average price of visits accounts for how costly each type of activity is. Visits to a certain type of amenities may occur at low frequency, but each visit may be quite costly (e.g., museum visits). In this case,

[21] A dataset in which I observe an individual's precise residential location and all the amenity venues that he visits would enable me to identify σ_k, while controlling for differential choice sets and cost vectors faced by each individual. Unfortunately, the American Time Use Survey (ATUS) that I use to estimate σ_k does not provide a precise geocode of individuals' residential locations. As a result, for each type of amenity, I only observe a cross-section of trip choices made by different individuals over more than a decade. I describe how I address the problem to estimate σ_k in the next section.

the frequency of visits by itself may underestimate the actual importance of the activity of interest.

Besides the formal logic of identification, the earlier Section 2.2 provides the intuition of why the frequency of visits can identify the taste or preference for access to each type of amenities.

5 Estimation

5.1 Data

I use the American Time-Use Survey (ATUS) to measure the frequency of visits to each type k of amenities $\sum_j x_{kj}$, the duration of visits h_k at destinations, and the observed travel time chosen by people before and after each visit (Hofferth, Flood, and Sobek (2018)).

I use the Consumer Expenditure Survey (CEX) data (2003-2015) and various other sources to recover the monetary costs of visiting various types of amenity establishments.[22] The CEX diary survey records household spending on small or frequently purchased items or services for two consecutive one-week periods. This dataset contains the expenditure amount for many amenity types.

To compute the amenity choice set and the travel time to each of the establishments in the choice set, I use two sources of data: the Zip Code Business Patterns (ZCBP) provided by the U.S. Census Bureau and the Google Distance Matrix API. I use the ZCBP data for the location of amenity business establishments. The ZCBP is a comprehensive dataset at the ZCTA level developed from the Census's Business Register. In this dataset, I can see the number of amenity establishments of each type in each Zip Code throughout the U.S. I use Google API and the National Household Travel Survey to impute the travel time matrix for the entire U.S.[23] I then combine the ZCBP data with the travel time matrix to construct the amenity choice set and the price vectors for residents living in each census tract.

I use the 2000 Decennial Census and the 2007-2011 American Community Survey for the residential location data in 2000 and 2010, respectively (Ruggles et al. (2015), Manson et al. (2017)).[24]

[22] CEX program is conducted by the Census Bureau on behalf of the Bureau of Labor Statistics and provides data on expenditures of consumers in the United States.

[23] See Su (2020) for the detailed imputation method.

[24] I use 2007-2011 ACS for 2010 because it is the last wave of ACS micro-data that contains consistent MSA geocode with 2000 Census micro-data.

5.2 Price of Visits

The price vectors of visits $p_{ikj} = \bar{p}_k + \gamma(h_k + t_{ij})$ consist of

1. **Monetary cost of the amenity services** $\bar{p}_k$,
2. **Opportunity cost of time in these amenities** γh_k**,**
3. **Opportunity cost of time traveling to and from these amenities** γt_{ij}.

5.2.1 Monetary Cost of Amenity Services

The monetary cost of the amenity services $\bar{p}_k$ is the money that one spends to acquire the services at the amenity establishments. For example, for restaurant amenities, the price that one pays for the meal served is the monetary part of the cost of visiting restaurant amenities. In the appendix, I describe how I approximate the monetary costs of amenity services (adjusted for 2010 dollars) for each k using a variety of data sources, including the CEX.

The measurement of $\bar{p}_k$ needs to be handled with care. If I assume that consumption spending is determined in a separate decision process along with numeraire consumption goods x_0, the monetary cost of amenities should be excluded in the price of visits. In other words, the monetary cost of amenities may have already been sunk by the time the agent chooses where to visit. In that case, the price of visits should just include the cost of time.

One consequence of excluding the monetary cost of amenity service from the cost of visits is that the percentage variation in the cost of travel time would be larger. Given a value of σ_k, a larger percentage variation in the cost of travel time means that the implied choice of trip time to amenities tends to be shorter. Therefore, to rationalize observed trip times, the estimates for σ_k would likely be smaller if I exclude the monetary cost in the price of visits.

I retain the monetary cost of amenities $\bar{p}_k$ for my main estimation. For robustness, I also report results excluding the monetary costs.[25]

5.2.2 Opportunity Cost of Using Amenities

I use the mean length of visits documented in the ATUS as the length of time required each time a resident engages in these activities h_k, and I use the travel matrix to generate the

[25] Note that when the service cost is included in the price of visits, $\bar{p}_k$ should only include the service fee for consuming services at type k amenity, not necessarily all expenditure incurred during the visits at these amenities. A good example is grocery shopping. The money that a person spends at the grocery shopping is to purchase consumption goods for later use, and should not be included as the price of visiting a grocery store, even though people spend the money at the grocery stores. A good way to think about the cost of a grocery visit is how much people pay others to purchase groceries for them. The payment is likely to include the opportunity cost of shopping activity and travel time to and from the stores. The cost of groceries itself is likely not part of the service fee.

length of travel time from each person i's residential location to amenity establishment j: t_{ij}.[26] To estimate σ_k, I take the average hourly earnings taken from the 2007-2011 American Community Survey data (\$24) as the opportunity cost of time γ. When I estimate θ_k and conduct welfare analysis on amenity access, I calibrate γ separately by age group and education group estimated from the ACS data.

The opportunity cost of travel time could vary widely based on the time of day, day of the week, the purpose of the trips, and the person. The U.S. Department of Transportation (DOT) guideline suggests that the average value of travel time for leisure activities should be a half of the prevailing hourly wage for project evaluation and 100% of the prevailing hourly wage for business-related travels (Small (2012), U.S. Department of Transportation (2014)). More recent literature estimating the value of time using quasi-experimental variation, on the other hand, produces a higher value of time ranging from 93% to 100% of hourly wage (Small et al., (2005), Buchholz et al. (2020), Goldszmidt et al. (2020)).[27] The economic geography literature provides a range of estimates for the location choice elasticity with respect to commuting time and wages. These elasticity estimates suggest the value of commuting time ranging from 174% to 288% of the hourly wage, granted that for our purpose, the value of leisure is likely smaller than the value of commuting time (Ahlfeldt et al. (2015), Tsivanidis (2019), Severen (2021)).

Based on these recent estimates, I depart from the DOT guideline and use 100% of the hourly wage as the opportunity cost of time. In Table A9 in the appendix, I re-conduct the welfare analysis using half of the hourly wage as γ.

5.3 Elasticity of Substitution - σ_k

Given σ_k, I use equation 2 to generate predicted travel time distribution. I search for the σ_k such that the model-predicted mean log travel time matches the observed mean log travel time.

My estimation of σ_k accounts for the choice sets that residents surveyed in the ATUS face. Ideally, I would like to use the precise geocode of each one of the residents' residential locations in the ATUS sample, which would have allowed me to re-create their choice sets precisely.[28] Unfortunately, precise geocode is unavailable in the ATUS data. For that reason,

[26] To see how the variation in time spent on each type of amenities can affect the price of visits, see Table 1.

[27] In Castillo (2020), the value of travel time inferred from demand response to surge pricing by Uber in Houston reaches 461% of the hourly wage.

[28] Couture (2016) notes that ignoring the quality variation between the amenity choices could bias the estimates for σ. Unfortunately, the data I use do not have information on the quality of establishments. I do conduct a qualitative analysis on how quality variation may impact the welfare analysis in appendix section E. However, I do not have rich enough data to account for quality variation for the estimation of σ.

I construct a method-of-moments (M-M) estimator that accounts for residential location heterogeneity to some degree by leveraging county- and MSA-level geocodes and demographic information reported in the ATUS survey.[29]

5.3.1 M-M Estimator

In the ATUS data, I observe individual characteristics such as race and education, and geographic location at the county and/or MSA levels. Conditional on individual i's personal characteristics $\mathbf{X}_i$ (race, college/non-college, and county/MSA) in the ATUS data, I compute the model-predicted mean log travel time using the conditional spatial distribution of residents across census tracts - $\Pr(c|\mathbf{X}_i)$ obtained from Census NHGIS data.[30] The model-predicted log travel time $\widehat{\ln t_{ki}} = E(\ln t|k, \mathbf{X}_i)$ for person i can be written as follows:

$$\widehat{\ln t_{ki}} = E(\ln t|k, \mathbf{X}_i) = \sum_{c} \Pr(c|\mathbf{X}_i) \cdot \sum_{j|c} \Pr(t_j|c, k) \cdot \ln t_j$$

For each observed trip to amenity type k in the ATUS, I use the observed demographic characteristics $\mathbf{X}_i$ of each person to generate a model-predicted travel time $\hat{t}_i$. I then search for $\hat{\sigma}_k$ such that the differences between the mean model-generated log travel times $\widehat{\ln t_{ki}}$ and the observed log travel time $\ln(t_{ki})$ over all the individuals are zero.[31]

[29] The reason why I should account for residents' residential location is that observed travel times are partly determined by residents' locations *relative* to the locations of the amenities. For example, if two people, A and B, both have a very high elasticity of substitution for gyms. Person A lives in a remote location far from gyms, and person B lives close to gyms. Person A would have to drive for a long time even if she chooses the closest gym, while person B's travel time to gyms would naturally be much shorter. If my data sample contains more people like person A than in my model sample, then σ_k is likely to be underestimated. If my data sample contains more people like person B than my model sample, then σ_k is likely to be overestimated. The source of bias comes from the fact that people surveyed in the ATUS data may face very different choice sets from the choice sets constructed for the model. Another source of bias would be selection by preference. People who visit gyms frequently may choose to live close to gyms. Therefore, the travel time to gyms reported by the ATUS data may disproportionately represent the travels made by those who visit gyms frequently, which tends to be smaller than the average travel time of the average resident. Precision in accounting for individuals' location-specific choice sets could reduce these types of biases.

[30] I compute $\Pr(c|X_i)$ using population counts at census tract level in 2010 in NHGIS data. X_i includes county/MSA, race and college attainment. By accounting for the heterogeneous spatial distribution of each demographic group X_i, I am able to partially account for the differential choice sets facing each trip choice in the ATUS observation. To illustrate this intuitively, let's go back to the example of person A and B in the last footnote. Say that demographic group A consists of a large number of people like person A (living in remote areas) and demographic group B consists of a large number of people like person B (living in crowded areas). For demographic group A, in expectation, more weight will be put on remote neighborhood in generating model-predicted travel time. For demographic group B, in expectation, more weight will be put on crowded neighborhoods in generating model-predicted travel time. The different spatial weight put on different demographic groups partially reflects different choice sets facing each group.

[31] Accounting for the differential spatial distribution of residents county or MSA can only partially mitigate some of the bias described in the previous two footnotes. Unfortunately, the ATUS data do not have precise

5.3.2 Results

Table 2 presents the estimates for $\hat{\sigma}_k$. I report the two sets of estimates in two columns. Column 1 shows baseline results which include both the cost of time (time spent at destination and travel time) and the monetary cost of amenity visits. Column 2 presents results that only include the cost of time but exclude the monetary cost of amenity visits. Column 3 presents results that exclude both the monetary cost and the cost of time spent at destinations. Column 4 presents a version of the baseline results in which the unit cost of time is 1/2 of the hourly wage.

There is significant heterogeneity in the sizes of the elasticities of substitution. The elasticity of substitution is very large for gyms 13.82 (0.36), much smaller for restaurants 7.50 (0.076), and unsurprisingly even smaller for museums 3.69 (0.89). This confirms the intuition that gyms are highly substitutable among each other while restaurants are much less substitutable, and museums are even less substitutable. It is important to keep in mind that the length of visits to museums is long (more than two hours), which means even a moderately large elasticity of substitution can rationalize long travel times associated with visiting museums because long travel time is not as long in the percentage term. The fact that the estimate for $\hat{\sigma}_{\text{museum}}$ is small means that the high cost (low percentage cost of travel time) of visits to museums alone is *not enough* to rationalize the observed long travel time, and $\hat{\sigma}_{\text{museum}}$ must be small to justify the observed long travel time associated with visiting museums. In Column 2, which excludes the monetary cost of visits in the price vector, the estimates for $\hat{\sigma}_k$ vary in a similar way as in Column 1 but tend to be smaller. Column 3 further excludes the time spent at destinations in the cost of visits, and the resulting estimates tend to be too small compared to the magnitudes of σ in other papers (Couture (2016), Hoelzlein (2019)). The subsequent analysis is based on estimates in Column 1.

Comparison with Couture (2016) Unlike this paper in which I estimate σ_k for 16 different amenities, Couture (2016) estimates σ_k specifically for restaurants using a different method and more geographically granular data. Fortunately, this provides me with an opportunity to compare the magnitude of my estimates. To do that, I estimate σ_k for restaurant-type amenities using my method and data but calibrate the cost of visits in the

geocode for individuals and the geocode of the businesses they visit. Couture (2016)'s estimates of σ_k for restaurants are estimated using the restricted version of the National Household Travel Survey, in which the exact locations of residents and restaurants are observed. The access to that information enables him to know the exact choice set under which each trip decision is made. Section 5.3.2 presents my attempt to replicate his results using the ATUS, which does not contain precise geocode. The difference is reasonably small.

same way as Couture (2016).[32] My estimation produces $\sigma_{\text{restaurant}} = 8.678$ (0.0699), which is almost on par with his estimate of 8.8. If I add fuel cost to the model (say \$2.88 per hour[33]), the estimate goes a bit further down to 7.542 (0.059).[34]

5.4 Tastes for Amenities - θ_k

Finally, I estimate the taste parameters for amenities θ_k by constructing the sample analogues of the mean frequencies of visits and mean price indexes shown in equation 3:

$$\hat{\theta}_k = \frac{\sum_i^N \sum_j x_{ikj}/N}{I_k \cdot \sum_i^M \frac{\sum_j p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{1-\sigma_k}}/M}.$$

N is the sample size used in the ATUS. M is the population size.

I calibrate price indexes differently for the four demographic groups, young (<40 years old)/old (>=40 years old) and with/without college degrees. For each demographic group, I take the average annual income of people who work positive hours in the ACS national data (2007-2011) as I_k.[35]

5.4.1 Results

I estimate θ_k separately for people younger than 40 years of age with or without college degrees and people older than or at 40 years of age with or without college degrees. The results are shown in Table 3. The taste parameters across amenity types are far from even, with restaurants and non-grocery shopping being the largest.

[32] Couture's way of calibrating the price of visits is different from mine. He includes the full expenditure per visit in each restaurant and does not account for the opportunity cost of time visiting restaurant establishments. To make the comparison consistent, I include both amenity categories of restaurant and bar and takeout.

[33] Couture (2016) mentions that fuel cost for a 12.5-minute trip is about \$0.6. I adjust it to approximate a one-hour trip.

[34] I further validate my estimates for σ_k by computing the model-predicted travel time distributions and comparing them with the travel time distribution observed in the ATUS data. Given the model parameters, I generate a trip choice distribution for each amenity location given each residential location, which would equivalently generate a travel time distribution for each residential location. I then aggregate up the travel time distribution based on the population of each residential location. Figure A1 in the appendix shows a reasonably good fit of the model-predicted distribution and the data distribution for log travel time to each of the 16 amenity types.

[35] The hourly earnings of young workers with college degrees: \$27.84; young workers without college degrees: \$13.31; old workers with college degrees: \$44.29; old workers without college degrees: \$21.90. The average income of young and with college degrees: \$60537.11; young and without college degrees: \$26766.26; old and with college degrees: \$96316.36; old and without college degrees: \$44867.46.

6 Value of Access to Consumption Amenities

6.1 Spatial Diffusion

With σ_k and θ_k estimated, I proceed to analyze the value of access to consumption amenities through the lens of the model. I first demonstrate how the value of amenities diffuses spatially. I conduct counterfactual exercises in which I add an additional amenity establishment onto a location and compute the model-predicted effect on the welfare value of residents living at various distances to the newly added establishment.

As mentioned previously, residents' indirect utility is a weighted sum of the price indexes of 16 composite amenity goods from the point of view of residents living in census tract c:

$$P_{ick} = \left(\sum_{j=1}^{J_k} \left(\bar{p}_k + \gamma_i \left(h_k + t_{cj} \right) \right)^{1-\sigma_k} \right)^{1/(1-\sigma_k)} .$$

As I add one more establishment indexed as $J_k + 1$ onto the map, the new price index at census tract c becomes:

$$\hat{P}_{ick} = \left(\sum_{j=1}^{J_k} \left(\bar{p}_k + \gamma_i \left(h_k + t_{cj} \right) \right)^{1-\sigma_k} + \left(\bar{p}_k + \gamma_i \left(h_k + t_{c,J_k+1} \right) \right)^{1-\sigma_k} \right)^{1/(1-\sigma_k)} .$$

The magnitude of the effect $\Delta \ln \left(\hat{P}_{ick} \right)$ depends on how close census tract c is from the location of the new addition: t_{c,J_k+1}, size of σ_k, size of h_k, and the total number of existing establishments within the MSA: J_k. The impact of the addition on the welfare value is weighted by the taste parameter θ_{ki} of amenity type k:

$$\Delta \hat{V}_{ic} = -\theta_{ki} \Delta \ln \left(\hat{P}_{ick} \right) .$$

Because the marginal utility of log income is 1 (equation 1), $\hat{V}_{ic}$ is measured in the equivalent log income unit.

6.1.1 Results

To demonstrate how the welfare effect of a new establishment diffuses across space, I pick out four types of amenities that likely exhibit different diffusion intensities: *restaurant, gym, laundry shop,* and *museum.* For each type of amenities, I add in a new establishment in downtown San Francisco (Zip Code 94103). I compute the change in the price indexes in all census tracts in the same MSA.

I normalize the overall size of the effect by dividing the welfare effect by the effect in the closest census tract to the newly added establishment.[36] I plot the normalized effect of the new amenity establishment in Figure 6 against the travel time between the census tract and the new amenity establishment.[37]

Note that the value of a new laundry shop declines quickly with distance, disappearing only as far as 10 minutes away. The value of a new gym diffuses slightly more, disappearing about 20 minutes away. The value of a new restaurant is much more spread out, with value extending substantially as far as 30 minutes away, and the effect does not disappear even 60 minutes away. The value of a new museum is the most spread out, extending much of its value as far as 60 minutes away. In other words, a museum benefits people throughout the MSA, even those who live very far away.

