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

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Abstract

Assessing the value of consumption amenities is faced with two challenges. First, because the value of local consumption amenities, such as restaurants, often extends to residents living beyond the immediate vicinity of the amenities, researchers must account for how the amenity benefits diffuse through space. Second, to evaluate how each type of amenity affects each location's overall amenity value, researchers must identify residents' preferences for each of the amenity types. I present a model of amenity choice that micro-founds spatial diffusion and amenity preferences. The model empirically links these features to visiting patterns, which are observable in the time-use data. I demonstrate that correctly accounting for spatial diffusion is important for accurately measuring consumption amenities' role in welfare inequality.

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1 Introduction

There has been growing evidence that spatial differences in the access to consumption amenities have a great impact on local residents' welfare and welfare inequality (Glaeser, Kolko, and Saiz (2000), Diamond (2016), Hoelzlein (2019), Almagro and Dominguez-Iino (2020), Couture and Handbury (2020), Couture, Gaubert, Handbury, and Hurst (2020), Su (2020)). However, despite growing recognition of the importance of consumption amenities in local residents' welfare, measuring the value of consumption amenities for residents remains difficult. Existing exercises often lack proper micro-foundations and typically use the count of amenity establishments to measure the level of amenity provision for residents living nearby.[1] Researchers would then determine the value of amenity provision by examining housing demand differentials across locations with different amenity provision levels (Oates (1969), Brueckner (1979), Yinger (1982), Epple (1987), Gyourko and Tracy (1989), Black (1999), Bayer, Ferreira, McMillan (2007), Albouy (2012)). While these methods may be suitable for evaluating amenities with well-defined spatial delineation such as school districts, they may face serious challenges evaluating the value of *consumption amenities* due to the following challenges:

First, the value of consumption amenities is *spatially diffused* (Glaeser, Kominers, Luca, and Naik (2016)). Take restaurants as an example. Because people often travel to a variety of different restaurants at a distance and not just the restaurants right next door, the value of a restaurant would likely diffuse beyond its immediate vicinity.[2] Moreover, the value of different types of amenities likely diffuses at *different rates*. While residents may value a restaurant at a long distance, they may not value a gym located in the same distance if residents only visit gyms closest to them. Because of the varying rates of spatial diffusion of consumption amenities, a simple count of amenity establishments either in the immediate neighborhood or in the entire metropolitan area will create a distorted representation of the level of amenity provision available to residents.

The second challenge is that, because residents value different types of consumption amenities differently, evaluating the overall value of consumption amenities requires appropriate *aggregation* weights to reflect residents' different valuations of different amenity types. Since there are a number of amenity types, researchers often lack enough spatial variation to separately identify how each type of amenity is valued by residents.

In my paper, I overcome both challenges by taking an alternative approach. I study

[1] Hoelzlein (2019) is a notable exception.

[2] 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.

people's usage of time interacting with different types of amenities and use the patterns of their time-use to recover the rates of spatial diffusion and aggregation weights using an amenity choice model. I motivate my approach by first documenting people's travel time to and from each type of amenity venue, frequencies of visits, and duration of visits.[3]

First, I find that the travel time to and from amenities is often very short for visiting certain amenities like gyms but longer for visiting other amenities like restaurants. The difference in travel time suggests that amenities like gyms are mostly valued by residents living nearby, while the value of other amenities like restaurants diffuses over a broader area. I argue that the different spatial diffusion of amenities can be explained by the different degrees of substitutability for venues within each amenity type. For example, gyms tend to serve a well-defined function and thus are largely substitutable with one another. Given the high substitutability among gyms, residents would likely choose to visit the gyms with the lowest cost of visits, namely the closest gyms. In contrast, the variety and styles of restaurants can be highly idiosyncratic. As a result, restaurants may be less substitutable with one another than gyms. Given the lower substitutability, residents would be less sensitive to the distance to restaurants.

Next, I find that people visit some amenities like restaurants much more frequently than other amenities like car repair shops. The heterogeneity in the frequencies of visits, by revealed preference, suggests that people value the provision of certain types of amenities more than they value others.[4]

Motivated by the documented patterns of time-use, I construct a model of amenity choice which allows residents at each location to choose a bundle of visits to amenities available to them based on their tastes for each type of amenities, the elasticities of substitution between amenity establishments, and price of visits to the establishments (travel time and monetary cost). Importantly, by allowing the elasticities of substitution for visiting different establishments to differ across amenity types, the model can reproduce the differing rates of spatial diffusion.

I estimate the elasticities of substitution and the tastes for different types of amenities by matching key data moments. I first construct the prices of visits to all amenity establishments for all residents based on the monetary cost of visits, duration of visits, and travel time to the amenities. I then estimate the elasticities of substitution by matching the model-predicted

[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.

[4] In this paper, I consider the term "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 amenities broadly.

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 price indexes and the frequency of visits to each type of amenities.

Equipped with the parameterized model, I show that the differential access to consumption amenities by high- and low-skilled residents contributes to the welfare inequality equivalent of 2.8% of the observed real income gap in 2000. Furthermore, with the spatial sorting of residents and consumption amenities from 2000 to 2010, welfare inequality increased by an equivalent of 2% of the concurrent increase in the observed real income gap. I only account for the differential access to consumption amenities for my welfare inequality analysis. Spatial variation in amenities such as neighborhood safety, aesthetic value, public goods such as school quality and infrastructures is not accounted for by this method.

Finally, I show that correctly accounting for spatial diffusion is important for accurately measuring consumption amenities' role in driving welfare inequality. First, I show that assuming the amenity value is restricted within the immediate neighborhoods could lead to an underestimation of the welfare inequality by skill. The result is largely driven by the fact that many high-skilled residents live in low-density developments, whose access to amenities requires a moderate travel time. Assuming away spatial diffusion could lead to a severe downward bias for the welfare of residents living close to but not right next to an abundance of amenities. Next, I show that assuming that amenity value diffuses over too broad an area could lead to an overestimation of the welfare inequality by skill. The result is partially driven by amenity sorting by local income, which leads to the clustering of amenities in high-income neighborhoods or MSAs. The abundance of amenity establishments around high-income neighborhoods or MSAs could inflate the value of amenities with actual weak spatial diffusion (such as gyms). And vice versa, around low-income neighborhoods or MSAs, the scarcity of amenity establishments could deflate the value of these amenities, leading to an overestimation of 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 different rates of spatial diffusion and the aggregation weights for different types of amenities.

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 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 various 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 activity types and amenity types.

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.

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.

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 explained if people's elasticity of substitution for restaurants is lower than the elasticity of substitution among gyms. In other words, residents value the variety of restaurants but not as much for gyms. This makes sense because gyms tend to be highly functional and relatively homogeneous across facilities, while restaurants tend to be more differentiated.

The differential valuation of variety for different types of amenities would imply that amenity benefits diffuse differently for different types of amenities. Since people are less sensitive to the cost of travel when they visit restaurants, a restaurant in a neighborhood potentially benefits residents over a broad area. In contrast, a gym may 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. The red line represents the average travel time to restaurants reported in the data. For restaurants, on average, the closest restaurants are about eight minutes away. 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 Frequencies of visits

In Figure 3, I show the frequencies of visits per month for various amenities. The frequencies of visits are extremely uneven across types of amenities. People on average visit restaurants or go shopping at very high frequencies but go to post offices or cultural sites such as museums and performing art venues at much lower frequencies. This strongly suggests that certain amenities matter more to residents than others.

Interestingly, I find striking heterogeneity in frequencies of visits 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, frequencies 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. Frequencies of visits to museums and performing art venues seem to differ mainly by education group. The strong heterogeneity suggests that preferences for each specific type of amenities are likely to differ by groups.

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.[5]

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, and thus leading to wide spatial 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 facts documented from the ATUS data, I construct a model framework to rationalize the way people choose amenities. In the model, I allow each resident to choose bundles of visit frequencies to amenity establishments to maximize utility. A resident faces a choice set that consists of all amenity establishments located within the MSA that she lives in.

[5] I also compute the duration of activities by education and age group. The duration of activities does not seem to be very different across demographic groups (education and age) in all amenity categories except laundry shops. The exception in the lengths of visiting laundry shops could be because low-skilled and low-income residents tend to visit coin laundry, while high-skilled and high-income residents tend to visit dry-cleaners, which requires significantly shorter waiting time than coin laundry, and thus the difference in durations.

3.1 Setup

Assume resident i has Cobb-Douglas utility function over the consumption of K different types of amenities and a numeraire consumption good x_0. θ_k is the Cobb-Douglas taste parameter on each composite amenity good k. Each composite good is defined as a CES aggregation of visits to amenity establishments made by resident i. x_{kj} is defined as the quantity of visits to establishment j of amenity type k. X_k measures the composite consumption within amenity type k. One could also think of X_k as the utility gained from the bundle of visits $(x_{k1}, x_{k2}, ..., x_{kJ_k})$. $\sigma_k = 1/(1-\rho_k)$ 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 amenity establishment j, she has to pay a monetary cost of visits or service price $\bar{p}_k$, which is specific to type k.[6] Moreover, visiting amenities requires time inputs: 1. time spent at the establishments h_k,[7] 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 earnings or the earning equivalent of the foregone utility of staying at home.[8]

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

[6]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.

