Willingness to Travel with Endogenous Distance: Evidence from the Changing Retail Landscape

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Abstract

Economists often use variation in consumers' distance from services as a source of demand variation. This approach typically treats consumer-supplier distance as exogenous, despite suppliers strategically choosing locations. We develop a novel class of instruments to address this endogeneity. These instruments exploit the spatial distribution of consumer demographics and can be constructed from standard cross-sectional data, making them useful in a variety of spatial applications. Our preferred instruments use the income composition of concentric discs centered on the Central Business District. Applying these instruments to smartphone geolocation data for millions of devices across 18 metropolitan areas, we estimate consumer preferences for general merchandise chains across income groups. We show that accounting for distance endogeneity significantly alters willingness-to-travel estimates, distorting welfare conclusions. Contrary to a prevailing "retail apocalypse" narrative, consumer surplus per trip remained stable from 2010 to 2019. Ignoring endogeneity falsely suggests substantial welfare declines for lower-income households.

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1 Introduction

In diverse settings such as retail, healthcare, public transportation, and school choice, economists frequently infer an individual's value for a service or amenity by measuring their willingness-to-travel to obtain it. In doing so, this work overwhelmingly treats the distance between consumers and suppliers as exogenous. Yet suppliers choose where to locate and do so strategically. If distance reflects these strategic choices, then treating distance as exogenous biases the estimation of the preference parameters that willingness-to-travel is meant to recover. While it is well understood that correctly measuring willingness-to-pay requires addressing the endogenous price-setting behavior of firms, most of the spatial literature has abstracted from the endogenous location-setting behavior of suppliers.

This paper makes three contributions. First, we highlight the importance of addressing distance endogeneity in order to accurately measure willingness-to-travel and introduce a novel class of instrumental variables to address it. These instruments are built using publicly available spatial demographic data; variants of these instruments can be applied to spatial contexts such as healthcare, school choice, and transportation — settings in which willingness-to-travel has been used to infer preferences. Second, we apply these instruments to the U.S. general merchandise retail sector, estimating a model of consumer shopping behavior using smartphone geolocation data for over 2.7 million devices in 18 metropolitan areas. Third, we show that failing to account for distance endogeneity leads to substantially distorted welfare conclusions about the so-called "retail apocalypse", demonstrating that the endogeneity bias is not merely a theoretical concern but alters policy-relevant conclusions.

The transformation of the U.S. retail landscape over the last decade has been characterized as the "retail apocalypse."[1] This shift from traditional brick-and-mortar retail to a hybrid (i.e., physical and online) retail environment may leave some shoppers, particularly low-income ones, traveling farther to reach diminished retail opportunities. This concern is amplified by the uneven adoption of ecommerce, as lower-income consumers spend

[1]See, for example, Peterson [2017], Townsend et al. [2017], and Thompson [2017].

a substantially smaller share of their consumption online (Dolfen et al. [2022]) and thus remain disproportionately reliant on physical stores, making it important to accurately measure how well brick-and-mortar retail serves them.

To reach this goal, we leverage smartphone geolocation data that allow us to observe visits to a wide set of specific named chains, regardless of payment choice (e.g., credit card versus cash). We show that the household income composition of visitors varies substantially across general merchandise chains. For example, low-income consumers represent a higher share of visitors to Dollar General and Family Dollar while high-income consumers gravitate to large warehouse clubs, such as Costco, as well as luxury department stores, such as Nordstrom.These differences in visit propensity could be attributed to dissimilar consumer preferences, differential proximity to chains across consumer incomes, or both.

To disentangle preference effects from proximity effects, we estimate a model of consumer shopping behavior. Consumers choose among retail chains based on chain-specific tastes and the individual cost of traveling to each chain, with preferences varying by income quartile and city. Retail chain fixed effects encompass the product assortment, prices, and store amenities that the chain offers. While we do not formally model trip chaining, we account for reduced travel costs based on the density of nearby retail opportunities.

A key challenge in estimating this type of location-choice model is the potential endogeneity of the distance between consumers and choices—in this case, stores. Despite the growing understanding of the importance of consumption-based spatial sorting [see, e.g. Couture et al., 2019, Almagro and Domínguez-Iino, 2022, Diamond and Gaubert, 2022], most empirical work using travel costs as an indicator of preferences does not address this endogeneity.[2] The intuition for the endogeneity is straightforward. Just as a firm sets prices to extract willingness-to-pay, a retailer may site stores to exploit consumer willingness-to-travel. A chain balances accessibility to consumers that it is trying to attract against the opportunity to harvest the travel willingness of their most loyal customers.

Our central methodological contribution is a novel instrumental variable strategy for

[2]Kluser et al. [2024] use the exogenous timing of entry to estimate distance elasticities of grocery consumers, but this does not address the endogeneity of the locations where stores enter. Shoag and Veuger [2018], Qian et al. [2024], and Zhou et al. [2024] address the endogeneity of retail locations to estimate spillovers on surrounding retail stores, rather than consumer store choice.

endogenous distances. The core idea is that the measured demographic composition of an area will impact chain location decisions— the preference externalities idea of Waldfogel [1999]. Our preferred instruments exploit the well-documented income gradient radiating outward from city centers [Duranton and Puga, 2015]. Specifically, they are built from the observed income composition of concentric discs centered on the central business district (CBD). Consider a consumer living 10 miles from the CBD. The instruments for this consumer are the share of each income quartile among all consumers residing within 10 miles of the CBD—that is, everyone at least as close to the city center as this consumer. These instruments can be constructed from publicly available spatial demographic data for a single cross-section, making them useful in settings where panel data and boundary-discontinuity approaches are unavailable.

Our preferred instrument, the disc design, has distinct advantages over a more naive preference externality design that constructs instruments based on the demographic composition around a consumer's immediate neighborhood–e.g., within a fixed radius of their home. The neighborhood instrument may violate the exclusion restriction if households spatially agglomerate on characteristics observable to the households and retailers but unobservable to the econometrician. A further difficulty with a neighborhood instrument that constructing such instruments requires the researcher to define what constitutes a neighborhood radius, a choice that is inherently arbitrary and to which estimates may be sensitive. In Monte Carlo simulations, we demonstrate that both the disc instrument and the neighborhood instrument reduce the substantial bias in naive willingness-to-travel estimates that ignore endogeneity. However, we demonstrate that the bias reduction of the neighborhood instrument varies with the arbitrarily-chosen neighborhood catchment boundary whereas the disc instrument requires no such arbitrary input.

Given these instruments, estimation follows the control function approach of Petrin and Train [2010]. The first stage regresses distance to each chain on the disc instruments and controls via OLS; the second stage estimates the demand model by simulated maximum likelihood, augmenting the specification with the first-stage residuals. We estimate chain fixed effects for 25 national retail chains and five random coefficients on chain categories, separately for each metropolitan area and income quartile. To quantify the importance of addressing endogeneity, we compare these estimates to those obtained under the assumption that distance is exogenous. We find substantial attenuation bias: ignoring endogeneity understates the magnitude of the distance coefficients by 37% on average for the first income quartile and 43% for the fourth.

The direction of the bias from endogenous store location is not determined a priori. If retailers co-locate with their most loyal consumers, then high-demand households will tend to live near stores, and abstracting from distance endogeneity will likely overstate distance costs. But an analogy to price endogeneity suggests the opposite is also possible: just as firms set prices to extract willingness to pay, retailers may site stores to exploit willingness to travel, locating further from loyal consumers who are willing to bear the cost to visit. A naive estimator observes these consumers purchasing despite long distances and concludes that distance matters less than it truly does, understating distance costs. On net, our findings suggest that the latter force dominates: accounting for endogeneity raises the magnitude of our distance cost estimates.

Combining our demand estimates with historical data on retail locations provided by Data Axle (formerly ReferenceUSA), we estimate changes in consumer surplus for general-merchandise retail trips over the last decade. We then decompose the welfare changes due to the entry and exit of national chains and the entry and exit of small regional chains. Contrary to the retail apocalypse narrative, we find that consumer surplus (per trip) has not significantly declined over the past decade. On net, higher-income households have benefited, while the lowest-income households have, if anything, experienced statistically insignificant declines. Gains attributable to the expansion of discount department stores, supercenters, and highly proximate dollar stores nearly cancel out the welfare losses attributable to the exit of smaller regional chains and traditional department stores. Crucially, ignoring distance endogeneity leads to nearly opposite conclusions that falsely align with the retail apocalypse narrative; these estimates would suggest that the lowest-income households have experienced larger (3×), statistically significant surplus declines while the highest-income households have experienced statistically insignificant surplus increases.

Beyond the retail application, our instrumenting approach is applicable wherever economists infer preferences from willingness-to-travel. The instruments require only cross-sectional data on the spatial distribution of consumer demographics and supplier locations, making them useful in settings where other approaches such as boundary-discontinuity or panel-data approaches unavailable. The direction of the bias from ignoring distance endogeneity will vary across applications but the potential for such bias is pervasive.

Our paper proceeds as follows. Section 2 briefly describes background information and the relevant literature. Section 3 describes our data sources. Section 4 provides model-free evidence documenting that substantial exit and entry of brick-and-mortar retailers over the last decade have changed the U.S. brick-and-mortar retail landscape. Section 4 also documents that consumers of different incomes differ substantially in their propensity to visit different retailers. Section 5 describes our model of consumer shopping choices. Section 6 discusses identification. Section 7 and 8 discuss our estimation and welfare results. Section 9 concludes the paper.

2 Literature and Background

While there is a growing literature estimating the process by which consumers and amenities make location decisions (e.g., Almagro and Domínguez-Iino [2022]), the resulting endogeneity of the distance between consumers and service providers has been largely overlooked in demand estimation. This distance endogeneity is a concern whenever willingness-to-travel is used to infer preferences and remains a concern whether or not prices and price endogeneity are also being considered.

Procedures have been introduced for specific settings or with specific data availability. For example, Bayer et al. [2007] proposes a method to estimate preferences for schools while addressing the endogeneity of neighborhood sorting using jurisdictional boundary discontinuities. Boundary discontinuities will likely not aid identification in circumstances such as full-choice school districts (as in Agte et al. [2024]) or consumer retail because location relative to a particular boundary is not a discontinuous determinant of school choice or store patronage.

Raval and Rosenbaum [2018] and Raval and Rosenbaum [2021] show that standard logit methodologies overestimate distance disutilities in the context of hospital choice. In their context, distance disutilities are biased because patients have an unobserved preference for the characteristics of their closest hospital, which conflates with travel elasticity. This ”home bias” is partially due to switching costs; consumers prefer to return to a previously visited hospital, which is likely to be the closest hospital. Raval and Rosenbaum [2018] and Raval and Rosenbaum [2021] use a “movers” fixed effects design to disentangle the home bias and travel disutility. The bias in naive logit estimates of the travel disutility that these authors identify is directionally opposite the one we identify in this paper. In our setting, the bias is driven in part by profit-maximizing firms harvesting the willingness-to-travel of loyal consumers, a bias more akin to the familiar price endogeneity. In a separate application, Kalnins and Lafontaine [2013] consider the location of headquarters and establishments. They instrument for distance using the percentage of local population with short commutes and find that firm survival is more negatively impacted by distance, controlling for endogeneity.

The problem of estimating demand in the presence of endogenous distance is closely related to the problem of estimating demand in the presence of endogenous entry because the endogenous distance problem in the retail setting is due to the strategic entry behavior of retailers. Recent work by Aguirregabiria et al. [2023], for example, addresses selection bias in demand estimation due to endogenous entry in the context of airline routes. The methods introduced there apply to zero-one entry into discrete markets and cannot be applied readily in the context of endogenous entry in retail, which requires a finer discretization of space to capture the spatial variation relevant to consumers. In our model, the entry decision is relevant through continuous distance.

The motivation behind our distance instrument and the rationale for our welfare analyses are both closely related to the study of preference externalities, a term first coined by Waldfogel [1999]. Presumably, if a chain exits, that is because insufficient consumers value its presence enough to induce the chain to pay the fixed costs of remaining in business. However, consumers can be worse off when their preferences differ from those of others in their community (e.g., George and Waldfogel [2003] and Waldfogel

[2008]). This observation forms the basis for an instrumenting strategy in Fan [2013], where firm presence overlaps markets. Notably, identification in these papers exploits binary firm actions—entry: a firm is more likely to be present in a discrete market that has a critical mass of loyal customers. Our paper differs in that firm proximity is measured in continuous space, and the bias from abstracting from distance endogeneity is ambiguous. Firms may strategically sort closer or farther away from loyal customers (in the latter case, because loyal consumers will travel to visit that firm).

Our estimates of the per trip income-specific welfare gains and losses from the changing configuration of brick-and-mortar retail are of interest in part because one could be concerned that the migration of higher-income consumers to e-commerce has led to the exit of stores that lower-income consumers would still substantially value. This preference externality effect could lead low-income consumers to suffer welfare losses due to increased travel to retail opportunities. Indeed, Dolfen et al. [2022] estimate the gains from e-commerce and show that they are substantially higher for richer households. This finding stems in large part from the differential take-up of e-commerce: households earning less than $50,000 per year spend 3.4% of their consumption spending online, while higher income consumers spend 9.7%. Estimates from their model also suggest that online competition led to a modest contraction (3%) of brick-and-mortar stores. This finding is consistent with Tran [2022], who exploits the uneven expansion of broadband on trips to physical stores and finds little evidence of the so-called retail apocalypse, as consumer spend has not declined significantly.

