Estimating the Demand for Walkable Neighborhoods: Evidence from a City-Wide Zoning Reform in Miami, FL*

Terrence Jewell†

October 29, 2025
Preliminary Draft
Click Here For Latest Version

Abstract

This paper estimates household demand for walkable neighborhoods in Miami following the city's zoning reform to increase walkability. I construct a behaviorally grounded walkability measure that integrates residents' observed 15-minute walking behavior with a CES-style price index capturing the richness and affordability of nearby amenities. Using smartphone mobility data, I show that baseline patterns reveal strong local activity—on average, 30.3 % of essential visits occur locally—and that greater local access significantly increases realized neighborhood usage and generates more frequent trip chains. A structural discrete-choice model reveals that households have a strong preference for walkability and are willing to pay about $24 per square foot for a one–standard–deviation increase in walkability. The results suggest that land-use reform and housing supply policy can meaningfully influence urban accessibility by enabling denser, mixed-use development consistent with revealed household preferences.

Keywords: Walkability, Zoning Reform, Housing Supply
JEL Codes: R14, R31, R41, R52

*I thank Holger Sieg, Kenneth Whaley, and Hugo Vaca Pereira Rocha for their detailed feedback and discussions. I am also grateful to the participants of the Real Estate Seminar at the Wharton School of the University of Pennsylvania for helpful comments. All remaining errors are my own.

†John Chambers College of Business and Economics, West Virginia University, 83 Bucharest Ave, Morgantown, WV 26505. Email: terrence.jewell@mail.wvu.edu

1 Introduction

Cities thrive on density—but they are also constrained by it. Dense environments expand the range of consumption possibilities: a greater variety of shops, restaurants, cultural venues, and everyday services become accessible within shorter distances, lowering the time cost of daily life and enriching urban the experience. Yet the same proximity that enables this richness also brings costs—crowding, noise, traffic congestion and crime that can undermine the quality of urban life (Glaeser, 2012; Duranton and Puga, 2020). Zoning regulations determine how density takes shape—where people live, work, and consume—and thus whether urban growth produces vibrant, mixed-use neighborhoods or low-density sprawl.

In 2010, the city of Miami, Florida, made a bold shift by dropping its traditional Euclidean zoning code.[1] Rather than separating land uses—such as commercial, industrial, and residential—the city reimagined growth around walkability, mixed-use neighborhoods, and a compact urban form. The goal was to reduce car dependence and encourage development around transit corridors, thereby making transit a viable, attractive choice that relieves congestion and supports a multimodal city.

In this paper, I estimate the demand for walkable neighborhoods in Miami, Florida. Walkability shapes how people move through the city, making it easier to combine multiple stops within a single outing—a behavior known as trip chaining—and thereby saving time (Miyauchi et al., 2025). More walkable areas also provide access to a greater variety of goods and services, which can lower the effective cost of local consumption (Dixit and Stiglitz, 1977). However, they can also blur traditional boundaries between commercial and residential life, bringing noise, increased foot traffic, and reduced privacy for local residents (Gyourko and McCulloch, 2024). A 2023 National Association of Realtors survey[2] reports growing demand for smaller yards and more walkable communities over large lots and greater automobile dependence. Yet many residents continue to resist higher density through NIMBY politics, viewing new development as a threat to neighborhood character. These perceived local costs make communities wary of zoning reforms that could otherwise expand access and promote

[1]Euclidean zoning originates from the 1926 Supreme Court case *Village of Euclid v. Ambler Realty Co.*, 272 U.S. 365, which upheld separating land uses by type.

[2]National Association of Realtors (NAR), *Community and Transportation Preferences Survey*, 2023.

a more walkable urban form. Yet despite this tension, we still know little about how much people actually value walkable urban environments. This paper aims to fill that gap by empirically estimating the demand for walkability in Miami.

Real estate platforms such as Zillow and Redfin rely on third-party indices like Walk Score to assess neighborhood walkability, incorporating measures of amenity proximity, street connectivity, and pedestrian infrastructure. However, these indices capture potential accessibility rather than observed walking behavior. In this paper, I construct a walkability measure that integrates observed shopping behavior with consumption accessibility. Building on recent work that uses mobility data to measure consumption behavior (Abbiasov et al., 2024), I use smartphone location data to observe residents' realized movement patterns within their neighborhoods. I construct 15-minute walking isochrones for each census block group in Miami using OpenRouteService, a routing platform based on OpenStreetMap data. Each isochrone represents the area reachable on foot within 15 minutes from the block group centroid along the pedestrian network, rather than simple Euclidean distances. Spatially joining these isochrones with the mobility data, I identify essential destinations accessible within each neighborhood's 15-minute walkshed. For each block group, I compute the share of total visits to essential destinations that occur within the local 15-minute isochrone and weight this share using a constant elasticity of substitution (CES) price index that captures local variety and effective cost (Dixit and Stiglitz, 1977). This framework accounts for local shopping behavior, the richness of nearby amenities, and the overall appeal of an area, providing a more behaviorally grounded measure of neighborhood walkability.

Using smartphone data provided by Advan from August through October 2024, baseline patterns show that, on average, 30.3 % of essential visits occur within residents' local 15-minute isochrones, meaning roughly one-third of total trips take place within a short walking distance. By contrast, Abbiasov et al. (2024) report a national median of just 14 % in 2019, with Southern regions averaging around 18 %.[3] Miami's comparatively high share suggests a stronger pattern of localized activity, consistent with the idea that zoning reform and mixed-use development promote shorter, neighborhood-oriented trips. Complementary descriptive

[3]For comparability, these shares are unadjusted visit shares and do not account for the CES-based price index.

evidence from mobility data provided by Veraset further shows that these local trips are often interconnected, with individuals linking multiple destinations within a single outing. This pattern highlights how dense, amenity-rich neighborhoods can generate consumption externalities, where proximity between destinations encourages coordinated local activity rather than isolated trips (Miyauchi et al., 2025).

To examine causality, I estimate the relationship between 15-minute usage and 15-minute access—that is, whether adding more establishments within walking distance causes people to take more local trips. A key challenge in identifying this causal effect is endogeneity. Residents who value walkable environments may self-select into more accessible areas, while businesses may choose to locate where demand is highest, generating reverse causality. Ideally, one could implement a border discontinuity design in which consumption access changes sharply across zoning or regulatory boundaries, allowing comparisons between otherwise similar block groups on either side. In practice, however, this approach is limited because neighborhood-level RDD studies typically employ bandwidths between 0.10 and 0.30 miles Bayer et al. (2007), whereas a 15-minute walk spans roughly 0.75 miles. As a result, residents on both sides of a boundary often share access to many of the same amenities within overlapping 15-minute isochrones, weakening the identifying variation on which such designs rely.

As an alternative strategy to address these endogeneity concerns, I instrument for current consumption access using historical floor-area ratios measured before 1934, a period preceding the introduction of zoning in Miami. These pre-zoning density patterns capture the city's early built environment and provide plausibly exogenous variation in potential development intensity, unlikely to be influenced by modern residential sorting or amenity location decisions. The IV results reveal a strong positive relationship between amenity access and local usage. A 1% increase in access raises local usage by about 0.35 percentage points, indicating that neighborhoods with greater amenity availability experience more localized trip behavior. Given a baseline mean of 0.303 for 15-minute usage, the estimates imply that a 1% increase in access increases local usage by roughly 1.1% relative to its mean.

I then estimate a residential choice model that follows a standard discrete choice framework (Berry et al., 1995; Bayer et al., 2007) and embeds my measure of walkability as a neighborhood attribute. Individuals maximize utility when choosing neighborhoods as a function of prices, location features, access to employment opportunities, and walkability, allowing residents to value both the positive and negative aspects of greater densification. To estimate the model, I employ the 2024 Municipal Roll File from the Miami-Dade County Office of the Property Appraiser. This dataset provides comprehensive property-level information for all parcels in the county, including ownership, building characteristics, and the land-use and zoning codes that govern development rights. I instrument for endogenous prices using differentiation IVs as proposed by (Gandhi and Houde, 2019).

I find that residents of Miami have a strong revealed preference for walkable neighborhoods. The estimated willingness to pay for a one–standard–deviation increase in walkability is approximately \$24 per square foot, relative to a median housing price of about \$305 per square foot. This premium indicates that households place substantial monetary value on neighborhoods offering greater access to amenities within walking distance. Preferences for employment accessibility and higher floor–area–ratios are also positive, while households display an aversion to higher prices and crime, as expected. These results highlight how zoning reform and housing supply policies can shape walkability by promoting denser, mixed-use development that better aligns the built environment with household preferences.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 provides background on Miami's zoning reform. Section 4 describes the data, outlines the instrumental variables framework, and presents the main empirical results. Section 5 introduces the residential choice model and details the construction of the walkability measure. Section 6 reports the demand estimation results, while Section 7 discusses elasticity and willingness-to-pay estimates. Section 8 concludes.

2 Literature Review

This work relates to several strands of existing research. The urban economics literature has traditionally viewed cities primarily as centers of production rather than consumption (Duranton and Puga, 2004; Enrico, 2011; Combes and Gobillon, 2015). Glaeser et al. (2001) argues that consumption amenities are an important determinant of residential choice and finds that high-amenity cities have grown faster than low-amenity cities. This paper contributes to a more recent wave of research emphasizing that the success of cities increasingly depends on their role as centers of consumption (Glaeser et al., 2001; Moretti, 2012; Diamond, 2016; Couture and Handbury, 2020; Baum-Snow and Hartley, 2020; Almagro and Domínguez-Iino, 2025; Miyauchi et al., 2025).

My work also contributes to a growing body of research that leverages smartphones and other large-scale datasets to study spatial mobility. Recent studies have drawn on travel surveys (Couture, 2016; Couture et al., 2018; Zarate Vasquez, 2022), credit card transactions (Agarwal et al., 2017; Allen et al., 2021; Dolfen et al., 2023), ride-sharing data (Gorback, 2022; Buchholz et al., 2025), car navigation records Hausman et al. (2023), and cellphone or smartphone location data (Büchel et al., 2020; Athey et al., 2021; Atkin et al., 2022; Couture et al., 2022; Abbiasov et al., 2024; Miyauchi et al., 2025) to analyze patterns of urban movement and consumption. This paper further relates to research showing that spatial concentration can benefit firms through retail colocation spillovers, while consumers gain from reduced travel times and greater access to variety (Thill and Thomas, 1987; Ushchev et al., 2015; Benmelech et al., 2019; Koster et al., 2019; Klenow et al., 2022; Oh and Seo, 2023; Qian et al., 2023; Miyauchi et al., 2025).