[7]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. For a bank visit, since the time spent there tend to be short, variation in travel time to and from the bank would be relatively costly compared to visits to restaurants.

[8]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.

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 price of visiting each amenity establishment being $p_{ikj} = \bar{p}_k + \gamma \left(h_k + t_{ij} \right)$.[9][10]

The utility-maximization problem can be divided into 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.[11]

3.2 Price indexes

By solving the cost-minimization problem of a CES utility, I can 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

[9] The main caveat of this model is that some consumption amenities may not require the resident to actually visit them but are still spatially diffused. Food delivery service is a good example. Living in a neighborhood with lots of restaurants nearby could be very valuable not necessarily because of the low cost of visiting them, but also because of the availability of delivery services. Other services such as babysitting and home repair services may also only be available in areas where demand for these services is abundant. The benefits of these services are spatially diffused, but the way the amenities spatially diffuse cannot be empirically inferred from visit and travel time data. Researchers may be able to estimate the value of these amenities if they have data on who their service providers are and how far the service providers travel to deliver these services. In the setting of this paper, the consumption amenity bundle excludes these amenities.

[10] 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 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 that 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.

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

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 $p_{ikj} = \bar{p}_k + \gamma \left(h_k + t_{ij} \right)$, which is the cost of visiting each amenity establishment j, consisting of monetary service prices $\bar{p}_k$, activity time h_k, and travel time t_{ij}.

The monetary service price $\bar{p}_k$ and activity time h_k play very important roles in partially capturing the heterogeneous spatial diffusion by amenity type. If $\bar{p}_k$ and h_k are very small, say a bank errand, the cost of visiting a far-away branch of the bank would be very high on a percentage term, and the resident would be very sensitive to distance when it comes to running bank errands. On the other hand, if $\bar{p}_k$ and h_k are large, say a trip to a nice restaurant for a long meal, the relative price difference between visiting a place far away and visiting another place nearby would be small on a percentage term, and the resident would likely not be very sensitive to distance. Going back to the concept of spatial diffusion, if $\bar{p}_k$ and h_k are large, residents are likely to benefit from the availability of establishments far away due to the relatively low cost of travel on a percentage term.

The elasticity of substitution σ_k governs residents' willingness to substitute visits to farther (costlier) locations with visits to closer (cheaper) locations. One can consider it as an inverse measurement 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 are relatively unimportant. Thus, amenities associated with larger σ_k would tend to have closer 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.

3.3 Aggregation

Given the price index of each amenity type k, the resident maximizes the upper-level Cobb-Douglas utility. The aggregate indirect utility from all amenities can be written as a linear combination of negative log price indexes of various amenity types, weighted by Cobb-Douglas taste parameters θ_k. Intuitively, the lower the prices of obtaining each unit of composite amenity, the better off the resident becomes. 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 and a key aggregation weight for welfare analysis.[12]

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

In the amenity choice model, given the choice set, each value of σ_k maps precisely into a distribution of amenity choices. I derive the trip choice probability by dividing the demand (visits) for establishment j by the total demand (visits) to all establishments.[13] The probability that resident i visits establishment j in a random week is given by the following equation:

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

Given each resident's location, choice set, and the size of σ_k, the model-predicted amenity choice distribution implies a travel time distribution.[14] Given the trip choice distribution and the travel time between the residents' home and the establishment, I can compute the

[12] Note if θ_k is construed as expenditure share, the expenditure share in this context should be interpreted broadly. Recall that the price 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, spending time 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.

[13] We know the demand for visiting each amenity establishment is $x_{ikj} = \theta_k I \frac{p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{1-\sigma_k}}$. This implies the fraction of time visiting establishment j is $\Pr(j|k,i) = \frac{x_{ikj}}{\sum_{j'} x_{ikj'}} = \frac{p_{ikj}^{-\sigma_k}}{\sum_{j'} p_{ikj'}^{-\sigma_k}}$.

[14] 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 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.

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, given amenity type k, the residents' amenity choice sets, and price vectors, I can identify σ_k by matching the model-predicted mean log travel time with mean log travel time observed in the data.

4.2 Frequencies of visits

Given residents' choice set, price vectors, and the sizes of σ_k, the taste parameters θ_k can be identified by the frequencies of visits. The frequency of visits to establishment j of amenity type k is 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 establishment of amenity type k, I can represent the average 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 normalized 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 identified by the average frequency of visits $E\left(\sum_j x_{ikj}\right)$ 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, the frequency of visits by itself may underestimate the actual importance of the activity of interest.

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

5 Estimation

5.1 Data

I construct the empirical moments using a combination of time-use data, geocoded data of amenity establishments, and trip time data. I construct a price vector for visiting each amenity establishment of each type of amenity k from each census tract c. Given the price vectors, I use the model to generate predicted travel time from each census tract for each amenity type k. I estimate σ_k by matching the model-predicted moments of trip time with the observed trip time. Next, I use the price vectors, the estimated σ_k, and the frequency of visits to construct moments to estimate θ_k.

I use the American Time-Use Survey (ATUS) to measure how frequently people visit each category of amenities $\sum_j x_{kj}$, the durations of visits h_k, and the travel time before and after each visit (Hofferth, Flood, and Sobek (2018)).

I use the Consumer Expenditure Survey (CEX) data (2003-2015) to recover the monetary costs of visiting various types of service amenity establishments.[15] The CEX diary survey records households 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 data, I can see how many restaurants, gyms, movie theaters, etc. in each zip code throughout the U.S. I use Google API and the National Household Travel Survey to impute travel time matrix for the entire U.S.[16] I then combine the ZCBP data with the travel time matrix to construct the amenity choice set and the price vectors from each census tract.

I use the 2000 Decennial Census and the 2007-2011 ACS data for residential location data in 2000 and 2010, respectively (Ruggles, Genadek, Goeken, Grover, and Sobek (2015), Manson, Schroeder, Van Riper, and Ruggles (2017)).[17]

[15] 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.

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

[17] I use 2007-2011 ACS for 2010 because it is the last wave of ACS micro-data that contains consistent

5.2 Price of visits

To conduct the estimation, I need to first construct the price vectors of visits $p_{ikj} = \bar{p}_k + \gamma (h_k + t_{ij})$, which consists of

1. **Monetary cost of the amenity services $\bar{p}_k$ (service prices)**,
2. **Opportunity cost of time in these amenities γh_k,**
3. **Opportunity cost of travel 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 dollar) 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.[18]

MSA geocode with 2000 Census micro-data.

[18] 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 grocery itself is likely not part of the service fee.

5.2.2 Opportunity cost of using amenities

A large component of the price of visits comes from the time spent in each activity. As I have discussed earlier, the variation in the lengths of visits is a major factor that may drive the varying rates of diffusion of amenity benefit across amenity types, even with identical elasticities of substitution. To see how the variation in time spent on each type of amenities can affect the price of visits, see Table 1.

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

5.3 Elasticity of substitution - σ_k

Given σ_k, I use the 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.

That said, I must be cautious with mapping the mean travel time to the elasticities of substitution. The potential problem of matching the model-predicted travel time with observed travel times is that observed travel times is 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 sample contains many people like person A, then σ_k is likely to be underestimated. If my sample contains many people like person B, 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.

To address this potential bias, my estimation of σ_k has to account for the choice sets that residents surveyed in the ATUS face. Ideally, I would like to use the precise geocode of these residents' residential locations, which enables me to recreate their choice sets precisely. Unfortunately, precise geocode is unavailable in the ATUS data. For that reason, 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 time-use survey.

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 spatial distribution of residents across census tracts - $\Pr(c|\mathbf{X}_i)$ obtained from Census NHGIS data. [19]

Conditional on living in census tract c, the travel time distribution $\Pr(t_j|c,k)$ is the following:

$$\Pr(t_j|c,k) = \frac{p_{k,cj}^{-\sigma_k}}{\sum_{j'} p_{k,cj'}^{-\sigma_k}}.$$

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.[20]

$$E(\widehat{\ln t_{ki}} - \ln(t_{ki})) = 0$$

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 results that include both the cost of time (activity time and travel time)

[19] 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 paragraph. 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 neighboorhood 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 partial reflects different choice sets facing each group.

[20] I match log travel time instead of travel time because travel time is likely to resemble lognormal distribution more than it does the normal distribution.

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.

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), and it is much smaller for restaurants 7.50 (0.076), and unsurprisingly it is even smaller for museums 3.69 (0.89). This confirms the intuition that gyms are highly substitutable among each other, and 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. The fact that the estimate for $\hat{\sigma}_{\text{museum}}$ is small means that the high cost (low percentage-wise cost of travel) 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. The subsequent analysis would be based on estimates in Column 1 (including the monetary cost).