6.2 Access Inequality due to Spatial Segregation and Sorting

Now that it is confirmed that the model can flexibly capture the variation in spatial diffusion intuitively, I return to the motivating goal of the paper and use the model to measure the well-being inequality driven by the difference in the spatial access to consumption amenities. I measure the gap in amenity access across skill groups by calculating how much the well-being of the low-skilled population would have increased if the low-skilled population were to live in the same residential locations as the high-skilled population.

In the first step, for each location of residence and time, I assign the set of price indexes of the 16 types of amenities and compute the indirect utility by aggregating these indexes based on low-skilled residents' taste parameters. I compute the mean utility for low-skilled residents $E_{L,t}\left(V_{L,t}\right)$ by aggregating over low-skilled population's residential locations.

In the second step, I calculate low-skilled residents' *counterfactual* mean utility if they were to live where high-skilled residents live and thus have the same access to amenities that high-skilled residents have: $E_{H,t}\left(V_{L,t}\right)$. The counterfactual utility gain will be given by the following equation:

$$E_{H,t}\left(V_{L,t}\right) - E_{L,t}\left(V_{L,t}\right) = -\sum_{k=1}^{16} \theta_k^L \left(E_{H,t}\left(\ln P_{ck,t}\right) - E_{L,t}\left(\ln P_{ck,t}\right)\right). \tag{4}$$

The utility gain calculated by the above equation represents how much low-skilled residents' welfare would have increased if the access to amenities were to be equalized across skills. In other words, the number measures the degree of amenity access inequality that is

[36] The normalized effect should be 1 at the closest census tract and decline the farther the census tracts are from the location where the new establishment is added.

[37] Figure A2 in the appendix shows the effects of the same exercises on maps.

driven by the differential access to consumption amenities by skill. Since the marginal utility of log income is 1, the measure of access inequality would be in the log income unit.[38]

6.2.1 Results

I start the exercise by calculating the access inequality due to spatial segregation in 2000, which is an equivalent of 0.93 percentage points of income gap (Table 4). For comparison, in 2000, the real income gap by skill is 33% in 2000.[39] Therefore, the access inequality to consumption amenities is equivalent to about 2.8% of the real income gap in 2000.

From 2000 to 2010, due to the two-sided sorting of residents and amenities, the access inequality increased to an equivalent of 1.04 percentage points of income gap, which is a 0.11 percentage points increase. Over the same period, the real income gap increased to 38.5%, which is a 5.5 percentage point increase. The increase in the welfare inequality driven by two-sided sorting is thus equivalent to about 2% of the concurrent increase in real income inequality.[40]

It is notable that my estimates of the increase in access inequality to consumption amenities are much smaller than other papers' estimates of the increase in welfare inequality driven by the inequality of general amenity access. Diamond (2016) estimates that spatial sorting and the endogenous amenity change across MSAs added an equivalent of 6.2 percentage points of the change in wage gap between college and non-college workers over the two decades between 1980 and 2000. Su (2022) show that within-city neighborhood sorting and the resulting change in amenity access added an equivalent of 1.4 percentage points of the change in the earnings gap between the skill groups between 1990 and 2010.[41] This implies

[38]This method of calculating access inequality does not allow preference heterogeneity. The fact that high-skilled residents have a higher opportunity cost of time and stronger tastes for some of the amenities are not factored in. This restriction is in fact essential for the setup of the counterfactual welfare exercise, which provides a well-defined framework for measuring access inequality. If I allow both the price indexes and tastes to vary by skill, the utility cannot be comparable because a comparison of utility levels directly across people is not well-defined. Both Diamond (2016) and Su (2022) only compute the change in welfare inequality based on the normalized change in amenities across locations, but never a static measure of welfare inequality for a similar reason.

[39]I compute the log real income by adjusting the log income with local log rents. I calculate rents using the same method introduced in Diamond (2016). I use the same budget share for rent: 0.62 used in Diamond's paper, which is calibrated from Moretti (2013).

[40]Table A1 shows the contributions of individual amenity types to welfare inequality and its change over time: $\theta_k^L \left(E_{H,t}\left(\ln P_{ck,t}\right) - E_{L,t}\left(\ln P_{ck,t}\right)\right)$. Both the levels of welfare inequality and the increase are driven by access to restaurants and non-grocery stores, owing largely to their large aggregation weights.

[41]Couture et al. (2021) instead examine income groups and demonstrate that within-city sorting by income added an extra well-being gap equivalent of 3.6 percentage points of the income gap between income groups above the 90th percentile and below 10th percentile between 1990 and 2014. The number may not be directly comparable to my exercise because their number also accounts for the differing housing cost due to spatial sorting, in addition to the differing amenity exposure. The rising housing cost exposure by the low-income population is the main driver of the inequality number in their paper.

that over each decade, on average, the changing access spatial amenities in general led by spatial sorting adds on the existing income gap by a range of 0.7 to 3.1 percentage points. The welfare contribution of access inequality to *consumption amenities*, therefore, constitutes only 4% to 16% of the prior estimates.

The contrast between my estimate and the prior estimates suggests that the access to *consumption amenities* may constitute a relatively small portion of the total amenity profile of a location. In the papers mentioned above, the amenities by construction include *all* components of amenities that residents value, either explicitly or implicitly, such as neighborhood safety, aesthetic value, clean air and water, job market, and public goods like school quality and infrastructures. My result suggests that while the access inequality to consumption amenities is important, most of the increase in amenity inequality from spatial sorting is likely driven by the differing exposure to *non-consumption* amenities.

6.2.2 Role of Spatial Diffusion

Next, I show that correctly accounting for spatial diffusion and aggregation weights is important for accurately assessing the role of consumption amenities, and some seemingly minor simplifying assumptions on diffusion patterns and aggregation could potentially inflate or diminish the role of consumption amenities.

To demonstrate the role of correctly accounting for spatial diffusion, I present two additional calibration exercises, in the second and third rows of Table 4. In the first calibration exercise shown on the second row, I set σ_k of every amenity type to 15, a high number, in which case people do not value variety much, which means that people would often visit the closest amenities. In this case, amenity value hardly diffuses beyond the amenity establishment's closest surrounding neighborhoods. In the second exercise shown on the third row, I set σ_k of every amenity type to 3, a relatively low number, in which case people greatly value variety, which means that people often visit amenities far from them. In this case, amenity value diffuses broadly over a very large area. I demonstrate that both extreme assumptions can lead to large inaccuracies when measuring the importance of the access inequality to consumption amenities.[42]

In the first exercise ($\sigma_k = 15$), the access inequality is much smaller than the baseline number. In this case, a resident's well-being is largely determined by the distance to the closest amenities. Residents' well-being tends to be high if they can find *any* amenities close

[42] To echo the comparison made between my approach and a simple count of establishments with different radius ranges, I compute alternative measures of amenity access to restaurants and gyms based on simple counting (Table A11 in the appendix). The inequality of amenity access based on simple counting tends to be very small if the radius is set to 5 minutes. As the radius increases, the inequality of access increases, highlighting the non-triviality of correctly accounting for spatial diffusion.

to them, and their well-being tends to be low if the closest amenities are far from them.[43] However, many of the high-income neighborhoods in the U.S. are low-density developments and tend to require some travel time to reach the closest amenities, even though the travel time tends to be reasonably short.[44] The prevalence of such a low-density residential layout means that the first calibration scheme, which sharply discounts the value of amenities at even a slight distance, could undervalue the benefit of amenities received by residents, especially by high-skilled residents. Hence, artificially assuming that amenity value diffuses weakly can underestimate the degree of access high-skilled residents have relative to low-skilled residents.

In the second calibration exercise ($\sigma_k = 3$), the model predicts a much larger access inequality than the baseline number. In this case, a resident's welfare is determined largely by the number of varieties of amenities he or she has access to within a relatively long distance, with some discounting by distance. This calibration could lead to bias in measuring access inequality in the opposite direction. U.S. cities exhibit a high degree of spatial segregation by skill and income. On top of that, the high-skill/income side of a city tends to be relatively close to a greater selection of amenities compared to the low-skill/income side of the city. This calibration, by construction, assumes that high-income people benefit from access to a large variety of amenities, even for amenities where variety does not matter much (e.g. gyms). For example, high-income neighborhoods tend to be near a larger number of gyms due to a higher local demand for gym facilities.[45] Since gyms are highly substitutable, the number of available gyms nearby *per se* does not necessarily increase the well-being of nearby residents. However, by assuming too much spatial diffusion, the model would overestimate the access inequality between the skill groups because high-skilled residents tend to live close to a larger variety of amenities than low-skilled residents do. Moreover, by assuming a strong degree of spatial diffusion, I also inflate the degree of amenity access residents living in large cities have. Take gyms again as an example. The value of access to gyms should largely depend on the distance to the closest facilities. If I erroneously assume the benefit of all gyms in the entire city diffuses to every resident living in it, then the residents living in larger

[43] The number of varieties in the proximity of the residents does not matter even as much, since the elasticity of substitution is fairly high.

[44] See appendix Figure A5 where I plot the log number of restaurants (plus one) within a specific radius against the census tracts' ratios of college-educated residents and non-college-educated residents. While the relationship is unambiguously positive when the radius is large, the relationship becomes ambiguous when I reduce the radius to 5 minutes. This suggests that many of the high-skilled neighborhoods do not have restaurants within 5 minutes, even though they are near a larger number of restaurants within 10, 20 minutes, or longer driving distance than low-skilled neighborhoods.

[45] See appendix Figure A6 where I plot the log number of gyms (plus one) within a specific radius against the census tracts' ratios of college-educated residents and non-college-educated residents. Within each radius, the number of gyms tends to be larger in higher-skilled neighborhoods.

cities would be assumed to have better access to gym amenities. Since high-skilled residents disproportionately live in larger U.S. cities, the city-size bias further inflates the estimated access inequality if σ_k is calibrated too low.[46]

6.2.3 Role of Aggregation Weights

Prior papers that assess the value of access to consumption amenities often rely on hedonic models and often focus on selected amenity types such as restaurants and grocery stores to proxy a neighborhood's access to consumption amenities (Couture and Handbury (2020), Almagro and Dominguez-Iino (2020), Miyauchi et al. (2021)). I show that there are two possible reasons that such an approach could lead to bias gauging the overall importance of consumption amenities.

First, assuming a researcher has the correct aggregation weights to all amenities, focusing the analysis only on amenities like restaurants and grocery stores is implicitly equivalent to assuming that the aggregation weights on all other amenities are zero. Table 5 shows the access inequality driven by each amenity type individually based on the estimates of my model. The reading of the table shows that while restaurants and grocery stores certainly drive the access inequality number disproportionately, ignoring other amenity types in the welfare calculation could strongly underestimate the overall measure of access inequality.

The second problem of such an approach is omitted variable bias. The access to restaurants and grocery stores is likely positively correlated with the provision of other consumption amenities *and* non-consumption amenities across locations. If the hedonic model does not include *all* amenities that are correlated with the provision of the selected amenities like restaurants and grocery stores, the estimated marginal value of access to restaurants and grocery stores will likely reflect more than just the marginal value of restaurants and grocery stores per se but rather all other amenities spatially correlated with them. The inflated marginal value estimates will lead to an upward bias in the aggregation weights for restaurants and grocery stores and thereby lead to the overestimation of the role of consumption amenities in driving up welfare inequality.

7 Caveats

Partly because of the straightforward micro-foundation and estimation procedure, the time-use approach does have a number of important caveats. I elaborate on these caveats in this section.

[46] For example, Figure A6e shows the relationship between MSAs' log number of gyms and the MSAs' college ratio. Higher-skilled MSAs tend to have a larger provision of gyms.

7.1 Alternative Consumption Amenities

The main caveat of this model is that some consumption amenities may not require the resident to actually *visit* them but still diffuse spatially. Food delivery services and home repair services are good examples. Living in a neighborhood with lots of restaurants and home repair services may also be valuable. While these amenities extend their service at a distance, which means that the value of the amenities diffuses spatially, they cannot be empirically accounted for from visit patterns reported by the consumers. Therefore, this approach will not able to capture the value of access to those types of amenities. In the setting of this paper, the consumption amenity bundle excludes these amenities.

7.2 Measurement of Variety

In the model, I use the number of establishments as the measurement of variety. Doing so assumes that every establishment represents a distinct variety. Whether this is an appropriate assumption depends on how dissimilar establishments are to one another. Take two McDonald's restaurants for a demonstration. In my model, the two McDonald's restaurants represent two distinct varieties. In reality, since McDonald's restaurants are identical, if residents were to choose between the two McDonald's, they would most likely choose the McDonald's closer to them. Thus visit pattern will drive up the estimate for σ of restaurant amenities. In another case, if the same residents were to choose between a Thai bistro and a McDonald's, residents may split their choice probabilities between the Thai bistro and McDonald's because these two restaurants are very dissimilar. In such a case, the visit pattern would drive down the estimate for σ.

Therefore, σ, in fact, captures both the **degree of dissimilarity** between the choices *and* the **degree of substitution** among options *given a certain degree of dissimilarity.* Given a choice set of establishments under each amenity category, the σ would be *specific to* the average degree of dissimilarity among the establishments of interest.

7.3 Heterogeneous Quality and Cost of Visits

The approach also abstracts away from the quality and the cost differences between the establishments, which could further contribute to welfare inequality. Unfortunately, I do not observe the quality and cost for different establishments. In Appendix F2, with some assumptions on the size and quality of amenities, I provide an analysis that may suggest that abstracting away from quality variation across establishments likely does not matter in the access inequality calculation for restaurant amenities. But for grocery stores, ignoring quality variation may lead to mild underestimation of access inequality.

The approach also shies away from congestion costs. Consumption amenities may be rival goods, especially when they are used at capacity. If demand exceeds amenity's capacity, the congestion force creates waiting time, which is costly. The residents likely internalize the congestion costs when they make amenity choices. Given the congestion force, adding amenities could lower overall waiting time and thus yield welfare benefits. The assumption of my estimation and welfare valuation is that in the equilibrium observed in the data, congestion force is absent or unimportant. Ideally, I should allow waiting time to a function of underlying demand for each establishment and estimate the shape of the congestion function. Unfortunately, since I do not have data on congestion in amenity usage, such implementation is infeasible.

7.4 Unobserved Neighborhood Quality of Amenity Locations

Another possible bias in the estimates of σ is unobserved location characteristics around the amenities in the trip choices. In the model, trip choices are made based solely on the *observed* cost of trips. However, some components of the trip costs may not be observable. For example, local crime in certain amenity destinations may deter respondents from visiting. This may encourage people who live close to a high-crime area to venture out farther for restaurant visits. Since the likelihood of crime around the destinations people visit is unobserved in my data, the avoidance of the high-crime areas would be erroneously attributed to a low σ. In other words, the substitution of amenity choice created by unobserved location characteristics such as crime can be loaded onto my estimate of σ.

7.5 Cross-Type Substitutability and Complementarity

Finally, by assuming a Cobb-Douglas utility, I implicitly assume that the elasticities of substitution *across* different types of amenities are one. Therefore, the utility derived from each amenity k only depends on the spatial distribution of amenity establishments of own amenity k and not any other amenities. However, the assumption may be violated if some degree of substitutability and complementarity exist among amenity types. Albouy et al. (2020) find evidence for complementarity between local public goods. They show that local law enforcement/safety and park, which are local public goods, are complementary. An example in the context of consumption amenity would be potential complementarity between restaurants and stores. If people like to bundle multiple purposes such as going to restaurants and shopping into one trip, the presence of restaurants may increase demand for shops as well. Alternatively, if the presence of restaurants makes residents cook less, it may decrease demand for grocery stores. My assumption precludes such possibilities.

8 Conclusion

Prior papers have shown that the spatial segregation and sorting by skill led to an increase in welfare inequality due to the divergence in access to amenities by skill. Consumption amenities are noted to be a very important component of the local amenity profile. However, estimating the access to consumption remains difficult due to its unique challenges: accounting for the spatial diffusion of the benefits of consumption amenities and the estimation of the aggregation weights. To overcome these challenges, I take an alternative approach of assessing the value of access to local consumption amenities using people's time-use patterns interacting with consumption amenities. I motivate my approach by showing that the travel time to and from the amenities vary significantly across different types of amenities, which suggests that for different types of amenities, the value of amenities diffuses across space with different degrees of intensity. I also find that the frequencies of visits and the duration of the visits vary significantly across different types of amenities, which indirectly reveals the marginal value of access or the welfare weights of each type of amenities.

Motivated by these findings, I construct an amenity choice model that rationalizes the different travel time choices and frequency choices. The model provides a theoretical basis for both spatial diffusion and the welfare weights for aggregation and can be empirically linked to observable time-use patterns. I then estimate model parameters using a combination of the American Time Use Survey, data on amenity locations, and a travel time matrix.

With the estimated model, I show that the spatial segregation by skill group led to unequal access to consumption amenities equivalent to 2.8% of the observed income inequality by skill in 2000. With spatial sorting of residents and amenities between 2000 and 2010, the welfare inequality increased by an equivalent of 2% of the concurrent rise in income inequality. A comparison between my result and estimates from other papers implies that access to *consumption amenities* is important but is only responsible for a portion of the increase of access to amenities overall. I then show that properly accounting for spatial diffusion of amenity benefits and the aggregation weights is important for correctly measuring the access inequality to consumption amenities.

I end the analysis with a discussion of the caveats of the proposed model. A key limitation of the model is that I can only measure the amenity value of consumption amenities where residents derive utility by visiting. Other amenities, such as neighborhood safety or school quality, cannot be measured by this method. Furthermore, because of my reliance on the ATUS data and the ZCBP data, I cannot observe the quality, the precise genres, and the brands of the establishments that the residents visit. Thus, my analysis cannot account for the quality difference of the amenities and have to rely on the number of establishments as a measure of variety. My approach also may be biased by unobserved factors influencing amenity choices such as crime near the physical locations of amenities. Finally, my method precludes the possibility that different amenity types may be substitutes or complements with each other, such as grocery stores and restaurants. Future researchers can revisit and address these caveats with more detailed geocoded transactional-level data.