The urban economics literature on the demand for walkable neighborhoods remains relatively limited. The most closely related work to this study is (Abbiasov et al., 2024), which constructs 15-minute walk isochrones to examine the relationship between amenity access and local shopping behavior. I extend this framework by constructing a measure of walkability that incorporates not only the share of local visits but also the richness and affordability of nearby amenities. Specifically, I augment the baseline 15-minute usage share with a CES-style price index Dixit and Stiglitz (1977), which accounts for both the number of distinct reachable establishments and the local price level, offering a more comprehensive representation of neighborhood walkability. To the best of my knowledge, this paper is the first to structurally estimate household demand for walkable neighborhoods. By embedding a new measure of walkability within a discrete choice framework, I quantify how much households value proximity, variety, and affordability of local amenities, providing new evidence on the behavioral foundations of urban walkability.

This paper also contributes to the broader literature on the costs and benefits of cities (Glaeser, 2012; Duranton and Puga, 2020). Prior work highlights how urban agglomeration fosters productivity and innovation (Duranton and Puga, 2004; Ellison et al., 2010; Enrico, 2011; Moretti, 2012; Carlino and Kerr, 2015; Moretti, 2021) and how density can reduce pollution Glaeser and Kahn (2010). At the same time, cities face costs related to disease (Glaeser and Cutler, 2022; Ellen et al., 2023), congestion (Duranton and Turner, 2011; Yang et al., 2020), crime (Glaeser and Sacerdote, 1999; Lacoe et al., 2018), and population pressures (Combes et al., 2019; Gyourko and McCulloch, 2024). This paper contributes to this literature by showing that policies promoting walkability and mixed-use development can help cities become more accessible, vibrant, and attractive places to live and work.

3 Institutional Background

The *Miami 21*—"Miami of the 21st Century"—zoning code was adopted by the City of Miami, Florida, in 2010, following a five-year development process that began in 2005. Spearheaded by Planning Director Ana Gelabert-Sanchez and the lead consultant team Duany Plater-Zyberk & Company, the initiative brought together elected officials, city departments, and the broader community to produce a comprehensive overhaul of Miami's zoning framework. Miami 21 received its first reading in 2009 and final approval in 2010. The reform's central aim was to guide Miami away from a suburban, car-oriented development pattern toward transit-oriented, pedestrian-friendly growth (Gelabert-Sánchez, 2020).

Traditional Euclidean zoning segregates land by use type (e.g., residential, commercial, industrial). In contrast, form-based codes (FBCs) emphasize the physical form of development and its relationship to the street and public realm rather than the separation of uses. Under an FBC, diverse functions—such as housing, shops, and offices—can coexist as long as buildings meet the prescribed form and design standards for their zone. Miami 21 introduced a transect system that organized the city into zones ranging from low-density neighborhoods to high-density urban cores, balancing predictability of scale with flexibility of use.[4]

[4]A transect is a planning framework that orders zones along a continuum from rural to urban intensity. Each transect zone defines standards for building form, street design, and public realm character appropriate

The Miami 21 effort was a comprehensive approach to planning and code development comprising six elements: zoning regulation, economic development, historic preservation, parks and open spaces, arts and culture, and transportation. Walkability was a central design principle: neighborhoods were planned so that most homes would be within a five–ten minute walk of schools, shops, parks, or transit. Streets were designed to be safe and inviting, with sidewalks, shade trees, and active frontages that contribute to a lively pedestrian experience. The code also expanded housing options by allowing a range of types—single-family homes, townhouses, and apartments—to accommodate different income levels and age groups. It further promoted the adaptive reuse of industrial land and supported work–live units in designated industrial areas (Gelabert-Sánchez, 2020).

Miami 21 also reformed the development process itself. By providing clear, prescriptive form standards, it made zoning more transparent, predictable, and efficient. A major change was the establishment of "development by right": if a project complied with the code's standards, it could be approved administratively without lengthy discretionary reviews. This reduced uncertainty for developers, streamlined permitting, and facilitated faster delivery of new housing and commercial space in Miami. Transit-oriented development (TOD) was explicitly embedded in the code. Projects near transit stops were incentivized through density bonuses, encouraging higher-intensity, mixed-use development within walkable areas (Gelabert-Sánchez, 2020).

4 Data and Instrumental Variable Evidence

4.1 Miami-Dade County, Florida

4.1.1 County Assessors

I employ the 2024 Municipal Roll File from the Miami-Dade County Office of the Property Appraiser. This dataset provides comprehensive property-level information for all parcels in the county, including ownership, building characteristics, and the land-use and zoning codes

to its position in the continuum, thereby enabling gradual transitions in density, scale, and use rather than abrupt shifts.

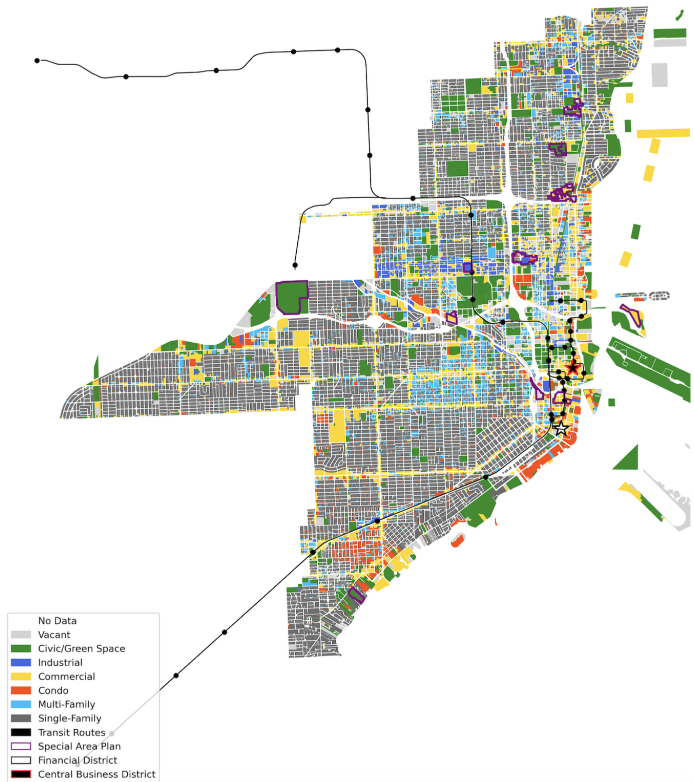
that govern development rights. To align the data spatially with other sources, I geocode each property address and map parcels to their corresponding census block groups. Summary statistics of key parcel-level characteristics are reported in Table 1 while Figure 1 highlights the distribution of land across uses in Miami, FL.

Table 1: Miami Parcel-Level Summary Statistics

	Mean	SD	Min	Max	obs
lotsize	6473	142349	0.00	25322300	131826
living sqft	3255	31129	0.00	4758615	131824
far	0.40	0.82	0.00	83	61689
units	1.65	11.77	0.00	1042	131826
bed	2.73	14.74	0.00	1541	131826
bath	2.18	13.84	0.00	1536	131826
yearbuilt	1977	29.21	1900	2023	125559
single-family	0.39	0.49	0.00	1.00	131826
multi-family	0.03	0.18	0.00	1.00	131826
condo	0.45	0.50	0.00	1.00	131826
vacant	0.04	0.19	0.00	1.00	131826
civic/green space	0.01	0.09	0.00	1.00	131826
industrial	0.02	0.12	0.00	1.00	131826
commercial	0.07	0.26	0.00	1.00	131826
mixed zoning	1.63	0.95	0.00	3.00	131826
mixed landuse	0.01	0.07	0.00	1.00	131826
t3	0.39	0.49	0.00	1.00	131826
t4	0.06	0.23	0.00	1.00	131826
t5	0.07	0.26	0.00	1.00	131826
t6	0.42	0.49	0.00	1.00	131826
tod zone	0.33	0.47	0.00	1.00	131826
cbd	0.25	0.44	0.00	1.00	131826
one km	0.11	0.31	0.00	1.00	131826
one-two km	0.09	0.28	0.00	1.00	131826
two-three km	0.09	0.28	0.00	1.00	131826
three-four km	0.11	0.31	0.00	1.00	131826
four-five km	0.12	0.32	0.00	1.00	131826
five-plus km	0.24	0.43	0.00	1.00	131826

Notes: The central business district (CBD) is defined as the area within 2 kilometers of the city center point. The ring variables (e.g., *one km*, *two-three km*) indicate parcels located within successive 1-kilometer bands beyond the CBD edge. The variables *T3* through *T6* correspond to Miami 21 transect zones, which range from low-density residential (*T3*) to high-intensity urban core (*T6*). The variable *mixed zoning* indicates whether mixed use is permitted within a parcel's zoning designation, while *mixed land use* reflects observed realizations of mixed-use development on the parcel.

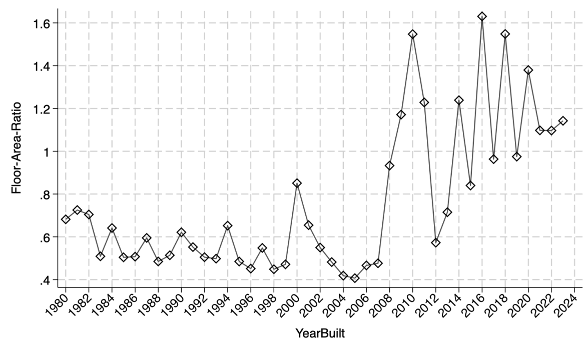
Figure 1: Distribution of land across uses in Miami.



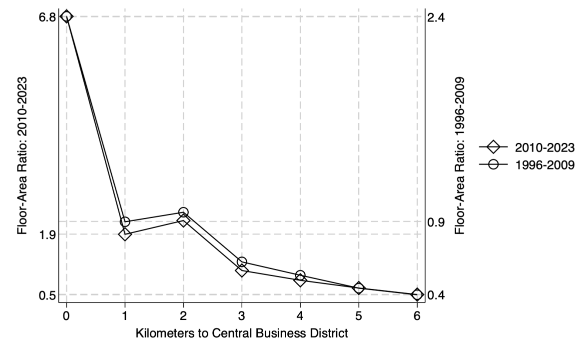
Notes. In Miami, *Special Area Plans (SAPs)* are planning tools that allow parcels of nine or more contiguous acres to be master-planned under more flexible design and infrastructure rules than standard zoning permits (e.g., Miami Freedom Park and River Landing). The city's two major transit systems are the *Metrorail*, a heavy-rail network, and the *Metromover*, a fare-free automated people mover serving Downtown, Brickell, and Omni. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figure 2 illustrates changes in density and mixed-use development. Panels (a) and (b) depict shifts in development intensity, measured by the floor-area ratio (FAR), while Panels (c) and (d) show changes in mixed-use construction before and after the 2010 reform using the assessors data. Panel (a) reveals a substantial increase in FAR following the reform, reflecting the upzoning that allowed greater building intensity, while Panel (b) shows that these gains were concentrated near the central business district (CBD), as indicated by the y-axes, reflecting a gradual shift toward a more compact urban core, as the reform intended. The mixed-use measures capture the number of residential dwelling units located within mixed-use buildings, such as structures combining ground-floor retail with residential units above. Following the adoption of Miami 21, this number rose significantly, reflecting a broader transition toward denser, integrated neighborhoods and a more walkable urban form.