Comparison with Couture (2016) Unlikely this paper in which I estimate σ_k for 16 different amenities, Couture (2016) estimates σ_k specifically for restaurants using different methods and data. Fortunately, this provides me 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 price of visits in the same way as Couture (2016).[21] My estimation produces $\sigma_{\text{restaurant}} = 6.95$ (0.070), which is 20% smaller than his estimate of 8.8. If I add fuel cost to the model (say \$2.88 per hour[22]), the estimate goes further down to 6.08 (0.06).

Predicted and observed travel time I further validate my estimates for σ_k by computing the model-predicted travel time distributions and compare them with the travel time distribution observed in the ATUS data. Given the model parameters, I generate a trip choice probability for each amenity location given each residential location, which would equiva-

[21] Couture (2016) results are estimated using the restricted version of the National Household Travel Survey, in which the exact locations of residents are observed. The access to that information enables one to know the exact choice set under which each trip decision is made. Therefore, a maximum likelihood estimation can be implemented in a straightforward way. In this paper, ATUS data do not reveal the exact geocode of the respondent. Therefore, potentially, the choice sets facing each respondent can be different depending on the location of their residences. Couture's way of calibrating the price of visits is also 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.

[22] 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.

lently 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 6 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.

5.4 Tastes for amenities - θ_k

Finally, I estimate the taste parameters for amenities θ_k, which are the aggregation weights for amenity types.

I construct the estimator for the taste parameter by constructing the sample analogues of the mean frequencies of visits and mean price indexes shown in equation 3:

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

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, as I do in the estimation section. For each demographic group, I take the average annual income from the ACS national data as I_{ic}. I use the American Community Survey 2007-2011. I take the sample of people who work positive hours.[23]

5.4.1 Results

Unlike the duration of visits or lengths of travel time, the frequencies of visits differ across education attainment and age. Therefore, 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 2. The taste parameters across amenity types are far from even, with restaurants and non-grocery shopping having the largest weights.

[23]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 consumption amenities

6.1 Spatial diffusion

With σ_k and θ_k estimated, I proceed to analyze the value of amenities through the lens of the model. I first evaluate the spatial diffusion of the value of amenities. 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. The price index is a CES aggregation of the prices of visits to all available amenity establishments (all J_k of them) 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 $J_k + 1$ onto the map, it should result in a new price index that reflects such addition. The following is the expression of the new price index at census tract c after the addition:

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

I then compute $\Delta \ln \left(\hat{P}_{ick} \right)$ for each census tract c in the same MSA as the newly added establishment. The magnitude of the effect depends on how close census tract c is from the location of the addition t_{c,J_k+1}, size of σ_k, size of h_k, and the total number of existing establishments within the MSA. The effect of adding a new restaurant is likely to be very different from the effect of adding a new gym or a new museum.

The impact of the addition on the welfare value is weighted by the taste parameter 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 effect of a new establishment diffuses across space, I pick out four types of amenities that exhibit different rates of diffusion: *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, assuming γ_i is identical across residents and equals \$24.

I normalize the overall size of the effect by dividing the changes in the value of amenities by changes in the closest census tract to the newly added establishment.[24] I plot the normalized effect of the new amenity establishment in Figure 7 against the travel time between the census tract and the new amenity establishment.

Note that the value of a new laundry shop declines at a very fast rate with distance to the affected location, disappearing only as far as 10 minutes away. The value of a new gym diffuses slightly more slowly, disappearing about 20 minutes away. The value of a new restaurant is much more spread out, with the value extending 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.

The sharp decline in amenity value with distance for a laundry shop is, for the most part, due to the large size difference in σ_k. The second reason is that the length of trips to museums is typically very long, which makes the percentage variation in the cost of trip time to museums relatively small. Another reason is that the MSA-wide number of museums is typically much smaller than either the number of restaurants or gyms and are more concentrated near downtown San Francisco. For residents that live outside of San Francisco, there are not many alternative museum choices near them. A large number of museums are already in San Francisco. If residents far away from the treated location have a lot of museum choices near them, then the rate of diffusion would be lower.[25]

6.2 Welfare inequality

Finally, I aggregate the price indexes to evaluate the contribution of the differential spatial access to amenities on welfare inequality. I use the indirect utility equation to compute the welfare difference for high-skilled (college-educated) and low-skilled residents due to the locations of residents and amenities.

[24]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.

[25]See Figure A2 in the appendix for the same exercises where the additions occur in Midtown Manhattan and West Los Angeles.

First, for low-skilled residents in each location of residence and time, I assign the contemporaneous price indexes based on the location and compute the indirect utility by aggregating these indexes based on their taste parameters. I compute the actual mean utility for low-skilled residents $E_{L,t}(V_{L,t})$ by aggregating over low-skilled residents' spatial distribution.

Then, 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. I aggregate the utility calculated for low-skilled residents over *high-skilled* residents' spatial distribution to obtain the counterfactual mean utility $E_{H,t}(V_{L,t})$. The counterfactual utility gain will be given by the following equation:

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

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 residents of different skills. In other words, the number measures the degree of implied welfare inequality that is driven by the differential access to consumption amenities by skill. Since the marginal utility of log income is 1, the welfare inequality calculated above is measured in log income unit.

6.2.1 Spatial sorting of residents and amenities (2000 - 2010)

I start the welfare exercise by calculating the welfare inequality due to differential access to consumption amenities in 2000. Table 5 shows that in 2000, the differential access to amenities accounts for an equivalent of about 0.93 percentage point of the observed income gap by skill. For comparison, in 2000, high-skilled workers earn 62.5% higher income than low-skilled workers. After adjustment of local difference for cost of living, the real income gap by skill is 33% in 2000.[26] The welfare gap driven by the differential access to 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 implied welfare inequality increased to an equivalent of 1.04 percentage point change in income, which is a 0.11 percentage point 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 equivalent to about 2% of the concurrent increase in real

[26] 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).

income inequality.[27]

One important reason for my relatively small implied welfare inequality number is that my method only attempts to capture access to the 16 *consumption* amenities included in the analysis. Many important amenities such as neighborhood safety, aesthetic value, public goods such as school quality and infrastructures are not accounted for by this method. In the next subsection, I further show that accounting for spatial diffusion can also have a material impact on welfare results.

6.2.2 The role of spatial diffusion

The key feature of my model is that it accounts for spatial diffusion of consumption amenity benefit in a micro-founded way. It turns out that correctly accounting for spatial diffusion is crucial for accurately capturing the role of the access to consumption amenities' in welfare inequality. I demonstrate the importance of accounting for spatial diffusion by presenting alternative results with two extreme calibration exercises. In the first calibration exercise, I set σ_k of every amenity type to 15, a very high number, so that amenity value hardly diffuses beyond its immediate surrounding neighborhoods. In the second exercise, I set σ_k of every amenity type to 3, a very low number, so that amenity value diffuses broadly over a very large area. I show that both exercises lead to large inaccuracies in assessing amenities' role in welfare inequality.

I first discuss the first exercise, in which I set σ_k of all amenity types to 15. This means that the amenity value of every type disappears quickly as distance increases. In this exercise, the implied welfare inequality and the increase in welfare inequality are both smaller than the baseline numbers. The intuition for this result is that in this case, a residents' welfare is assumed to be determined by how close the closest amenity establishment is from them. Residents' welfare is high if they can find *any* amenities close enough to them. The number of varieties does not matter as much, as establishments are highly substitutable. However, many of the high-income neighborhoods in the U.S. are low-density type developments and tend to require some travel time to reach the closest amenities, even though the travel time tends to be reasonably short. The prevalence of such a low-density layout means that the current calibration scheme, which sharply discounts the value of amenities at even a slight distance, could dampen the welfare benefit of amenities, especially for high-skilled residents, and lead to a downward bias for welfare inequality.

In the second calibration exercise, I set σ_k of all amenity types to 3. In this exercise, the

[27] 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.

amenity value would diffuse over a very broad area. The implied welfare inequality and the increase in welfare inequality are both much larger than the baseline numbers. The intuition for this result is that a residents' welfare is determined largely by the number of varieties of amenities over a very broad area. In contrast to the first case, if the high-income side of a city has convenient access to a great selection of amenities compared to the low-income side of the city, the exercise would capture such spatial disparity into the welfare inequality. However, having too much spatial diffusion built into the model could lead to bias in the presence of amenity sorting. For example, high-income neighborhoods tend to have a larger number of gyms due to higher demand for gym facilities. But residents tend to only travel to the gyms close to them, and the number of available gym varieties per se does not have much welfare impact on nearby residents. If we erroneously set σ_k too low, the model would overestimate the welfare benefit of gyms in high-income neighborhoods and underestimate the welfare benefit of gyms in low-income neighborhoods.

7 Caveats

Despite the intuitive micro-foundation and straightforward estimation procedure, the method used in this paper does have a number of important caveats. I elaborate on these caveats in this section.