The question of how changing proximity to retail opportunities impacts different demographic groups differently has been studied most extensively in the area of food, grocery stores, and "food deserts" whereas our study focuses on potential "retail deserts." Allcott et al. [2019] estimate a model of food demand and obtain counterfactuals suggesting that offering low-income households the same products and prices available to high-income households reduces nutritional inequality by only about 10%; the remaining 90% is driven by differences in product demand, rather than proximity. Both Caoui et al. [2022] and Chenarides et al. [2021] explore the impacts of dollar store expansion on grocery stores and access to food. Cao [2022] finds that a substantial fraction of dollar store sales stems from low-priced, private-label goods, creating welfare gains for low-income households. Both Cao [2022] and Chevalier et al. [2022] show that dollar stores tend to choose locations close to low-income consumers.

A closely related paper to ours is Cook [2022], who uses smartphone geolocation data to examine the willingness of above-median income and below-median income consumers to travel to a variety of amenities including restaurants, shops, services, and entertainment places. The focus is on measuring the extent to which the preferences of above- and below-median income consumers are correlated. The author shows that preferences are somewhat heterogeneous but that the income sorting of locations is limited: neighborhoods that are amenity-rich have amenities favored by both income types, and neighborhoods that are amenity-poor lack amenities desired by both income types. However, Cook [2022] does not estimate a demand system accounting for location endogeneity.

More broadly, our analysis connects to work on segregation in urban consumption patterns [Davis et al., 2019, Boar and Giannone, 2023, Couture et al., 2025], and spatial competition among retailers [Ellickson et al., 2020].

3 Data

3.1 Data Sources

Our primary data are smartphone movement data in 2019 from Precisely PlaceIQ, a location data and analytics firm. Precisely PlaceIQ collects pings from devices across smartphone applications.[3] A raw ping records a device's GPS coordinates and is timestamped. These raw pings are joined with a map of establishments, which are characterized by two-dimensional polygons. A timestamped set of pings in a polygon constitute a visit by a device to establishments included in the polygon on a given day. Often, a polygon contains a single establishment (e.g., a Walmart and its parking lot). We focus on smartphone visits to establishments that Precisely PlaceIQ identifies as general merchandise

[3]Devices include both Android and iOS devices and are uniquely identified by a unique advertising identifier. The set of smartphone applications from which Precisely PlaceIQ collects data are unknown to us.

stores with a NAICS classification code of 452. We remove visits to establishments that last for short periods of time and aggregate device's daily visits to the device-week level. We remove device-weeks in which a device visits an establishment more than 10 times in a week. We do this to avoid misclassifying devices of service staff (e.g., delivery personnel or store employees) as consumers.

Additionally, we use identity and outlet locations for multi-unit retail chains provided by Data Axle, formerly known as Infogroup Reference USA. We use these data in our counterfactuals to define consumer access (and distance) to retail outlets in 2010 and 2019. Data Axle is a private sector source of US business microdata and may be subject to the issue of over-representing small establishments with less than five employees. This over-representation issue is documented in Barnatchez et al. [2017] for NETS, another widely used US business microdata. To reduce the measurement error in consumer access to retail outlets, we exclude establishments with no more than five employees from our analysis. We compare the county-level store counts derived from the cleaned Data Axle data for NAICS code 452 with the corresponding store counts from the U.S. Census Bureau's County Business Patterns (CBP) data. CBP provides county-level establishment counts by NAICs code but does not identify particular establishment names. The county-level store counts from Data Axle are extremely similar to those from CBP (see Figure 1 for evidence).

Other data we leverage include Census data files and surveys to obtain tract-level and zip-level estimates of population by income bin and boundaries for 2010 and 2019.[4] Finally, in a robustness check, we use Census block to Census block travel times provided by Cook [2022].

3.2 Strengths and Weaknesses of Using Smartphone Geolocation Data

Smartphone movement data have strengths and weaknesses. Previous studies of how shopping behavior varies with demographics typically relied on either microdata from a selected consumer panel [e.g., Cao, 2022, Caoui et al., 2022] or on consumer credit

[4]We use the 2010 Census and 2015–2019 American Community Survey, the 2019 TIGER/line for tract, zip, and CBSA shapefiles.

and debit card data [e.g., Dolfen et al., 2022, Relihan, 2022].[5] These studies provide important results on shopping behavior. However, Canilang et al. [2020] and Dolfen et al. [2022] show that the consumer propensity to own credit cards is lower for low-income consumers than for high-income consumers. Furthermore, credit card usage varies by age, income, and transaction type [see Foster et al., 2020]. For example, the 2019 Survey of Consumer Payment Choices shows that in a typical month, consumers with income less than $40,000 per year made 8 credit card transactions, 17 cash transactions, and 18 debit card transactions. In contrast, consumers with income greater than $75,000 made 26 credit card transactions, 13 cash transactions, and 28 debit card transactions. The survey also reports that 30% of in-person retail purchase transactions were made with cash. These limitations make the use of smartphone data appealing, because we capture store visits, regardless of payment choice.

Additionally, smartphone data are largely representative of the U.S. population [e.g., Chen and Pope, 2020, Couture et al., 2022]. Couture et al. [2022] and Couture et al. [2024] discuss the reliability of the Precisely PlaceIQ data that we use in this study. Recently, Klopack and Luco [2025] compare the use of smartphone visits and card expenditures in measuring local consumption.

Another advantage of smartphone data is that they permit disclosing retailer identities. The providers of payment card, government, and shopper panel datasets typically forbid the disclosure of identifiable information, such as the identities of specific retailers. This forecloses identifying which specific retailers influence consumer shopping behavior and hence contribute disproportionately to welfare. In contrast, our smartphone data have no such data use restrictions.

While the Precisely PlaceIQ data provide rich details on individual visit decisions, there are several limitations and challenges inherent in movement data that affect our estimation approach and welfare quantification. First, these smartphone data have only become available in recent years; we cannot examine historical shopping behavior. Therefore, we combine our model estimates with alternative data sources to examine changes in

[5]Dolfen et al. [2022] use data from credit and debit purchases excluding PIN-enabled debit card purchases. Relihan [2022] uses data from credit and debit purchases for JPMorgan Chase customers and finds them to skew somewhat more male and higher-income than the census at large.

retail opportunities over time as well as the ensuing consumer welfare changes. Second, like credit card data, smartphone data do not provide information on what specific items consumers purchased. The overall transaction size and prices are also not observed in the smartphone data. This motivates our decision to capture the price-assortment bundle through chain fixed effects and report consumer surplus measures in terms of willingness-to-travel.

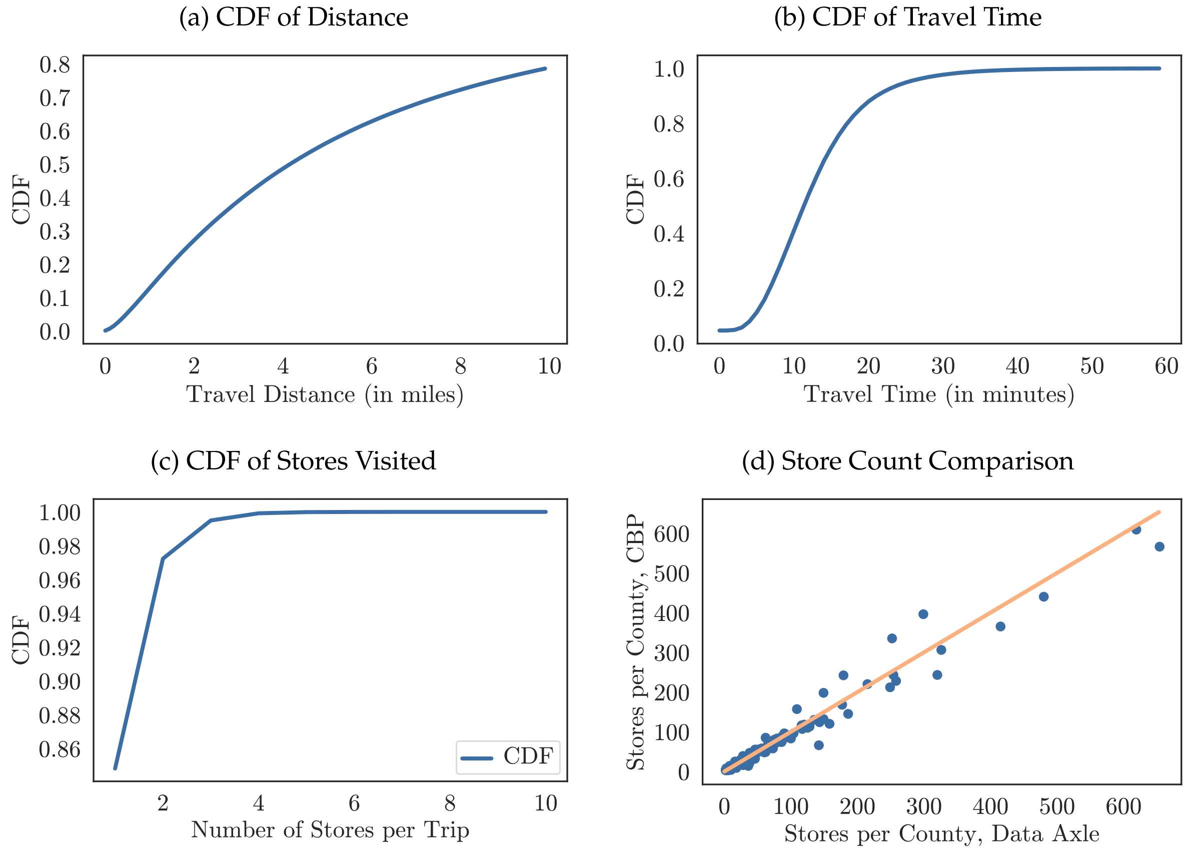
3.3 Summary Statistics

We focus on devices originating in 18 of the top 20 largest core-based statistical areas (CBSAs) and for which Precisely PlaceIQ provides income estimates based on the building the device resides. We exclude New York and Los Angeles for computational reasons. The CBSAs we consider comprise over 28% of the U.S. population and about 29% of the urban population in the country. Since we are mainly interested in the impact of the changes in retail opportunities along the income dimension, we assign devices to income quartiles calculated using the Precisely PlaceIQ data and national Census income quartile cutoffs.

We identify and study a set of 25 general merchandise chains that were commonly present between 2010 and 2019 in the CBSAs we study (Table A.1 in the Appendix). These national chains account for over 63% and over 82% of establishments in the general merchandise sector in 2010 and 2019, respectively. They also represent 93% of visits to general merchandise stores in 2019 in our smartphone data sample. We classify visits to other identified establishments belonging to NAICS 452 as visits to "fringe" stores. Typically these are smaller and regional chains. In our model, we collapse the fringe into a single representative option.

While in principle a consumer can visit any store at any distance and combine multiple store visits into a trip, most trips consist of a visit to a single store and to the outlet of a chain that is closest to home. Panel (a) in Figure 1 shows the distribution of visits by the distance between a consumer's home location and the general merchandise establishment the consumer visits, up to 10 miles. We find that 79 percent of store visits are within 10 miles of an individual's residence. In our estimation, for tractability reasons, we confine each device's choice set to the set of general merchandise stores within 10 miles of the

Figure 1: Key Data Distributions and Store Count Comparison



Note: Panel (a) uses the universe of shopping trips to general merchandise stores in the core-based statistical areas over the study period. Panels (b) and (c) show the visits that are included in panel (a). Panel (d) shows concordance between Data Axle store counts and store counts in County Business Patterns (CBP) in 2019.

device's home location. In panel (b), we show the distribution of travel times (in minutes) for the visits included in panel (a) using the data provided by Cook [2022]. The panel shows that, overwhelmingly, consumers visit retailers that are within a 30-minute travel time of their residence. In panel (c), we plot the CDF of the number of stores visited per trip. Nearly 85% of trips to general merchandisers represent visits to a single chain only. The average number of stores visited per trip is 1.2. In our estimation, we will adjust for the potential for "trip chaining" using the proximity of a given store to other general merchandise stores.

Our final data sample includes over 2.7 million devices and over 44 million retail visits across nearly 11,000 unique retail outlets from 43 retail chains. Table 1 contains summary statistics for the sample. On average, a device visits over three general merchandise stores each week. A majority of these visits are to the set of identified chains. Additionally, on average, a device has access to 16 of the 25 identified chains within 10 miles of the device's residence. There are often several outlets of a given chain within the 10-mile radius; we estimate that the number of outlets of inside chains is roughly 73. The number of fringe outlets a consumer has access to is much lower, about five. We report summary statistics by income quartile in Table A.2 in the Appendix.

Table 1: Summary Statistics for the Data Sample

Variable	Mean	25th Pctile.	Median	75th Pctile.
per device, week				
Number of visits to inside chains	1.86	1.00	1.00	2.00
Number of visits to fringe stores	1.26	1.00	1.00	1.00
per device				
Number of inside chains in choice set	15.99	14.00	17.00	20.00
Number of fringe outlets in choice set	4.63	2.00	4.00	7.00
Number of outlets of inside chains	73.46	34.00	64.00	104.00
Number of stores visited per trip	1.20	1.00	1.00	1.00
Number of unique chains	43			
Number of outlets	10,882			
Number of devices	2,759,690			
Total number of visits	44.256 mil.			

Note: Summary statistics for the 2019 Precisely PlaceIQ smartphone data.