References

[1] Ahlfeldt, Gabri, Stephen Redding, Daniel Sturm, and Nikolaus Wolf, 2015. "The Economics of Density: Evidence from the Berlin Wall," *Econometrica* 83(6), 2127-2189.

[2] Albouy, David, 2012. "Are Big Cities Bad Places to Live? Estimating Quality-of-Life across Metropolitan Areas." Working Paper. `https://doi.org/10.3386/w14472`

[3] Agarwal, Sumit, Bradford Jensen, and Ferdinando Monte, 2018. "Consumer Mobility and the Local Structure of Consumption Industries," NBER Working Paper No. 23616

[4] Albouy, David, Peter Christensen and Ignacio Sarmiento, 2020. "Unlocking Amenities: Estimating Public-Good Complementarity," *Journal of Public Economics*, 182: 104110. `https://doi.org/10.1016/j.jpubeco.2019.104110`

[5] Almagro, Milena and Dominguez-Iino, 2020. "Location Sorting and Endogenous Amenities: Evidence from Amsterdam," Working Paper

[6] Bayer, Patrick, Fernando Ferreira, Robert McMillan, 2007. "A Unified Framework for Measuring Preferences for Schools and Neighborhoods," *Journal of Political Economy*, 115(4): 588-638. `https://doi.org/10.1086/522381`

[7] Black, Sandra, 1999. "Do Better Schools Matter? Parental Valuation of Elementary Education," *Quarterly Journal of Economics*, 114(2): 577-599. `https://doi.org/10.1162/003355399556070`

[8] Broda, Christian and David Weinstein, 2006. "Globalization and the Gains from Variety." *Quarterly Journal of Economics*, 121(2): 541-585. `https://doi.org/10.1162/qjec.2006.121.2.541`

[9] Broda, Christian and David Weinstein, 2010. "Product Creation and Destruction: Evidence and Price Implications." *American Economics Review*, 100(3): 691-723. https://dx.doi.org/10.1257/aer.100.3.691

[10] Buchholz, Nicholas, Laura Doval, Jakub Kastl, Filip Matejka, and Tobias Salz, 2020. "The Value of Time: Evidence From Auctioned Cab Rides," NBER Working Paper No. 27087

[11] Castillo, Juan, 2021. "Who Benefits From Surge Pricing?," Working Paper.

[12] Couture, Victor, 2016. "Valuing the Consumption Benefits of Urban Density," Working Paper.

[13] Couture, Victor, Cecile Gaubert, Jessie Handbury, and Erik Hurst, 2021. "Income Growth and the Distributional Effects of Urban Spatial Sorting," Working Paper.

[14] Couture, Victor and Jessie Handbury, 2020. "Urban Revival in America." *Journal of Urban Economics*, 119: 103267. https://doi.org/10.1016/j.jue.2020.103267

[15] Diamond, Rebecca, 2016. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000." *American Economic Review*, 106(3): 479-524. http://dx.doi.org/10.1257/aer.20131706

[16] Epple, Dennis, 1987. "Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated products." *Journal of Political Economy*, 95(1): 59–80. https://doi.org/10.1086/261441

[17] Glaeser, Edward, Jed Kolko, and Albert Saiz, 2001. "Consumer City," *Journal of Economic Geography,* 1(1): 27-50. https://doi.org/10.1093/jeg/1.1.27

[18] Glaeser Edward, Scott Duke Kominers, Michael Luca, and Nikhil Naik, 2016. "Big Data and Big Cities: The Promises and Limitations of Improved Measures of Urban Life," *Economic Inquiry,* 56(1): 114-137. https://doi.org/10.1111/ecin.12364

[19] Goldszmidt, Ariel, John List, Robert Metcalfe, Ian Muir, Kerry Smith, and Jenny Wang, 2020. "The Value of Time in the United States: Estimates from Nationwide Natural Field Experiments, " Working Paper.

[20] Gyourko, Joseph and Joseph Tracy, 1989. "The Importance of Local Fiscal Conditions in Analyzing Local Labor Markets," *Journal of Political Economy*, 97(5): 1208-1231. https://doi.org/10.1086/261650

[21] Handbury, Jessie, 2019. "Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities." Working Paper. http://doi.org/10.3386/w26574

[22] Hoelzlein, Matthias, 2019. "Two-Sided Sorting and Spatial Inequality in Cities," Working Paper.

[23] Hofferth, Sandra L., Sarah M. Flood, and Matthew Sobek. American Time Use Survey Data Extract Builder: Version 2.6 [dataset]. College Park, MD: University of Maryland and Minneapolis, MN: University of Minnesota, 2017. https://doi.org/10.18128/D060.V2.6.

[24] Jaravel, Xavier, 2019. "The Unequal Gains from Product Innovations: Evidence from the U.S. Retail Sector", *Quarterly Journal of Economics* 134(2): 715–783. https://doi.org/10.1093/qje/qjy031

[25] Manson, Steven, Jonathan Schroeder, David Van Riper, and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 12.0 [Database]. Minneapolis: University of Minnesota. 2017.

[26] Miyauchi, Yuhei, Kentaro Nakajima, and Stephen Redding, 2021. "Consumption Access and the Spatial Concentration of Economic Activity: Evidence from Smartphone Data," Working Paper

[27] Moretti, Enrico. 2013. "Real Wage Inequality." *American Economic Journal: Applied Economics* 5(1): 65-103. http://dx.doi.org/10.1257/app.5.1.65

[28] Murphy, Daniel, 2018. "Home Production, Expenditure, and Economic Geography," *Regional Science and Urban Economics* 70: 112-126. https://doi.org/10.1016/j.regsciurbeco.2018.03.003

[29] Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek, 2015. Integrated Public Use Microdata Series: Version 7.0 [dataset]. Minneapolis: University of Minnesota, 2017.

[30] Severen, Christopher, 2021. "Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification," *Review of Economics and Statistics, forthcoming*

[31] Small, Kenneth, "Valuation of Travel Time," *Economics of Transportation*, 2012,1, 2–14.

[32] Small, Kenneth, Clifford Winston, and Jia Yan, 2005 "Uncovering the Distribution of Motorists' Preference for Travel Time and Reliability," *Econometrica* 73(4) 1367-1382.

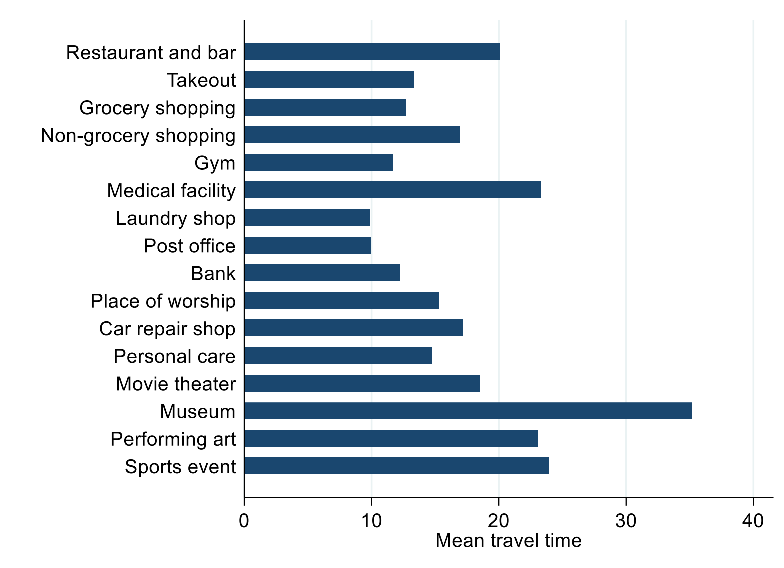
[33] Su, Yichen, 2020. "The Rising Value of Time and the Origin of Urban Gentrification." Working Paper. https://dx.doi.org/10.2139/ssrn.3216013

[34] Tsivanidis, Nick, 2019. "Evaluating the Impact of Urban Transit Infrastructure: Evidence from Bogota's TransMilenio," Working Paper.

[35] U.S. Department of Transportation, Federal Highway Administration, 2017 National Household Travel Survey. URL: https://nhts.ornl.gov.

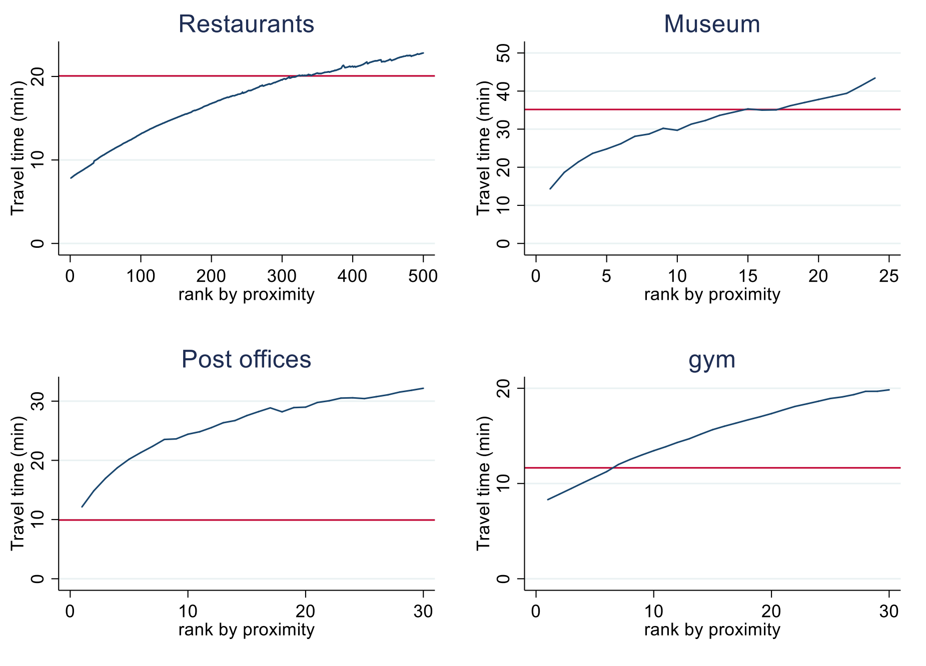
[36] U.S. Department of Transportation, Office of the Secretary of Transportation, 2014. "Revised Departmental Guidance on Value of Travel Time in Economic Analysis," URL: https://www.transportation.gov/sites/dot.gov/files/docs/USDOT%20VOT%20Guidance%202014.pd

Figure 1: Mean Travel Time Associated with 16 Types of Amenities



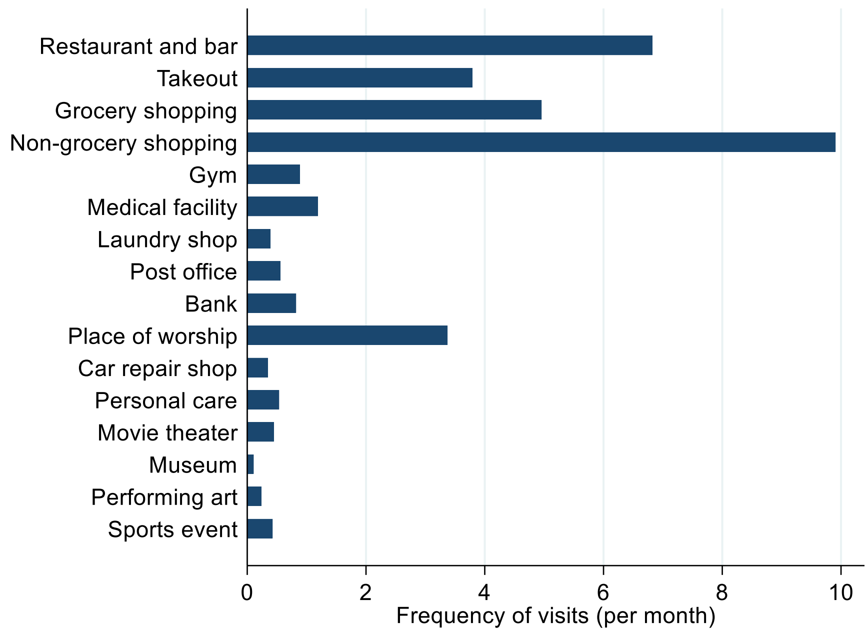
Notes: The data source is the American Time Use Survey (ATUS) 2003-2015. The statistics are generated with observations pooled across all surveys during these years. The sample includes the travel episodes that connect respondents' homes and location of activities.

Figure 2: Travel Time and Rank by Proximity



Notes: I select 4 of the 16 amenity types for the above figures. For each census tract, I search for all the amenity establishment within each amenity type, and rank each amenity by proximity (travel time), and I plot mean travel time against the proximity rank. The red line represents the average travel time reported in the ATUS data.

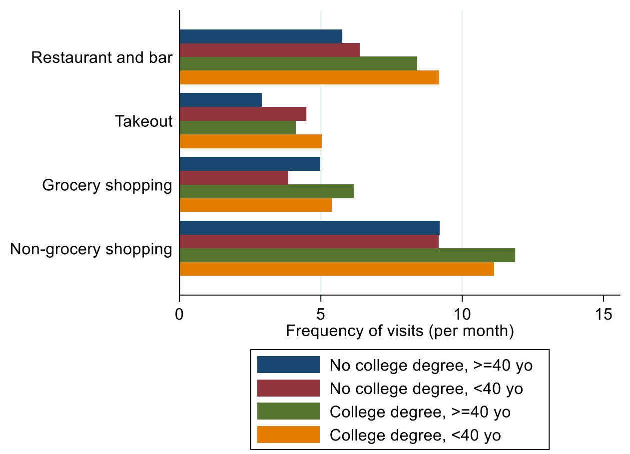
Figure 3: Frequency of Visits to 16 Types of Amenities



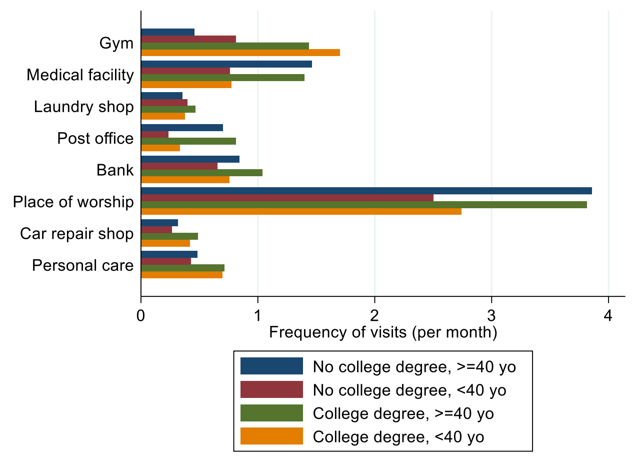
Notes: The data source is the American Time Use Survey (ATUS) 2003-2015. The statistics are generated with observations pooled across all surveys during these years. I categorize activities reported in the ATUS into 16 amenity categories. The classification table is shown in the appendix. The frequency is computed by dividing the total number of visits by the total number of days/cases multiplied by 30.

Figure 4: Frequency of Visits to 16 Types of Amenities – by Education Attainment and Age

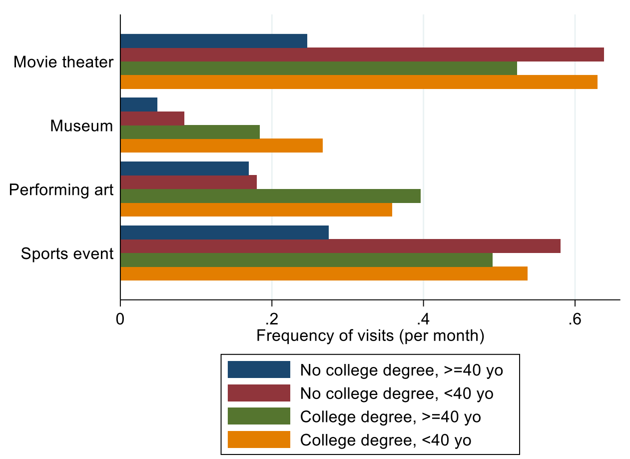
a) Restaurant, Takeout, Grocery, and Non-Grocery



b) Gym, Medical Facility, Laundry, Post Office, Bank, Worship, Car Repair, and Personal Care

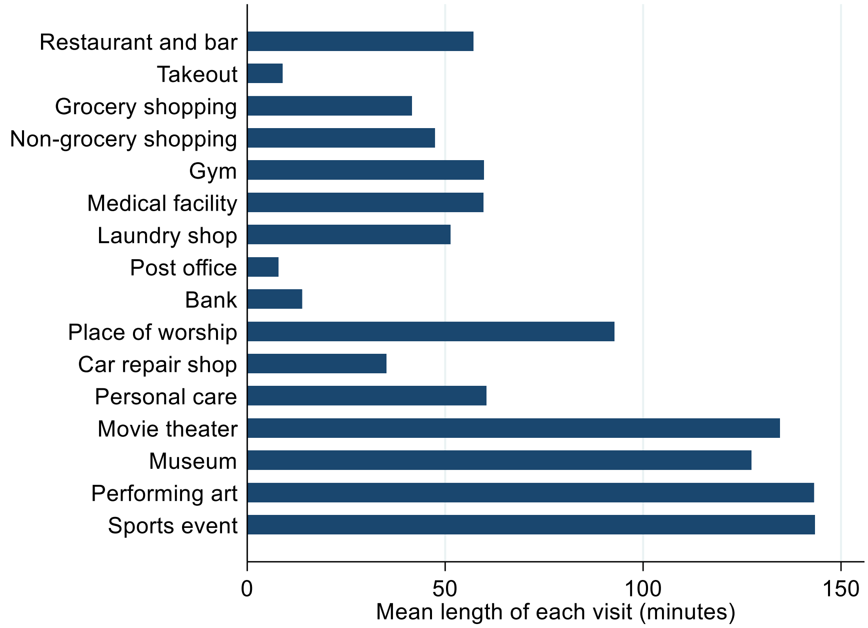


c) Movie, Museum, Performing Arts, Sports



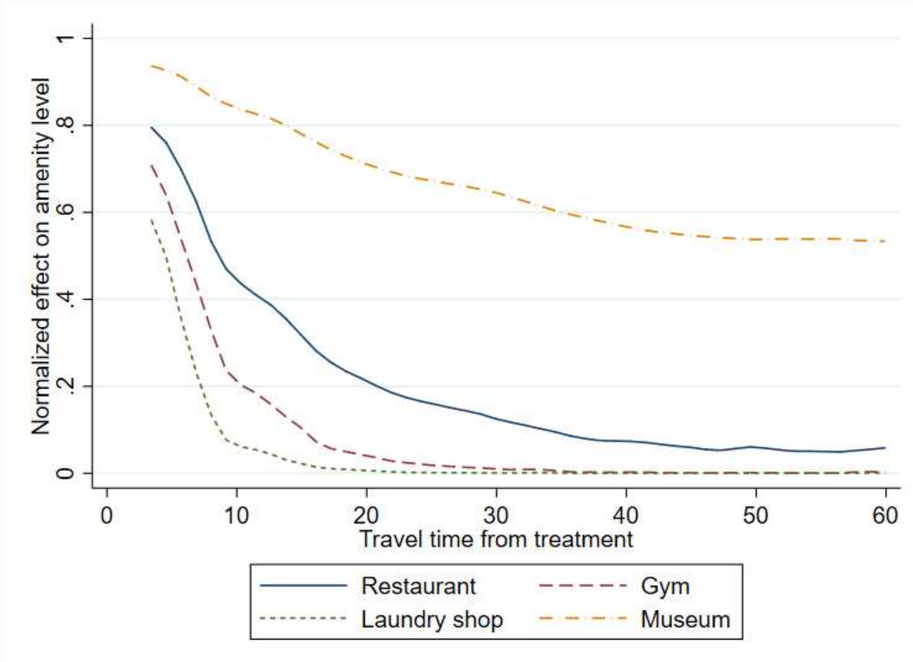
Notes: The data source is the American Time Use Survey (ATUS) 2003-2015. The statistics are generated with observations pooled across all surveys during these years. I categorize activities reported in the ATUS into 16 amenity categories. The classification table is shown in the appendix. I further divide the sample into those with college or without college degrees, and those younger than 40 years old and those at least 40 years old. The frequency is computed by dividing the total number of visits by the total number of days/cases multiplied by 30.