7.1 Alternative consumption amenities

First, the basic assumption of the model is that the consumption amenity benefits residents by lowering the price indexes of *visits*. However, there are other consumption amenities that are spatially diffused but may not manifest themselves in visit patterns. Food delivery service and home repair services are good examples. Living in a neighborhood with lots of restaurants or lots of available home repair services may also be valuable. While these amenities are also spatially diffused, they cannot be empirically accounted for from visits. Therefore, I must exclude these amenities from my model.

7.2 Measurement of variety

In the model, I take 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. If residents were to choose between the two McDonald's, they would most likely choose the McDonald's closer to them. The model would infer a very large σ for 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. Thus, the model would infer a very small σ.

Therefore, σ captures both the **degree of dissimilarity** between the choices *and* the **degree of substitution** among options *given a certain degree of similarity.* 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

The study 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 particular, the research abstracts away from congestion cost. 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 would internalize the congestion cost 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 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, Christensen, and Sarmiento (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

In this paper, I take an alternative approach to assessing the value of local consumption amenities using people's time-use patterns. I show that my approach can overcome two difficulties of evaluating the value of consumption amenities: spatial diffusion of amenity value and the estimation of the aggregation weights. I first motivate my approach by documenting how people spend their time at different types of amenities, in terms of their frequencies of visits, duration of each visit, travel time to and from the amenity venues. I find 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 amenities' value diffuses very differently. I also find that the frequencies of visits and the duration of the visits vary significantly across different types of amenities. I argue that the heterogeneity of time devoted to each type of amenities reveals how people value different types of amenities differently.

Motivated by these findings, I construct a model that rationalizes how people make amenity choices, characterized by their choice of travel time and their frequencies of visits. The model can predict different rates of spatial diffusion and can be empirically linked to time-use patterns, which are observable in the data. I then estimate key model parameters using a combination of the American Time Use Survey, Zip-Code Business Patterns, which provide amenity locations, and a travel time matrix.

With the estimated model, I show that the differential access to consumption amenities between high- and low-skilled residents leads to a welfare inequality equivalent of 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. I then show that properly accounting for spatial diffusion of consumption amenities is important in correctly measuring consumption amenities' role in welfare inequality.

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. 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 geocoded transactional-level data.

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Figure 1: Mean travel time associated with 16 types of amenities

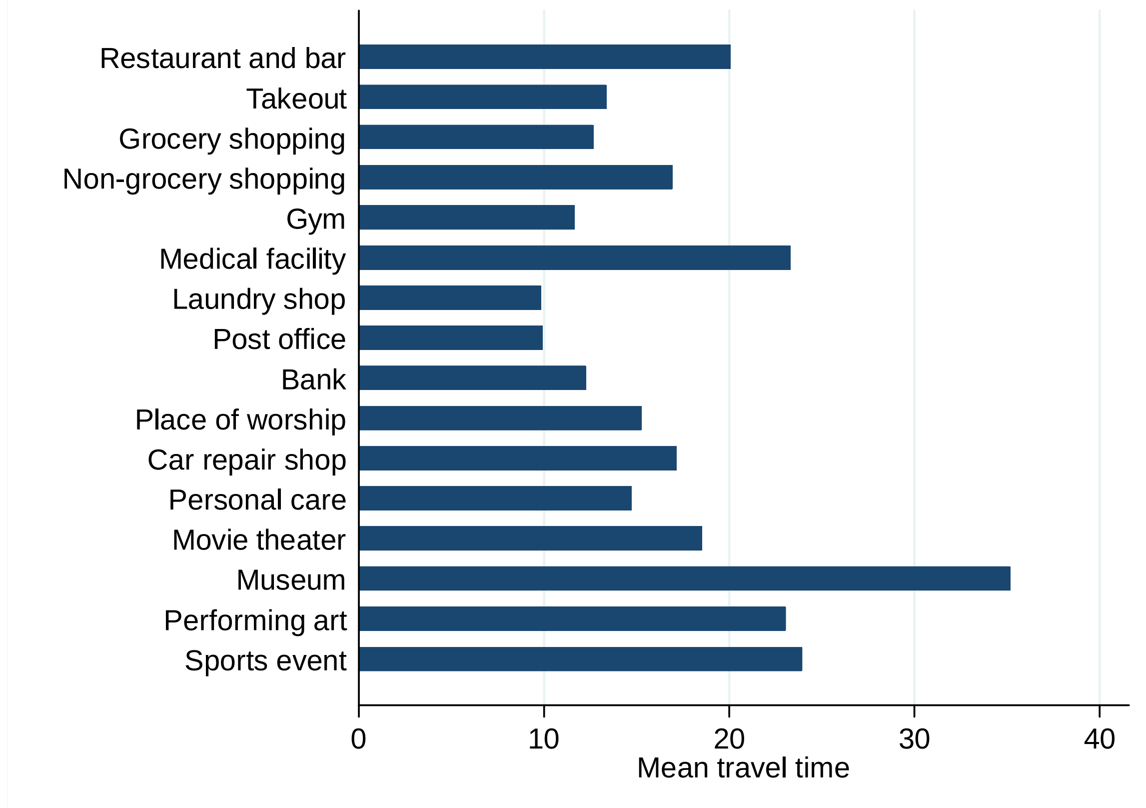
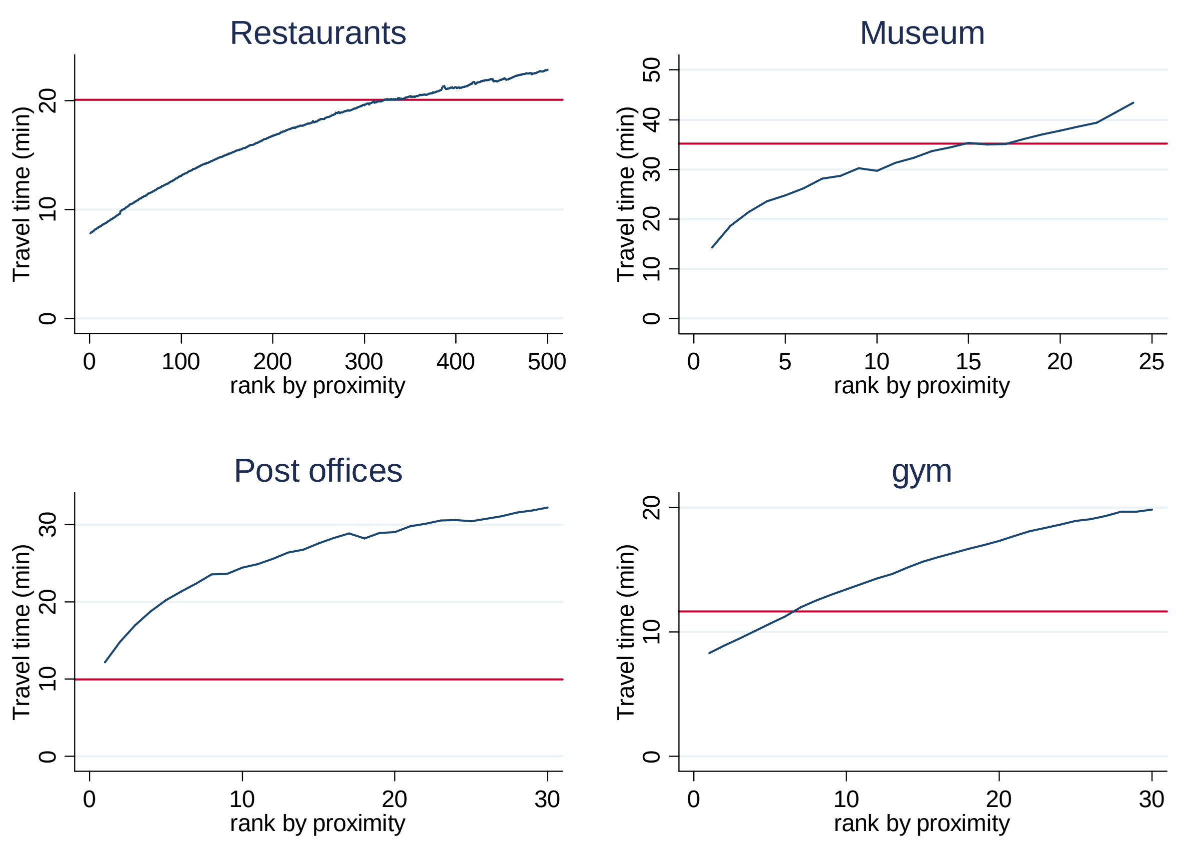
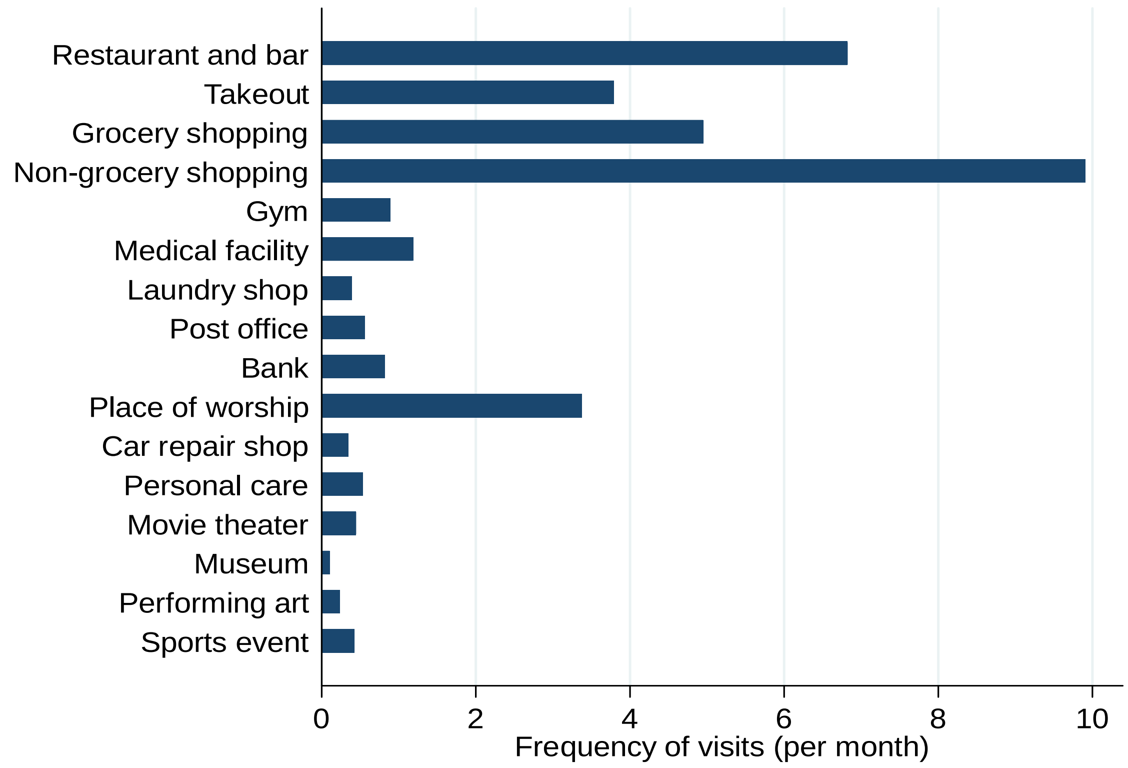