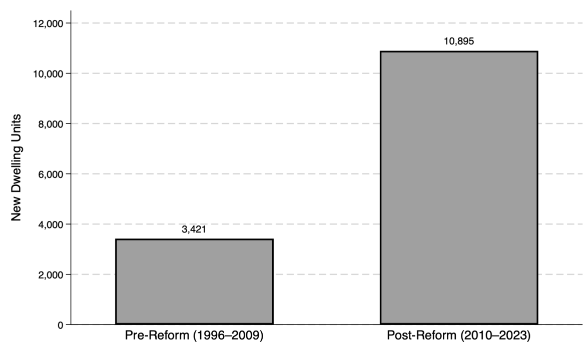
Figure 2: Upzoning and Mixed-Use Supply Changes



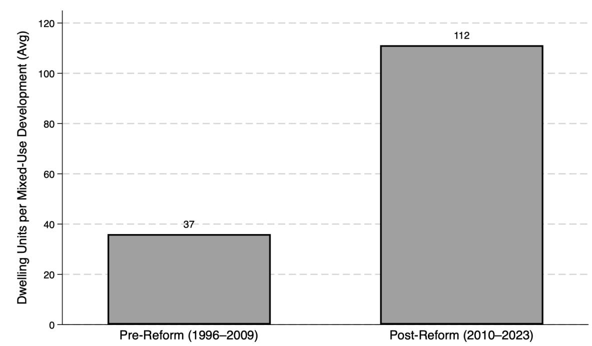
(A) FAR Change Over Time



(B) FAR Change by Distance to CBD



(C) New Dwelling Units Within Mixed-Use Projects



(D) Average New Dwelling Units per Mixed-Use Project

Note: The floor-area ratio is calculated as total building living square footage divided by lot size, based on all property types. Distance to the central business district is measured in kilometers. The central business district is defined as the area within 2 kilometers of the city center point and is labeled as 0 on the x-axis of Panel (b).

4.1.2 Miami Police Department

To measure neighborhood crime levels, I use publicly available calls-for-service data released by the Miami Police Department for the year 2024. These incident-level records include the type and geographic location of each reported call. I classify incidents into three broad categories—violent crime, property crime, and public order or personal offenses—and aggregate them to the census block group level.[5]

[5]Eligible call types include violent offenses, property offenses, vandalism, narcotics, prostitution, fraud, and domestic violence. Crime rates are calculated as total calls per 100 residents using ACS 2019–2023 block

4.2 Smart Phone Data

4.2.1 Advan

The Advan Monthly Patterns dataset provides visitor and demographic aggregations for points of interest (POIs) in the U.S. over a monthly period. This dataset is generated from cellphone location data collected from 1,000 apps across 5 million devices nationwide along with monthly updates. It includes aggregated raw counts of visits to POIs, detailing how often people visit, the duration of their stays, their origins, subsequent destinations, and more. The data is anonymized and aggregated to offer insights into visitor volume and overall behavioral patterns. The dataset provides each POI's geographical coordinates (latitude and longitude), classifies it according to the North American Industry Classification System (NAICS) code and records the number of visits originating from each home census block group in the city. I use Advan data from August through October 2024 for the analysis.

I classify essential destinations as establishments that provide food, healthcare, childcare, financial and postal services, pharmacies, personal care, education, and places of community or cultural importance.[6] These categories capture the types of services and resources that are most critical for meeting residents' daily and social needs.

Following a similar approach to Abbiasov et al. (2024), I construct 15-minute walking isochrones for each census block group in the city of Miami. An isochrone represents a geographic area that a person can reach within a specified time frame. To generate these isochrones, I employ OpenRouteService, a routing platform that calculates travel times along real-world transportation networks. OpenRouteService is built upon OpenStreetMap, a collaborative, open-source mapping project that provides detailed data on roads, sidewalks,

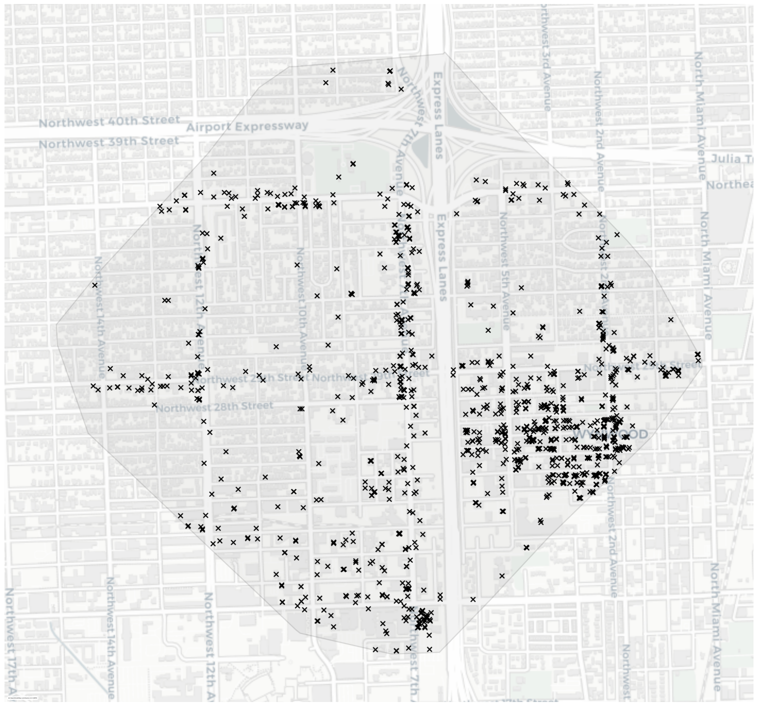
group populations and are winsorized at the 99th percentile to mitigate the influence of extreme values.

[6]Essential categories include: 445131 Convenience Retailers; 621493 Freestanding Ambulatory Surgical and Emergency Centers; 812112 Beauty Salons; 722511 Full-Service Restaurants; 621498 All Other Outpatient Care Centers; 621492 Kidney Dialysis Centers; 621410 Family Planning Centers; 445110 Supermarkets and Other Grocery Retailers; 491110 Postal Service; 812310 Coin-Operated Laundries and Drycleaners; 621111 Offices of Physicians (except Mental Health Specialists); 622110 General Medical and Surgical Hospitals; 722513 Limited-Service Restaurants; 813110 Religious Organizations; 445120 Convenience Stores; 446110 Pharmacies and Drug Stores; 712190 Nature Parks; 624410 Child Care Services; 812111 Barber Shops; 611110 Elementary and Secondary Schools; 522110 Commercial Banking; 621112 Offices of Physicians, Mental Health Specialists; 722514 Cafeterias, Grill Buffets, and Buffets; 722515 Snack and Nonalcoholic Beverage Bars.

trails, and other geographic features worldwide. This approach offers a more accurate depiction of walkable consumption access within each neighborhood, considering the actual pedestrian street network rather than simply calculating straight-line distances. For instance, a resident separated from a nearby grocery store by an expressway would need to detour to the nearest pedestrian overpass or intersection before reaching the destination—an additional travel cost that a straight-line distance measure would overlook.

Using the OpenRouteService API, I specify a 'foot-walking' profile with a 900-second (15-minutes) time range for each census block group. I use the centroid of its boundary as the starting point to compute the corresponding isochrone. The resulting isochrone polygons delineate the estimated walkable area around each block group center. I then spatially join these polygons with the smart phone dataset to identify which destinations fall within the reachable range for each block group. This process yields a neighborhood-specific set of establishments that are physically accessible on foot within 15 minutes. Figure 3 provides an example of the isochrone construction for a block group in the Wynwood neighborhood of Miami, roughly five miles east of Miami International Airport.

Figure 3: 15-Minute Walk Isochrone Example in Miami[a]



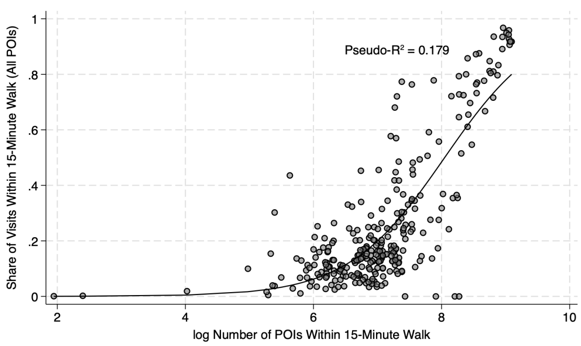
[a]*Notes.* The isochrone delineates the area reachable within a 15-minute walk from the centroid of a census block group. Isochrones are computed using the OpenRouteService API with a `foot-walking` profile, based on the OpenStreetMap pedestrian network. This example illustrates the estimated walkable range for a block group in the Wynwood neighborhood of Miami.

For the city of Miami, the average share of essential visits occurring within residents' local 15-minute isochrones is 0.303, indicating that roughly 30% of all trips take place within a short walking distance. In comparison, Abbiasov et al. (2024) report a national median of only 14% in 2019, with regional variation ranging from about 34% in the Northeast to under 18% in the South. Miami's baseline of approximately 30% therefore reflects a notably higher degree of localized activity, consistent with the idea that zoning reform and broader allowances for mixed-use development can facilitate shorter, more neighborhood-oriented trip patterns.

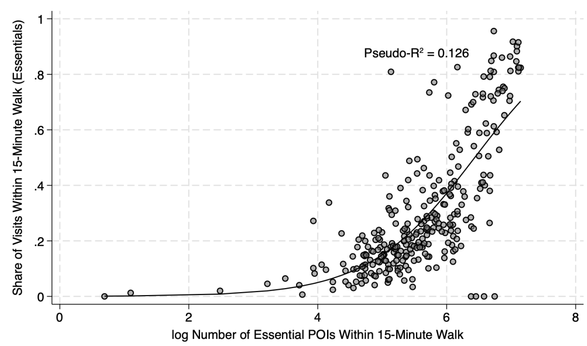
Figure 4 illustrates the relationship between 15-minute access and 15-minute usage across Miami's neighborhoods. Here, *15-minute access* refers to the number of essential destinations reachable within a 15-minute walk from the center of each block group, while *15-minute usage* measures the share of all resident visits that occur within that same walkable area. As the figure shows, neighborhoods with greater access to destinations exhibit substantially higher shares of visits occurring within walking distance—shown for all establishments in Panel (a) and for essential amenities in Panel (b)—with the relationship steepening at higher levels of access.