Figure 5: Mean Length of Visits to 16 Types of Amenities



Notes: The data source is the American Time Use Survey (ATUS) 2003-2015. The statistics are generated with observations pooled across all surveys during these years. I categorize activities reported in the ATUS into 16 amenity categories. The classification table is shown in the appendix.

Figure 6: Differential Rates of Spatial Diffusion (Downtown SF – Zip Code: 94103)



Notes: I plot the model-implied effects of adding an additional establishment on levels of amenities. I normalize the treatment effect for each amenity type by the treatment effect on the closest census tract (each curve starts out as 1). In this graph, the treatments occur in Zip Code 94103, which is located in Downtown San Francisco.

Table 1: Components in the Cost of Visit

	Monetary cost	Cost of time spent on site	Cost of visit (net of travel cost)	Cost of visits (travel time: 10 mins)	Cost of visits (travel time: 30 mins)	Percentage difference in Cost of visits (10 vs. 30 mins)
Restaurant and bar	8.83	22.84	31.67	35.67	43.67	22%
Takeout	8.83	3.58	12.41	16.41	24.41	49%
Grocery shopping	0	16.63	16.63	20.63	28.63	39%
Non-grocery shopping	0	18.98	18.98	22.98	30.98	35%
Gym	10.45	23.90	34.35	38.35	46.35	21%
Medical facility	28.05	23.85	51.90	55.90	63.90	14%
Laundry shop	6.69	20.55	27.24	31.24	39.24	26%
Post office	0	3.16	3.16	7.16	15.16	112%
Bank	0	5.55	5.55	9.55	17.55	84%
Place of worship	0	37.11	37.11	41.11	49.11	19%
Car repair shop	73.49	14.05	87.54	91.54	99.54	9%
Personal care	18.90	24.17	43.07	47.07	55.07	17%
Movie theater	7.35	53.81	61.16	65.16	73.16	12%
Museum	3.70	50.95	54.65	58.65	66.65	14%
Performance arts	2.14	57.28	59.42	63.42	71.42	13%
Sports event	4.76	57.36	62.12	66.12	74.12	12%

Notes: See the paper for the description and data source for the monetary costs of visits for each amenity type. Cost of time spent is computed by multiplying the mean lengths of visits with $24, which is the average hourly wage.

Table 2: Estimates for σ_k

	Baseline	Monetary Cost of Visits Excluded	Monetary Cost, Time at Destination Excluded	Value of Time ½ of Prevailing Wage
Restaurant and bar	7.50***	6.066***	1.972***	8.924***
	(0.076)	(0.059)	(0.0152)	(0.093)
Takeout	7.30***	4.33***	3.0116***	10.195***
	(0.092)	(0.047)	(0.0307)	(0.1385)
Grocery shopping	7.92***	7.92***	2.805***	7.92***
	(0.057)	(0.057)	(0.0160)	(0.057)
Non-grocery shopping	6.53***	6.53***	2.301***	6.53***
	(0.042)	(0.042)	(0.0115)	(0.042)
Gym	13.82***	10.58***	2.925***	17.0455***
	(0.36)	(0.27)	(0.0542)	(0.463)
Medical facility	7.11***	4.26***	1.475***	9.919***
	(0.22)	(0.12)	(0.0347)	(0.313)
Laundry shop	16.53***	13.41***	3.719***	19.656***
	(0.74)	(0.58)	(0.124)	(0.903)
Post office	32.35	32.35	26.164	32.35
	(103.35)	(103.35)	(92.771)	(103.35)
Bank	4.87***	4.87***	2.949***	4.87***
	(0.11)	(0.11)	(0.0597)	(0.11)
Place of worship	10.07***	10.07***	2.235***	10.07***
	(0.14)	(0.14)	(0.0224)	(0.14)
Car repair shop	18.80***	5.14***	2.167***	32.330***
	(0.74)	(0.16)	(0.0565)	(1.314)
Personal care	12.17***	8.044***	2.388***	16.272***
	(0.38)	(0.24)	(0.0519)	(0.533)
Movie theater	12.01***	10.87***	2.146***	13.146***
	(0.48)	(0.43)	(0.0676)	(0.525)
Museum	3.69***	3.52***	0.883***	3.848***
	(0.89)	(0.85)	(0.183)	(0.934)
Performance arts	10.30***	10.018***	1.898***	10.588***
	(0.83)	(0.80)	(0.126)	(0.853)
Sports event	11.80***	11.098***	2.275***	12.500***
	(0.81)	(0.76)	(0.131)	(0.863)

Notes: The first column reports the estimates for σ_k assuming that all components are included in the cost of visits, and the unit cost of travel time is the prevailing hourly wage. The second column reports the estimates for σ_k assuming that monetary cost is excluded in the cost of visits. The third column reports the estimates for σ_k assuming that both monetary cost and the time spent at destination are excluded in the cost of visits. The fourth column reports the estimates for σ_k assuming that all components are included but the unit of cost of travel time is ½ of the prevailing hourly wage. The subsequent analysis in model experiment would be based on the estimates on the first column.

Table 3: Estimates for the Taste Parameters θ_k

	Overall	<40 and with college degree	<40 and without college degree	>=40 and with college degree	>=40 and without college degree
Restaurant and bar	7.43***	9.35***	8.58***	7.89***	6.57***
	(0.032)	(0.010)	(0.076)	(0.066)	(0.048)
Takeout	1.93***	2.28***	3.44***	1.50***	1.60***
	(0.012)	(0.036)	(0.038)	(0.020)	(0.018)
Grocery shopping	3.11***	3.27***	2.52***	3.74***	3.20***
	(0.016)	(0.050)	(0.030)	(0.038)	(0.026)
Non-grocery shopping	7.43***	8.052***	7.17***	8.60***	7.070***
	(0.025)	(0.074)	(0.050)	(0.056)	(0.038)
Gym	0.93***	1.65***	1.081***	1.27***	0.50***
	(0.012)	(0.048)	(0.030)	(0.030)	(0.014)
Medical facility	1.98***	1.17***	1.79***	1.77***	2.60***
	(0.023)	(0.051)	(0.051)	(0.042)	(0.041)
Laundry shop	0.33***	0.30***	0.41***	0.34***	0.31***
	(0.0067)	(0.019)	(0.016)	(0.014)	(0.010)
Post office	0.12***	0.069***	0.056***	0.16***	0.16***
	(0.0021)	(0.0046)	(0.0029)	(0.0049)	(0.0037)
Bank	0.29***	0.25***	0.24***	0.35***	0.30***
	(0.0040)	(0.011)	(0.0073)	(0.0096)	(0.0063)
Place of worship	3.96***	3.11***	3.068***	4.33***	4.64***
	(0.026)	(0.070)	(0.047)	(0.059)	(0.043)
Car repair shop	0.85***	0.89***	1.080***	0.89***	0.85***
	(0.018)	(0.053)	(0.053)	(0.036)	(0.030)
Personal care	0.70***	0.83***	0.77***	0.73***	0.67***
	(0.012)	(0.038)	(0.029)	(0.025)	(0.67)
Movie theater	0.82***	1.094***	1.32***	0.88***	0.47***
	(0.016)	(0.053)	(0.041)	(0.034)	(0.018)
Museum	0.20***	0.47***	0.17***	0.32***	0.093***
	(0.0078)	(0.036)	(0.015)	(0.021)	(0.0083)
Performance arts	0.44***	0.63***	0.35***	0.69***	0.32***
	(0.011)	(0.041)	(0.021)	(0.031)	(0.015)
Sports event	0.80***	0.97***	1.20***	0.86***	0.53***
	(0.016)	(0.051)	(0.039)	(0.035)	(0.020)

Notes: The reported values are estimates for the taste parameters θ_k for the 16 types of amenities. All reported estimates are percentage points ($\theta_k \times 100$). Standard errors reported in parentheses. For the estimates in the first column (overall estimates), I normalize θ_k with overall mean income taken from the ACS 2007-2011, \$50,403.01. For the estimates in the other columns, I normalize θ_k with mean income measures for each subgroup taken from the ACS 2007-2011. For <40 age & college, I use \$60,537.11 as the mean income measure; for <40 and without college degree, \$26766.26; for >=40 and with college degree, \$96,316.36; for >=40 and without college degree, \$44,867.46.

Table 4: Access Inequality to Amenities by Skill Group

	Unit: 100 × ln (V)			
	2000	2010	2000 - 2010	% 2000-2010
Baseline	0.93175	1.0399	+ 0.10815	+ 11.61%
σ = 15	0.59236	0.63836	+ 0.04599	+ 7.75%
σ = 3	1.48441	3.2462	+ 1.76179	+ 118.69%

Notes: I compute the access inequality to amenities between high-skilled and low-skilled residents. The residents include those aged between 25 and 65. High-skilled residents are defined as residents with college degrees, and low-skilled residents are defined as residents with no college degrees. Access inequality is calculated as the difference between the counterfactual mean utility of low-skilled residents if they are spatially distributed in the same way as high-skilled residents and the mean utility of low-skilled residents based on their actual spatial distribution. The first row presents welfare results with σ calibrated to the value estimated for each amenity type. In the second and third row, I calibrate σ to 15 and 3, respectively.

Table 5: Access Inequality by Each Amenity Type

	Unit: 100 × ln (V)			
	2000	2010	2000 - 2010	% 2000-2010
Restaurant and bar	0.229	0.261	+ 0.0312	+ 13.59%
Takeout	0.082	0.089	+ 0.0072	+ 8.71%
Grocery shopping	0.072	0.081	+ 0.0094	+ 13.07%
Non-grocery shopping	0.291	0.317	+ 0.0256	+ 8.81%
Gym	0.019	0.019	+ 0.0005	+ 2.93%
Medical facility	0.076	0.085	+ 0.0096	+ 12.73%
Laundry shop	0.008	0.009	+ 0.0010	+ 12.06%
Post office	0.005	0.004	- 0.0013	- 24.71%
Bank	0.013	0.016	+ 0.0029	+ 22.27%
Place of worship	0.051	0.067	+ 0.0160	+ 32.09%
Car repair shop	0.008	0.009	+ 0.0010	+ 13.03%
Personal care	0.017	0.020	+ 0.0030	+ 17.50%
Movie theater	0.021	0.021	+ 0.0002	+ 0.74%
Museum	0.010	0.011	+ 0.0010	+ 9.62%
Performance arts	0.012	0.013	+ 0.0006	+ 5.27%
Sports event	0.019	0.019	+ 0.0001	+ 0.33%

Notes: I compute the access inequality to amenities between high-skilled and low-skilled residents. The residents include those aged between 25 and 65. High-skilled residents are defined as residents with college degrees, and low-skilled residents are defined as residents with no college degrees. Access inequality is calculated as the difference between the counterfactual mean utility of low-skilled residents if they are spatially distributed in the same way as high-skilled residents and the mean utility of low-skilled residents based on their actual spatial distribution. The numbers in each row represent the counterfactual utility difference driven by only the differential access of the designated amenity type.

Appendix for Online Publication

A Matching NAICS Codes into Amenity Categories

I use Zip Code Business Patterns (ZCBP) as the source of the geographic location of consumption amenities. ZCBP records the counts of business establishments by the ZCTA and by the NAICS industry code. In this section, I demonstrate how I match the NAICS code into the 16 amenity categories. In the following table, the left column lists the 16 amenity categories. For each category, I list the corresponding NAICS code matched with it.

	NAICS codes
Restaurant and bar	722 - - -
Takeout	722 - - -
Grocery shopping	445120, 445110, 445210, 445220, 445230, 445291
	445292, 445299, 445310, 446110, 446120, 446130
	446191, 446199
Non-grocery shopping	448110, 448120, 448130, 448140, 448150, 448190
	448210, 448310, 448320, 451110, 451120, 451130
	451140, 451211, 451212, 452210, 452311, 452319
	453110, 453210, 453220, 453310, 453910, 453920
	453930, 453991, 453998
Gym	713940, 713920, 713990, 713910
Medical facility	621111, 621112, 621210, 621310, 621320, 621330
	621340, 621391, 621399, 621410, 621420, 621491
	621492, 621493, 621498
Laundry shop	812320, 812310
Post office	491110, 492110
Bank	522110, 522120, 522130, 522190
Place of worship	813110
Car repair shop	811111, 811112, 811113, 811118, 811121, 811122
	811191, 811192, 811198
Personal care	812111, 812112, 812113, 812191, 812199
Movie theater	512131
Museum	712110, 712120, 712130
Performing art	711110, 711120, 711130, 711190
Sports	711211, 711212, 711219

A.1 Matching ATUS Activity Codes into Amenity Categories

In the American Time Use Survey (ATUS), activities recorded in the data are classified in a six-digit code. The code is designed in a highly detailed fashion, and therefore, multiple categories of activities may be classified as similar activities (within the same amenity category). In the following table, the left column lists the 16 amenity categories. For each category, I list the corresponding ATUS activity codes matched with it.

	Activity code	location of the activity
Restaurant and bar	110101, 110201, 110299	104
Takeout	70103	104
Grocery shopping	70101	N/A
Non-grocery shopping	70104, 70105, 70199, 70201	N/A
Gym	130101, 130102, 130103, 130104, 130105, 130107, 130108, 130109, 130110, 130113, 130114, 130115, 130117, 130119, 130120, 130121, 130122, 130123, 130124, 130125, 130126, 130127, 130128, 130129, 130130, 130132, 130133, 130134, 130135, 130136, 130199, 130301, 130399, 130401	112
Medical facility	80401, 80403, 80499	N/A
Laundry shop	20102	N/A
Post office	20903	N/A
Bank	80201, 80202, 80203, 80299	N/A
Place of worship	140101, 140102, 140103, 140105, 149999	N/A
Car repair shop	90501, 90502, 90599	N/A
Personal care	80501, 80502, 80599	N/A
Movie theater	120403	N/A
Museum	120402	N/A
Performing art	120401	N/A
Sports	130201, 130202, 130203, 130204, 130205, 130206, 130207, 130209, 130210, 130212, 130213, 130214, 130215, 130216, 130217, 130218, 130219, 130220, 130221, 130222, 130223, 130224, 130225, 130226, 130227, 130229, 130232, 130299, 130302, 130402, 139999	N/A

A.2 Monetary Cost of Amenity Visits

Restaurant/Bar

For restaurants/bar (including to-go services) amenities, I use the CEX expenditure diary to compute the average per-person expenditure per week on eating outside ones' home.[1] I then divide the value by the average frequencies of visiting restaurants (documented from ATUS) to impute the average spending on each meal per person. I use the imputed average spending on outside meals as the monetary cost of restaurant services.

Grocery and Non-Grocery Shopping

For grocery and non-grocery shopping, I do not include the monetary expenditure of shopping as part of the cost of visits. This is because the expenditure incurred during shopping activities is for the consumption goods purchased during these activities, not for the permission to engage in shopping activities or services provided during the shopping activities. A shopper typically does not need to pay an entrance fee or service fee to walk around supermarkets or shopping. In this paper, I assume the primary cost of shopping is the cost of the time spent on shopping.

Medical Facilities, Laundry, Car Repair, Personal Care, and Gym

Visiting hospitals and other medical facilities usually incurs some amount of out-of-pocket costs. These costs could vary by quite a lot, depending on the exact purposes of the visits. In this paper, I approximate the out-of-pocket cost of visiting medical facilities using the CEX expenditure diary and divide it by the frequency of visits documented in ATUS.[2] The cost of visiting medical facilities do not include insurance costs.

[1] CEX spending categories attributed to restaurant/bar: lunch at fast food, lunch at full service, dinner at fast food, dinner at full service, snacks at fast food, snacks at full service, breakfast at fast food, breakfast at full service, beer at fast food, beer at full service, wine at fast food, wine at full service, alcoholic beverage excluding beer/wine fast food, alcoholic beverage excluding beer/wine full service.

[2] CEX spending categories attributed to the out-of-pocket medical expenditure: physicians' services, dental services, eye exams, treatment or surgery, glass/lens service, glasses repaired, lab tests and x-rays, services by medical professionals other than physicians, hospital care not specified, care in convalescent in nursing home, other medical care service, such as ambulance service.