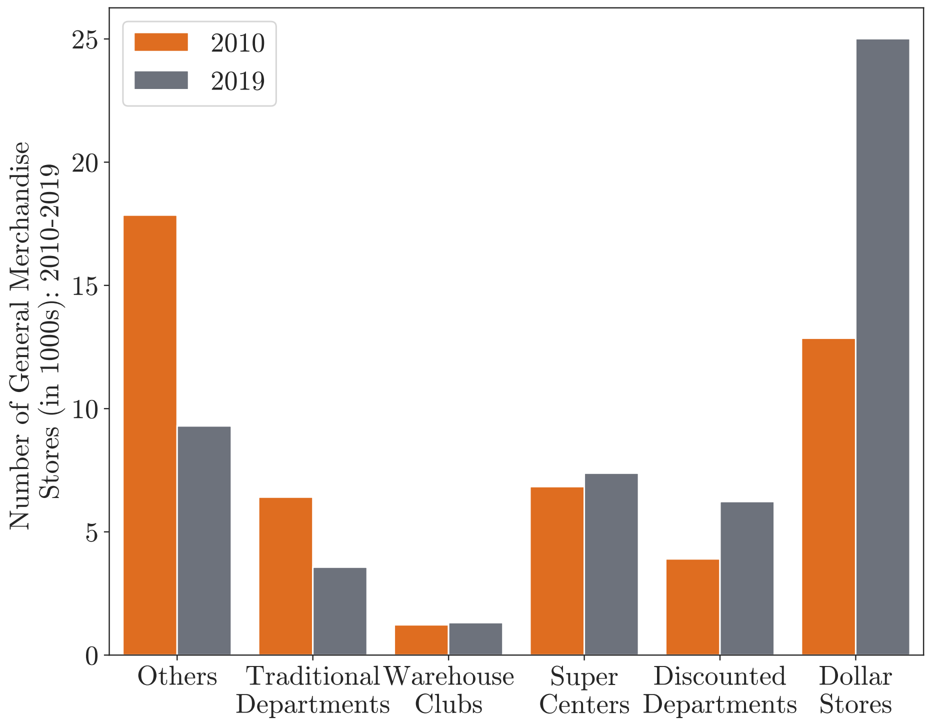
4 Evidence on the Changing Retail Landscape

We provide three new facts about the evolution of the general merchandise store category between 2010 and 2019 and about the shopping patterns of consumers by their demographics.

Fact 1: The number of general merchandise stores in the United States increased between 2010 and 2019. In contrast to the press around the retail apocalypse, the total number of general merchandise stores increased from 49,089 to 52,807 between 2010 and

2019. Figure 2 shows the count of general merchandise stores (NAICS: 452) across the U.S. for 2010 and 2019 using the data from Data Axle. To better understand the changing retail landscape, we group the "inside good" general merchandise stores into five types: traditional department stores, warehouse clubs, supercenters, discount department stores, and dollar stores.[6]

Figure 2: Number of General Merchandise Stores in the U.S. in 2010 and 2019



Note: The figure reports the number of general merchandise (NAICS 452) stores with more than five employees listed in Data Axle reference Solutions in the U.S. in 2010 and 2019 by category. "Traditional Departments" includes Bloomingdale's, Dillard's, JCPenney, Kohl's, Macy's, Neiman Marcus, Nordstrom, Saks Fifth Avenue, and Sears; "Warehouse Clubs" includes BJ's Wholesale Club, Costco, and Sam's Club; "Supercenters" includes Target, Walmart, and Big Lots; "Discount Departments" includes Burlington Coat Factory, Marshalls, Ross Dress For Less, TJ Maxx, Citi Trends, and Five Below; "Dollar Stores" includes Dollar General, Dollar Tree, Family Dollar, and 99 Cents Only; and "Others" includes general merchandise stores that are not associated with the aforementioned national chains.

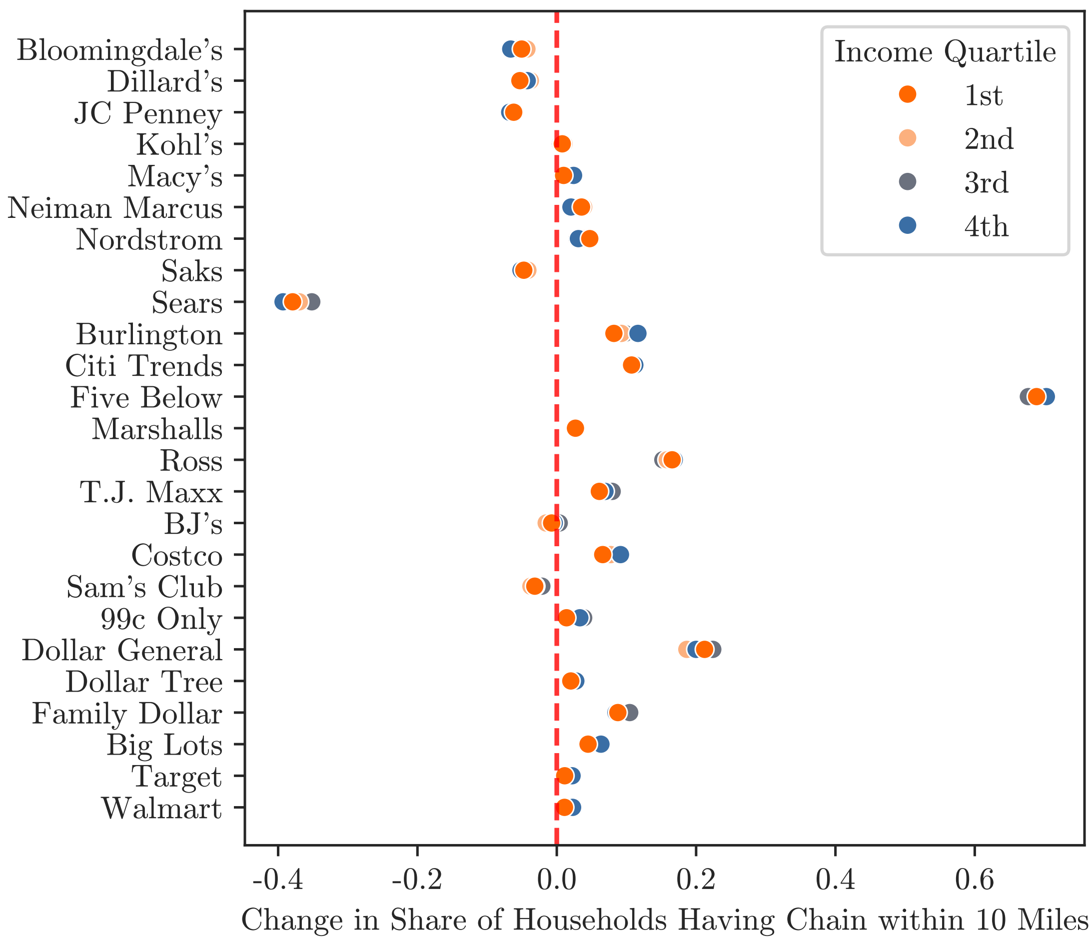
The plot reveals that the increase in the number of general merchandise stores was mainly driven by dollar stores and, to a lesser extent, supercenters and discount department stores. The number of dollar stores—including Dollar General, Dollar Tree, and Family Dollar—more than doubled over the decade and, by 2019, was greater than the

[6]The chains categorized are the 25 chains enumerated in Table 2. Kmart is excluded from our analysis due to having very few locations and visits.

total count of all other general merchandise stores. During the same period, however, the number of traditional department stores and regional chains declined.

Fact 2: Access to the set of identified chains increased from 2010 to 2019. Figure 3 depicts how access to general merchandise chains changed differentially for households in different income quartiles. For each income quartile, we plot the change in the share of households with access to each general merchandise chain from 2010 to 2019, where access is defined as having a store within 10 miles.

Figure 3: Share of Households within 10 Miles of General Merchandise Stores in 2010 and 2019 by Household Income Groups



Note: This figure uses U.S. Census data on household residences and income combined with Data Axle data on store locations. The figure shows the change in the share of households having at least one outlet of a particular chain within 10 miles by income quartile for 2010 and 2019.

Overall, access to most of these chains has increased over the decade, with the exception of traditional department stores. In particular, expansion of dollar stores has increased their proximity to households of all income levels. The share of households within 10 miles of a Dollar General increased by over 20 percent for all income groups. In addition, households' access to discount department store chains, especially Five Below, improved on both the intensive and extensive margins. The share of households with access to Five Below stores increased by more than 60 percentage points. Our analyses below will consider not only extensive margin access but proximity within the 10 mile zone.

Fact 3: There are substantial differences in the income of consumers who visit the set of identified chains. We examine the shopping patterns of households of different income levels in 2019 over general merchandise chains. In principle, these patterns could be driven by both preferences and proximity to different chains for different income groups. Figure 4 plots the income distribution of individuals who visited each general merchandise chain in 2019.[7] Our smartphone device sample consists of more devices from higher-income quartiles, and so we normalize the plot so that each (national) income quartile represents 25% of visits.[8] Dollar stores are among the chains with the largest share of visitors from the lowest income quartile. Among discount department store chains, Citi Trends stands out from other chains. The majority of visits to Citi Trends are from the two lowest income quartiles, while other discount department store chains see at least 60% of visits coming from the two highest income quartiles and around 40% from the highest income quartile.[9] High-end department stores such as Nordstrom, Bloomingdale's, Saks Fifth Ave, and Nieman Marcus draw over half of their visits from the highest income quartile. The visitor mix at supercenters falls somewhere in between, with Walmart's customers skewing low-income, while Target's customers skewing high-income. The chain with

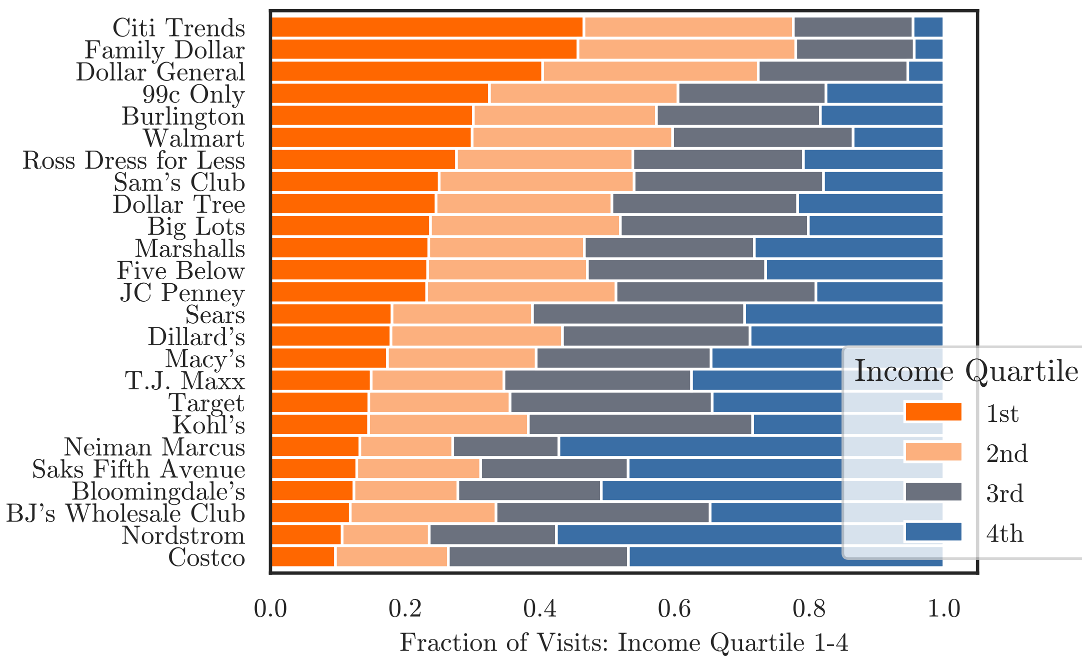
[7] We are not able to document the changes in households' shopping patterns from 2010 to 2019 because the Precisely PlaceIQ smartphone location data are not available for 2010.

[8] More precisely, let $s_{i,j}$ be the percentage of visits of members of households from income quartile i visiting chain j. In the data, $\sum_i s_{i,j} = 1 \forall j$, but $\sum_j s_{i,j} / \sum_i \sum_j s_{i,j} \neq .25 \; \forall i$. In the figure, we re-weight $s_{i,j}$ by first calculating $\tilde{s}_{i,j} = s_{i,j} / \sum_j s_{i,j}$ for each i, and then re-scaling the distribution for each j, i.e., $\hat{s}_{i,j} = \tilde{s}_{i,j} / \sum_i \tilde{s}_{i,j}$.

[9] According to its 2022 10-K filing, Citi Trends is a "value retailer of apparel, accessories and home trends for way less spend, primarily for African American and Latinx families in the United States" and stores are located "at the crossroads of low to moderate income households."

the most representative clientele is Five Below, access to which increased dramatically between 2010 and 2019.

Figure 4: Household Shopping Patterns by Household Income Groups



Note: The figure uses Precisely PlaceIQ data to show the share of 2019 visitors to each chain represented by members of each household income quartile. Chains are ordered from the highest to lowest share of income quartile of visitors. The figure is normalized so that each income quartile represents 25% of the total area. The same figure without the normalization is shown in Figure A.1.

The differences in chain visits across income quartiles potentially reflect a mix of both proximity and preferences. For example, while most consumers in our data have both a Target and a Walmart within 10 miles, the proximity within those zones may differ. The higher share of high-income visitors to Target relative to Walmart can reflect both the differences in their location strategies and the differences in product prices and assortment varieties. Disentangling these effects requires a demand estimation strategy.

5 A Model of Consumer Shopping Choices

We model consumer store-choice decisions using a discrete choice framework and study the trade-offs of visiting physical stores versus online stores. Although we abstract from the consumer's decision to shop online, we discuss the impact of online shopping on our results. We present the model for a representative CBSA to minimize the number of indices required. However, in estimation, all model parameters are CBSA specific.

Let i denote a consumer and $y(i)$ their income. We assign $y(i)$ to be the quartile of national household income based on the residence-level income information observed in the Precisely PlaceIQ demographic data. All parameters also vary by income quartile.