Figure 5 illustrates how 15-minute usage varies across income deciles. I construct income deciles using population-weighted deciles of median household income. Specifically, each census block group is ranked by median income, and its population is used as a weight when partitioning the total population into ten equally sized deciles. The figure shows that usage stays fairly steady across the middle income groups but is higher at both the low and high ends of the income distribution, forming a U-shaped pattern. This suggests that 15-minute usage tends to be a necessity for lower-income residents and more of a luxury for wealthier ones.

Figure 4: 15-Minute Usage vs. 15-Minute Access



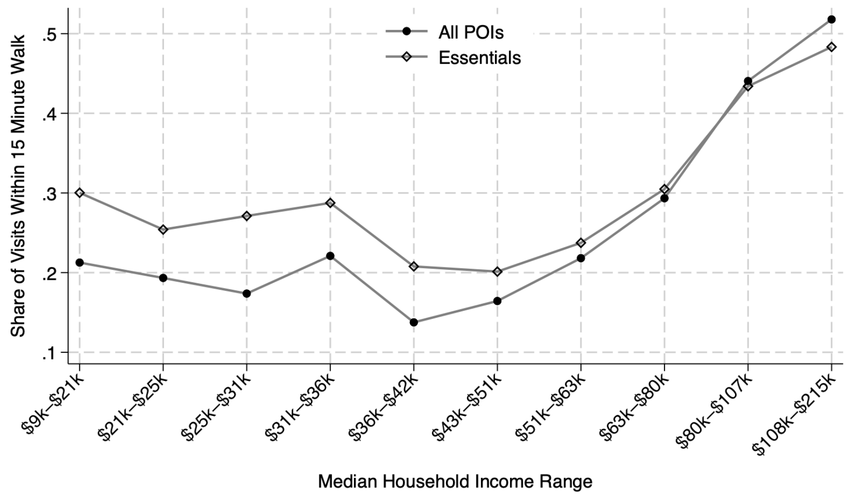
(A) All POIs



(B) Essentials

Notes. Each panel plots the share of visits occurring within a 15-minute walk (*usage*) against the log number of reachable POIs (*access*) for all destinations (left) and essentials (right). Fitted curves are estimated using a fractional logit model to ensure predicted values remain between 0 and 1

Figure 5: 15-Minute Usage by Income Decile[a]



[a] *Notes.* Income deciles are based on population-weighted rankings of median household income. Each census block group is ranked by its median income, and population is used as a weight when dividing the citywide distribution into ten equally sized income groups. This ensures that each decile represents an equal share of Miami's residents, providing a balanced basis for comparing usage patterns across the income spectrum.

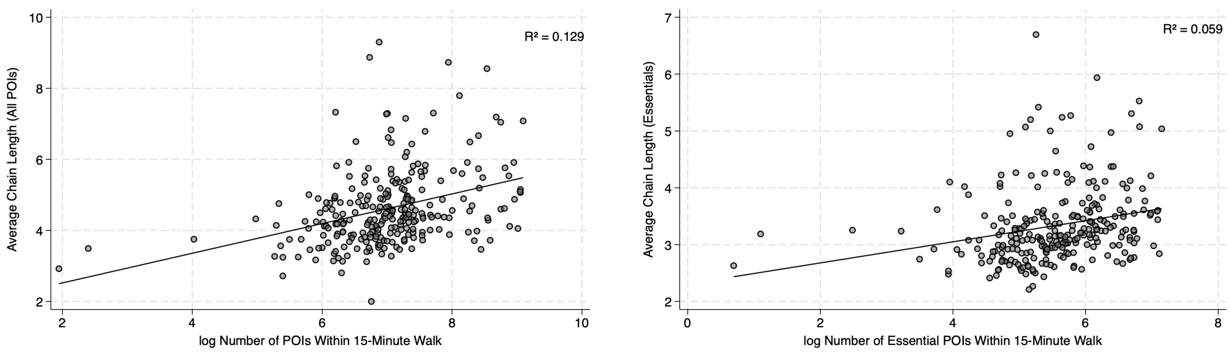
4.2.2 Veraset

As noted in Miyauchi et al. (2025), accounting for travel itineraries—or trip chains—provides an additional view of how people move through cities and consume amenities. Instead of making separate trips, individuals often link multiple stops within a single journey, lowering total travel costs and generating "consumption externalities" between nearby locations. When destinations are close and convenient to visit together, they act as complements; when they are farther apart, they compete as substitutes. These interactions help explain why amenities cluster and how changes in one area can ripple across the urban network.

Unlike the Advan dataset, which summarizes visits in aggregate, the Veraset dataset tracks the movements of individual devices over time, allowing observation of how people link multiple destinations within a single outing rather than counting visits in isolation. Each visit for the tracked devices is time-stamped, recording the date and time a user enters each establishment. I define a *trip chain* as a continuous sequence that begins at home, includes two or more visits to points of interest, and ends at home—all occurring within a resident's 15-minute walking isochrone. I use these data for the months of August through October

2024. Figure 6 illustrates the relationship between average trip-chain length and 15-minute access, shown for all establishments in Panel (a) and for essential amenities in Panel (b). The positive association indicates that neighborhoods with greater amenity access support longer, more connected trip chains—consistent with the idea that higher amenity density can generate consumption externalities, where proximity between destinations encourages linked local activity rather than isolated visits.

Figure 6: Average Trip-Chain Length vs 15-Minute Access.[a]



(A) Average Trip-Chain Length (All POIs)

(B) Average Trip-Chain Length (Essentials)

[a] *Notes.* Trip-chain length measures the average number of destinations linked within a single outing that begins and ends at home. Each point represents a census block group, with 15-minute access defined as the log count of reachable POIs within the local isochrone. The positive relationship suggests that greater amenity density foster more connected, multi-stop activity patterns.

4.2.3 SafeGraph

I use SafeGraph spending and transaction data as inputs to construct a CES-style price index, following the framework introduced by (Dixit and Stiglitz, 1977). The Spend dataset aggregates anonymized debit and credit card transactions at individual points of interest across the U.S. on a monthly basis. It includes spending information from more than 10 million customers at over 1.1 million POIs representing 5,454 parent brands. When aggregated to the brand level, SafeGraph's Spend data align closely with firm-level financial indicators such as quarterly revenue, supporting its validity as a measure for local consumption activity.[7] [8] I use these data for the months of August through October 2024.

4.3 Verisk Property Data

To measure housing prices at the census block group level, I use property data from Verisk (formerly Infutor). I focus on owner-occupied single-family homes and condominiums, using their estimated market values from the 2024 extract, which represents the most recent update available at the time of download. To mitigate the influence of outliers, I exclude properties in the top 1% of the value distribution and those with market values below $50,000. Because this dataset reflects the existing housing stock rather than only recent transactions, it provides a more stable measure of neighborhood-level home values.

4.4 U.S. Census Data

4.4.1 American Community Survey

I use data from the 2019–2023 five-year American Community Survey (ACS) to incorporate demographic, housing, socioeconomic, and commuting characteristics at the block-group level. These measures provide important context for understanding neighborhood conditions and are primarily used as control variables in the instrumental variables regression analysis.

4.4.2 LEHD Origin–Destination Employment Statistics

To measure workplace earnings, I use the 2020 Workplace Area Characteristics (WAC) files from the Longitudinal Employer–Household Dynamics (LEHD) Origin–Destination Employment Statistics (LODES) program, published by the U.S. Census Bureau. These data report the number of jobs at each workplace location by broad earnings category. Using this information, I compute an average wage for each census block group, which serves as an input for constructing the residential commuter market access measure.

[7] In one such validation, SafeGraph's spending data closely track quarterly revenue for major firms like McDonald's, Chipotle, and Target, even when companies report online sales separately.

[8] SafeGraph also assesses geographic representativeness by comparing its state-by-state customer home location data to the true proportions reported by the 2019. U.S. Census. SafeGraph's panel density closely mirrors actual population density, with an average percentage point difference of less than 1% and a maximum variation of +/-4% per state.

4.4.3 Census Transportation Planning Products

To measure commuting patterns, I use the most recent Census Transportation Planning Products (CTPP) files covering 2016–2020. The CTPP is a special tabulation of the ACS that reports flows between home and work locations across travel-time intervals. I use these data to estimate expected commute times for each census block group.

4.5 Instrumental Variables Estimation

A primary concern in estimating the causal effect of 15-minute usage on 15-minute access is endogeneity. Residential sorting may arise if individuals who value walkable environments self-select into more accessible neighborhoods. Similarly, amenity sorting may occur if businesses choose to locate in areas with high local demand, generating reverse causality between access and usage. Ideally, one could estimate a border discontinuity design in which access changes sharply—such as across zoning or regulatory boundaries—and compare otherwise similar block groups on either side. However, because the dependent variable is inherently distance-based, adjacent block groups often share consumption access to many of the same amenities within their 15-minute isochrones, undermining the validity of such a design.

As an alternative approach to address these concerns, I instrument for current access using historical floor-area ratios measured prior to 1934, denoted by FAR_j^{pre1934}—a period preceding the implementation of zoning regulations in Miami. These historical density characteristics capture the built environment before land-use controls were established and provide plausibly exogenous variation in potential development intensity that is unlikely to be correlated with contemporary residential sorting or amenity location decisions.

The relationship between amenity access and local usage is estimated using a population-weighted two-stage least squares (2SLS) framework.

Second Stage:

$$\text{Usage}_j^{\text{15-min}} = \beta_0 + \beta_1 \widehat{\text{Access}}_j^{\text{15-min}} + \mathbf{X}_j'\gamma + \varepsilon_j, \tag{1}$$

First Stage:

$$\text{Access}_j^{\text{15-min}} = \pi_0 + \pi_1\, FAR_j^{\text{pre1934}} + \mathbf{X}_j'\delta + \nu_j. \tag{2}$$

Here, $\text{Usage}_j^{\text{15-min}}$ denotes the share of visits by residents of block group j that occur within their local 15-minute walking isochrone, and $\text{Access}_j^{\text{15-min}}$ measures the log number of amenities accessible within that same isochrone. The vector $\mathbf{X}_j$ contains ACS controls, including demographic, socioeconomic, housing, commuting, and employment characteristics. The disturbance terms ε_j and ν_j capture unobserved determinants of usage and access, respectively.