For laundry[3], car repair[4], and personal care[5], I approximate the monetary cost of visits using data straight from CEX data and divide them by the frequencies of visits from ATUS.

For gym activities, gym due is the natural candidate for the monetary cost of visiting gyms. I approximate the per-visit cost of going to gyms by dividing the average monthly gym due by the average frequency of visits per month by gym members.[6] I impute the frequency of visits per month by gym members by dividing the frequency of visits estimated (0.88) from the overall population by the share of the U.S. population that have gym memberships (16%).

Post Office, Bank, and Places of Worship

I assume no monetary cost associated with visiting post offices, banks, or places of worship. Similar to the reasoning for not including the monetary cost for shopping activities, the money one spends at post offices or banks is typically in exchange for postal services or banking services, which serves customers far beyond the premise of the visits itself. I assume that there is no monetary cost associated with *visiting* post offices and banks. I assume that visiting places of worship (churches, mosques, temples, synagogues, etc.) does not incur any monetary cost, either.

Movie, Museum, Performing Art, and Sports

I use data from the National Association of Theatre Owners to compute the average ticket price in the United States and use it as the monetary cost of seeing a movie.[7] I use the average art museum admission price reported by the Association of Art Museum Directors to approximate the monetary cost of visiting museums.[8] I impute the cost of visiting sports events by dividing the CEX expenditure on sports events by the average frequency of visits to sports events documented in the ATUS.

[3] CEX spending categories for laundry: apparel laundry and dry cleaning - coin-operated, alteration, repair, tailoring of apparel, and accessories, apparel laundry and dry cleaning not coin operated.

[4] CEX spending categories for car repair: miscellaneous auto repair and servicing, body work, painting, repair and replacement of upholstery, vinyl/convertible top, and glass, clutch and transmission repair, drive shaft, and rear-end repair, brake work, excluding brake adjustment, steering or front end repair, cooling system repair, motor tune-up, lubrication and oil changes, front end alignment, wheel balance and rotation, shock absorber replacement, brake adjustment, gas tank repair and replacement, exhaust system repair, electrical system repair, motor repair, and replacement.

[5] CEX spending categories for personal care: personal care services for females, including haircuts, personal care services for males, including haircuts.

[6] https://www.healthline.com/health-news/gym-memberships-can-be-a-trap

[7] National Association of Theatre Owners website: http://www.natoonline.org/data/ticket-price/

[8] Art Museums by the Numbers:
https://aamd.org/sites/default/files/document/Art%20Museums%20By%20The%20Numbers%202015.pdf

Statistics regarding the mean admission price of performing art events are difficult to come by. The CEX does not have a precise spending category for performing art events. The closest category is "admission fees for entertainment activities, including lectures, movie, theatre, concert." I make the assumption that this category includes spending related to movies, museums, and performing art events. Since I acquire movie ticket and museum ticket information from outside the CEX, I am able to impute the expenditure amount on performing art using movie and museum ticket prices, frequencies of visits to movies and museums, and the overall expenditure on the broad category in the CEX.

B Two-Step Utility-Maximization Problem

I solve the utility-maximization problem in two steps.

B.1 Step I: Solve for Minimal Cost Function for the CES Composite Amenity Good

First, I minimize the cost of achieving any level of consumption amenity X_k. Given the size of target consumption amenity X_k, the cheapest way to obtain that level of X_k is the solution of the following cost-minimization problem:

$$\min_{x_{k1},\dots,x_{kJ_k}} \sum_{j=1}^{J_k} p_{kj}x_{kj}$$

$$\text{s.t.} \quad \left(\sum_{j=1}^{J_k} x_{kj}^{\rho_k}\right)^{1/\rho_k} \geq X_k.$$

Using standard CES solution steps, the cost function is $c(\mathbf{p}_k, X_k) = \left(\sum_{j=1}^{J_k} p_{kj}^{1-\sigma_k}\right)^{1/(1-\sigma_k)} X_k$, which is linear in X_k. This means the cheapest way to produce each unit of composite amenity good X_k costs $\left(\sum_{j=1}^{J_k} p_{kj}^{1-\sigma_k}\right)^{1/(1-\sigma_k)}$ per unit. This unit cost of composite amenity good can also be understood as a form of price index of amenity type k.

B.2 Step II: Maximize Cobb-Douglas Utility Given the Unit Cost of Composite Amenity Good

Once I get the unit price of each type of composite amenity good X_k, I treat each composite good X_k as if it is a homogeneous good on its own, and solve for the utility-maximizing demand for each good. In this setting, a consumer faces K different amenity goods, each with price P_k. Using the standard Cobb-Douglas solution, the demand for each good is:

$$X_k = \frac{\theta_k I}{P_k}, \text{ where } P_k = \left(\sum_{j=1}^{J_k} p_{kj}^{1-\sigma_k}\right)^{1/(1-\sigma_k)}$$

$$\text{where } x_0 = \theta_0 I.$$

The indirect utility can be obtained by plugging the demand function back into the log-transformed utility function. The log-transformed utility can be written as a linear combination of the log unit price of each amenity good weighted by the budget share:

$$V_i^a = \alpha + \ln(I) - \sum_{k=1}^{K} \theta_k \ln(P_{ik}).$$

C Standard Errors of the M-M Estimate

I derive the asymptotic variance for the M-M estimator. To start, I define the sample moment $g(t_i, \mathbf{X}_i, \sigma_k) = \widehat{\ln t_i} - \ln(t_i)$. And I further define $G = E\left(\frac{\partial g(t_i, \mathbf{X}_i, \sigma_k)}{\partial \sigma_k}\right)$. Below is the asymptotic distribution of the M-M estimator:

$$\sqrt{N}\left(\hat{\sigma}_k - \sigma_k\right) \sim N\left(0, \left(G'G\right)^{-1} G'\Omega G \left(G'G\right)^{-1}\right).$$

Since Ω is only one dimension and can be approximated by s^2, I can rewrite the asymptotic distribution:

$$\sqrt{N}\left(\hat{\sigma}_k - \sigma_k\right) \sim N\left(0, s^2\left(G'G\right)^{-1}\right).$$

To compute G, I differentiate the sample moment. I rewrite the choice probability into a form similar to a logit choice functional form. For simplicity, I denote the price of visiting each amenity j from census tract c as $p_{k,cj} = \bar{p}_k + \gamma(h_k + t_{cj})$. The moment condition can be written as:

$$\begin{aligned} g(t_i, \mathbf{X}_i, \sigma_k) &= \widehat{\ln t_i} - \ln(t_i) \\ &= \sum_c \Pr(c|\mathbf{X}_i) \cdot \sum_{j|c} \frac{\exp(-\sigma_k \ln(p_{k,cj}))}{\sum_{j'} \exp(-\sigma_k \ln(p_{k,cj'}))} \cdot \ln t_{cj} - \ln(t_i). \end{aligned}$$

Now I take differentiation:

$$\begin{aligned}\frac{\partial g\left(t_i, \mathbf{X}_i, \sigma_k\right)}{\partial \sigma_k} &= \sum_c \Pr\left(c|\mathbf{X}_i\right) \cdot \sum_{j|c} \frac{\exp\left(-\sigma_k \ln\left(p_{k,cj}\right)\right)}{\sum_{j'} \exp\left(-\sigma_k \ln\left(p_{k,cj'}\right)\right)} \cdot \\ &\quad \left[\frac{\sum_{j'} \exp\left(-\sigma_k \ln\left(p_{k,cj'}\right)\right) \ln\left(p_{k,cj'}\right)}{\sum_{j'} \exp\left(-\sigma_k \ln\left(p_{k,cj'}\right)\right)} - \ln\left(p_{k,cj}\right)\right] \cdot \ln t_{cj}.\end{aligned}$$

I compute the derivatives of each sample moment and construct G, and use it to compute the asymptotic estimator for the standard error of the M-M estimator for σ_k.

D Comparison between the ATUS and Alternative Data Sources

D.1 National Household Travel Survey

Besides American Time Use Survey (ATUS), other data sources such as the National Household Travel Survey (NHTS) also provide information on travel patterns. In this section, I compare the travel time, travel frequency, and the duration of visits reported in the ATUS and the NHTS to show that the patterns in ATUS generally hold in other data.

The challenge with a simple comparison between the two data sets is that while ATUS reports a very detailed activity code, the NHTS provides a much broader categorization of activities. Therefore, I am not able to compare the two data sets by each of the 16 amenity types.

The NHTS data provide variables “whyto” and “whyfrom”, which contain the information that indicates the purposes of the trips. The categories for trip purposes are much coarser than the categories in the ATUS. Moreover, the coding of these variables in NHTS changes over time: the 2017 NHTS coding is different from the one in the 2001 and 2009 NHTS. For that reason, to validate the numbers produced by the ATUS, I harmonize the trip purposes provided by the ATUS to be consistent with each version of the NHTS's coding (2001/2009 vs. 2017), by creating a set of common categories of activities.

Since the NHTS categories are much broader and more ambiguous, even though I define common categories to make them comparable across ATUS and NHTS, some inconsistencies are expected. For example, the NHTS categories of “buy services” can be quite ambiguous, even though examples are given in parenthesis in the codebook. Another example would be “go to gym/exercise/play sports”. In the NHTS, the category does not specify the location of the activities. Since exercises can take place in gyms, outdoors, mountains, nearby parks, it is difficult to pinpoint the exact definition of the activities. In contrast, the ATUS is much more specifically defined. Thus, inconsistencies could naturally arise due to the ambiguity of NHTS' definition of some activities. It is also informative to compare how travel time *varies* across amenity categories as reported in ATUS and in NHTS.

See Table A1 for a crosswalk between ATUS and the 2017 NHTS. See Table A2 for a crosswalk between ATUS and the 2001/2009 NHTS.

D.1.1 Travel time

Table A3 shows the mean travel time and its standard deviation by the common category using the ATUS and NHTS data, separately for 2017 and for 2001/2009.

The travel time to restaurants is very similar as reported in the ATUS and NHTS. The striking similarity between the two datasets for restaurant trips may be attributed to the fact that restaurant trips are quite well-defined and I am likely comparing apple to apple.

In contrast, travel time for grocery and non-grocery shopping runs and gyms/exercise varies tends to be longer in the NHTS data than in the ATUS data, and so is the standard deviation. First, regarding the travel time for shopping, the definition in NHTS is "Buy goods (groceries, clothes, appliances, gas)" in 2017 and "Shopping/errands" or "Buy goods: groceries/clothing/hardware store" in 2001/2009 and there are very limited alternative trip purposes to choose from. Given the lack of detailed trip categories, I expect respondents to categorize some of their general errands as shipping trips. In contrast, in the ATUS, while grocery and non-grocery shopping are defined similarly, there are overwhelmingly more activities categories to choose from. Therefore, it is much less likely that respondents would throw in other trips into the shopping trip category. Hence, I expect NHTS likely contains more measurement errors for the shopping trips. Second, regarding gyms/exercise, I restrict ATUS data to only include trips whose destination is a gym or health club, while NHTS trips may include exercising activities anywhere, including in the park, mountain, or even along the roads. Since the purpose of my analysis is to measure the value of gym amenity establishments, the ATUS data should be a more relevant data source.

Travel time of medical trips tends to be somewhat larger in the NHTS. But they are in the same ballpark.

In the category of buy services, the NHTS definitions are different across time. Buy services in 2017 includes "dry cleaners, banking, service a car, pet care", whereas buy services in 2001/2009 includes "video rentals, dry cleaner, post office, car service, bank". These definitions vary quite arbitrarily. I conduct an imperfect match with the ATUS data (see Table A1 and A2). The travel time in the two datasets is shorter than other trips and is somewhat but not starkly different from each other.

For personal care, I can only find an appropriate category for the 2001/2009 NHTS. The definition consists of "Use personal services: grooming/haircut/nails" and "Pet care: walk the dog/vet visits". The travel time in this category matches well with the ATUS.

Travel time to religious services also matches reasonably well across ATUS and NHTS. I believe this is because religious activities are relatively well-defined in all datasets.

Entertainment activities are defined differently in 2001/2009 vs. 2017 in the NHTS. For NHTS in 2001/2009, entertainment is defined as "Go out/hang out: entertainment/theater/sports event/go to bar". For NHTS in 2017, entertainment is defined as "Recreational activities (visit parks, movies, bars, museums) ". One can see that the definitions are drastically different over the years. I match them to the best of my ability with the ATUS. The travel time matches reasonably well under both definitions.

Museum/library is a category that I create to cover visits to museums in the ATUS. In the 2001/2009 NHTS data, museum/library include "Visit public place: historical site/museum/park/library". For the ATUS sample, I match the visits to museums, libraries, and socializing activities in non-home locations. This is not exactly a perfect match because ATUS does not have specific information regarding visits to parks or historical sites. The travel time is slightly longer in the NHTS data than in the ATUS data.

D.1.2 Frequency of visits

Table A4 shows the frequency of visits by the common category using the ATUS and NHTS data.

The ATUS data report a slightly higher frequency for trips to restaurants in the NHTS data. This is likely because the ATUS activities for eating and drinking include drinking, which includes going to bars. However, in the NHTS data, the same category specifically refers to meals, not drinks.

For grocery and non-grocery shopping, the frequency of visits does not differ very much.

For the gym and exercise category, the frequency of visits is much higher in the NHTS data. This should be entirely unsurprising since the NHTS trips include exercise activities outdoors outside of any gyms or health clubs while the definition for ATUS is restricted to activities in gyms or health clubs, as explained in the previous subsection.

Visits for medical purposes are considerably more frequent in the NHTS data. I suspect that such discrepancy might again be the result of ATUS having a much more refined classification of activities. Many trips such as taking children to care or personal therapy may fall into other categories in the ATUS data but are all swept into the medical category in the NHTS due to a much more limited selection of categories.

Both categories of "buy services" and "personal care" see significantly higher frequency of visits in the NHTS. I believe this is again due to the fact that the definitions of NHTS trips are much broader.

Visits to religious services have somewhat a similar frequency, though the frequency in the ATUS data is slightly higher than that in the NHTS data.

The frequency to visit entertainment venues is similar under 2017 NHTS definition, but higher in ATUS under the 2001/2009 NHTS definition. For NHTS in 2001/2009, entertainment is defined as "Go out/hang out: entertainment/theater/sports event/go to bar". This is a very broad definition, which could give rise to very large discrepancy.

Frequency of visits to museum/library also has a bit discrepancy. I believe this is again due to ATUS not having a separate category for visits to parks but the NHTS includes visits to parks.

D.1.3 Dwell time

Table A5 shows the dwell time at destinations by the common category using the ATUS and NHTS data.

Trips to restaurants last longer in the NHTS than in ATUS data. This is likely again for the same reason: ATUS activities for eating and drinking include going to bars, which may have lowered the average time at destination.

Grocery and non-grocery shopping time last slightly longer in the ATUS than in the NHTS.

Gym and exercise time lasts shorter in the ATUS than in the NHTS. This could be driven by the fact that people's outdoor activities (biking or hiking), which are not included in the ATUS, last longer than gym sessions.

Time spent in categories of "buy services" compares quite well.

Time spent at religious service does appear shorter in ATUS data. This may be because the NHTS data mix in other community services besides religious services.

Time spent at entertainment venues appears significantly shorter in the ATUS data. Again, this is very likely attributed to the broad definitions of entertainment activities in the NHTS data.

Lastly, time spent at museum/library is roughly similar in the ATUS and NHTS data.

D.2 SafeGraph

In addition, I extract the data on the frequency of travel and duration of trips from SafeGraph. SafeGraph provides geospatial information on mobility and foot traffic based on cell phone location information. I use the "monthly patterns" data provided by the SafeGraph.

The data provide information on the number of visits to each place of interest. Each place of interest is categorized with a detailed NAICS code, which enables me to classify them into the 16 amenity types. I use the sample of trips conducted in the month of December of 2019.

I use the SafeGraph data to further compare the **duration of visits** and the **frequency of visits** in the ATUS data (not travel time). Below I explain how such comparison is done and why I do not compare travel time using the SafeGraph data.

Another caveat of the SafeGraph data is that the "visits" are based on cell phone logs. Therefore, I cannot distinguish the "visits" of employees from the genuine visits of customers. If some establishments have a large number of part-time employees relative to the number of their customers, the Safegraph data could report distorted values for both the duration of visits and the frequency of visits.

D.2.1 Duration of visits

The data contain a variable that shows the distribution of visitors to each place of interest by their duration of visits (discrete ranges of minutes of stays). That allows me to compare the distribution of the duration of visits observed in the ATUS data with the same distribution observed in SafeGraph data. Figure A3 shows the histogram of the duration of visits (dwell time at destination) as reported in the ATUS and as observed in the SafeGraph data, separately for each amenity type. Note that since the two types of amenities, restaurant/bar and takeout, involve the same destination locations, they are indistinguishable in the SafeGraph data. As a result, I merge them under the type "Restaurant and bar".

The histograms indicate that the variation in the duration of visits across amenity types compares quite well in the ATUS data and in the SafeGraph data, with some exceptions. Grocery shopping seems to see a shorter dwell time in the SafeGraph data. This may be because the SafeGraph data includes convenient store stops while the ATUS data may not. Laundry shop, post office, bank, car repair shop, personal care venues' dwell time is longer in the SafeGraph data. This may be because, in these establishments, customer-to-employee ratios may be lower than other amenities. As a result, employees staying at their workplace for a prolonged period of time would bring up the distribution of dwell time of all "visitors".

D.2.2 Frequency of visits

The number of recorded visits to establishments of different types of amenities allows me to compute the relative frequency of visits to each type of amenities compared to other amenities. For example, if people visit restaurants much more frequently than museums, the aggregate number of visits to restaurants observed in SafeGraph should be far larger than the aggregate number of visits to museums. I can then compare the patterns recovered from SafeGraph with the patterns documented in the ATUS data.

Figure A4 presents the comparison between the SafeGraph data and the ATUS data. In sub-figure a), I plot the total visits reported by SafeGraph data in one month (December 2019). In sub-figure b), I plot the monthly frequency of visits reported in the ATUS data. Since the units of the two figures are different, the magnitude of the values is not directly comparable. But one can look at the relative sizes of the visiting intensity under different amenity types, which match somewhat well across the two datasets.