We define J_i to be consumer i's choice set. This set contains all stores located within 10 miles of consumer i's residence. Recall that we impose this restriction because it keeps data construction manageable but also captures 79% of consumer trips within their CBSA. We partition consumer i's choice set J_i into two sets, denoted by J_i^c and J_i^f. The first set contains the set of brick-and-mortar stores of identified retail chains. The second set denotes fringe (e.g., regional and smaller chain) stores. We consider both Kmart and Stein Mart as fringe stores because they registered drastic reductions in the number of open stores from 2010 to 2019. We capture this welfare effect (via the fringe term) in counterfactuals.

We use j to denote an arbitrary choice. We abstract from the choice among stores that are part of the same chain as this approach greatly simplifies the choice set without introducing substantial measurement error. We estimate that 78% of consumer visits to a chain store are to the closest location of that chain from consumer i's residence.

We model each consumer trip independently. Conditional on visiting a NAICS 452 store, a consumer's indirect utility of visiting chain j is given by

$$u_{i,j} = \begin{cases} v_{i,j}\left(x_{i,j}, dist_{i,j}; \beta_{y(i)}\right) + \xi_{i,j} + \varepsilon_{i,j} & j \in J_i^c \\ \Gamma(J_i^f) + \varepsilon_{i,0} & j \in J_i^f \end{cases}, \tag{5.1}$$

where $v_{i,j}(\cdot)$ is a function of covariates $x_{i,j}$ and straight line distance from i to chain j, $dist_{i,j}$. The terms $\xi_{i,j}$ and $\varepsilon_{i,j}$ are unobserved preferences.

Unlike most prior work that involves location-choice models, we allow for the possibility that the unobservable chain preferences ($\xi_{i,j}$) are potentially correlated with distance ($dist_{i,j}$) because chains locate strategically, as we discuss in Section 6. We assume that the second set of unobservables ($\varepsilon_{i,j}, \varepsilon_{i,0}$) follow type-1 extreme value distributions.

The function $v_{i,j}(\cdot)$ characterizes chain quality and distance costs, which we assume is linear and of the form

$$v_{i,j} = \beta^{0}_{y(i),j} + \beta^{d1}_{y(i)} dist_{i,j} + \beta^{d2}_{y(i)} density_{i,j}. \tag{5.2}$$

The parameter $\beta^{(1)}_{y(i),j}$ is a chain–income-quartile fixed effect that captures the average utility consumer i of income $y(i)$ derives from visiting chain j. It is offset by a shopping cost, which also varies by income grouping.

The shopping cost has two elements. The first element captures the travel cost consumers incur and increases in distance, $dist_{i,j}$. Because we assume consumers choose a representative store, we calculate distance as the trip-weighted mean distance between consumer i and stores of chain j. If a consumer never visits a specific chain, we use the trip-weighted mean distance to the specified chain among consumers living in the same zip code.

The second element in our shopping cost specification is $density_{i,j}$, which we include to account for trip chaining. Trip chaining occurs when a consumer visits multiple retail outlets on a single trip, reducing the effective distance traveled to a store. Trip chaining may be more likely to occur when stores are co-located—for example, within a mall. To account for the possibility that consumers experience a lower effective travel cost when stores are co-located, we control for density. Like distance, density is measured for each consumer-chain pair. We define $density_{i,j}$ as the natural log of 1 plus the number of other general merchandise stores within 0.1 miles of that location of chain j. When there is more than one outlet of chain j within 10 miles of consumer i's residence, we take the trip-weighted average of this log proximate store count across each of the outlets of chain j within 10 miles of consumer i's residence. For an isolated store, $density_{i,j}$ is zero.

A complete analysis of trip chaining is complex and is the focus of ongoing research spatial economics (see, for example, Relihan [2022], Miyauchi et al. [2021], Oh and Seo [2023]). In our data, more than 75% of trips involve a single visit to a NAICS 452 retailer. We abstract from trip chaining and instead estimate a rich set of controls, i.e., chain- and income-specific preferences.

We assume that the deterministic utility of choosing a fringe store is equal to

$$\Gamma(J_i^f) = \omega_{y(i)} \log\left(\left|J_i^f\right| + 1\right), \tag{5.3}$$

where $\omega_{y(i)}$ captures the income-specific taste for fringe stores, and $\left|J_i^f\right|$ is the total number of fringe stores available in consumer i's location. This functional form allows utility to increase with the number of fringe stores available to consumer i, as in Ackerberg and Rysman [2005]. We normalize preferences to choosing a fringe store instead of specifying the outside option to be not visiting any store, to avoid modeling the frequency of store visits. For example, if we chose to model the frequency to be daily, then devices that visit more than one store would violate the assumption of a single discrete choice.

We allow parameters to vary across income quartiles but not over time. This is reasonable given that the typical device is tracked only for a couple of months.

5.1 Estimation

We estimate using maximum likelihood. We do not follow the approach of Berry [1994] and Berry et al. [1995] due to the significant number of zero-visit observations.[10] Even aggregating geography to the zip code level, we find the percentage of zeros to be 66% and 41% at the daily and weekly levels, respectively.

In Section 6, we discuss the potential endogeneity between distance and unobserved preferences ξ caused by the co-location of stores and consumers and the instrumental variable strategy we use to address it. In practice, we implement this strategy using a control function approach, following Petrin and Train [2010]. The control function is

$$dist_{i,j} = \Pi\left(z_{i,j}, x_{i,j}; \delta_{y(i)}\right) + \mu_{i,j}, \tag{5.4}$$

where z are instruments that are relevant for distance but do not enter consumers' utility functions.

[10] In both approaches, estimation requires taking the log of quantity, which is undefined when zero devices visit a given option.

Assuming that μ and ξ are jointly normal over j and that Π is linear in parameters, i.e., $\Pi := [z_{i,j}, x_{i,j}]^T \delta_{y(i)}$, we can rewrite the utility of choosing a non-fringe chain as

$$u_{i,j} = v_{i,j}\left(x_{i,j}, dist_{i,j}; \beta_{y(i)}\right) + \rho_{y(i)}\mu_{i,j} + \sigma_{y(i),j}\eta_{i,j} + \varepsilon_{i,j}, \tag{5.5}$$

where $\eta_{i,j}$ are standard normal draws and ρ captures the degree of endogeneity.[11]

$$s_{i,j} = \int \int \mathrm{I}\left[u_{i,j} > u_{i,j'} \ \forall j' \in J_i\right] dF(\eta)\, dF(\varepsilon) \tag{5.6}$$

$$= \int \frac{\exp\left(v_{i,j} + \mu_{i,j}\rho + \sigma_j \eta_{i,j}\right)}{\exp\left(\Gamma(J_i^f)\right) + \sum_{j' \in J_i^c} \exp\left(v_{i,j'} + \mu_{i,j'}\rho + \sigma_{j'}\eta_{i,j'}\right)} dF(\eta_1 \mid \sigma_1) \times \ldots \times dF\left(\eta_{J_i} \mid \sigma_{J_i}\right). \tag{5.7}$$

Estimation proceeds in two steps. Due to the size of the data, we split estimation by CBSA-income quartile, though our notation continues to be for a representative CBSA. In the first step, we estimate the control functions using OLS and compute their residuals as

$$\widehat{\mu}_{i,j} = dist_{i,j} - \Pi\left(z_{i,j}, x_{i,j}; \widehat{\delta}_{y(i)}\right). \tag{5.8}$$

We plug these residuals into equation 5.7. Because equation 5.7 does not have a closed-form solution, we use Monte Carlo integration to numerically compute its values.[12]

In the second step, we estimate the demand parameters, $\theta_{y(i)} := (\beta_{y(i)}, \rho_{y(i)}, \sigma_{y(i)})$, via simulated maximum likelihood. Specifically, given a set of devices (I) for a particular CBSA-income quartile group, we define $N_{i,j}$ to be the total number of visits i makes to option j. We can aggregate visits because the model does not have time-varying parameters. The log-likelihood for the data is

$$\max_{\boldsymbol{\theta}_{y(i)}} \sum_{i,j} \left(N_{i,j} \cdot \log\left(\frac{1}{H} \sum_{h=1}^{H} s_{i,j}^{(h)}\left(\theta_{y(i)}\, ; \, x_{i,j}, dist_{i,j}, \widehat{\mu}\right)\right)\right). \tag{5.9}$$

[11]The co-location of stores and consumers arises from the endogenous siting of stores with respect to agglomerations of consumers with similar preferences. We approximate this complex endogeneity problem as a bivariate normal distribution. This approximation may result in some misspecification that could be alleviated with richer models of unobservables.

[12]We select $H = 100$ Halton draws per consumer-chain to compute choice probabilities.

We estimate CBSA-income quartile–specific random coefficient parameters for each of the five groups of chains we consider: warehouse stores, traditional stores, discount stores, supercenters, and dollar stores. The mapping of chains into groupings is shown in Figure 3. In total, we estimate distance, density, and fringe preferences, (up to) 25 chain preferences, five random coefficients, and the control function parameters for each CBSA-income quartile. We compute standard errors using bootstrap, sampling devices with replacement.

As a robustness check, we also estimate the model using travel times (in minutes) between the Census block of consumer i's residence and the Census block of the store using the data provided by Cook [2022] instead of distance. We allow travel time to be endogenous and estimate the model using the same approach.

6 Endogeneity Problem, Instruments, and Identification

The disutility from traveling is identified by measuring the propensity of individuals within an income quartile to visit more proximate versus more distant stores. Conditional on the disutility of distance, we infer willingness-to-travel to a given chain relative to another by the relative frequency with which consumers visit stores from each chain. Intuitively, if we observe a consumer driving past a Walmart to visit a Target, it must be because that consumer values shopping at Target more.

6.1 Endogeneity Problem

We instrument for distance because store locations are endogenous. Match quality between consumers and a given chain likely varies by consumer characteristics that are unobserved by the econometrician but potentially observed by chains. A profit-maximizing chain will choose store locations strategically based on the spatial distribution of these consumer characteristics, among other factors (e.g., competition). This endogeneity problem is also conceivably a concern for other settings where distances are commonly taken as exogenous (transportation, school choice, healthcare, etc.).

The potential bias introduced by endogenous distance is more complex than the familiar price endogeneity. The standard price endogeneity problem involves unobservable qualities ξ_js, that are typically assumed to be common to all customers, being correlated with prices, which are also typically assumed to be common to all consumers. In our setting, individual-specific match quality may be correlated with individual-specific distance, i.e., $\xi_{i,j}$ is correlated with $dist_{i,j}$.

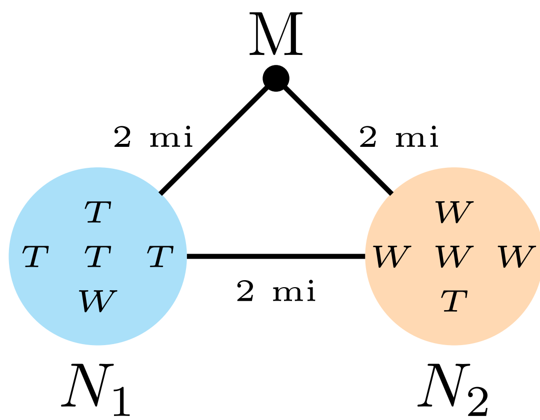
To be concrete about the concern, consider that chain location preferences vary with consumer characteristics. Our model explicitly accounts for one such characteristic: consumer income. Chain preferences may also vary across other dimensions of household characteristics, such as household composition and ethnicity, that are unobserved by the econometrician. That is, just as households have chain tastes specific to their income group y, $\beta^{(1)}_{y(i),j}$, they may also have chain tastes specific to an unobserved household type k and have type-specific chain preferences, $\beta^{(0)}_{k(i),j}$. Since we do not explicitly model these type-specific chain preferences, they enter the unobserved component of indirect utility, $\xi_{i,j}$.

Suppose that households sort spatially by type k and this type is observable to chain executives, who pay a fixed cost of entry to select a finite number of locations in which to enter. If chains locate stores strategically with respect to agglomerations of their most loyal customers, distance $dist_{i,j}$ will reflect unobserved type-specific preferences, $\beta^{(0)}_{k(i),j}$, that enter the unobserved component of utility, $\xi_{i,j}$.

The direction of the ensuing bias is ambiguous. On the one hand, the chain may systematically locate its stores to be accessible to those consumers who particularly value it. This co-location will result in a negative correlation between $dist_{i,j}$ and $\xi_{i,j}$. Ignoring this while inferring a distance disutility and taste for the store would result in consumers appearing very unwilling to travel, and the distance disutility parameters would be biased away from zero. Further, consumers would not appear to value the store very much because consumers would not travel far from home to visit it.[13]

[13] Similarly, consider a policymaker locating transportation infrastructure. The policymaker may locate train or bus routes near people who particularly like public transportation. People who particularly like public transportation will choose to live near this infrastructure. Inference regarding tastes for the infrastructure and distance costs could be biased.

Figure 5: Illustration of Location endogeneity



On the other hand, if the chain exploited its loyal customer type's willingness-to-travel and located closer to agglomerations of other potential customers, we would observe a positive conditional correlation between $dist_{i,j}$ and $\xi_{i,j}$. In this case, abstracting from distance endogeneity would result in consumers appearing less sensitive to distance than they are, and the estimates of distance disutility parameters would be biased toward zero. This latter intuition is closest to the classic price endogeneity problem.[14]

A simple example can help illustrate this intuition. Consider the neighborhoods N_1 and N_2 pictured in Figure 5. The "W"'s indicate residents with an unobservable "Walmart" type and the "T"'s indicate residents with an unobservable "Target" type. To make the example very simple, suppose that consumers of both types would patronize either supercenter if it was the only supercenter in their choice set, but the Walmart types would bypass a Target and travel up to 1.5 miles more to visit a Walmart and Target types would travel up to 1.5 miles more to reach a Target.