Table 2 reports a strong positive relationship between amenity access and local usage. In the OLS models, a 1% increase in access is associated with roughly a 0.20 percentage-point increase in local usage. When instrumenting for access, the effect rises to 0.35 percentage points per 1% increase in access, suggesting that endogeneity likely biases the OLS estimates downward. The first-stage F-statistics confirm that the instrument is strong. The dependent variable, 15-minute usage, has a baseline mean of 0.303, indicating that approximately 30% of visits occur within residents' local isochrones on average. At this baseline, the IV estimate implies that a 1% increase in access raises local usage by about 1.1% relative to its mean.

Compared with the national baseline reported by (Abbiasov et al., 2024)—where the median U.S. resident made only 14% of daily trips within a 15-minute walk in 2019, ranging from about 34% in the Northeast to under 18% in the South—Miami's 2024 baseline of roughly 30% reflects greater local activity and highlights how zoning reform and broader allowances for mixed-use development can encourage more local trips and reduce average trip durations.

Table 2: Access → Usage Estimates (OLS and IV)

Dependent variable:	15-minute Usage			
	OLS		IV Estimates	
	(1)	(2)	(3)	(4)
15-minute Access	0.195***	0.160***	0.288***	0.345***
	(0.018)	(0.019)	(0.033)	(0.064)
Controls		✓		✓
Observations	255	255	226	226
First-stage F-stat	-	-	43.57	21.14

Standard errors in parentheses. Models clustered at block-group level.
Control variables include: pre-zoning (1934) number of parcels from assessor data; and ACS 5-year (2019–2023) estimates for: renter share, unemployment rate, share Hispanic, share who commute by walking or by car, share with commute time less than 15 minutes, share of college graduates, share aged 25–34, share Black, share in finance occupations, and share in the finance industry.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Residential Choice Model

My model of residential housing demand follows a standard discrete choice framework (Berry et al., 1995; Bayer et al., 2007). Following the setup and notation of (Conlon and Gortmaker, 2020), I begin with the following problem. There are $i = 1, 2, \ldots, I$ individuals who choose among $J \in \{0,1,\ldots,J\}$ discrete alternatives, where the alternatives are one of 288 Census block groups within the city Miami. The outside option ($j = 0$) is living outside the city- the remainder of Miami-Dade County - taken by roughly 85% of the individuals in the data. Individual utility from choosing to live in block group j is defined as:

$$u_{ij} = \underbrace{\delta_j}_{\text{mean utility}} + \underbrace{\mu_{ij}}_{\text{individual-specific utility}} + \epsilon_{ij} \tag{3}$$

where the mean utility is, in vector-matrix form, $\delta = p_j\alpha + X_1^{ex}\beta^{ex} + \xi$. Here, α is the scalar coefficient on price p, and β^{ex} is a $K_1^{ex} \times 1$ vector of parameters on the $J \times K_1^{ex}$ submatrix of exogenous characteristics X_1^{ex} in location j. X_1^{ex} includes the average age, in years, of the stock of building units (all property types) as well as the average floor-area ratio of these units. X_1^{ex} also includes estimates of crime rates per 100 people and an index of residential commuter market access (RCMA) that measures the extent to which j is located near high-paying jobs.

The measure discounts destination wages by commute times:

$$\text{RCMA}_i \;=\; \sum_{i \in \mathcal{I}_j} \frac{w_i}{d_{ij}}\,,$$

where $d_{ij} = e^{\kappa\,\tau_{ij}}$ are the iceberg commuting costs. I set $\kappa = 0.01$, following micro-estimates from (Tsivanidis, 2023). τ_{ij} is the expected commute time (in minutes) from block group i to block group j, and w_i is the average wage in block group i. [9] $\mathcal{I}_j$ is the set of all possible jobs in block groups i that a resident of j could reach, including all block groups in Broward, Palm Beach, and Miami-Dade counties, which together make up the Miami metropolitan area. [10] X_1^{ex} also includes a measure of walkability, my main characteristic of interest, which I discuss in greater detail later in this section.

The model incorporates both observable heterogeneity (through demographics, d') and unobservable taste heterogeneity (ν), where ν denotes independent draws from the standard normal distribution. The $K_2 \times K_2$ lower-triangular matrix Σ is the Cholesky root of the covariance matrix governing the unobserved component of heterogeneity. The $K_2 \times D$ matrix Π captures how random coefficients vary systematically with demographics d. Thus, the

[9] **Construction of destination wages.** The LEHD WAC reports counts of jobs at the workplace by three earnings ranges—\$1–\$15k, \$15–\$40k, and \$40k+. To recover an average wage for each job location i, I assign representative values of \$15,000, \$27,500, and \$50,000 to these three ranges (the \$50,000 value is a conservative proxy for the upper tail), multiply each range's job count by its representative value, and sum to form a wage bill. Total jobs at i are taken from WAC's total-jobs field when available, otherwise from the sum of the three range counts. The destination wage entering RCMA is then w_i = (wage bill)/(total jobs). This bin-imputation is necessary because WAC provides job counts by earnings categories rather than observed wages.

[10] **Construction of commute times.** I use the CTPP—which reports tract-to-tract commuting flows by *travel-time bins*—to recover expected minutes between the parent tract of home block group j and the parent tract of job block group i. Because CTPP provides a distribution over bins (not a mean), I compute

$$\tau_{ij} \;=\; \frac{\sum_b \text{count}_{ijb}\, m_b}{\sum_b \text{count}_{ijb}},$$

where count_{ijb} is the number of commuters from j to i in bin b and m_b is that bin's midpoint in minutes. For the three open-ended upper bins—90–119 minutes, 120–179 minutes, and 180+ minutes—I assign a conservative midpoint of 105 minutes. This tract-level τ_{ij} is then attached to the corresponding block-group pair via their parent tracts.

individual-specific portion of utility, in vector-matrix form, is

$$\mu = X\big(\Sigma\nu' + \Pi d'\big).$$

Last, the term ϵ_{ijt} represents the idiosyncratic preference shocks.

Consumers choose among J discrete alternatives, selecting the option that yields the highest utility:

$$d_{ij} = \begin{cases} 1 & \text{if } u_{ij} \geq u_{ik} \text{ for all } j \neq k, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Aggregate market shares are obtained by integrating individual choice probabilities over the distribution of heterogeneous consumer tastes:

$$s_j(\delta) = \int d_{ij}(\delta, \mu_i)\, d\mu_i\, d\epsilon_i. \tag{5}$$

When ϵ_{ij} are independently and identically distributed Type I Extreme Value (Gumbel), the conditional choice probabilities take the mixed logit form:[11]

$$s_j(\delta, \theta_2) = \int \frac{\exp(\delta_j + \mu_{ij})}{\sum_{k \in J} \exp(\delta_k + \mu_{ik})}\, f(\mu_i \mid \tilde{\theta}_2)\, d\mu_i \tag{6}$$

where $f(\mu_i \mid \tilde{\theta}_2)$ denotes the mixing distribution over heterogeneous consumer types i, and θ_2 parameterizes this heterogeneity. The vector θ_2 includes all of the random coefficients of the model, including the heterogeneous taste for price α.

Market shares are inverted to recover mean utilities, which are then related to product characteristics, prices, and an error term. With the addition of instruments Z_j^D, moment conditions of the form $\mathbb{E}[\xi_j' Z_j^D]$ can be constructed.

[11] I approximate the integral using Gauss–Hermite quadrature with 15 nodes. Specifically, market shares are computed as $s_j \approx \sum_{i \in I} w_i\, s_{ij}$, where w is the $I \times 1$ vector of corresponding weights and s_{ij} is the probability that agent i chooses product j.

5.1 The Estimator

I construct a GMM estimator using the sample analogue of the demand moments to form:

$$g^D(\theta) = \frac{1}{N} \sum_j \xi_j Z_j^D \tag{7}$$

and construct a nonlinear GMM estimator for $\theta = [\beta,\alpha,\tilde{\theta}_2]$ with a weighting matrix W:

$$\min_\theta q^D \equiv g^D(\theta')W g^D(\theta). \tag{8}$$

I divide the parameter space θ into two components: the $K_1 \times 1$ vector θ_1, which contains the demand parameters β, and the $K_2 \times 1$ vector θ_2, which contains the remaining parameters, including the price coefficient α. The full program can be written explicitly as:

$$\begin{aligned}
&\min_\theta q^D \equiv g^D(\theta')W g^D(\theta) \\
&g^D(\theta) = \frac{1}{N} \sum_j Z_j^{D\prime} \xi_j \\
&\xi_j = \delta_j - [x_j, v_j]\beta + \alpha p_j \\
&\mathcal{S}_j \equiv s_j(\delta, \theta_2) = \int \frac{\exp(\delta_j + \mu_{ij})}{\sum_{k \in J} \exp(\delta_k + \mu_{ik})} f(\mu_i \mid \tilde{\theta}_2)\, d\mu_i
\end{aligned} \tag{9}$$

This estimator and its econometric properties are discussed in (Berry et al., 1995) and (Berry et al., 2004). In practice, the program must be solved twice: first to obtain a consistent estimate of $\hat{W}(\hat{\theta})$, and then again to obtain the efficient GMM estimator.

5.2 The Nested Fixed Point Algorithm

In addition to providing an estimator, (Berry et al., 1995) outline an algorithm for solving equation (9) that simplifies the problem. Since the parameters on exogenous regressors enter the model linearly, I concentrate out θ_1 and perform a nonlinear search only over θ_2, treating $\hat{\theta}_1(\theta_2)$ as an implicit function of the other parameters. Following Conlon and Gortmaker (2020), the modified algorithm proceeds as follows:

Algorithm 1 Nested Fixed Point

For each guess of θ_2:

(a) Solve $\mathcal{S}_j = s_j(\boldsymbol{\delta}, \theta_2)$ for $\hat{\boldsymbol{\delta}}(\boldsymbol{\mathcal{S}}, \theta_2) \equiv \hat{\boldsymbol{\delta}}(\theta_2)$

(b) Take $\hat{\boldsymbol{\delta}}(\mathcal{S}_j,\, \theta_2)$ and use linear IV-GMM to recover $[\hat{\theta_1}(\theta_2)]$

$$\hat{\delta}_j(\mathcal{S}_j, \theta_2) + \alpha p_j = [x_j, v_j]\beta + \xi_j \tag{10}$$

(c) Construct the residuals:

$$\hat{\xi}_{jt}(\theta_2) = \hat{\delta}_{jt}(\theta_2) - [\, x_{jt}, v_{jt}\,]\hat{\beta}(\theta_2) + \alpha p_j. \tag{11}$$

(d) Form the sample moments:

$$g_D(\theta_2) = \frac{1}{N}\sum_j \hat{\xi}_j(\theta_2) Z_j^D, \tag{12}$$

(e) Construct the GMM objective: $\mathrm{q}(\theta_2) = \mathrm{g}(\theta_2)' W \mathrm{g}(\theta_2)$

5.3 Identification

Estimating substitution patterns in random-coefficient demand models is often plagued by weak identification, because conventional instruments do not capture how products compete in characteristics space. Gandhi and Houde (2019) propose differentiation IVs, which directly exploit observable differences between products that summarize how isolated or crowded a product is relative to its competitors. By grounding the instruments in measures of differentiation, this approach strengthens the reduced-form correlation with market shares, and yields precise estimates of substitution patterns without relying on supply-side restrictions. Differentiation IVs are now widely used in applied work across settings such as automobiles, consumer packaged goods, and school choice, confirming their robustness and establishing them as an empirical best practice (Miller and Weinberg, 2017; Miravete et al., 2018; Coşar et al., 2018; Singleton, 2019; Dubé et al., 2021).