D.2.3 Why not the travel time distribution from SafeGraph?

I do not compute the travel time distribution from SafeGraph. I do not have bilateral visitation data of where consumers live and where they shop. Such data are not provided by SafeGraph. In the data that I do have, for each place of interest, I can see the number of visitors by the census block group of the visitors' residence. However, the data set is censored on the left-hand side at 4, which means that among all the visitors to restaurant x, if there is one and only one visitor that comes from census block group c, the data report there are 4 visitors that come from census block group c. This creates a very significant bias because the place of interest and residence pairs with a long distance will likely receive much larger sample weight than they should. This could create a very large upward bias in the estimates of the average travel time. This proves to be a very large problem because most of the place of interest and residence pairs record 4 as the number of visitors, which means that most of the observations are in fact affected by the censoring. Hence, I do not compute travel time from SafeGraph.

E Welfare Exercise - Quality Differentials

I do not have data on the differential quality of services offered across amenity establishments. Each amenity establishment is treated equally in terms of quality in measuring amenity access.[9] In other words, being close to a very high-end/high-quality restaurant versus being close to a low-end/low-quality restaurant have the exact same effect on residents' welfare calculation. This may be a strong assumption. If high-skilled population tend to have

[9] While quality measurement could certainly have helped account for amenity quality, even for researchers who have access to some quality measurement, say the average spending/price of services at each consumption venue or the ratings of services, etc., it is still likely that such variables do not fully capture the quality of the amenities.

closer proximity to high-quality amenities, while low-skilled population tend to live farther from high-quality amenities, my results could be understating the true extent of the access inequality.

In order to get a qualitative sense of how much bias ignoring the quality differentials across establishments might create in calculating welfare inequality, I conduct an additional welfare exercise for restaurants and grocery stores in which I assume larger establishments carry higher-quality amenity services. My dataset does provide a breakdown of establishment sizes. While I realize the assumption cannot be easily verified directly, I would argue that it is a plausible one. Intuitively, larger restaurants and grocery stores are likely more able to offer a larger variety of products, creating some economies of scale. Larger restaurants may also be more likely to offer accommodative services such as special requests or accessibility. Larger grocery stores may be more likely to have dedicated customer service compared to small mom-and-pop stores.

E.1 Test of the Assumption with SafeGraph Data

Moreover, I use SafeGraph data to verify this assumption to some degree. While I do not have data on the quality of each establishment, I can indirectly test the assumption by looking at whether larger restaurants and grocery stores are more likely to be visited people living in high income neighborhoods and/or neighborhoods with a higher share of college-educated residents. Such a pattern would validate my assumption if restaurant and grocery store quality is a normal good.

Since in SafeGraph data, I can observe a distribution of the number of visitors by their home residence census block group, I can calculate the average home-neighborhood income of its visitors for each amenity establishment. I can then regress the average visitors' neighborhood income on the establishment size (number of employees). The bias from the left-censoring should not be a big concern here, because I am not using travel time or distance for this exercise. Recall the main source of bias comes from the fact that farther census block groups tend to bump into the left-censoring boundary more frequently.

Table A6 shows that the larger restaurants and grocery stores are indeed more likely to be visited by customers who live in wealthier neighborhoods. Concerned by whether the result is mechanically driven by the fact that larger establishments may be more likely to locate near wealthier neighborhoods, I also control for the income level and the skill mix of the neighborhoods the establishments are located. The results remain. This provides some validation that larger restaurants and grocery stores may be plausibly higher-quality.

E.2 Quality/Size-Adjusted Price Index

Based on such assumption, I proceed to augment the amenity choice model with a quality coefficient which differs by establishment size: λ_{kj}, such that the price index for amenity type k is:

$$P_k = \left(\sum_{j=1}^{J_k} \left(\frac{p_{kj}}{\lambda_{kj}} \right)^{1-\sigma_k} \right)^{1/(1-\sigma_k)}$$

In the data, slightly less than half of the restaurant establishments are those that employ 4 or fewer workers. Slightly more than half of the grocery establishments are those that employ 4 or fewer workers. Therefore, for the sake of the analysis, I will classify establishments with 5 or more employees as large establishments and assume that they offer a fixed percentage higher quality of service. I let $\lambda_{kj} = 1.2$ if j is a large establishment (5 employees or more) and $\lambda_{kj} = 1$ if j is a small establishment (fewer than 5 employees). This assumption sets the quality of large establishments to be 20% higher than small establishments. Based on that assumption, I can write the price index as follows:

$$P_k = \left(\sum_{j \in S} p_{kj}^{1-\sigma_k} + \left(\frac{1}{1.2} \right)^{1-\sigma_k} \sum_{j \in L} p_{kj}^{1-\sigma_k} \right)^{1/(1-\sigma_k)}$$

Using the adjusted price index, I re-calculate the access inequality for restaurants and grocery stores, separately. Table A10 shows the access inequality between the high- and low-skilled residents (in equivalent log-income terms) in 2000 as well as how the inequality changed from 2000 to 2010. I plot two rows of results for each amenity type, one under the case of $\lambda_{kj} = 1$ for all amenities (both large and small) and one under the case of $\lambda_{kj} = 1.2$ if establishments are large. Note that if I assume $\lambda_{kj} = 1$ for all amenities, the access inequality is identical to the one shown in Table 5, which is the baseline number.

We can see that the access inequality in either 2000 or 2010 is not significantly different under the two assumptions on λ_{kj}, within a 5% difference for restaurant amenities and within 7% difference for grocery amenities.

F Welfare Exercise - Gains from Variety vs. Saving from Travel Time

One key exercise in Couture (2016) is that he tries to distinguish how much the welfare gain from living in higher-density neighborhoods is due to the gain in access to more variety of amenity venues and how much of the gain is the due to the reduction in travel time with more convenient access to amenities. To put my welfare analysis in the context of his analysis, I conduct an additional exercise, in which I decompose the access inequality between the high- and low-skilled groups into components driven by the differential access to variety and components driven by differential travel time to amenities.

In the exercise, I want to separate how much the spatial variation in the price index is driven by the travel time or by the access to variety. I decompose them statistically.

First, I compute the price index for each type of amenities for each census tract for each demographic type (by age and education).

Then, I use the model to compute the predicted mean travel time $\hat{t}$ for residents for each type of amenities for each census tract for each demographic type.

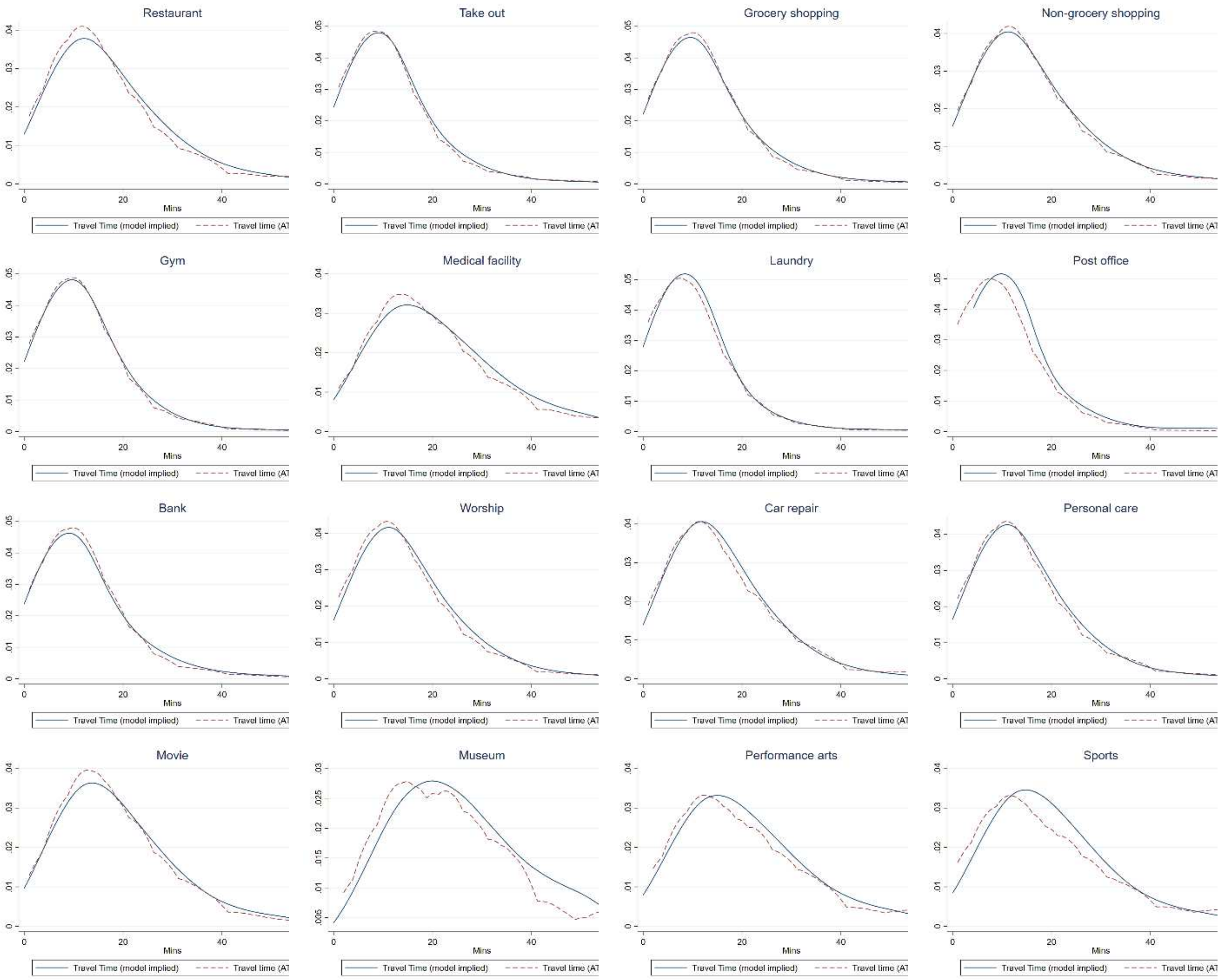
Among each demographic type and amenity type, I run the following regression:

$$\ln(P_{ick}) = \alpha_k + \beta_k \hat{t}_{ick} + \varepsilon_{ick}$$

Then, the variation predicted by the intercept and mean travel time captures the component of the price index driven by the variation in travel time, and ε_{ick} captures the variation in the price index that is due to the variation in the access to variety. Based on this exercise, I re-calculate the access inequality driven by the variation in travel time in 2000 and 2010, and I present the results in Table A9. The access inequality driven by the differential travel costs is around 12% of the overall access inequality to consumption amenities. Compared to Couture (2016), the number is small. However, it makes sense given that Couture's number is comparing between neighborhoods with the highest density and neighborhoods with the lowest density. Travel time is likely much higher in a very sparse setting than in an extremely compact setting. However, for my exercise, the comparison is between the average high-skilled resident's neighborhood vs. the average low-skilled resident's neighborhood. Variety seems to matter more in my comparison. In addition, my exercise includes all 16 types of amenities, while Couture's exercise only includes restaurants.

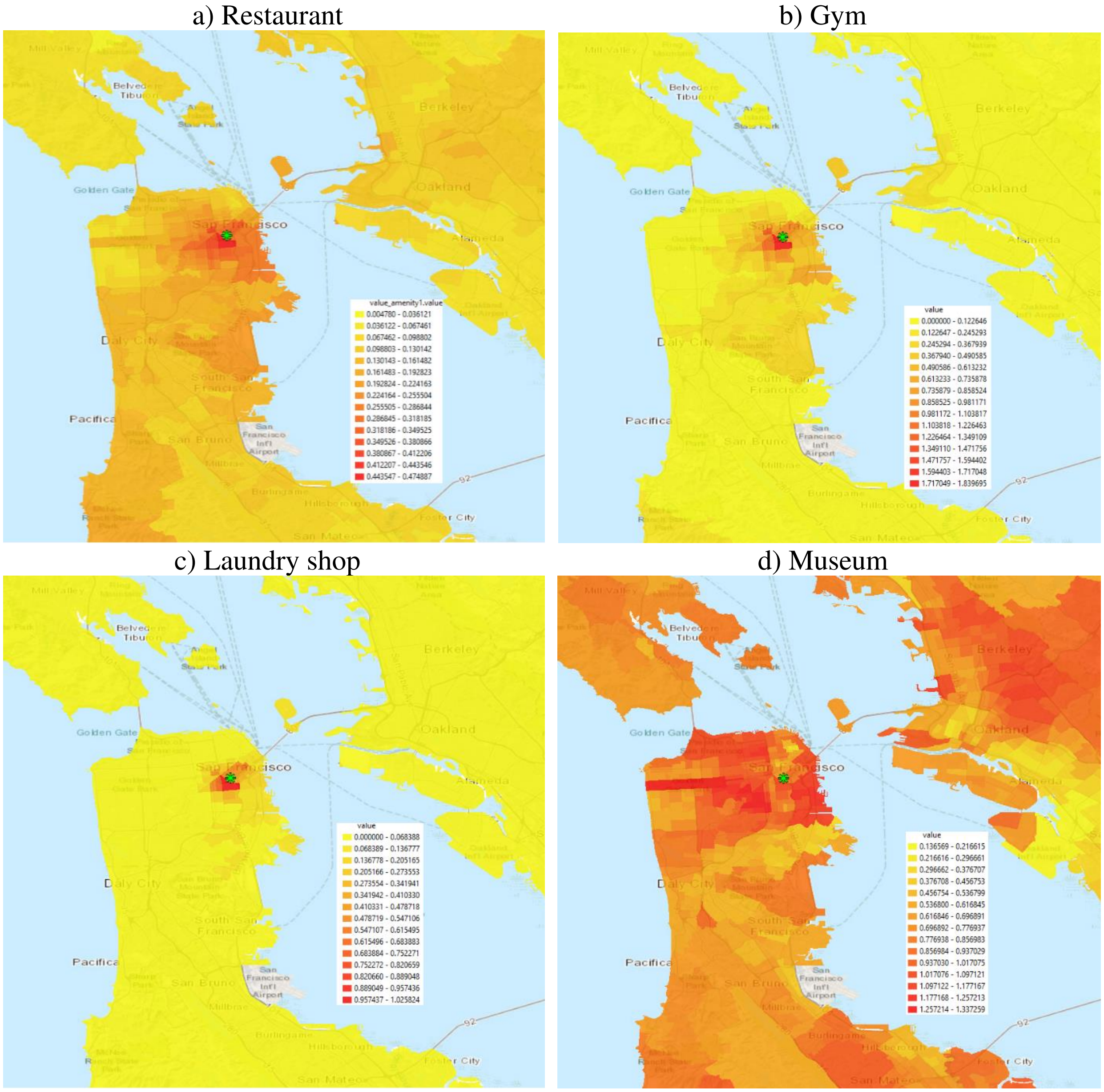
Figures and Tables for Appendix

Figure A1: Model-Implied Travel Time Distributions and the ATUS Data



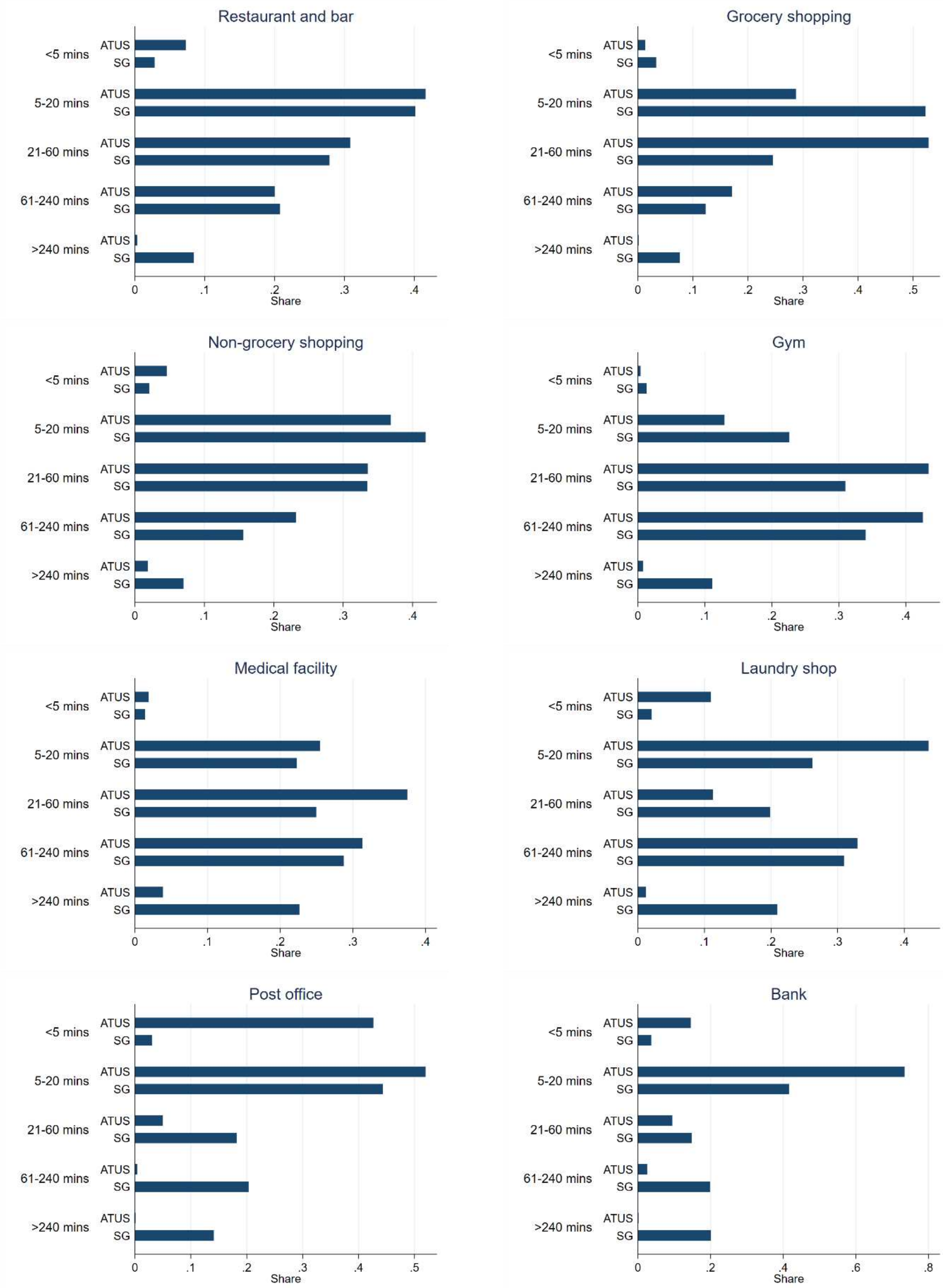
Notes: The dashed lines represent the travel time densities observed in the American Time Use Survey (ATUS). The solid lines represent the travel time densities implied by the amenity choice model. The σ estimates are based on cost of visits inclusive of the monetary costs. The density uses Epanechnikov kernel with bandwidth of 5.