Were the Target and Walmart to colocate at M, the split of visitors to the two stores would correctly reflect the relative preferences for Walmart and Target in the population. Intuitively, our model without instruments could identify the relative preferences. How-

[14]Indeed, if consumers have high willingness-to-pay due to an unobserved demand shock, the producer will raise the price to appropriate some of the consumer surplus. In the distance context, if a consumer has a high willingness-to-travel due to an unobserved match with the chain, the retailer can appropriate some of the consumer surplus by building fewer stores, in less costly locations.

ever, consider the situation in which a Walmart is situated at M and Target management is considering where to site a new store. A common intuition is that stores would locate themselves near most of their customers at N_1. However, in this circumstance, the optimal location of the Target may well be N_2. By locating at N_2, farther from most Target-loyal consumers, Target is able to capture Walmart types while harvesting the willingess-to-travel of Target types. Because the location choice of the Target is in part determined by the characteristics of the consumers that are unobservable to the econometrician, a classic endogeneity problem is introduced.

6.2 Proposed Class of Instruments

One approach to addressing this endogeneity problem is to fully model the location-choice problem. However, that is challenging, due to the combinatorics of potential entry points and modeling strategic response. We instead propose an instrumental variables approach that exploits the fact that our endogenous variable—the distance between consumers and stores—is continuous. We model the distance of a given chain j from a consumer i's residence as a function of the observed demographic mix near i's residence that makes siting a store proximate to i more or less attractive to chain j.

The relevance of this instrument relies on the very strategic behavior that generates the endogeneity problem we seek to overcome: the observed demographic mix near a consumer's residence is predictive of its distance to a given chain because chains are siting stores strategically relative to the spatial distribution of the observable characteristic. This instrument is plausibly exogenous as long as the model explicitly controls for how chain preferences vary with the observable characteristic used to construct the instrument.

In our setting, the observable characteristic is household income, $y(i)$. Our instrument exploits strategic chain siting relative to consumers of different observable income types within a CBSA. That is, we expect that a consumer's proximity to agglomerations of different income groups will partially explain their proximity to different retail chains. Then, conditional on the consumer's income-specific tastes, we predict which chains they visit through this channel (and not through a channel in which distance predicts unobserved preferences $\xi_{i,j}$).

Formally, we seek instruments $z_{i,j}$ that, conditional on covariates, (i) predict distance of consumer i from chain j and (ii) are not correlated with unobserved chain preferences $\xi_{i,j}$. Since one of the covariates is consumer i's income group $y(i)$, the relevance condition (i) requires that the instruments predict how much closer to (or further from) chain j household i is than households in the same income group in the same CBSA. The exclusion restriction (ii) implies that the instruments cannot predict why, for a given $dist_{i,j}$, a given household i may be more or less likely to select a chain j than other members of the same income group in the same CBSA. This exclusion restriction will be violated if the instruments predict household i's unobserved chain preferences because, for example, the instruments predict household characteristics that explain within-income differences in chain tastes.

The instrumental variables strategy we propose above can be used in a variety of settings using publicly available data. It first requires the econometrician can model—and therefore control for—systematic variation in household venue preferences along a certain characteristic. It then requires that both households and stores sort spatially according to this characteristic. This sorting could be endogenous—e.g., establishments strategically site near or far from clusters of households that share the characteristic, and households sort spatially on the characteristic in order to be proximate to establishments they prefer—or not—e.g., establishments and households are sorting spatially due to another factor such as land costs. With such a characteristic in hand, the econometrician then needs to select a moment (or set of moments) of the local distribution that predict consumer proximity to stores from different retail chains, without predicting how a consumer's chain preferences deviate from their income group.

6.3 Instrument Construction: Choice of Spatial Units

Key to maintaining the exclusion restriction is the set of moments of the local demographic composition selected for the instrument. We consider two instrument constructions, both of which can be built from publicly available spatial demographic data. The two instruments face different threats to identification; we discuss these threats and explain our preference for one of them, though we show that both perform well in Monte Carlo simulations and yield similar demand estimates in our application.

A natural first approach instruments for distance using the income mix proximate to a consumer's neighborhood—e.g., within a radius r of their home, as depicted in Figure 6-(a). If there is sufficient mass of certain income groups nearby, it is more (or less) likely that a particular chain locates close by, and the interaction between a chain fixed effect and the share of each income quartile q within r miles of a consumer i's residence, $share^{\text{neigh.}}_{q,l(i)}$, will predict the distance of i to chain j.

An alternative approach exploits regularities in the spatial structure of U.S. cities. Land values and commuting times vary systematically with distance from the central business district (CBD) [Duranton and Puga, 2015], and, depending on the income elasticity of demand for land and commuting costs, the income mix of residents also varies with distance to the CBD. Our "disc" instruments exploit this variation. Figure 6-(b) provides a graphical representation of their construction. Consider that any location (given by latitude and longitude) can be characterized by its polar coordinates relative to the CBD: (r, φ). Going outward from the CBD, we define a disc for every consumer equal to the region from the CBD bounded by their r, as determined by their residence. For every disc, we calculate the share of the CBSA's income quartile q population that resides within the same distance r or closer to the CBD, which we denote by $share_{q,r}$.[15]

We then model the distance of an individual i to chain j, or the control function, as a linear function of the share of the CBSA's residents in income quartile q that reside within the same or closer distance to the CBD as individual i, or $share_{q,r(i)}$. We include all income quartiles in the control function. That is, $dist_{i,j}$ is modeled as

$$dist_{i,j} = \sum_{q \in \{1,2,3,4\}} \delta^{(1)}_{q,y(i),j} share_{q,r(i)} + x_{i,j}\beta_{y(i)} + \mu_{i,j}, \tag{6.1}$$

Critically, parameters are chain-specific and vary by the income quartile of consumer i, which allows us to estimate differences across chains in their predicted distance from the same consumer. The unobservable and potentially endogenous component of the distance

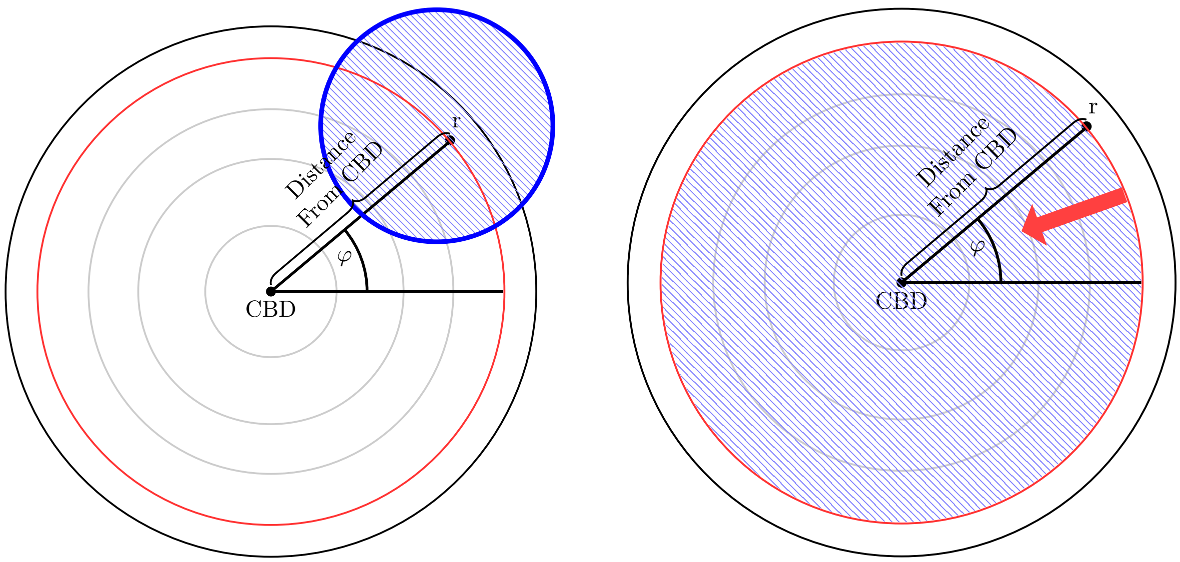
[15] In practice, we calculate the share of the population that resides in Census tracts whose centroids are a distance r or less from the CBD.

instrument is $\mu_{i,j}$. We estimate equation 6.1 using OLS. While the predicted distance for a consumer located at (r, φ) includes the income share and density data for the entire disc formed by r, the difference in the predicted distance for a consumer located at (r, φ) and (r', φ') would be due to the characteristics of the annulus from r to r'.

Figure 6: Instrument Construction for Spatial Data

(a) Neighborhood Instrument

(b) Disc Instruments



Note: Panel (a): Exploiting the preference externality idea, the figure shows instruments constructed based on a 5-mile radius around each consumer's residence. Panel (b): Depicted are disc instruments of radius r from the central business district (CBD). We compute, by income quartile, the share of the CBSA population that resides within r.

Both instruments are relevant because of the strategic siting behavior that generates the endogeneity problem we seek to overcome: the observed income mix near a consumer's residence is predictive of distance to a given chain because chains site stores strategically relative to the spatial distribution of income. Both instruments are plausibly exogenous as long as the model explicitly controls for how chain preferences vary with the observable characteristic (household income) used to construct the instrument. However, the two instruments face *different* threats to identification, both of which must operate within a CBSA–income quartile cell.

The neighborhood instrument is vulnerable if, conditional on income, households with distinct chain preferences sort *angularly*—that is, into local neighborhoods with different income mixes. For example, conditional on household income, households with school-age children tend to reside in neighborhoods with high-income households to access schools with better test scores. If such households also have stronger unobservable preferences for certain chains (say, Costco), and those chains consider both income and family size in their siting decisions, then $share^{\text{neigh.}}_{q,l(i)}$ will be correlated with the household type–specific preference component of $\xi_{i,j}$, violating the exclusion restriction.

The disc instrument is vulnerable to a different form of sorting: if, conditional on income, households with distinct chain preferences sort *radially* by distance to the CBD. Using the notation introduced above, we expect that $Cov[k, share_{q,r}|y] \leq Cov[k, share^{\text{neigh.}}_{q,l}|y]$, since centrality r is more general than location l, as location l potentially involves sorting on both centrality r and direction φ. Critically, under the disc construction every consumer at the same CBD distance receives identical instrument values regardless of where around the ring the consumer sits: a consumer on the north side of the city and one on the south side—maximally separated in space—share the same instruments, so local sorting on unobservables is averaged away rather than embedded in the instruments.

In the context of the simple example in Figure 5, the disc instruments will improve on the neighborhood instrument if N_1 and N_2 are on the same ring—that is, at the same distance r from the CBD. The exclusion restriction for the disc instrument would be satisfied if households sort to r by income and then agglomerate into local neighborhoods in different directions φ from the CBD on characteristics that predict their chain preferences (i.e., chain type "W" or "T"). The ring instrument will not improve on the direct local income mix instrument (akin to the neighborhood instrument) if N_1 and N_2 were on different rings because households of the same income sorted to different rings r due to their chain type.

We prefer the disc instruments for two reasons. First, U.S. cities display strong income gradients radiating outward from the CBD [Duranton and Puga, 2015], providing substantial first-stage power, while the averaging-over-angles property mitigates the angular sorting that threatens the neighborhood instrument. The disc exclusion restriction requires only that, conditional on income, unobserved chain preferences do not sort radially—a weaker condition in cities where within-income sorting is primarily local and angular.[16]

[16]As is often the case with instrumenting strategies, there may be a trade-off between the explanatory

Second, the disc design eliminates the need to specify an arbitrary catchment radius. The radius of each consumer's disc is pinned to their own CBD distance, so no researcher-chosen tuning parameter enters the instrument. In contrast, the neighborhood instrument requires the researcher to select the radius r, and estimates may be sensitive to this choice.

In Appendix B.7, we conduct Monte Carlo simulations that demonstrate the importance of instrumenting for distance and illustrate the sensitivity of the neighborhood instrument to radius selection. The simulations generate a city with endogenous store locations and realistic spatial sorting of consumers by both income and an unobserved type that affects chain preferences. We estimate the model using a naive (exogenous distance) estimator, an oracle estimator that observes the true type, and control function estimators using both the disc and neighborhood instruments across 60 different radius values. The central finding is that both instrument substantially reduce the bias that arises from treating distance as exogenous: the naive estimator attenuates the distance coefficient toward zero and both the disc and neighborhood instruments recover estimates much closer to the true parameter (Figures B.4 and B.2). This reinforces the importance of addressing distance endogeneity in applications like ours. A secondary finding concerns the practical implementation of the neighborhood instrument: its performance varies considerably with the chosen radius. At the best radius, the neighborhood instrument achieves bias reduction comparable to the disc instrument, but at many other radii it performs substantially worse. The disc instrument, by contrast, requires no radius selection and delivers stable bias reduction across simulation replications.

As we will show below, in our empirical application, the disc instrument and the neighborhood instrument with a five mile radius produce similar demand estimates to each other but produce substantially different estimates from the naive estimates produced assuming exogeneity.[17]

power of the instruments and the degree of bias. In what follows, we show that our preferred instruments still have substantial explanatory power.

[17]We show demand estimates using the Figure 6-(a) instruments in the Appendix. While they have a stronger first stage than our preferred instruments, the results from using them in our context are quite similar to the results from using our preferred instruments.

6.3.1 Alternative Instruments

Other instruments can be constructed depending on the application. It may be desirable to exclude proximate neighbors when constructing the instruments if the threat to identification is particularly strong. One approach is to exclude a region around a given consumer's angle φ. With this approach, a sector (or, in simpler terms, a slice) is removed from our original disc instruments. Alternatively, it may be desirable to exclude some distance bands from the CBD. This would result in constructing annuluses, or regions defined between concentric circles. That is, the instrument would be a "washer." Figure A.2 in the Appendix depicts how these alternative instruments can be constructed with the same underlying data.