Following Gandhi and Houde (2019), I begin by constructing a predicted price $\hat{p}_j$ to address the endogeneity of prices. The idea is to purge observed prices of any correlation with unobserved quality by projecting p_j onto exogenous cost shifters and product characteristics.

This ensures that the moment condition $E[\xi_j \mid x, \hat{p}] = 0$ holds.

Formally, I estimate

$$p_j = f(\mathbf{X}_j^S) + \mathbf{Z}_j'\boldsymbol{\delta} + u_j,$$

where p_j is the observed average price per square foot for product j. The function $f(\cdot)$ denotes a flexible reduced-form regression—implemented using spline basis expansions—that maps structural characteristics (FAR, lot size, year built, square footage) into predicted prices. The vector $\mathbf{Z}_j$ includes the share of each block group permitting mixed-use development under varying regulatory intensities (fully open, limited, and restricted), the realized shares of mixed-use and multifamily land, and the share of each block group located within a transit-oriented development zone.

The fitted values from this regression yield the predicted price $\hat{p}_j$, which serves as a stand-alone cost shifter for price. Panel A of Table 3 reports the results from this first-stage regression. The model explains a substantial share of the variation in prices ($R^2 = 0.65$), indicating that both physical and regulatory characteristics systematically shape observed price differences across block groups.

Table 3: First-stage price prediction and IIA test

Panel A: First-stage predicted price regression

	(1)
Dependent variable	Price Per Square Foot
R^2	0.655
F-statistic	22.82
Observations	288

Panel B: IIA test

	(1)
Wald joint test: $H_0\colon \gamma_2 = 0$	6561.97
p-value (robust $\chi^2_{(45)}$)	< 0.0001

Notes: Panel A reports the first-stage reduced-form regression of price per square foot on physical and zoning characteristics. Predicted prices $\hat{p}_{jt}$ from this regression serve as exogenous inputs in constructing the differentiation IVs. Panel B reports the robust Wald χ^2 test of the differentiation-IV coefficients (γ_2 block) from the log-odds regression. Rejection of H_0 indicates that product differentiation significantly predicts log-odds, rejecting the IIA restriction.

With $\hat{p}_j$ in hand, I construct instruments that summarize the degree of differentiation between product j and its rivals. I first define the basic distance terms:

$$d_{j,j'}^{(1)} = x_{j'}^{(1)} - x_j^{(1)}, \qquad d_{j,j'}^{\hat{p}} = \hat{p}_{j'} - \hat{p}_j,$$

which measure differences in observable product characteristics $x^{(1)}$ and in predicted prices $\hat{p}$ between j and each rival j'.

I then implement two specific formulations as outlined in Gandhi and Houde (2019). The first is the quadratic differentiation IV:

$$z_j = \left\{ x_j,\ \omega_j,\ \sum_{j'} \big(d_{j,j'}^{(1)}\big)^2,\ \sum_{j'} \big(d_{j,j'}^{(\hat{p})}\big)^2 \right\},$$

which captures how isolated product j is by aggregating squared distances from all rivals in characteristics and predicted price space.

The second is the local differentiation IV:

$$z_{jt} = \left\{ x_{jt},\ \omega_{jt},\ \sum_{j'} \mathbf{1}\big(|d_{j,j'}^{(1)}| < sd_1\big),\ \sum_{j'} \mathbf{1}\big(|d_{j,j'}^{\hat{p}}| < sd_{\hat{p}}\big) \right\},$$

which emphasizes crowding by counting how many rivals lie within one standard deviation along either dimension.

In addition, I construct interaction terms which capture the covariance between two dimensions of differentiation. Finally, I include the predicted price $\hat{p}_j$ itself as a stand-alone cost shifter along with the zoning regulation variables to incorporate exogenous cost variation directly into the instrument set.

5.3.1 IIA Test

A key concern in discrete-choice demand models is whether the restrictive *Independence of Irrelevant Alternatives* (IIA) assumption holds. Under IIA, substitution patterns depend only on relative market shares, implying that the odds of choosing product j relative to the outside option are unaffected by the characteristics of other products. If this property were true, product differentiation would play no role in shaping substitution patterns, and instruments based on differences across products would have no power. Testing IIA therefore provides a direct diagnostic of instrument relevance: if differentiation matters for explaining log-odds, then IIA is violated and the Differentiation IVs are informative.

Formally, I estimate the regression

$$\ln\left(\frac{s_j}{s_0}\right) = x_j\hat{\gamma}_1 + \hat{\gamma}_p\hat{p}_j + A_j^{-w}(\mathbf{x}_j, \mathbf{w}_j)\gamma_2 + \varepsilon_j,$$

where s_j is the market share of product j and s_0 is the outside share. The vector x_j includes observed product characteristics and cost shifters, and $\hat{p}_j$ is the predicted price obtained from exogenous cost shifters. The term $A_j^{-w}(\mathbf{x}_j, \mathbf{w}_j)$ collects the Differentiation IVs, which summarize how distinct product j is from its rivals.

The null hypothesis of the IIA test is $H_0 : \gamma_2 = 0$. Failing to reject H_0 would imply that product differentiation has no effect beyond market shares and predicted price, consistent with the logit IIA structure. Rejecting H_0 confirms that differentiation systematically predicts log-odds, establishing the relevance of the Differentiation IVs and supporting their use as strong instruments in the non-linear IV estimation.

Table 2, Panel B, reports the results of the IIA test. Rejecting H_0 confirms that differentiation systematically predicts log-odds, establishing the relevance of the Differentiation IVs and supporting their use as strong instruments in the non-linear IV estimation. The Wald test strongly rejects the null, indicating that the IIA restriction does not hold and that product differentiation meaningfully explains variation in observed substitution patterns.

5.4 Measure of Walkability

.

The baseline measure of walkability used in previous sections is the share of visits made by residents of each block group that occur within their local 15-minute walking isochrone. This share captures the extent to which daily activity remains local. However, similar usage shares across locations can mask large differences in the richness of nearby amenities and the overall appeal of a location. For example, a 30% local visit share in a block group with only

20 reachable essential establishments is not necessary comparable in terms of walkability to the same share in one with 80 reachable establishments.

Assuming consumers exhibit "love of variety" preferences, I augment the 15-minute usage share with a price index that captures both local variety and effective cost. In the standard Dixit and Stiglitz (1977) framework, consumers derive utility not only from consuming larger quantities of each good but also from accessing a greater number of distinct varieties. The corresponding price index—interpreted as the cost of obtaining one unit of utility—declines as the number of available varieties increases.

Formally, for each block group j, I construct a CES price index:

$$P_j = p_j \, M_j^{-1/(\sigma-1)},$$

where M_j is the number of distinct reachable establishments within the 15-minute isochrone. As a proxy for consumption price at each location, p_j, I use the average expenditure per transaction from SafeGraph spending and transaction data.[12] The price index declines with increasing variety (M_j) and rises with higher average local expenditures (p_j), implying that neighborhoods with richer and more affordable local service options exhibit lower effective price levels.

I set the elasticity of substitution to $\sigma = 2.5$, a value substantially lower than those used in comparable urban or retail contexts. Miyauchi et al. (2025) estimate an elasticity of $\sigma = 4.6$ for non-traded service consumption across Tokyo, Japan. Hottman et al. (2016) estimates a median elasticity of substitution across barcoded goods in the retail sector of 6.9. Couture et al. (2024) assumes an elasticity of substitution of 6.8 across the non-traded services supplied by neighborhoods. My chosen $\sigma = 2.5$ is deliberately smaller because it aims to reflect substitution possibilities confined to a 15-minute walk. [13]

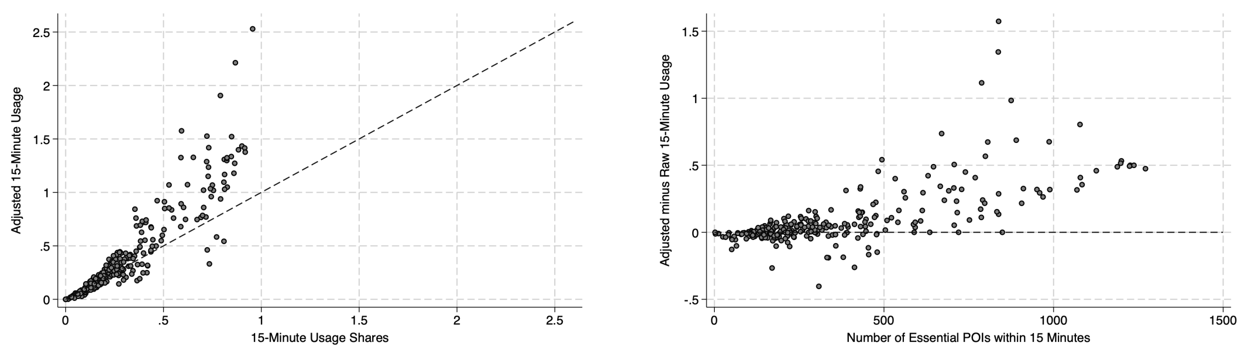
Figure 7 highlights the differences between the two walkability measures. Panel (a)

[12] This proxy does not account for variation in basket size across transactions and should therefore be interpreted as an average per-transaction expenditure rather than a unit price measure. To partially address this limitation, I residualized p_j with respect to demographic and amenity-density variables to remove systematic bias from local income and demand composition.

[13] I also abstract from travel costs as modeled in Miyauchi et al. (2025), which include both trip-level costs (rising with travel time between destinations) and intermediate-stay costs (such as the effort of finding parking, entering or exiting a station, or interrupting a trip).

compares the walkability index with the raw 15-minute usage shares. Most observations lie above the 45-degree line, indicating that the adjustment increases measured walkability in neighborhoods with richer local variety. The upward deviations become more pronounced for block groups where amenities are more abundant, reflecting the additional utility gained from access to a wider set of establishments. Panel (b) plots the difference between the walkability index and the 15-minute usage shares against the number of essential POIs within 15 minutes. The positive relationship shows that the adjustment systematically raises walkability scores in amenity-dense areas, consistent with "love-of-variety" preferences. However, some observations lie above or below the zero line even at similar values of M_j. These residual differences reflect heterogeneity in estimated local prices from the SafeGraph data: neighborhoods with higher local prices (p_j) exhibit lower effective walkability, while those with lower prices achieve higher effective walkability.