Figure 2: Travel time and rank by proximity



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.

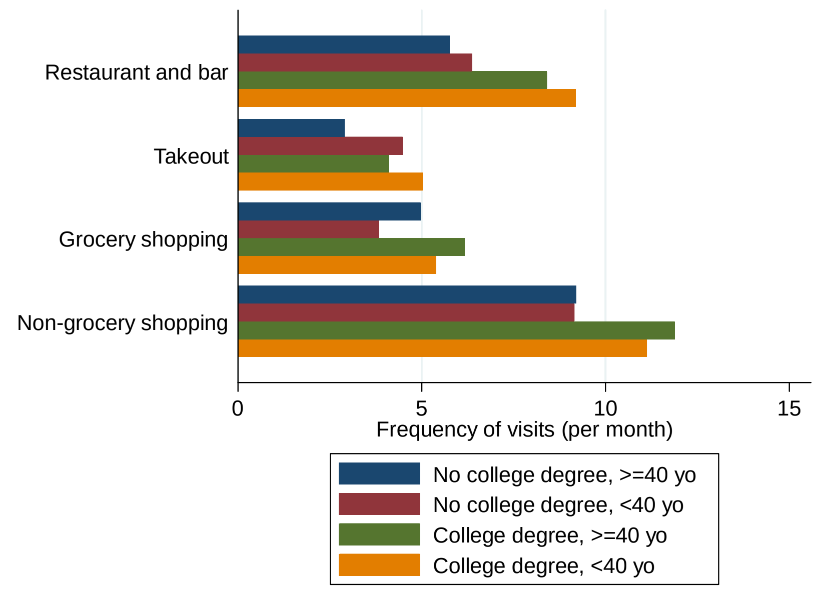
Figure 3: Frequency of visits to 16 types of amenities



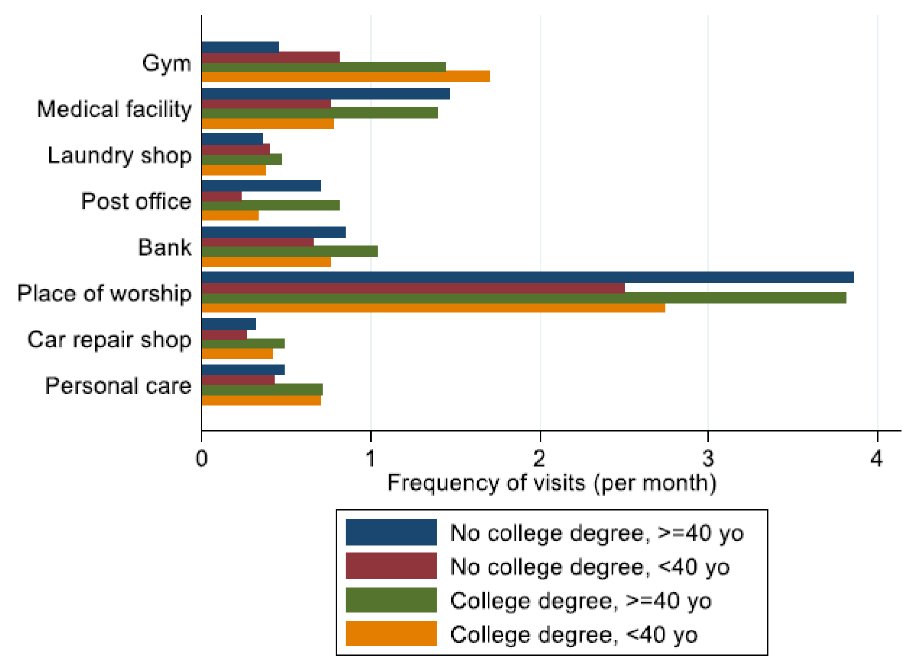
Notes: The data source is the American Time Use Survey (ATUS) 2003-2015. The statistics are generated with observations pooled across all surveys during these years. I categorize activities reported in the ATUS into 16 amenity categories. The classification table is shown in the appendix. The frequency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

Figure 4: Frequency of visits to 16 types of amenities – by education attainment and age

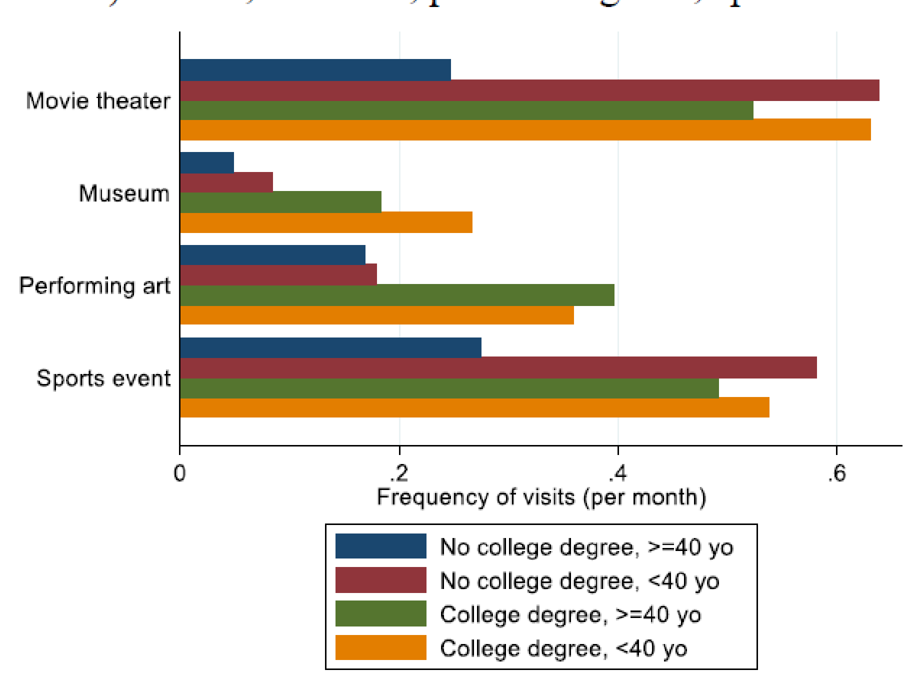
a) Restaurant, takeout, grocery, and non-grocery



b) Gym, medical facility, laundry, post office, bank, worship, car repair, and personal care