Our control function (6.1) could instead be written as a function of the product of the share of the total CBSA population residing at the same or closer distance as i to the CBD and the shares of those residents that fall in each income quartile. Some of the power of this set of instruments may therefore be derived from the factors related to the population density at different distances from the city. To the extent that these factors drive supply (e.g., land values act as a direct cost shifter), they do not threaten our identification argument. Using population density alone, however, provides insufficient power to estimate our model. Cost shifters that vary with population density (e.g., the availability and cost of certain retail footprints) likely impact siting decisions of different chains similarly. To predict chain-specific distances, we rely on the additional power that we get from the income-specific population shares.

One could argue that the fringe count is also endogenous. In the Appendix, we consider this possibility and estimate a specification that instruments for both distance and the fringe count. Overall, we find that those estimates are qualitatively similar.

7 Parameter Estimates

Due to the large number of parameters estimated, we summarize our results here. In the Appendix, we plot the distribution of estimated coefficients across income quartiles and CBSAs in Figure A.3.[18] In Table 2, we report income quartile–level estimates, aggregated over CBSAs using income quartile–specific population counts. Standard errors are reported using bootstrap aggregation.

For comparison purposes, we estimate a variant of our model where distance is assumed to be exogenous. When distance is exogenous, we remove the control function and retain ξ as random effects and estimating the variances using the same chain groupings. A summary of these demand estimates in Table 3.

7.1 Disutility from Distance

Focusing on Table 2, we first highlight that the average first-stage partial F-stat and partial R^2 suggest that our instruments are strong and explain significant variation in the observed distances. Directionally, our estimates show that consumers have a disutility of travel to stores. The similarity of the travel disutility estimates across income groups may be surprising. There are likely two countervailing effects: while higher-income groups likely have higher time costs, budget constraints may limit travel options for lower-income groups.

[18] Estimates for every CBSA-income quartile separately are available at https://tinyurl.com/CCHPW-additionaldemand.

Table 2: Summary of Demand Estimates, Distance Endogenous (Disc Instruments)

Income Quartile		Inc. 1	Inc. 1 SE	Inc. 2	Inc. 2 SE	Inc. 3	Inc. 3 SE	Inc 4.	Inc. 4 SE
Parameter									
Distance	β^{d1}	-0.444	(0.020)	-0.469	(0.010)	-0.475	(0.009)	-0.540	(0.010)
Density	β^{d2}	0.339	(0.083)	0.206	(0.018)	0.177	(0.014)	0.141	(0.015)
Fringe	ω	1.478	(0.769)	1.354	(0.066)	1.340	(0.023)	1.130	(0.018)
Control Function	ρ	0.181	(0.016)	0.221	(0.007)	0.212	(0.006)	0.242	(0.007)
Chain Preferences									
BJ's Wholesale Club		1.903	(1.436)	2.474	(0.730)	2.389	(0.584)	2.577	(0.450)
Costco		2.236	(0.929)	3.248	(0.328)	3.545	(0.406)	4.217	(0.354)
Sam's Club		0.636	(1.348)	1.478	(0.898)	2.633	(0.703)	2.427	(0.819)
Bloomingdale's		-0.856	(1.590)	0.998	(0.872)	0.259	(0.647)	2.206	(0.568)
Dillard's		-2.771	(1.654)	0.443	(0.727)	-0.363	(0.801)	1.054	(0.508)
JC Penney		0.104	(0.784)	1.168	(0.558)	0.860	(0.453)	0.726	(0.390)
Kohl's		-0.164	(0.862)	1.672	(0.446)	1.271	(0.569)	1.567	(0.323)
Macy's		0.562	(0.973)	1.685	(0.577)	1.402	(0.468)	2.027	(0.378)
Neiman Marcus		-1.805	(1.272)	-0.133	(0.758)	-0.091	(0.685)	1.207	(0.484)
Nordstrom		-0.538	(1.066)	0.602	(0.710)	0.408	(0.683)	1.953	(0.489)
Saks Fifth Avenue		-1.194	(1.213)	0.074	(0.816)	0.124	(0.747)	0.787	(0.680)
Sears		-3.595	(1.229)	-1.006	(0.717)	-1.250	(0.734)	-1.083	(0.572)
Burlington		3.000	(0.881)	3.144	(0.437)	3.012	(0.305)	3.130	(0.267)
Citi Trends		3.111	(1.647)	2.942	(0.427)	2.730	(0.828)	2.117	(0.630)
Five Below		0.845	(0.941)	1.175	(0.491)	1.227	(0.445)	1.437	(0.401)
Marshalls		2.406	(0.862)	2.743	(0.524)	2.869	(0.603)	3.149	(0.363)
Ross Dress for Less		3.399	(1.043)	3.467	(0.815)	3.451	(0.707)	3.933	(0.521)
T.J. Maxx		2.299	(1.026)	2.851	(0.718)	3.047	(0.646)	3.228	(0.559)
Big Lots		0.061	(0.752)	1.340	(0.301)	1.363	(0.261)	1.618	(0.234)
Target		3.125	(1.014)	3.730	(0.709)	4.126	(0.706)	4.733	(0.471)
Walmart		5.424	(1.091)	5.330	(0.660)	5.257	(0.593)	4.875	(0.516)
99c Only		2.033	(1.192)	2.910	(0.315)	1.322	(0.583)	1.617	(0.255)
Dollar General		2.522	(0.860)	2.419	(0.467)	2.042	(0.519)	1.266	(0.419)
Dollar Tree		3.814	(0.847)	3.874	(0.376)	3.607	(0.395)	3.818	(0.327)
Family Dollar		3.010	(0.846)	3.080	(0.442)	2.593	(0.446)	1.816	(0.374)
Random Coefficients	σ_k								
Warehouse Stores		2.438	(0.286)	1.788	(0.172)	1.915	(0.122)	2.148	(0.118)
Traditional Stores		2.935	(0.335)	1.998	(0.225)	2.378	(0.195)	2.411	(0.153)
Discount Stores		0.990	(0.265)	0.763	(0.150)	0.627	(0.130)	0.437	(0.100)
Supercenters		2.094	(0.281)	1.284	(0.121)	1.066	(0.107)	0.855	(0.111)
Dollar Stores		1.459	(0.233)	1.028	(0.144)	1.388	(0.128)	1.339	(0.127)
Summary									
Number of Visits		1,476,820		7,737,705		11,797,999		13,796,397	
Number of Devices		130,157		605,128		886,500		1,132,056	
Avg. First Stage Partial R^2		18.9%		13.5%		11.6%		12.8%	
Avg. First Stage Partial F-stat		237.1		720.4		873.9		1514.0	

Note: This table summarizes our demand estimates across 18 CBSAs and all income quartiles for the case when distance is allowed to be endogenous. To aggregate our estimates, we use income-specific CBSA populations as weights. Standard errors are also aggregated using bootstrap aggregation with 1,000 block bootstraps.

Table 3: Summary of Demand Estimates, Distance Exogenous

Income Quartile		Inc. 1	Inc. 1 SE	Inc. 2	Inc. 2 SE	Inc. 3	Inc. 3 SE	Inc 4.	Inc. 4 SE
Parameter									
Distance	β^{d1}	-0.278	(0.016)	-0.270	(0.006)	-0.274	(0.005)	-0.310	(0.006)
Density	β^{d2}	0.357	(0.074)	0.245	(0.021)	0.193	(0.017)	0.148	(0.016)
Fringe	ω	1.404	(0.799)	1.292	(0.078)	1.248	(0.025)	0.994	(0.017)
Chain Preferences									
BJ's Wholesale Club		1.299	(1.559)	1.540	(0.593)	1.522	(0.511)	1.485	(0.427)
Costco		1.698	(0.939)	2.254	(0.323)	2.738	(0.385)	3.088	(0.358)
Sam's Club		0.066	(1.427)	-0.424	(1.075)	1.834	(0.663)	1.299	(0.931)
Bloomingdale's		-1.482	(1.618)	-0.288	(0.854)	-0.658	(0.588)	1.197	(0.577)
Dillard's		-3.301	(1.798)	-1.005	(0.717)	-0.750	(0.770)	0.348	(0.492)
JC Penney		-0.286	(0.785)	0.135	(0.584)	0.109	(0.437)	-0.133	(0.382)
Kohl's		-0.464	(0.867)	0.734	(0.423)	0.680	(0.494)	0.901	(0.322)
Macy's		0.011	(0.971)	0.508	(0.570)	0.601	(0.437)	1.057	(0.358)
Neiman Marcus		-2.548	(1.384)	-1.375	(0.761)	-0.929	(0.634)	0.259	(0.500)
Nordstrom		-1.103	(1.050)	-0.584	(0.707)	-0.418	(0.651)	1.021	(0.489)
Saks Fifth Avenue		-1.875	(1.260)	-1.156	(0.793)	-0.996	(0.685)	0.073	(0.688)
Sears		-4.219	(1.289)	-2.125	(0.691)	-1.997	(0.695)	-2.102	(0.592)
Burlington		2.195	(0.923)	2.129	(0.452)	2.052	(0.288)	2.030	(0.283)
Citi Trends		2.367	(1.764)	1.928	(0.437)	1.646	(0.960)	0.943	(0.638)
Five Below		-0.007	(1.022)	0.079	(0.477)	0.318	(0.410)	0.469	(0.367)
Marshalls		1.683	(0.871)	1.713	(0.526)	1.896	(0.569)	2.165	(0.338)
Ross Dress for Less		2.613	(1.088)	2.490	(0.794)	2.639	(0.646)	2.748	(0.525)
T.J. Maxx		1.518	(0.973)	1.813	(0.718)	2.121	(0.604)	2.478	(0.556)
Big Lots		-0.990	(0.771)	-0.005	(0.325)	0.180	(0.264)	0.053	(0.232)
Target		2.174	(0.974)	2.614	(0.668)	3.155	(0.668)	3.626	(0.481)
Walmart		4.628	(1.076)	4.462	(0.629)	4.355	(0.543)	3.742	(0.511)
99c Only		0.943	(1.162)	1.941	(0.335)	0.730	(0.568)	0.458	(0.267)
Dollar General		1.672	(0.910)	1.364	(0.483)	0.891	(0.489)	-0.285	(0.464)
Dollar Tree		3.031	(0.863)	3.000	(0.363)	2.734	(0.377)	2.685	(0.337)
Family Dollar		2.244	(0.862)	2.103	(0.435)	1.481	(0.392)	0.162	(0.389)
Random Coefficients	σ_k								
Warehouse Stores		2.085	(0.298)	1.740	(0.170)	1.612	(0.126)	1.933	(0.113)
Traditional Stores		2.520	(0.339)	1.952	(0.221)	2.027	(0.182)	1.935	(0.169)
Discount Stores		0.894	(0.275)	0.650	(0.143)	0.381	(0.125)	0.223	(0.102)
Supercenters		2.125	(0.284)	1.512	(0.123)	1.095	(0.116)	0.941	(0.107)
Dollar Stores		1.553	(0.242)	1.235	(0.147)	1.462	(0.126)	1.445	(0.136)
Summary									
Number of Visits		1,476,820		7,737,705		11,797,999		13,796,397	
Number of Devices		130,157		605,128		886,500		1,132,056	

Note: This table summarizes our demand estimates across 18 CBSAs and all income quartiles for the case when distance is assumed to be exogenous. To aggregate our estimates, we use income-specific CBSA populations as weights. Standard errors are also aggregated using bootstrap aggregation with 1,000 block bootstraps.

Figure 7a demonstrates that the disutility from distance is overall greater (more negative) when we account for endogenous proximity.[19] This result, that consumers appear to

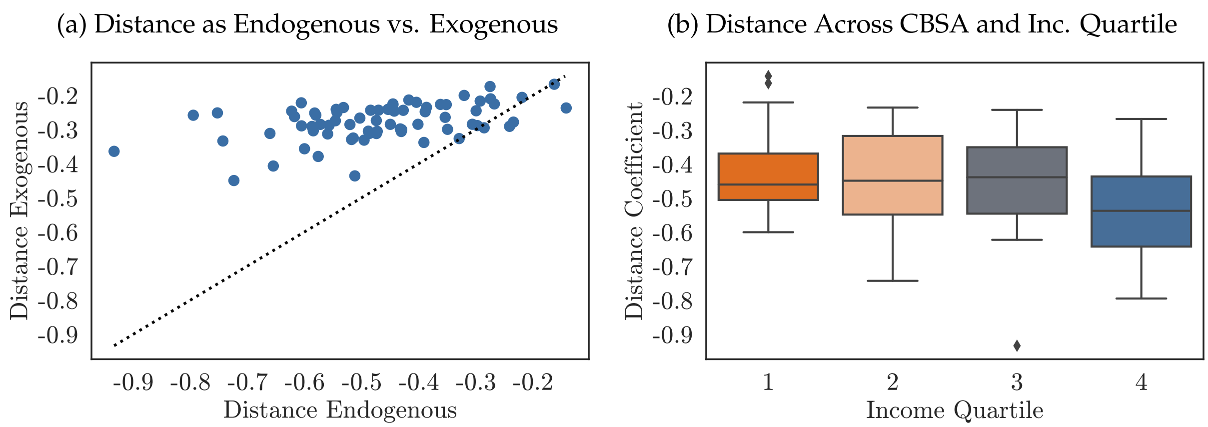
[19] Theoretically, the endogeneity problem could go the other way. Indeed, we find that for one CBSA (Tampa, FL) and three income quartiles, the endogeneity parameters are negative meaning that the unobserved preference is negatively correlated with distance. See Table C.4. For the overall finding that distance

view distance as more costly when the endogeneity of distance is controlled for, echoes the familiar results regarding price endogeneity and aligns with the direction of the bias demonstrated in our Monte Carlo simulations. Figure 7a also shows that the distance disutility parameters are more dispersed across CBSAs when we account for endogenous proximity.