Figure 7: Comparison of Walkability Index vs Usage Share



(A) Walkability Index vs Usage Share

(B) Difference Between Measures

Notes: Each point represents a census block group in the City of Miami. Panel (a) compares the walkability index with the raw 15-minute usage share, where most observations lie above the 45-degree line, indicating that the adjustment increases measured walkability in neighborhoods with richer local variety. Panel (b) plots the difference between the walkability index and the 15-minute usage share against the number of essential POIs within 15 minutes. The positive slope indicates that the adjustment raises walkability scores in amenity-dense neighborhoods, consistent with CES "love-of-variety" preferences. Observations above or below the zero line at similar M_j values reflect heterogeneity in estimated local prices from the SafeGraph data: neighborhoods with higher local prices (p_j) exhibit lower effective accessibility, while those with lower prices exhibit higher effective walkability.

6 Demand Estimation Results

Table 4 reports the estimated demand parameters.[14] Panel A presents the mean utility coefficients for each product characteristic. On average, households derive higher utility from more walkable neighborhoods, areas with greater employment accessibility, and those with higher floor area ratios. The coefficients on price and crime are negative as expected, indicating that residents, on average, dislike higher housing costs and crime rates. Panel B reports the heterogeneity parameters related to walkability. All coefficients are close to zero and statistically insignificant, suggesting that preferences for walkability exhibit little variation across income groups or unobserved factors.

[14]Income draws are constructed from ACS block-group data by fitting a lognormal distribution to pooled median incomes weighted by population. I then draw 1,000 individual incomes from this fitted distribution and standardize the draws to have mean zero and unit variance.

Table 4: Demand Parameter Estimates: Mean Utility and Heterogeneity

Panel A: Mean Utility Coefficients	
Product Characteristic	**Estimate**
Outside Option	−8.224 (5.618)
Walkability Index	0.06931 (0.02414)
Price ($/ft^2)	−0.002827 (0.0009233)
RCMA	0.1238 (0.06217)
Age	0.0008411 (0.002955)
Far	0.06194 (0.02585)
Crime	−0.02793 (0.005459)
Panel B: Heterogeneity Estimates	
Σ_{walk}:	0.0000001919 (0.00001159)
Π_{income}:	0.000007537 (0.0003161)
Π_{income^2}:	−0.000001478 (0.02412)

Notes: Panel A reports mean utility coefficients (β) with robust standard errors in parentheses. Panel B reports the heterogeneity parameters: Σ_{walk} is the standard deviation of the random coefficient on walkability, and Π terms capture income-related taste heterogeneity. Price is measured in $/sqft.

7 Elasticities and Willingness-to-Pay Estimates

7.1 Elasticities

To assess how neighborhood demand responds to neighborhood attributes, I examine elasticities with respect to each attribute and home prices. The own-price elasticity measures the percentage change in a block group's market share resulting from a one-percent change in its own price per square foot, holding all other characteristics constant. The own-price elasticity for block group j is defined as

$$\varepsilon_{jj}^{p} = \frac{p_j}{s_j}\frac{\partial s_j}{\partial p_j},$$

where s_j denotes the market share of block group j, p_j is its average housing price per square foot, and $\frac{\partial s_j}{\partial p_j}$ is the partial derivative of share with respect to price. Because price typically enters utility with a negative coefficient, ε_{jj}^{p} is expected to be negative, reflecting that higher prices reduce neighborhood demand.

The elasticity with respect to any neighborhood characteristic x_j is defined analogously as

$$\varepsilon_{jj}^{x} = \frac{x_j}{s_j}\frac{\partial s_j}{\partial x_j},$$

Positive values of ε_{jj}^{x} indicate that improvements in the attribute increase neighborhood demand, holding all else constant.[15] [16] Panel A of Table 5 reports the estimated elasticities. On average, neighborhood demand is relatively inelastic with respect to most attributes, though there is meaningful variation across block groups. The price elasticity of demand is negative and less than one in magnitude, consistent with limited substitutability across neighborhoods. Elasticities for walkability and employment accessibility are small and centered near zero, indicating modest short-run responsiveness. In contrast, the elasticity with respect to building age is positive and elastic, although its associated mean utility coefficient is statistically insignificant, suggesting that this sensitivity is not robust. Figure 8 illustrates the distribution of price and walkability elasticities across neighborhoods.

[15] RCMA is standardized before estimation to improve numerical conditioning. Its large raw scale could otherwise distort the curvature of the GMM objective function, so centering and scaling to unit variance help the optimizer converge more reliably. The walkability measure is likewise standardized to facilitate interpretation

[16] Because walkability and RCMA are standardized rather than measured in their raw units, their elasticities are interpreted as semi-elasticities: they represent the percentage change in a block group's market share resulting from a one-standard-deviation increase, whereas other elasticities describe percentage responses to percentage changes.

7.2 Willingness-to-Pay

Willingness-to-pay for neighborhood attribute x, denoted WTP_x, measures how much an individual is willing to pay in higher housing prices to obtain an additional unit of a neighborhood attribute. In the discrete choice framework, WTP_x is defined as the ratio of the mean utility coefficient on that attribute, β_x, to the price coefficient, β_p. Formally, the willingness-to-pay is given by

$$\text{WTP}_x = -\frac{\beta_x}{\beta_p},$$

where the negative sign reflects that higher prices lower utility, so WTP_x is expressed as a positive monetary value. Panel B of Table 5 reports the implied WTP_x estimates for each neighborhood attribute. Households are willing to pay about \$24.52 per ft^2 for a one–standard–deviation increase in walkability—a sizable premium relative to the median housing price of \$306 per ft^2. This suggests that residents place substantial value on neighborhoods offering greater amenity access within walking distance. Employment accessibility and higher floor area ratios also command positive premiums, while the WTP for building age is negligible, and the negative WTP for crime is as expected. Overall, the results highlight walkability as a central determinant of neighborhood demand in Miami.

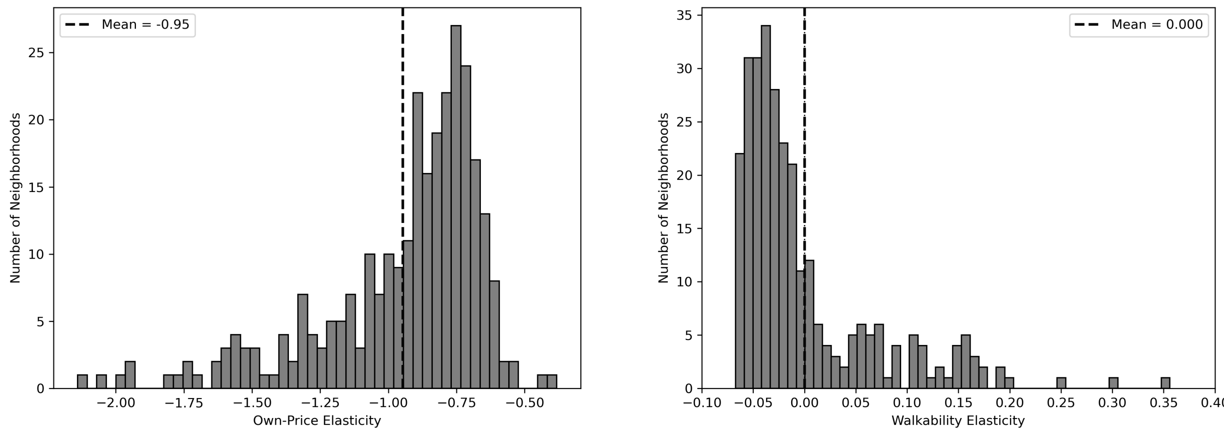
Table 5: Elasticity and Willingness-to-Pay Estimates

Panel A: Elasticity Estimates			
Neighborhood Attribute	**Mean**	**Min**	**Max**
Walkability Index	0.000	-0.067	0.356
Price ($\$/\text{ft}^2$)	-0.947	-2.151	-0.384
RCMA	0.000	-0.302	0.292
Building Age	1.655	1.628	1.697
Far	0.070	0.011	1.872
Crime	-0.171	-1.246	-0.000

Panel B: Willingness-to-Pay (WTP) Estimates	
Neighborhood Attribute	**WTP ($\$/\text{ft}^2$)**
Walkability Index	$24.52
RCMA	$43.80
Building Age	$0.30
Far	$21.91
Crime	$9.88(-)

Notes: Panel A reports elasticities, which measure the percentage change in neighborhood demand associated with a one-percent change in the corresponding attribute or a one–standard-deviation change (for the standardized variables walkability and RCMA). Positive elasticities indicate that higher values of the attribute raise demand, while negative values indicate deterrent effects. Panel B reports implied WTP values, interpreted as the dollar amount per square foot that households are willing to pay for a one unit improvement in each attribute. WTP is calculated as the ratio of the mean utility coefficient of the attribute to the price coefficient. The symbol (–) denotes a negative WTP, indicating that higher values of the attribute reduce willingness to pay.

Figure 8: Distributions of Elasticity Estimates



(A) Distribution of Own-Price Elasticities

(B) Distribution of Walkability Elasticities

Note: Figure 8 shows the elasticity estimates for price in panel (a) and walkability in panel (b). Price elasticities are all negative, reflecting the expected inverse relationship between housing cost and demand, while walkability elasticities are centered around zero and exhibit a long right tail but remain inelastic throughout the distribution.

8 Conclusion

The City of Miami's 2010 zoning reform was designed to promote walkability by encouraging mixed-use, higher-density development and reducing car dependence. This paper evaluates how these changes shape neighborhood accessibility and household preferences by estimating the demand for walkable neighborhoods. I develop a behaviorally grounded measure of walkability that combines residents' observed 15-minute walking behavior with a CES-style price index capturing the richness and affordability of nearby amenities. Linking this measure to detailed mobility data, this analysis quantifies the economic value households place on walkability.

The results show that Miami residents exhibit a strong preference for walkable neighborhoods. Baseline mobility patterns indicate that 30.3 % of essential visits occur within residents' 15-minute walksheds—nearly twice the share observed across the broader Southern region (Abbiasov et al., 2024)—and that denser, amenity-rich areas generate more frequent trip chains, reflecting more integrated patterns of daily activity. Instrumental-variable estimates show that increased local access directly increases neighborhood usage, indicating that accessibility drives behavior rather than simply reflecting it. The structural discrete-choice model further shows that households have a strong overall preference for walkability and are willing to pay about $24 per square foot for a one–standard–deviation increase in walkability.