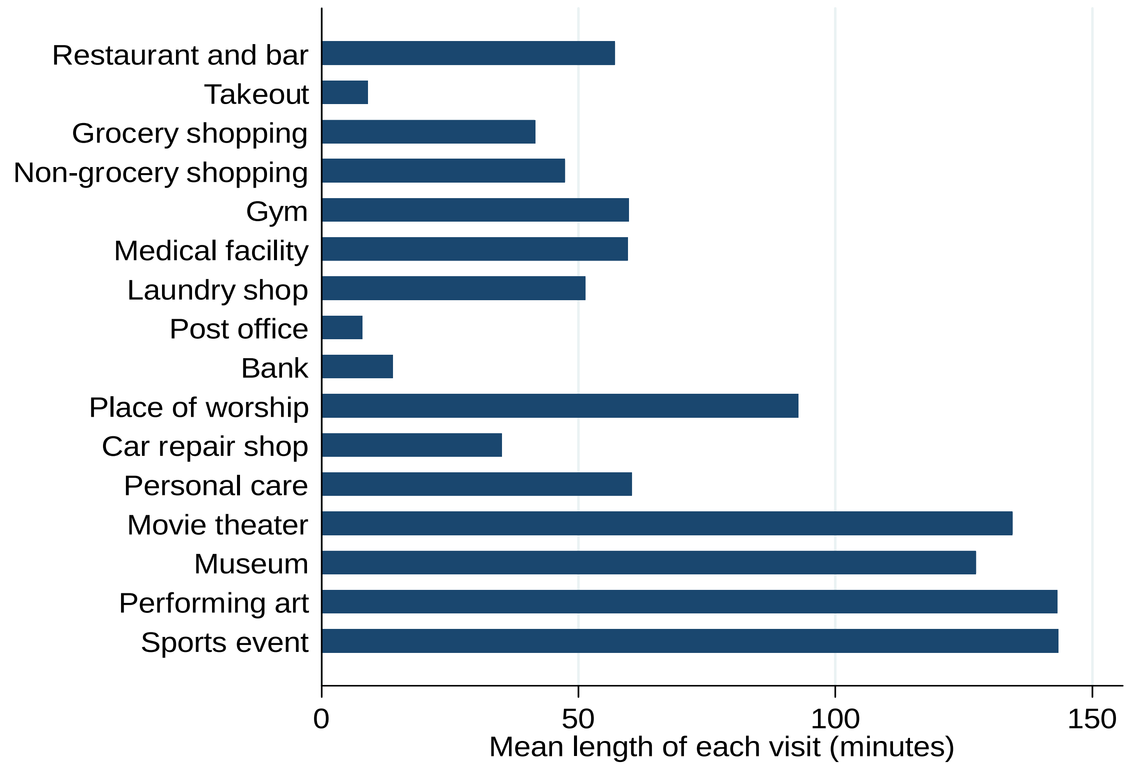


c) Movie, museum, performing arts, sports



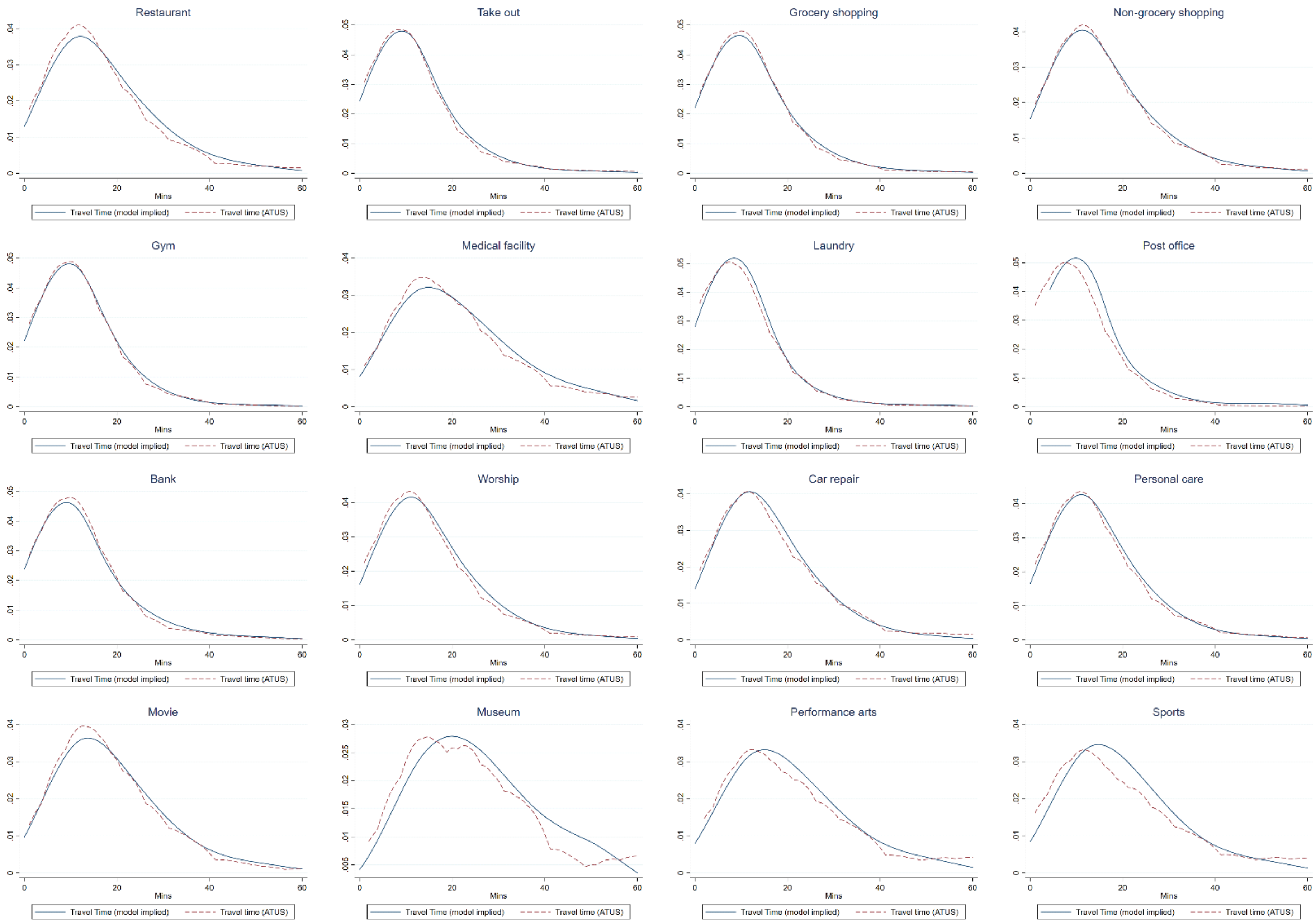
Notes: The data source is the American Time Use Survey (ATUS) 2003-2015. The statistics are generated with observations pooled across all surveys during these years. I categorize activities reported in the ATUS into 16 amenity categories. The classification table is shown in the appendix. I further divide 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 day/case multiplied by 30.

Figure 5: Mean length of visits to 16 types of amenities



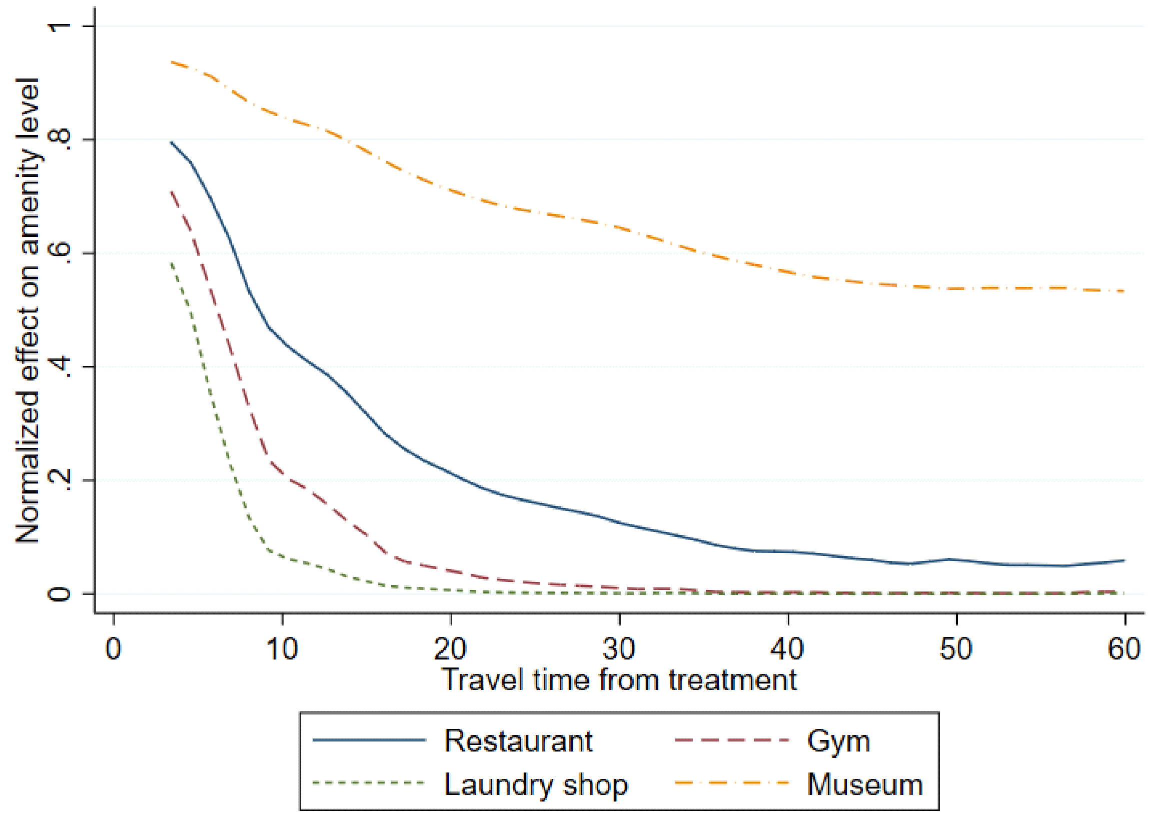
Notes: The data source is the American Time Use Survey (ATUS) 2003-2015. The statistics are generated with observations pooled across all surveys during these years. I categorize activities reported in the ATUS into 16 amenity categories. The classification table is shown in the appendix.