One concern is that our distance from the CBD instrument is correlated with travel speed. Appendix Tables D.1 and D.2 and Figures D.1 and D.2 summarize parameter estimates obtained when using time in place of distance. When we use time to proxy for travel cost, we find again that accounting for endogenous proximity reveals larger and more disperse travel cost elasticities. The time and distance elasticities both increase by approximately 60% when we account for endogenous proximity.

Consistent with our hypothesis about trip chaining, the estimates on the log density parameter are positive, meaning that consumers prefer stores that are co-located with other stores over stand-alone stores, ceteris paribus. For example, a low-income consumer is willing to travel 1 mile further to visit a store that has one neighboring store than they would to visit a stand-alone store of the same chain.

Figure 7: Distance Coefficients



Note: Panel (a) shows distance coefficient estimates obtained when endogeneity for all CBSA-income quartiles is both accounted for and not accounted for. Panel (b) presents a histogram of distance coefficients estimated when endogeneity is accounted for, across CBSAs for each income quartile separately.

is positively correlated with the unobserved preference, see Table C.3 as an example.

7.2 Chain Tastes

To examine the tastes for the various chains and the differences in tastes across consumer incomes, for each CBSA, we use the parameter estimates to calculate a mile-normalized taste measure for each pair of chains and income quartiles:

$$\tilde{\beta}_{y(i),j} = \int \frac{\beta_{y(i),j} + \beta^{d2}_{y(i)}\text{median}\left(density_{\cdot,j}\right) + \sigma_j \eta_{i,j} - \omega_{y(i)}\text{median}\left(\Gamma(J^f_\cdot)\right)}{\left|\beta^{d1}_{y(i)}\right|} dF\left(\eta \mid \sigma\right) \tag{7.1}$$

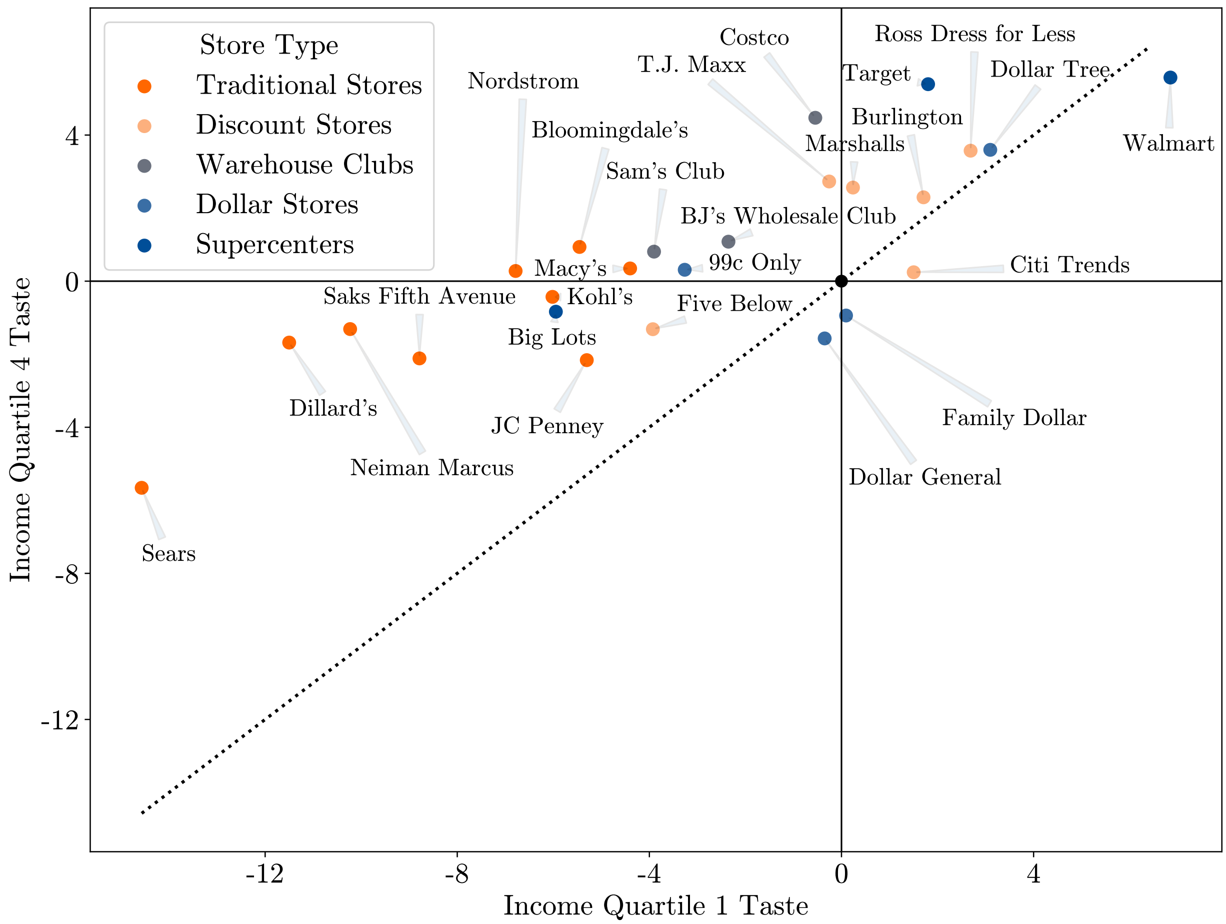
$$= \frac{\beta_{y(i),j} + \beta^{d2}_{y(i)}\text{median}\left(density_{\cdot,j}\right) - \omega_{y(i)}\text{median}\left(\Gamma(J^f_\cdot)\right)}{\left|\beta^{d1}_{y(i)}\right|}. \tag{7.2}$$

This taste measure uses the CBSA-specific median store density surrounding stores of each chain (i.e., median($density_{r(j)}$)) to adjust for the differences in travel cost across chains, which arise from the varying degree of store co-location across chains. It is calculated relative to the fringe store set of the median size (i.e., median($|J^f_\ell|$)) in each CBSA. The taste measure can be interpreted as the number of additional miles a consumer in income quartile y would be willing to travel to visit a store of chain $r(j)$ rather than patronize the fringe store opportunities.

Figure 8 illustrates these normalized taste parameter estimates for the 25 identified chains, averaged across CBSAs. We plot the taste parameters for consumers in the lowest-income quartile on the x-axis against those for consumers in the highest-income quartile on the y-axis. The positive correlation exhibited in Figure 8 shows that the preference ranking over general merchandise chains is similar between low- and high-income consumers. For example, Walmart is the most preferred chain for both lowest- and highest-income consumers, and traditional department store chains are among the least preferred chains by consumers. The overall low taste for the chains relative to the fringe opportunities reflects our specification's amalgamating the fringe opportunities; each trip to the fringe represents a consumer's trip to their most preferred option within the fringe, and the fringe is likely more tailored to local tastes than the national chains are.

While the chain tastes of high- and low-income consumers are positively correlated overall, there are notable differences in chain tastes across consumer incomes. For exam-

Figure 8: Distance-Normalized Chain Taste Parameters



ple, while higher-income consumers are nearly indifferent between Walmart and Target, lower-income people much prefer Walmart.

The disparity between consumer tastes can be illustrated by the positions of the parameters relative to the 45-degree line in Figure 8. Unsurprisingly, Family Dollar, Dollar General, and Cititrends sit below the 45-degree line, meaning they are more valuable to low-income consumers relative to the fringe chains than they are to high-income consumers; this finding is consistent with Cao [2022]. Meanwhile, both warehouse clubs (Costco, BJ's, and Sam's Club) and department stores (such as Dillards, Nordstrom, Bloomingdales, and Macy's) tend to be relatively more favored by higher-income consumers.

There are also stark differences within categories of stores that the casual observer might view as close substitutes. For example, our estimates suggest that Dollar General, Family Dollar, and Dollar Tree are quite different, with Dollar Tree being relatively more valued by higher-income consumers than are Dollar General and Family Dollar. While Walmart is the most-preferred chain, its sister chain Sam's Club is less preferred to rival warehouse clubs Costco and BJ's by both lower- and higher-income consumers.

Our estimates allow us to quantify the relative utility that the income groups receive from the different chains. In Figure 8, the horizontal distance between two points defines the additional distance a consumer in income quartile 1 would be willing to travel to visit an outlet of the right-hand chain relative to the left-hand chain. The vertical distance reflects the same marginal willingness-to-travel of a consumer in income quartile 4.

For example, our estimates suggest that, given the disutility for distance and the tastes for each chain, a consumer in the lowest income quartile would be close to indifferent between having a Dollar General co-located with the consumer (at a distance of zero) and having a Walmart located 6 miles away. We estimate that for a Walmart any closer than 6 miles, the consumer will prefer that Walmart over the Dollar General next-door.

8 Consumer Surplus Estimates for 2010–2019

Given the expansion of some national chains, particularly dollar stores, and the decline of regional chains over the past decade, we next consider whether consumers of different income levels obtain higher or lower per trip consumer surplus from the 2010 brick-and-mortar retail options than from the 2019 store configurations. To do this, we combine the consumer preferences we obtained in the previous section with DataAxle data on store locations in 2010 and 2019 and Census data on household locations in 2019. Recall that our dataset does not contain smartphone geolocation data for 2010. Thus, holding fixed the consumer preferences estimated for 2019 and consumer locations from 2019, we consider how consumer surplus per trip would differ if the identities and locations of retail stores were the same as in 2010. Suppose, for example, many stores that were liked by and proximate to a particular demographic group closed and were not replaced. Our methods would estimate lower per trip welfare due to both consumers traveling farther to visit their preferred stores and visiting less-preferred proximate stores.

To calculate the overall consumer surplus per trip for a representative consumer from each income quartile, we first calculate the number of consumers in each income quartile residing in each Census tract of our CBSAs in 2019. We assume that each consumer resides at the centroid of their Census tract of residence in 2019. We then calculate distances from these consumers to stores available in 2019 and to stores available in 2010 using the DataAxle data on store locations. For each income quartile, we calculate the population-weighted average consumer surplus per trip for a representative consumer in that income quartile in 2019 based on the estimated preferences for each store. Then, we recalculate this using the 2010 store locations. Changes in the general merchandise sector affect consumer surplus through store entry and exit from each consumer's choice set and through changes in the distance cost paid to visit individual stores. As a robustness check, we also consider consumer locations and population weights using the 2010 Census, thereby allowing for changes in both retailer and consumer locations. These results can be found in the Appendix (Table A.3 and Table A.4).

For each consumer, we measure the change in per trip consumer welfare associated with the changing retail landscape as the change in the inclusive value over the consumer's choice set; that is, for consumer i,

$$\Delta CS_i = \frac{\int \ln\Big(\sum_{j \in J_{i,2019}} \exp(\nu_{i,j}^{2019} + \sigma_j \eta_{i,j})\Big) dF(\eta) - \int \ln\Big(\sum_{j \in J_{i,2010}} \exp(\nu_{i,j}^{2010} + \sigma_j \eta_{i,j})\Big) dF(\eta)}{|\beta_{y(i)}^{d1}|}, \quad (8.1)$$

where $\nu_{i,j}^t$, defined in Equation 5.2, is the deterministic indirect utility consumer i derives from chain j, calculated using the estimated preference parameters combined with the distances between consumers and stores of chain j in $t = 2010$ and $t = 2019$.

Note that Equation 8.1 is denominated in mileage equivalents. That is, if the change in consumer surplus from 2010 to 2019 was -1, the representative consumer would have their consumer surplus fall over this period by an amount equivalent to the disutility of traveling an extra mile per trip. We can also express the consumer surplus changes in dollars. To do so, we can follow Dolfen et al. [2022] and calculate a travel cost that is derived from evidence in the literature and includes both a time cost and a direct cost of travel. During the period we study, the travel cost estimate is c = \$3.36 per mile round-trip.

The calculated consumer surplus change captures both the extensive margin changes of a consumer's choice set characterized in Figure 3. Thus, for example, if consumers were visiting all of the same stores in 2010 and 2019 but traveling less far for them in 2019, we would observe a welfare increase. If they were making the same number of trips and traveling the same distances but more-preferred stores had replaced less-preferred ones, we would also observe a welfare increase.

Since consumers live in different locations with different choice sets, we aggregate the welfare measure across consumers. Table 4 shows the average consumer welfare change associated with the changing retail landscape for each income quartile per trip. Table 5 presents these consumer welfare results obtained when assuming exogenous distance per trip. In addition, we compute bias-corrected confidence intervals for counterfactuals, which we report at the 95th percentile.

Table 4: Consumer Welfare Change from 2010 to 2019 by Income Quartile, Distance Endogeneity Accounted for with Disc Instrument

Income Quartile	1	2	3	4
ΔW	-0.220	-0.139	-0.053	0.115
Conf. Interval	$(-0.477, 0.275)$	$(-0.320, -0.043)$	$(-0.245, 0.093)$	$(0.034, 0.231)$
Δ Fringe Only	-0.577	-0.400	-0.382	-0.183
Conf. Interval	$(-1.851, -0.471)$	$(-1.049, -0.376)$	$(-0.387, -0.387)$	$(-0.246, -0.166)$
Δ Chains Only	0.372	0.312	0.283	0.359
Conf. Interval	$(0.273, 1.942)$	$(0.245, 0.414)$	$(0.160, 0.509)$	$(0.338, 0.474)$

Note: Aggregate welfare per trip by income quartile is reported using our preference estimates when we adjust for endogenous distances using our disc instrument. The first row represents our overall estimates, and the subsequent rows represents the estimates from counterfactuals with different assumptions. Specifically, the second row reports the consumer surplus change from 2010 to 2019 calculated when holding the configuration of national chains at their 2019 values but adjusting the regional and smaller chains from 2010 to 2019 configurations. The third row reports the estimated consumer surplus change from 2010 to 2019 calculated when holding the smaller regional chains fixed at the 2019 level for both time points but adjusting the national chains from 2010 to 2019 configurations. Confidence intervals for the counterfactuals are reported at the 95th percentile level and are bias-corrected.