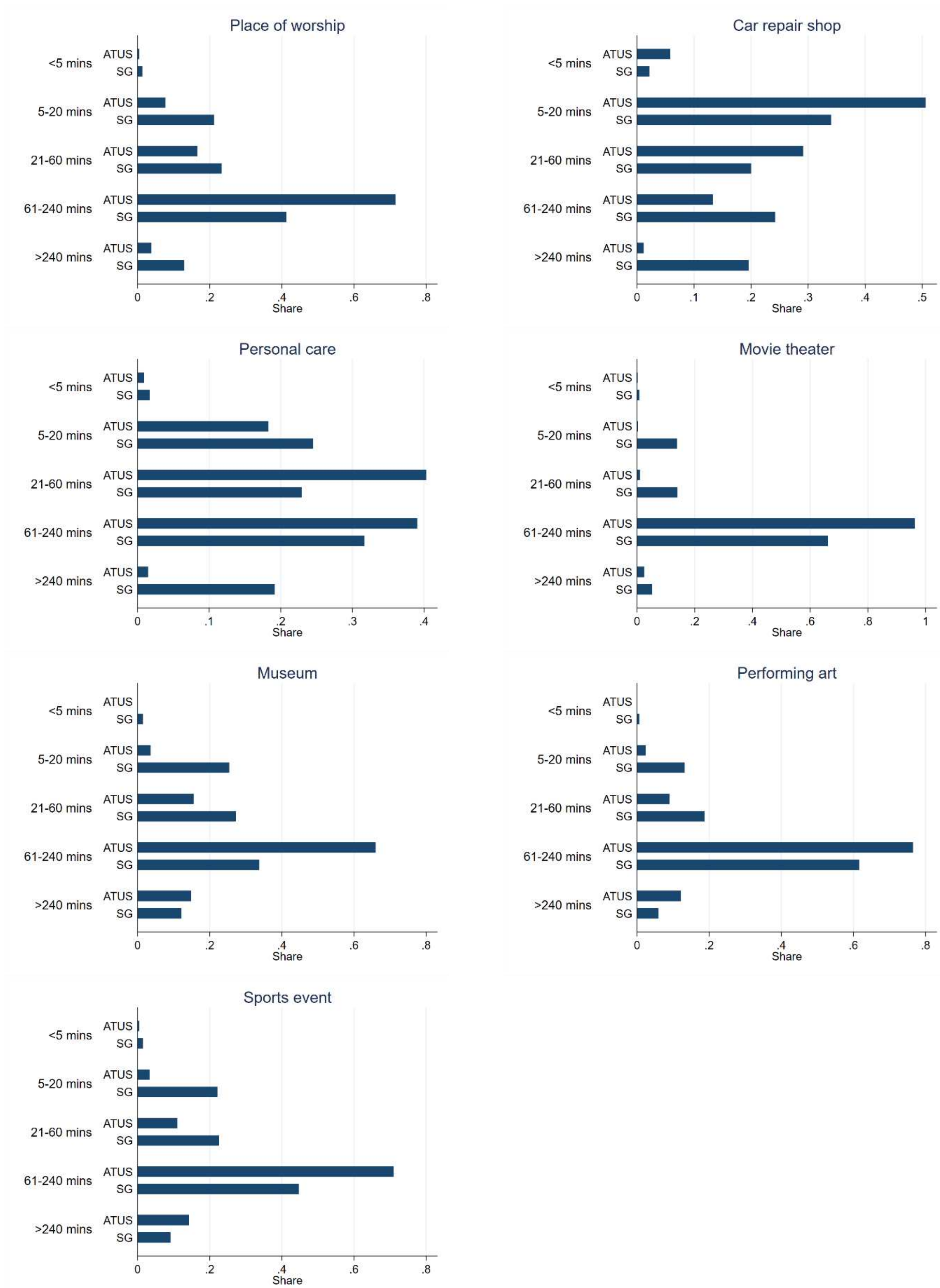
Figure A2: The Geography of Spatial Diffusion of Marginal Amenity in Zip Code 94103



Notes: The asterisk presents the target zip code (94103) where an additional establishment is added. For each respective amenity type, I compute the treatment effect on the price indexes for each of the four age/education group. I use the change in price indexes to compute the treatment effect on utility, and I calculate the welfare value of the treatment as the equivalent income increment that results in the same increase in utility. The values plotted on the map are the welfare value of the amenity treatment averaged over the four age/education group living in each census tract.

Figure A3: Comparison between ATUS and SafeGraph – Histogram of duration of visits

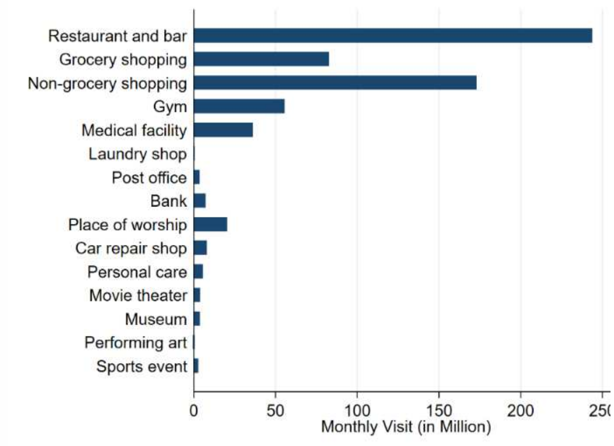




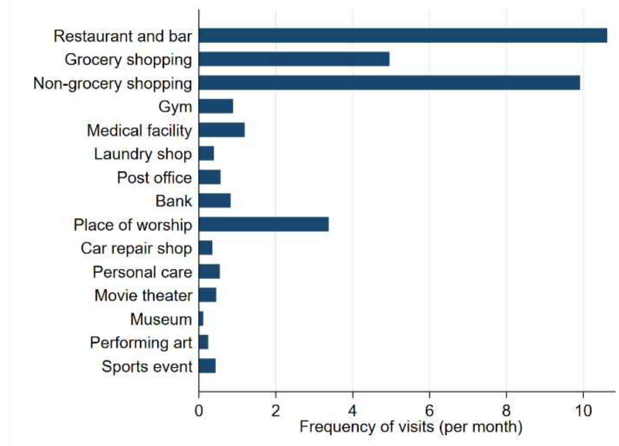
Notes: This set of graphs show the distribution of amenity visitors by the dwell time at the destination locations. The values shown are the shares of total visitors observed in ATUS or SafeGraph (SG) data whose dwell time fall in the designated bins.

Figure A4: SafeGraph Total Number of Visits to Amenities vs. ATUS Frequency of Visits

a) SafeGraph



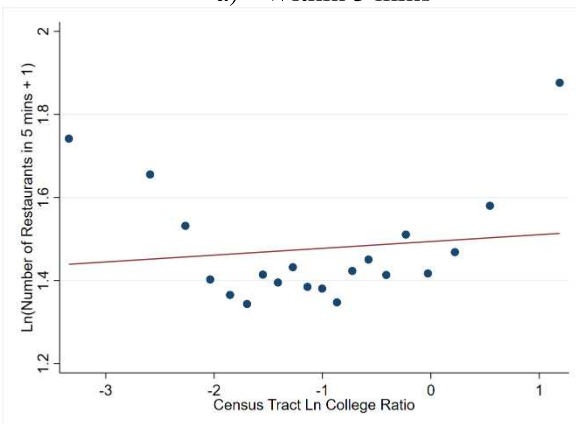
b) ATUS



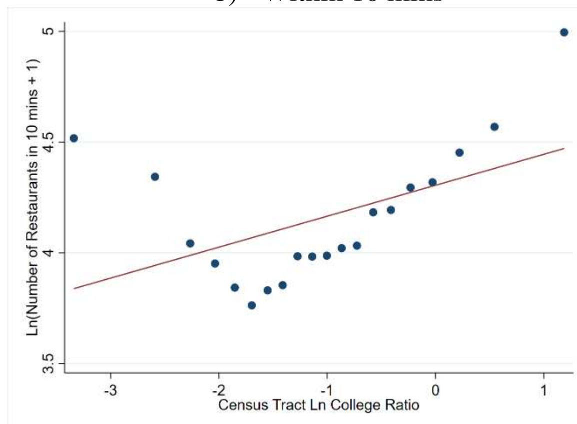
Notes: The bar graph on the left shows the total monthly visits recorded in the SafeGraph data in the month of December in 2019 by amenity category. The amenity category is defined by the crosswalk introduced in the appendix linking the NAICS code and the names of the categories. The category "Takeout" shown in Figure 3 is removed because the amenity establishments involved are the same as "Restaurant and bar". The bar graph on the right shows the frequency of visits by amenity type in the ATUS data.

Figure A5: Binned Scatterplot of Ln Restaurants on Local College Ratio

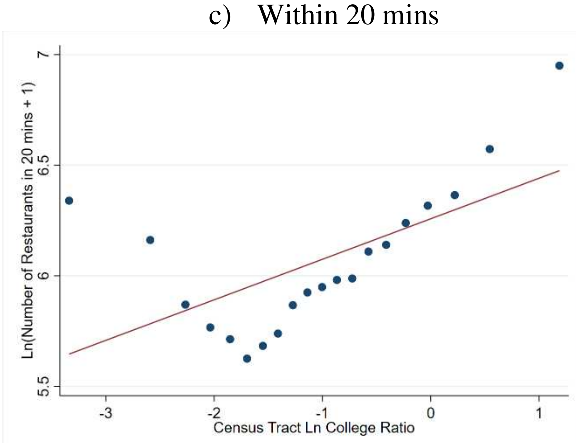
a) Within 5 mins



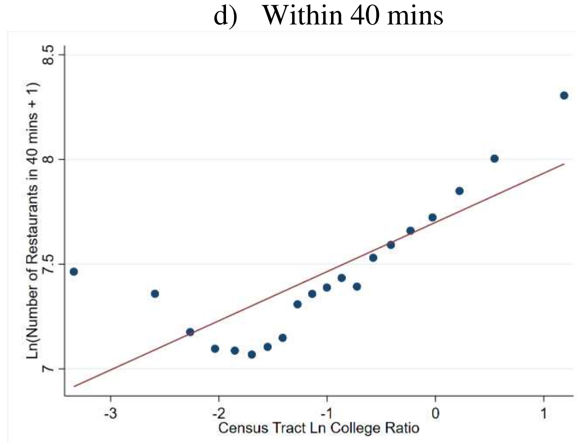
b) Within 10 mins



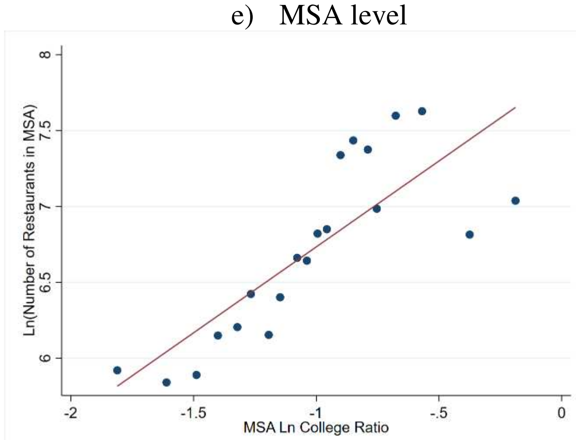
c) Within 20 mins



d) Within 40 mins



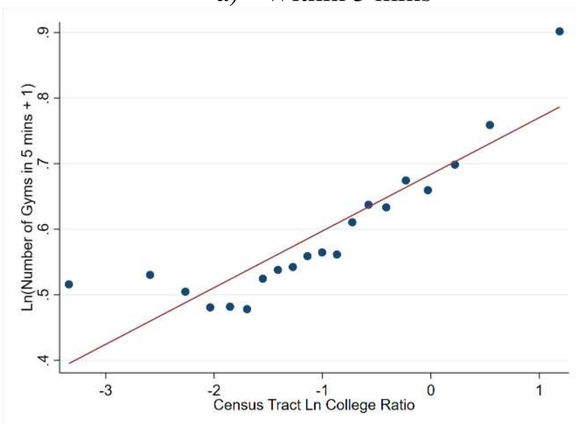
e) MSA level



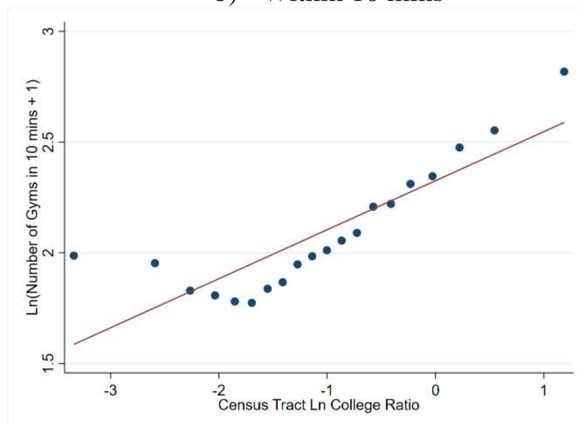
Notes: In subfigure a) – d), I show the binned scatterplot between the log of the number of restaurants plus one located within 5 mins, 10 mins, 20 mins, and 40 mins of each census tract against the log ratio between the number of college-educated residents and the number of non-college-educated residents of each census tract. Note that since many census tracts have zero restaurants nearby, I add one before taking log. In subfigure e), I show the binned scatterplot between the log of the number of restaurants in each MSA against the MSA's log college ratio.

Figure A6: Binned Scatterplot of Ln Gyms on Local College Ratio

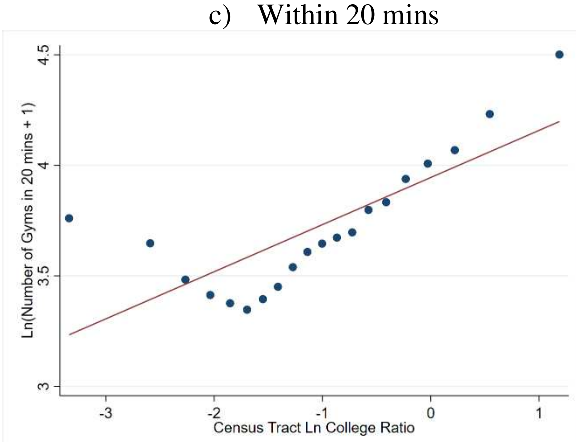
a) Within 5 mins



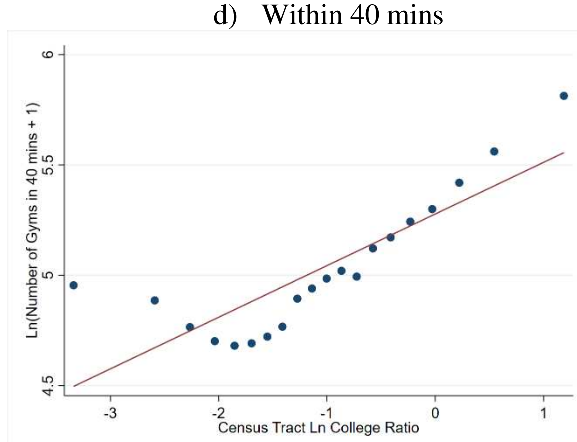
b) Within 10 mins



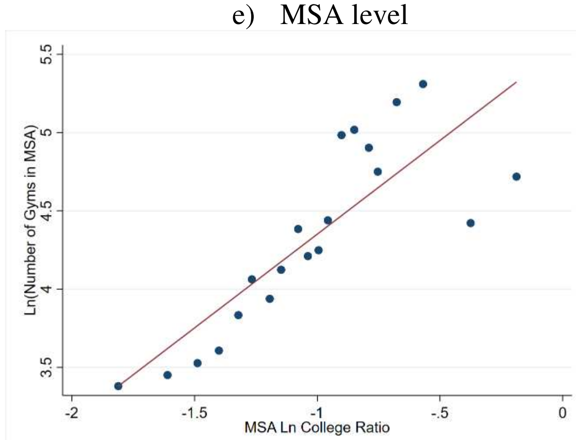
c) Within 20 mins



d) Within 40 mins



e) MSA level



Notes: In subfigure a) – d), I show the binned scatterplot between the log of the number of gyms plus one located within 5 mins, 10 mins, 20 mins, and 40 mins of each census tract against the log ratio between the number of college-educated residents and the number of non-college-educated residents of each census tract. Note that since many census tracts have zero gyms nearby, I add one before taking log. In subfigure e), I show the binned scatterplot between the log of the number of gyms in each MSA against the MSA's log college ratio.

Table A1: Mapping ATUS Activities and NHTS Trip Purposes to Common Categories: 2017

Common Category	ATUS (all sample)	NHTS (2017)
Restaurant	Restaurant and Take-out	Trip purpose: 13
Grocery/Non-grocery	Grocery or non-grocery	Trip purpose: 11
Gym/Exercise/Sports	Gym	Trip purpose: 16
Medical	Medical	Trip purpose: 18
Buy services	Laundry shop, post office, bank, car repair, or personal care	Trip purpose: 12
Religion	Worship	Trip purpose: 19
Entertainment	Movie, museum, park (doing recreational activities (activity >= 120301 and activity <= 120399) outdoors away from home (where =109)), or socializing and communicating with others (activity = 120101) away from anyone's home or workplace (where does not = 101, 102, 103)	Trip purpose: 15

Notes: This table explains the definitions of the common categories used for comparison between the ATUS activities and the NHTS trips. Since the definitions of trip purposes change from 2009 to 2017, I define the common categories separately for 2017, which I show in this table. "Whyto" and "whyfrom" in the NHTS data contain the trip purpose codes shown in the table.