Density presents both challenges and opportunities for urban welfare. By concentrating people, jobs, and amenities within accessible distances, it reduces travel time, broadens access to services, and strengthens local economic activity. Yet higher density can contribute to traffic congestion, crowding, noise, and crime, underscoring the need for thoughtful planning to balance intensity with neighborhood quality. The evidence from Miami shows that well-calibrated zoning reforms that expand allowable density and increase housing supply within and around mixed-use areas can meaningfully influence local travel behavior, accessibility, and residential location decisions.

References

Abbiasov, T., C. Heine, S. Sabouri, A. Salazar-Miranda, P. Santi, E. Glaeser, and C. Ratti (2024). The 15-minute city quantified using human mobility data. *Nature Human Behaviour 8*(3), 445–455.

Agarwal, S., J. B. Jensen, and F. Monte (2017). Consumer mobility and the local structure of consumption industries. Technical report, National Bureau of Economic Research.

Allen, T., S. Fuchs, S. Ganapati, A. Graziano, R. Madera, and J. Montoriol-Garriga (2021). Urban welfare: Tourism in barcelona. *Unpublished manuscript*.

Almagro, M. and T. Domínguez-Iino (2025). Location sorting and endogenous amenities: Evidence from amsterdam. *Econometrica 93*(3), 1031–1071.

Athey, S., B. Ferguson, M. Gentzkow, and T. Schmidt (2021). Estimating experienced racial segregation in us cities using large-scale gps data. *Proceedings of the National Academy of Sciences 118*(46), e2026160118.

Atkin, D., M. K. Chen, and A. Popov (2022). The returns to face-to-face interactions: Knowledge spillovers in silicon valley. Technical report, National Bureau of Economic Research.

Baum-Snow, N. and D. Hartley (2020). Accounting for central neighborhood change, 1980–2010. *Journal of urban economics 117*, 103228.

Bayer, P., F. Ferreira, and R. McMillan (2007). A unified framework for measuring preferences for schools and neighborhoods. *Journal of political economy 115*(4), 588–638.

Benmelech, E., N. Bergman, A. Milanez, and V. Mukharlyamov (2019). The agglomeration of bankruptcy. *The Review of Financial Studies 32*(7), 2541–2586.

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–890.

Berry, S., O. B. Linton, and A. Pakes (2004). Limit theorems for estimating the parameters of differentiated product demand systems. *The Review of Economic Studies 71*(3), 613–654.

Büchel, K., M. V. Ehrlich, D. Puga, and E. Viladecans-Marsal (2020). Calling from the outside: The role of networks in residential mobility. *Journal of urban economics 119*, 103277.

Buchholz, N., L. Doval, J. Kastl, F. Matejka, and T. Salz (2025). Personalized pricing and the value of time: Evidence from auctioned cab rides. *Econometrica 93*(3), 929–958.

Carlino, G. and W. R. Kerr (2015). Chapter 6 - agglomeration and innovation. In G. Duranton, J. V. Henderson, and W. C. Strange (Eds.), *Handbook of Regional and Urban Economics*, Volume 5 of *Handbook of Regional and Urban Economics*, pp. 349–404. Elsevier.

Combes, P.-P., G. Duranton, and L. Gobillon (2019). The costs of agglomeration: House and land prices in french cities. *The Review of Economic Studies 86*(4), 1556–1589.

Combes, P.-P. and L. Gobillon (2015). The empirics of agglomeration economies. In *Handbook of regional and urban economics*, Volume 5, pp. 247–348. Elsevier.

Conlon, C. and J. Gortmaker (2020). Best practices for differentiated products demand estimation with pyblp. *The RAND Journal of Economics 51*(4), 1108–1161.

Coşar, A. K., P. L. Grieco, S. Li, and F. Tintelnot (2018). What drives home market advantage? *Journal of international economics 110*, 135–150.

Couture, V. (2016). Valuing the consumption benefits of urban density. *University of California, Berkeley, Working Paper*.

Couture, V., J. I. Dingel, A. Green, J. Handbury, and K. R. Williams (2022). Jue insight: Measuring movement and social contact with smartphone data: a real-time application to covid-19. *Journal of Urban Economics 127*, 103328.

Couture, V., G. Duranton, and M. A. Turner (2018). Speed. *Review of Economics and Statistics 100*(4), 725–739.

Couture, V., C. Gaubert, J. Handbury, and E. Hurst (2024). Income growth and the distributional effects of urban spatial sorting. *Review of Economic Studies 91*(2), 858–898.

Couture, V. and J. Handbury (2020). Urban revival in america. *Journal of Urban Economics 119*, 103267.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980–2000. *American economic review 106*(3), 479–524.

Dixit, A. K. and J. E. Stiglitz (1977). Monopolistic competition and optimum product diversity. *The American economic review 67*(3), 297–308.

Dolfen, P., L. Einav, P. J. Klenow, B. Klopack, J. D. Levin, L. Levin, and W. Best (2023). Assessing the gains from e-commerce. *American Economic Journal: Macroeconomics 15*(1), 342–370.

Dubé, J.-P., A. Hortaçsu, and J. Joo (2021). Random-coefficients logit demand estimation with zero-valued market shares. *Marketing Science 40*(4), 637–660.

Duranton, G. and D. Puga (2004). Micro-foundations of urban agglomeration economies. In *Handbook of regional and urban economics*, Volume 4, pp. 2063–2117. Elsevier.

Duranton, G. and D. Puga (2020, August). The economics of urban density. *Journal of Economic Perspectives 34*(3), 3–26.

Duranton, G. and M. A. Turner (2011, October). The fundamental law of road congestion: Evidence from us cities. *American Economic Review 101*(6), 2616–52.

Ellen, I. G., R. Howland, and S. Glied (2023). Demons of density do higher-density environments put people at greater risk of contagious disease? *Journal of Housing Economics 59*, 101905.

Ellison, G., E. L. Glaeser, and W. R. Kerr (2010). What causes industry agglomeration? evidence from coagglomeration patterns. *American Economic Review 100*(3), 1195–1213.

Enrico, M. (2011). Chapter 14 - local labor markets**this research was funded by a grant from the university of kentucky center on poverty research. i am grateful to giacomo de giorgi, craig riddell, issi romen, michel serafinelli, david wildasin, the editors and especially pat kline and gilles duranton for useful comments on an earlier version. i thank ana rocca for excellent research assistance. i thank richard hornbeck for help with the data on total factor productivity from the census of manufacturers. any opinions and conclusions expressed herein are those of the author and do not necessarily represent the views of the us census bureau. all results based on data from the census of manufacturers have been reviewed to ensure that no confidential information is disclosed. Volume 4 of *Handbook of Labor Economics*, pp. 1237–1313. Elsevier.

Gandhi, A. and J.-F. Houde (2019). Measuring substitution patterns in differentiated-products industries. Technical report, National Bureau of Economic Research.

Gelabert-Sánchez, A. (2020). Miami 21 form-based code, miami, florida. In *Reflective Planning Practice*, pp. 174–194. Routledge.

Glaeser, E. (2012). *Triumph of the city: How our greatest invention makes us richer, smarter, greener, healthier, and happier*. Penguin.

Glaeser, E. and D. Cutler (2022). *Survival of the City: The Future of Urban Life in an Age of Isolation*. Penguin.

Glaeser, E. L. and M. E. Kahn (2010). The greenness of cities: Carbon dioxide emissions and urban development. *Journal of urban economics 67*(3), 404–418.

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

Glaeser, E. L. and B. Sacerdote (1999). Why is there more crime in cities? *Journal of political economy 107*(S6), S225–S258.

Gorback, C. (2022). Ridesharing and the redistribution of economic activity. *Available at SSRN 4956559*.

Gyourko, J. and S. E. McCulloch (2024). The distaste for housing density. Technical report, National Bureau of Economic Research.

Hausman, N., P. R. Samuels, M. C. Cohen, and R. Sasson (2023). Urban pull: The roles of amenities and employment. *Available at SSRN 4798884*.

Hottman, C. J., S. J. Redding, and D. E. Weinstein (2016). Quantifying the sources of firm heterogeneity. *The Quarterly Journal of Economics 131*(3), 1291–1364.

Klenow, L. E. P. J., J. D. Levin, and R. Murciano-Goroff (2022). Customers and retail growth.

Koster, H. R., I. Pasidis, and J. van Ommeren (2019). Shopping externalities and retail concentration: Evidence from dutch shopping streets. *Journal of Urban Economics 114*, 1–29.

Lacoe, J., R. W. Bostic, and A. Acolin (2018). Crime and private investment in urban neighborhoods. *Journal of Urban Economics 108*, 154–169.

Miller, N. H. and M. C. Weinberg (2017). Understanding the price effects of the millercoors joint venture. *Econometrica 85*(6), 1763–1791.

Miravete, E. J., M. J. Moral, and J. Thurk (2018). Fuel taxation, emissions policy, and competitive advantage in the diffusion of european diesel automobiles. *The RAND Journal of Economics 49*(3), 504–540.

Miyauchi, Y., K. Nakajima, and S. J. Redding (2025). The economics of spatial mobility: Theory and evidence using smartphone data. *The Quarterly Journal of Economics*, qjaf038.

Moretti, E. (2012). *The new geography of jobs*. Houghton Mifflin Harcourt.

Moretti, E. (2021, October). The effect of high-tech clusters on the productivity of top inventors. *American Economic Review 111*(10), 3328–75.

Oh, R. and J. Seo (2023). What causes agglomeration of services? theory and evidence from seoul. *Yale University, mimeograph*.

Qian, F., Q. Zhang, and X. Zhang (2023). Identifying agglomeration spillovers: Evidence from grocery store openings.

Singleton, J. D. (2019). Incentives and the supply of effective charter schools. *American Economic Review 109*(7), 2568–2612.

Thill, J.-C. and I. Thomas (1987). Toward conceptualizing trip-chaining behavior: A review. *Geographical Analysis 19*(1), 1–17.

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

Ushchev, P., I. Sloev, and J.-F. Thisse (2015). Do we go shopping downtown or in the 'burbs? *Journal of Urban Economics 85*, 1–15.

Yang, J., A.-O. Purevjav, and S. Li (2020, February). The marginal cost of traffic congestion and road pricing: Evidence from a natural experiment in beijing. *American Economic Journal: Economic Policy 12*(1), 418–53.

Zarate Vasquez, R. D. (2022). Spatial misallocation, informality, and transit improvements: Evidence from mexico city. Technical report, The World Bank.