Figure 6: 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 7: 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 costs 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

	Monetary cost of visits included	Monetary cost of visits excluded
Restaurant and bar	7.50***	6.066***
	(0.076)	(0.059)
Takeout	7.30***	4.33***
	(0.092)	(0.047)
Grocery shopping	7.92***	7.92***
	(0.057)	(0.057)
Non-grocery shopping	6.53***	6.53***
	(0.042)	(0.042)
Gym	13.82***	10.58***
	(0.36)	(0.27)
Medical facility	7.11***	4.26***
	(0.22)	(0.12)
Laundry shop	16.53***	13.41***
	(0.74)	(0.58)
Post office	32.35	32.35
	(103.35)	(103.35)
Bank	4.87***	4.87***
	(0.11)	(0.11)
Place of worship	10.07***	10.07***
	(0.14)	(0.14)
Car repair shop	18.80***	5.14***
	(0.74)	(0.16)
Personal care	12.17***	8.044***
	(0.38)	(0.24)
Movie theater	12.01***	10.87***
	(0.48)	(0.43)
Museum	3.69***	3.52***
	(0.89)	(0.85)
Performance arts	10.30***	10.018***
	(0.83)	(0.80)
Sports event	11.80***	11.098***
	(0.81)	(0.76)

Notes: The left column reports the estimates for σ_k assuming that monetary cost is included in the cost of visits. The right column reports the estimates for σ_k assuming that monetary cost is excluded in the cost of visits. The subsequent analysis in model experiment would be based on the estimates on the left 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***	1.1659***	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 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, $50403.01. 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 $60537.11 as the mean income measure; for <40 and without college degree, $26766.26; for >=40 and with college degree, $96316.36; for >=40 and without college degree, $44867.46.

Table 4: Welfare inequality due to access to amenities

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

Notes: I compute the welfare inequality 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. Welfare 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 3 and 15, respectively.

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 is 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.[28] I

[28] 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

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.[29] The cost of visiting medical facilities do not include insurance costs.

For laundry[30], car repair[31], and personal care[32], 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.[33] I impute the frequency

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.

[29] 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.

[30] 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.

[31] 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.

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

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

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.[34] I use the average art museum admission price reported by the Association of Art Museum Directors to approximate the monetary cost of visiting museums.[35] 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.

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.

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

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

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:

$$\min_{x_{k1},\ldots,x_{kJ_k}} \sum_{j=1}^{J_k} p_{kj}x_{kj}$$
$$\text{s.t.} \quad \left(\sum_{j=1}^{J_k} x_{kj}^{\rho_k}\right)^{1/\rho_k} \geq X_k.$$

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:

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

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:

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

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

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

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:

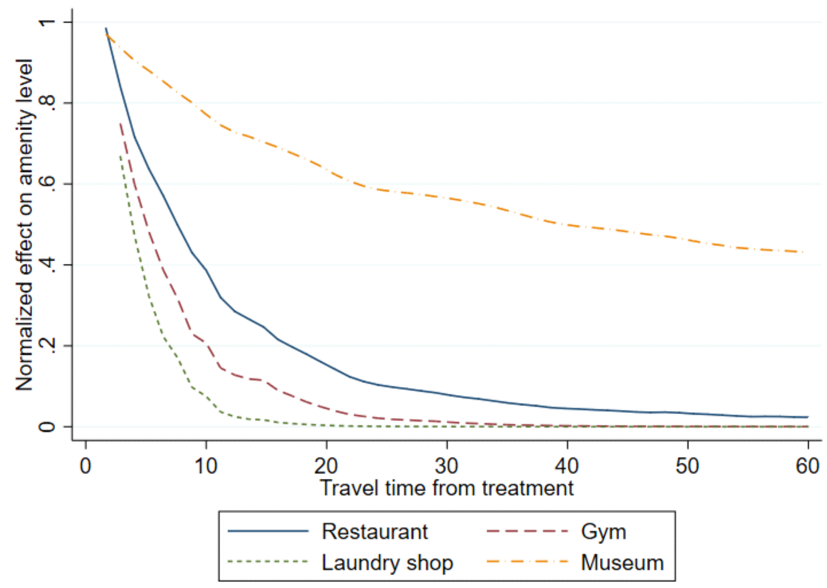
$$\begin{aligned} \frac{\partial g(t_i, \mathbf{X}_i, \sigma_k)}{\partial \sigma_k} &= \sum_c \Pr(c|\mathbf{X}_i) \cdot \sum_{j|c} \frac{\exp(-\sigma_k \ln(p_{k,cj}))}{\sum_{j'} \exp(-\sigma_k \ln(p_{k,cj'}))} \cdot \\ &\quad \left[\frac{\sum_{j'} \exp(-\sigma_k \ln(p_{k,cj'})) \ln(p_{k,cj'})}{\sum_{j'}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

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.