Table A2: Mapping ATUS Activities and NHTS Trip Purposes to Common Categories: 2001 and 2009

Common Category	ATUS (all sample)	NHTS (2001/2009)
Restaurant	Restaurant and Take-out	Trip purpose: 80, 82, or 83
Grocery/Non-grocery	Grocery or non-grocery	Trip purpose: 40 or 41
Gym/Exercise/Sports	Gym	Trip purpose: 51
Medical	Medical	Trip purpose: 30
Buy Services	Laundry shop, bank, or post office	Trip purpose: 42
Personal Care	Personal care	Trip purpose: 63 or 64
Religion	Worship	Trip purpose: 22
Entertainment	Movie, performing arts, or socializing and communicating with others (activity = 120101) away from anyone's home or workplace (where does not = 101, 102, 103)	Trip purpose: 54
Museum/Library	Museum, library (where = 110) or park (doing recreational activities (activity >= 120301 and activity <=120399) outdoors away from home (where =109)).	Trip purpose: 55

Notes: This table explains the definitions of the common categories used for comparison between the ATUS activities and the NHTS trips. Since the definitions of trip purposes change from 2009 to 2017, I define the common categories separately for 2001 and 2009, which I show in this table. "Whyto" and "whyfrom" in the NHTS data contain the trip purpose codes shown in the table.

Table A3: Comparison of Travel Time in ATUS and NHTS

Type		2017 NHTS Definition		2001/2009 NHTS Definition	
		ATUS	NHTS	ATUS	NHTS
Restaurant	Mean	17.01	18.39	17.01	17.07
	SD	22.39	26.61	22.39	19.40
Grocery/Non-Grocery	Mean	12.76	17.61	12.76	16.28
	SD	10.87	24.80	10.87	18.42
Gym/Exercise/Sports	Mean	11.86	15.62	11.86	19.09
	SD	8.61	17.03	8.61	21.00
Medical	Mean	23.10	28.66	23.10	25.30
	SD	19.72	28.38	19.72	25.69
Buy services (2017 NHTS)	Mean	13.47	16.78	-	-
	SD	12.80	19.90	-	-
Buy services (2001/2009 NHTS)	Mean	-	-	10.83	12.91
	SD	-	-	9.33	13.38
Personal Care	Mean	-	-	14.60	14.76
	SD	-	-	11.15	14.10
Religion	Mean	15.52	17.63	15.52	14.91
	SD	15.92	20.17	15.92	13.35
Entertainment (2017 NHTS)	Mean	26.32	28.85	-	-
	SD	46.46	46.09	-	-
Entertainment (2001/2009 NHTS)	Mean	-	-	25.65	24.61
	SD	-	-	44.81	32.12
Museum/Library	Mean	-	-	19.44	25.75
	SD	-	-	33.43	38.88

Notes: Travel time includes trips between the destinations and home. The panel headed by “2017 NHTS Definition” compares the travel time across the common amenity categories defined specifically for the 2017 NHTS sample. The panel headed by “2001/2009 NHTS Definition” compares the travel time across the common amenity categories defined for the 2001 and 2009 NHTS. The entire ATUS 2003-2015 sample is used for both panels. The common amenity categories are defined in Table A1 and A2.

Table A4: Comparison of Frequency of Visits in ATUS and NHTS

	2017 NHTS Definition		2001/2009 NHTS Definition	
Type	ATUS	NHTS	ATUS	NHTS
Restaurant	10.66	8.93	10.66	8.08
Grocery/Non-Grocery	14.76	16.04	14.76	18.23
Gym/Exercise/Sports	0.89	3.71	0.89	4.35
Medical	1.19	1.83	1.19	2.03
Buy services (2017 NHTS)	2.09	2.57	-	-
Buy services (2001/2009 NHTS)	-	-	1.77	4.13
Personal Care	-	-	0.54	1.27
Religion	3.37	2.81	3.37	2.22
Entertainment (2017 NHTS)	4.61	4.28	-	-
Entertainment (2001/2009 NHTS)	-	-	4.75	2.31
Museum/Library	-	-	1.00	0.60
	-	-		

Notes: The frequency of visits are monthly. The panel headed by “2017 NHTS Definition” compares the frequency of visits across the common amenity categories defined specifically for the 2017 NHTS sample. The panel headed by “2001/2009 NHTS Definition” compares the frequency of visits across the common amenity categories defined for the 2001 and 2009 NHTS. The entire ATUS 2003-2015 sample is used for both panels. The common amenity categories are defined in Table A1 and A2.

Table A5: Comparison of Dwell Time in ATUS and NHTS

Type		2017 NHTS Definition		2001/2009 NHTS Definition	
		ATUS	NHTS	ATUS	NHTS
Restaurant	Mean	39.18	45.03	39.18	48.04
	SD	37.92	44.37	37.92	51.10
Grocery/Non-Grocery	Mean	45.53	35.78	45.53	38.39
	SD	46.89	38.52	46.89	47.75
Gym/Exercise/Sports	Mean	59.75	74.96	59.75	79.05
	SD	40.49	64.40	40.49	97.67
Medical	Mean	59.64	84.53	59.64	72.84
	SD	65.03	80.17	65.03	77.05
Buy services (2017 NHTS)	Mean	35.22	31.74	-	-
	SD	45.16	44.29	-	-
Buy services (2001/2009 NHTS)	Mean	-	-	19.45	18.01
	SD	-	-	34.14	38.06
Personal Care	Mean	-	-	60.42	73.42
	SD	-	-	48.60	73.42
Religion	Mean	92.77	120.61	92.77	122.19
	SD	63.16	81.18	63.16	77.43
Entertainment (2017 NHTS)	Mean	71.88	147.74	-	-
	SD	78.02	112.35	-	-
Entertainment (2001/2009 NHTS)	Mean	-	-	76.99	142.59
	SD	-	-	81.65	111.12
Museum/Library	Mean	-	-	75.39	89.31
	SD	-	-	76.35	100.24

Notes: The dwell time is the reported time spent at destination during each visit (in minute). The panel headed by "2017 NHTS Definition" compares the dwell time across the common amenity categories defined specifically for the 2017 NHTS sample. The panel headed by "2001/2009 NHTS Definition" compares the dwell time across the common amenity categories defined for the 2001 and 2009 NHTS. The entire ATUS 2003-2015 sample is used for both panels. The common amenity categories are defined in Table A1 and A2.

Table A6: Relationship between establishment sizes and visitor profiles

	Log Number of Visitors							
	Restaurants and Bars				Grocery Stores			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log Avg Residence Median Income of Visitors	1.139***		0.748***	0.301***	0.680***		0.0313	0.0427**
	(0.0198)		(0.0291)	(0.0189)	(0.0258)		(0.0373)	(0.0200)
Log Residence College Share of Visitors		0.752***	0.392***	0.056***		0.651***	0.637***	0.101***
		(0.0133)	(0.0197)	(0.0127)		(0.0162)	(0.0231)	(0.0136)
Amenity Establishment Tract FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Observations	676,552	676,557	676,550	683,332	250,735	250,741	250,733	263,321

Notes: Each observation of the regression represents an establishment. Column (1) – (4) include restaurants and bars. Column (5) – (8) include grocery stores. The outcomes of the regressions are the log number of visitors to each establishment in a month. The regressor "Log Avg Residence Median Income of Visitors" is the average of the visitors' home census tracts' median income. The regressor "Log College Share of Visitors" is the average of the visitors' home census tracts' share of college-educated residents. I also include a fixed effect for the census tract in which the amenity establishment is located in for all columns, except column (4) and (8).

Table A7: Estimates for the taste parameters θ_k, no monetary or time cost at destination

	Overall	<40 and with college degree	<40 and without college degree	>=40 and with college degree	>=40 and without college degree
Restaurant and bar	1.60***	2.08***	1.56***	1.91***	1.39***
	(0.0069)	(0.0223)	(0.0138)	(0.0160)	(0.0102)
Takeout	0.52***	0.66***	0.64***	0.54***	0.41***
	(0.0032)	(0.0105)	(0.0070)	(0.0071)	(0.0045)
Grocery shopping	0.74***	0.78***	0.60***	0.89***	0.76***
	(0.0039)	(0.0118)	(0.0072)	(0.0091)	(0.0061)
Non-grocery shopping	1.99***	2.16***	1.92***	2.30***	1.89***
	(0.0067)	(0.0200)	(0.0133)	(0.0149)	(0.0102)
Gym	0.13***	0.24***	0.12***	0.20***	0.07***
	(0.0017)	(0.0070)	(0.0034)	(0.0047)	(0.0020)
Medical facility	0.42***	0.26***	0.28***	0.47***	0.53***
	(0.0048)	(0.0114)	(0.0079)	(0.0112)	(0.0084)
Laundry shop	0.05***	0.04***	0.05***	0.05***	0.04***
	(0.0010)	(0.0028)	(0.0020)	(0.0023)	(0.0014)
Post office	0.07***	0.04***	0.03***	0.10***	0.09***
	(0.0012)	(0.0028)	(0.0017)	(0.0030)	(0.0022)
Bank	0.12***	0.10***	0.10***	0.14***	0.12***
	(0.0016)	(0.0046)	(0.0030)	(0.0040)	(0.0026)
Place of worship	0.66***	0.51***	0.51***	0.72***	0.77***
	(0.0043)	(0.0115)	(0.0077)	(0.0098)	(0.0072)
Car repair shop	0.07***	0.08***	0.06***	0.10***	0.07***
	(0.0016)	(0.0050)	(0.0028)	(0.0040)	(0.0023)
Personal care	0.10***	0.13***	0.08***	0.13***	0.09***
	(0.0017)	(0.0058)	(0.0032)	(0.0043)	(0.0026)
Movie theater	0.12***	0.16***	0.17***	0.13***	0.07***
	(0.0022)	(0.0076)	(0.0053)	(0.0051)	(0.0026)
Museum	0.05***	0.13***	0.04***	0.09***	0.02***
	(0.0021)	(0.0094)	(0.0037)	(0.0057)	(0.0022)
Performance arts	0.07***	0.10***	0.06***	0.11***	0.05***
	(0.0018)	(0.0066)	(0.0033)	(0.0051)	(0.0024)
Sports event	0.12***	0.15***	0.17***	0.13***	0.08***
	(0.0024)	(0.0077)	(0.0056)	(0.0054)	(0.0030)

Notes: The reported values are estimates for the taste parameters θ_k for the 16 types of amenities. All estimates are percentage points ($\theta_k \times 100$). Standard errors reported in parentheses. For the estimates in the first column (overall estimates), I normalize θ_k with overall mean income taken from the ACS 2007-2011, $50,403.01. For the estimates in the other columns, I normalize θ_k with mean income measures for each subgroup taken from the ACS 2007-2011. For <40 age & college, I use $60,537.11 as the mean income measure; for <40 and without college degree, $26,766.26; for >=40 and with college degree, $96,316.36; for >=40 and without college degree, $44,867.46.

Table A8: Estimates for the taste parameters θ_k with value of time ½ of prevailing wage

	Overall	<40 and with college degree	<40 and without college degree	>=40 and with college degree	>=40 and without college degree
Restaurant and bar	4.437***	5.466***	5.614***	4.352***	3.976***
	(0.019)	(0.058)	(0.050)	(0.036)	(0.029)
Takeout	1.369***	1.579***	2.646***	0.961***	1.149***
	(0.008)	(0.025)	(0.029)	(0.013)	(0.013)
Grocery shopping	1.556***	1.634***	1.261***	1.868***	1.598***
	(0.008)	(0.025)	(0.015)	(0.019)	(0.013)
Non-grocery shopping	3.714***	4.026***	3.584***	4.299***	3.535***
	(0.012)	(0.037)	(0.025)	(0.028)	(0.019)
Gym	0.575***	1.002***	0.738***	0.722***	0.314***
	(0.008)	(0.029)	(0.020)	(0.017)	(0.009)
Medical facility	1.390***	0.797***	1.378***	1.119***	1.854***
	(0.016)	(0.035)	(0.039)	(0.026)	(0.029)
Laundry shop	0.196***	0.173***	0.266***	0.189***	0.188***
	(0.004)	(0.011)	(0.011)	(0.008)	(0.006)
Post office	0.065***	0.037***	0.029***	0.086***	0.083***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Bank	0.143***	0.127***	0.119***	0.174***	0.150***
	(0.002)	(0.006)	(0.004)	(0.005)	(0.003)
Place of worship	1.981***	1.556***	1.534***	2.164***	2.322***
	(0.013)	(0.035)	(0.023)	(0.030)	(0.022)
Car repair shop	0.776***	0.792***	1.052***	0.622***	0.783***
	(0.017)	(0.047)	(0.051)	(0.025)	(0.027)
Personal care	0.473***	0.545***	0.568***	0.446***	0.458***
	(0.008)	(0.025)	(0.022)	(0.015)	(0.013)
Movie theater	0.447***	0.593***	0.768***	0.461***	0.257***
	(0.009)	(0.029)	(0.024)	(0.018)	(0.010)
Museum	0.105***	0.246***	0.091***	0.164***	0.049***
	(0.004)	(0.018)	(0.008)	(0.011)	(0.004)
Performance arts	0.224***	0.323***	0.185***	0.350***	0.164***
	(0.006)	(0.021)	(0.011)	(0.016)	(0.008)
Sports event	0.426***	0.508***	0.665***	0.445***	0.284***
	(0.008)	(0.027)	(0.022)	(0.018)	(0.011)

Notes: The reported values are estimates for the taste parameters θ_k for the 16 types of amenities. All estimates are percentage points ($\theta_k \times 100$). Standard errors reported in parentheses. For the estimates in the first column (overall estimates), I normalize θ_k with overall mean income taken from the ACS 2007-2011, $50,403.01. For the estimates in the other columns, I normalize θ_k with mean income measures for each subgroup taken from the ACS 2007-2011. For <40 age & college, I use $60,537.11 as the mean income measure; for <40 and without college degree, $26,766.26; for >=40 and with college degree, $96,316.36; for >=40 and without college degree, $44,867.46.

Table A9: Access Inequality – Robustness Checks

	Unit: 100 × ln (V)			
	2000	2010	2000 - 2010	% 2000-2010
Value of Time ½ of Wage	0.542	0.604	+ 0.0621	+ 11.46%
Monetary Cost, Time at Destination Excluded	0.926	1.065	+ 0.139	+ 15.01%
Cross-MSA Spatial Segregation Only	0.54772	0.66514	+ 0.1174	+ 21.44%
Due to Change in Travel Time	0.1099	0.09959	- 0.0103	- 9.38%

Notes: I compute the access inequality to amenities between high-skilled and low-skilled residents. The residents include those aged between 25 and 65. High-skilled residents are defined as residents with college degrees, and low-skilled residents are defined as residents with no college degrees. Access inequality is calculated as the difference between the counterfactual mean utility of low-skilled residents if they are spatially distributed in the same way as high-skilled residents and the mean utility of low-skilled residents based on their actual spatial distribution. The first row presents robustness check of the baseline results in Table 4 where I reduce the value of time γ to ½ of the prevailing wage. The second row presents the robustness check of the baseline results in Table 4 in which I exclude the monetary cost and the time spent at destinations. In the third row, I remove the difference in spatial distribution between neighborhoods by assuming the high- and low-skilled populations have the same cross-neighborhood distribution. But I allow the population distribution across MSAs to be given by the data. In the fourth row, I present the results from the welfare decomposition exercise where I compute the access inequality driven by the differential travel time implied by the model.

Table A10: Access Inequality to Restaurants/Bars and Grocery Stores – Quality Varying by Size

		Unit: 100 × ln (V)			
		2000	2010	2000 - 2010	% 2000-2010
Restaurant and bar	λ=1	0.229	0.261	+ 0.0312	+ 13.59%
	λ=1.2	0.232	0.260	+ 0.0274	+ 11.79%
Grocery Shopping	λ=1	0.072	0.081	+ 0.0094	+ 13.07%
	λ=1.2	0.075	0.086	+ 0.0108	+ 14.32%

Notes: I compute the access inequality to amenities between high-skilled and low-skilled residents. The residents include those aged between 25 and 65. High-skilled residents are defined as residents with college degrees, and low-skilled residents are defined as residents with no college degrees. Access inequality is calculated as the difference between the counterfactual mean utility of low-skilled residents if they are spatially distributed in the same way as high-skilled residents and the mean utility of low-skilled residents based on their actual spatial distribution. I show the access inequality and its change for restaurant/bar and grocery stores. For each amenity type, I allow λ to take either 1 or 1.2. In the case of λ=1, the numbers are the same as in Table 5. Large establishment is defined as establishment with 5 or more employees.

Table A11: Log Count as Alternative Measurement of Access – Access Inequality

		Unit: Log (Count + 1)			
		2000	2010	2000 - 2010	% 2000-2010
Restaurant and bar	5 Mins	0.0317	0.0608	+ 0.0291	+ 92%
	10 Mins	0.1948	0.2182	+ 0.0233	+ 11.97%
	20 Mins	0.2377	0.2636	+ 0.0260	+ 10.93%
	40 Mins	0.2616	0.2948	+ 0.0332	+ 12.69%
Gym	5 Mins	0.0855	0.0989	+ 0.0134	+ 15.70%
	10 Mins	0.2400	0.2575	+ 0.0175	+ 7.30%
	20 Mins	0.2421	0.2710	+ 0.0289	+ 11.93%
	40 Mins	0.2458	0.2841	+ 0.0383	+ 15.59%

Notes: I compute the log count of the establishments (plus one to avoid log of zero) within 5 mins, 10 mins, 20 mins, and 40 mins of each census tract. I then compute the average log count exposed to college-educated and non-college educated population weighted by census tract level population in 2000 and 2010. Then I compute the difference between the average log count by college-educated population and the non-college educated population, as well as the change in the difference over time from 2000 to 2010. I report the results of the exercise for restaurants and bars as well as gyms.