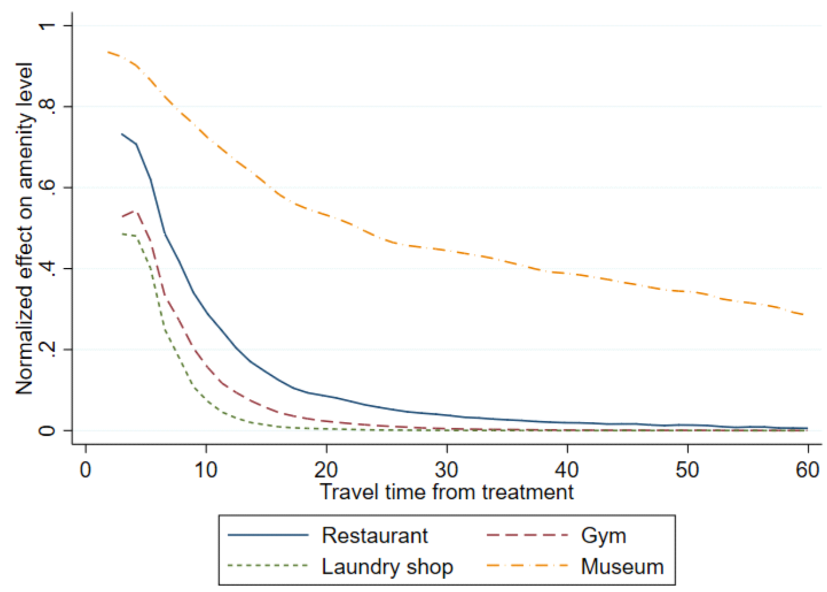
Figures and Tables for Appendix

Figure A1: Differential rates of spatial diffusion

a) Midtown Manhattan, Zip code: 10018



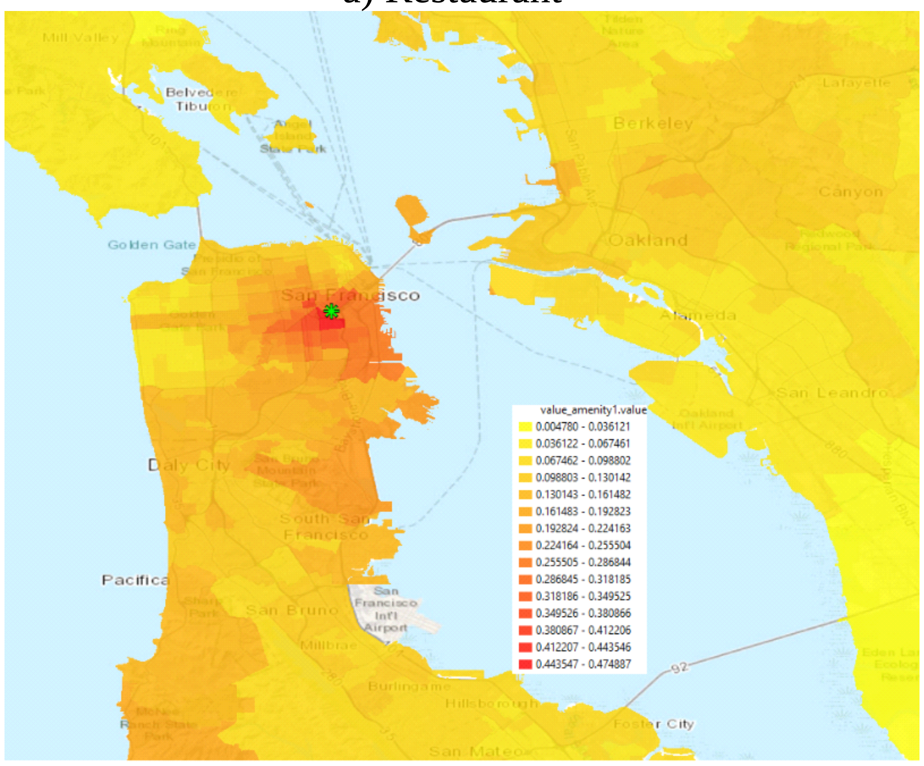
b) West Los Angeles, Zip code: 90036



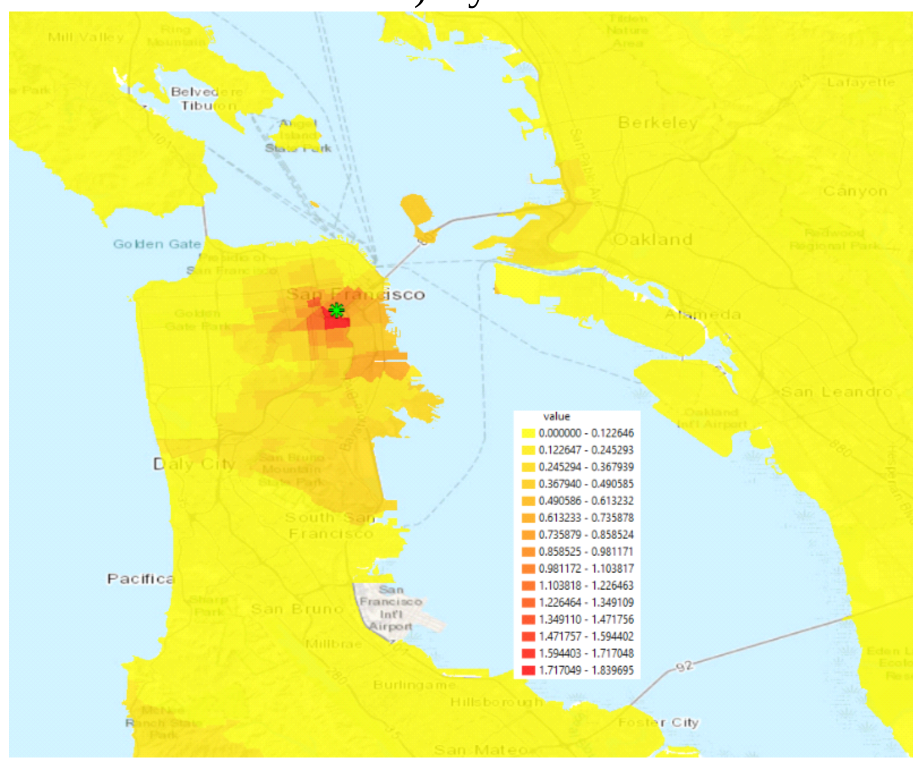
Notes: I plot the model-implied effects of adding an additional establishment on levels of amenities. I normalize the treatment effect for each amenity type by the treatment effect on the closest census tract (each curve starts out as 1). Figures above respectively show the effects of treatments that occur at two locations: Midtown Manhattan, NY (zip code: 10018), West Los Angeles (zip code: 90036).

Figure A2: The geography of spatial diffusion of marginal amenity in zip code 94103

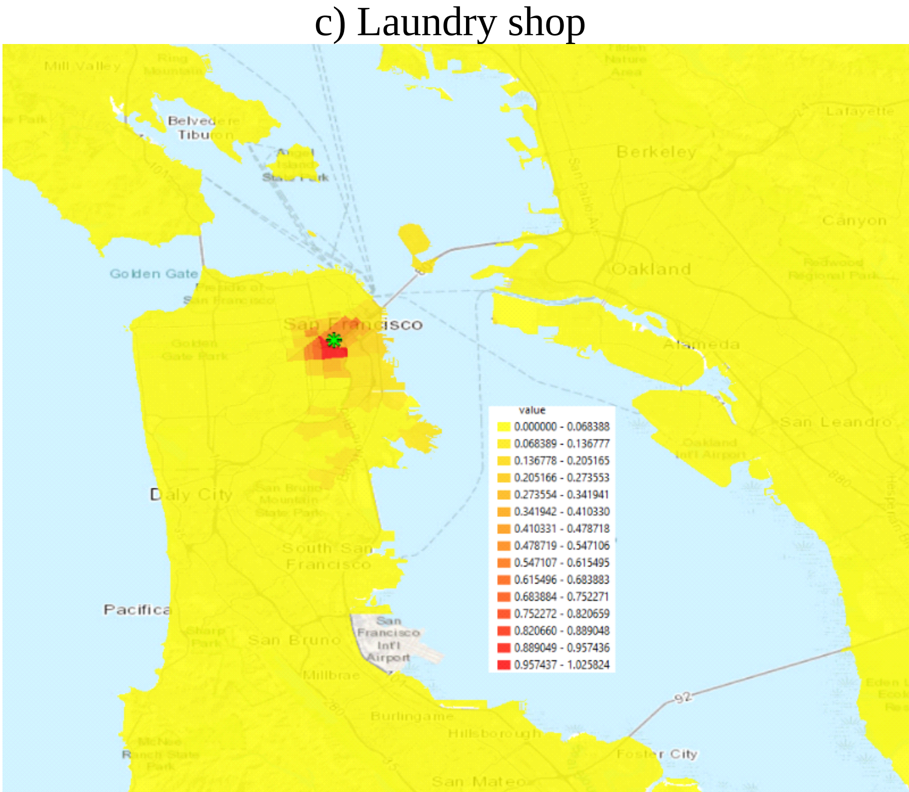
a) Restaurant



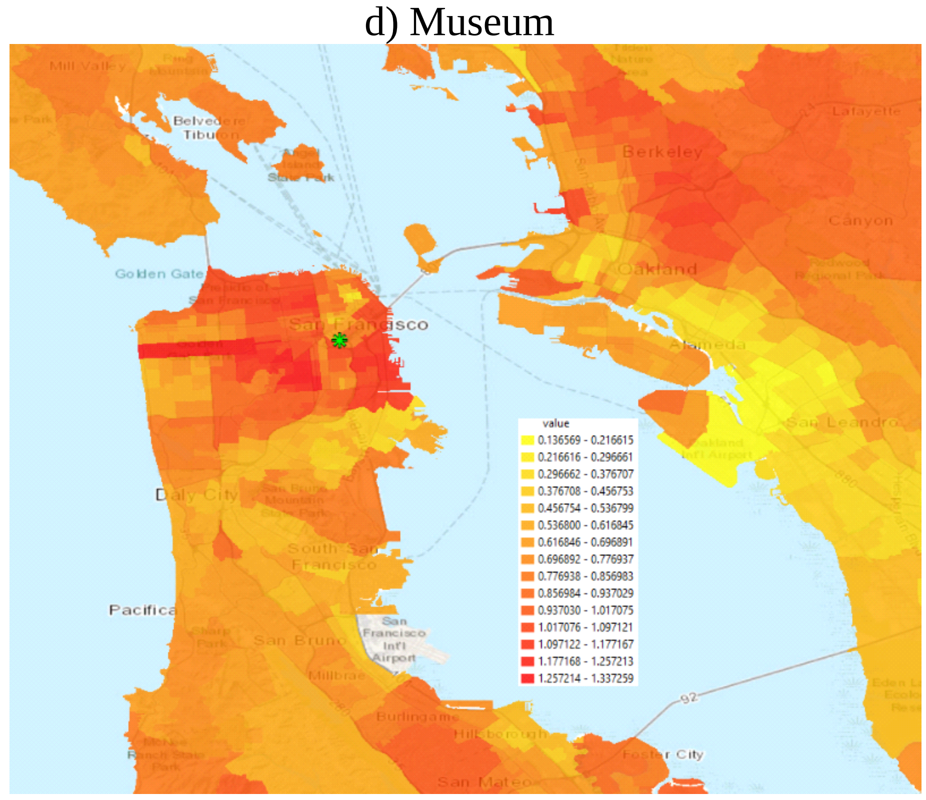
b) Gym



c) Laundry shop



d) Museum



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.

Table A1: Welfare inequality driven 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 welfare inequality 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. Welfare 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.