The first row of Table 4 and the first row of Table 5 present the overall consumer surplus change per trip by income quartile for the case in which preferences are estimated treating distance as endogenous and exogenous, respectively. Note that the estimated consumer

Table 5: Consumer Welfare Change from 2010 to 2019 by Income Quartile, Distance Exogenous

Income Quartile	1	2	3	4
ΔW	-0.514	-0.459	-0.261	0.061
Conf. Interval	$(-1.705, -0.222)$	$(-0.755, -0.367)$	$(-0.626, -0.060)$	$(-0.101, 0.221)$
Δ Fringe Only	-0.987	-0.786	-0.584	-0.313
Conf. Interval	$(-1.990, -0.837)$	$(-1.137, -0.780)$	$(-0.673, -0.591)$	$(-0.386, -0.315)$
Δ Chains Only	0.354	0.388	0.346	0.466
Conf. Interval	$(0.038, 0.692)$	$(0.209, 0.614)$	$(0.105, 0.653)$	$(0.413, 0.679)$

Note: Aggregate welfare per trip by income quartile is reported using our preference estimates obtained when not adjusting for endogenous distances. The first row represents our overall estimates, and the subsequent rows provide the estimates from counterfactuals with different assumptions. Specifically, the second row reports the estimated consumer surplus change from 2010 to 2019 calculated when holding the configuration of national chains at their 2019 values but adjusting the regional and smaller chains from 2010 to 2019 configurations. The third row reports the estimated consumer surplus change from 2010 to 2019 calculated when holding the smaller regional chains fixed at the 2019 level for both time points but adjusting the national chains from 2010 to 2019 configurations. Confidence intervals for the counterfactuals are reported at the 95th percentile level and are bias-corrected.

welfare change from 2010 to 2019 is substantially more negative in the exogenous distance specifications; neglecting distance endogeneity biases welfare estimates substantially.

Focusing on Table 4, three of the four income quartiles have slightly lower welfare in 2019 than in 2010. The first row suggests that for the lowest-income consumers, the change in consumer surplus is as if low-income consumers had to travel 0.220 miles farther in 2019 to reach retail opportunities equivalent to those available in 2010. However, the estimate is not significantly different from zero. For income quartile 2, we find a statistically significant decline in consumer surplus equal to 0.140 miles per trip. Using the travel cost of \$3.36 per mile leads to a consumer surplus decline estimate of 47 cents per trip. We find insignificant surplus declines for income quartile 3 and a small but positive surplus change for income quartile 4.

The second row reports the results we obtained by repeating the exercise but holding the 25 named national chains at their 2019 levels and calculating the consumer surplus change from 2010 to 2019 resulting from the change in smaller and regional chains. These regional chains have shrunk substantially over the decade. The last rows limit our attention to the 25 named chains rather than the smaller fringe stores. When considering only the 25 named national chains, we estimate that welfare per trip has grown over the decade for all consumer groups. Our estimates suggest that the largest consumer surplus loss attributable to the shrinkage of regional chains and the largest gains attributable to the growth of national chains are both estimated to accrue to the lowest income groups.

By comparing Table 4 (distance is endogenous) to Table 5 (distance is exogenous), we find that abstracting from distance endogeneity leads to the incorrect conclusion—consistent with the retail apocalypse narrative—that consumers have experienced statistically significant surplus declines over the last decade. Focusing on the first row, we see coefficients of near -0.5 for below-median-income households. This translates to over a \$1.5 decline in surplus per trip using the miles-to-dollars conversion in Dolfen et al. [2022]. The overstatement in the surplus loss for income quartile 2 is more than a factor of three. For income quartile 1, the overstatement is a factor of two; accounting for distance endogeneity, we cannot conclude that there has been a surplus decline for these consumers.

Given the large growth in e-commerce over this time period, our focus here on per trip welfare may be counterintuitive. While we have learned from Dolfen et al. [2022] that e-commerce gains have accrued disproportionately to high-income consumers, there are some gains for all consumer groups. For any group to be dramatically worse off following the 2010 to 2019 e-commerce growth and brick-and-mortar readjustment, the per trip welfare experienced by that group would likely have to fall substantially. Indeed, we do not find evidence of per trip surplus decrease, as even the lowest-income consumers, who have benefited the least from e-commerce, have a mile-equivalent per trip utility change close to zero.

To further understand the pattern of consumers' welfare changes across incomes, we measure the consumer welfare contribution of the change of each chain during the 2010–2019 period, using the estimates that account for distance endogeneity, holding consumers and other chains at their 2019 locations.

To put it formally, for chain k, its welfare impact on consumer i of returning that chain to its 2010 location, holding constant the rest of the consumer's 2019 choice set, is defined as follows:

$$\Delta CS_{i,k} = \frac{\int \ln\Big(\sum_{j \in J_{i,2019}} \exp(\nu_{i,j}^{2019} + \sigma_j \mu_{i,j})\Big) dF(\mu)}{|\beta_i^{d1}|} \tag{8.2}$$

$$- \frac{\int \ln\Big(\sum_{j \in J_{i,2010} \setminus k} \exp(\nu_{i,j}^{2019} + \sigma_j \mu_{i,j}) + \exp(\nu_{i,k}^{2010} + \sigma_j \mu_{i,k})\Big) dF(\mu)}{|\beta_i^{d1}|}. \tag{8.3}$$

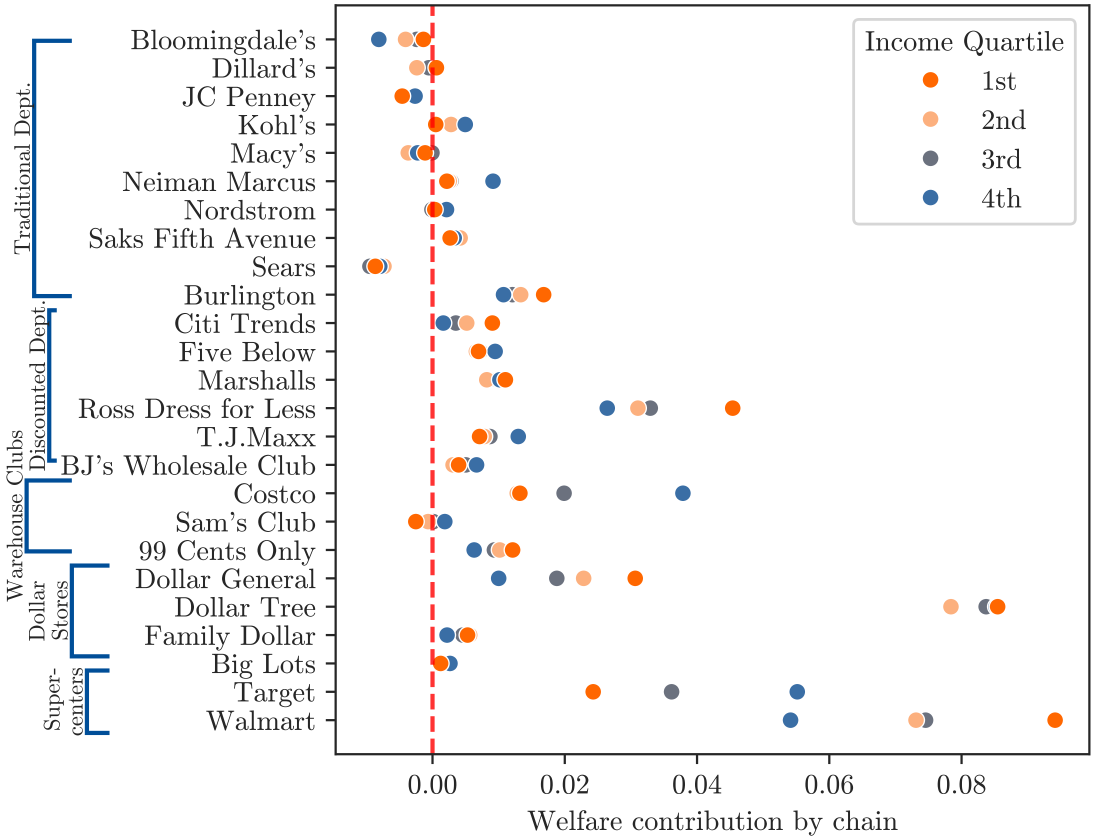
Essentially, this measure isolates the welfare change based on entry or exit for firm k, holding all else the same. We calculate this for each income quartile for each chain.

We report results in Figure 9. The units are consumer surplus changes per (representative) trip expressed in mileage equivalents, again aggregated using population weights. Consider Walmart, Dollar Tree, and Ross Dress for Less. Table 2 shows that the highest preference coefficients for the lowest-income-quartile consumers are for these chains. They all expanded on net over the decade. Figure 9 shows that the growth of these three chains accounted for about half of the total consumer surplus per representative trip gain that low-income consumers received from national chain expansion over the decade.

The Walmart expansion is particularly instructive. As shown in Figure 3, the consumers' probability of having Walmart available as an option did not improve substantially over the decade, and average distance to Walmart improved modestly for the consumers in all income quartiles. However, the very large preference for Walmart, particularly for low-income consumers, leads this modest expansion to contribute substantially and disproportionately to the consumer surplus growth of those in the lowest income quartile.

Taken together with Table 4, the results suggest that the expansion of discount chains, particularly the dollar and discount stores and Walmart, improved per trip welfare for lower-income consumers that nearly compensated for the decline in traditional department stores and the smaller regional chains. The sources of gains for the highest-income consumers are more broadly dispersed. While Dollar Tree is only the fifth most preferred of the chains for this group, its massive expansion over the decade leads it to be the largest positive driver of consumer surplus for this income group in the period considered.

Figure 9: Consumer Welfare Change Drivers: Chain-Level Contributions



9 Conclusion

We introduce a novel instrument for the endogenous distance between consumers and stores. Echoing the familiar bias in estimating the price elasticity of demand, accounting for distance endogeneity leads to estimating consumers to be more sensitive to distance than when distance endogeneity is not accounted for.

We apply our method to the setting of retail choice, examining consumer preferences for brick-and-mortar general merchandise retailers. By using smartphone geolocation data, we can both examine situations in which consumers pay with cash and report findings for individual identified chains. This would not be possible if we used payment card, government, or shopper panel datasets instead. We show substantial differences in preferences across chains by consumers in different income groups. We use our preference estimates to estimate the consumer surplus change experienced by consumers in the four income quartiles over the 2010–2019 decade. During this period, perhaps partially due to e-commerce, among other causes, there has been a substantial decline in the number of regional chains and department stores but an expansion in discount and dollar stores. Our estimates suggest that these two changes in the retail landscape roughly cancel each other out for the lowest-income consumers, but benefit the highest-income consumers if these changes are measured as consumer surplus per trip. However, our results show that welfare estimates that do not account for endogeneity overstate the welfare loss to the lowest-income consumers, leading to an incorrect conclusion that is consistent with the retail apocalypse narrative.

Looking forward, the near-saturation of dollar store retailers may limit the potential welfare gains achievable by their continued expansion in the future. Our results also suggest that regulations that restrict the siting of large big-box supercenters, particularly Walmart, could have disproportionate negative impacts on low-income consumers.

Our instrumenting approach may be useful in other settings where economists infer consumer tastes for different services by measuring willingness-to-travel. These include transportation, school, and healthcare choices; the direction of the bias in measuring distance disutility may vary across settings. Our instrumenting method relies only on publicly available data for a single cross-section and thus may be particularly useful when border discontinuity or panel data approaches are unavailable.

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Appendix – For Online Publication

A Additional Tables and Figures

Table A.1: Chains in each type of general merchandise stores

	Chain
Traditional Department	Bloomingdale's, Dillard's, JC Penney Macy's, Neiman Marcus, Nordstrom Saks Fifth Avenue, Kohl's, Sears
Discount Department	Citi Trends, Five Below, Burlington, Marshalls, Ross Dress for Less, T.J. Maxx
Warehouse Club	BJ's Wholesale Club, Costco, Sam's Club
Dollar Store	99c Only, Dollar General, Dollar Tree, Family Dollar
Supercenters	Big Lots, Target, Walmart
Others	Soma, Meijer, Dollar Plus, Von Maur, Boscov's, 99 Ranch Market, Christmas Tree Shops, etc.

Table A.2: Summary Statistics for the Data Sample, by Income Quartile

Variable	1st	2nd	3rd	4th
per device, week				
Number of visits to inside chains	1.98	1.95	1.89	1.78
Number of visits to fringe stores	1.28	1.28	1.27	1.23
per device				
Number of inside chains in choice set	16.04	15.96	15.72	16.23
Number of fringe stores in choice set	5.33	5.09	4.54	4.40
Number of weeks observed	6.96	7.91	8.62	8.52
Number of outlets of inside chains	97.87	85.29	72.19	65.31
Number of stores visited per trip	1.22	1.21	1.20	1.19
Number of unique chains	43	43	43	43
Number of outlets	10,492	10,828	10,803	10,590
Number of devices	130,455	606,531	888,539	1,134,165
Total number of visits	1.858 mil.	9.681 mil.	15.023 mil.	17.694 mil.

Summary statistics for the sample split by income quartile. We use the household income provided by Precisely PlaceIQ and calculate the quartiles based on the national distribution of income.

Table A.3: Additional Counterfactuals, Accounting for Endogeneity

Income Quartile	1	2	3	4
ΔW, Actual	-0.299	0.360	-0.199	0.027
ΔW, No Moves	-0.220	-0.088	-0.141	0.078
ΔW, No Δ Fringe	0.282	0.763	0.185	0.212
ΔW, No Δ Fringe nor Moves	0.367	0.277	0.293	0.275

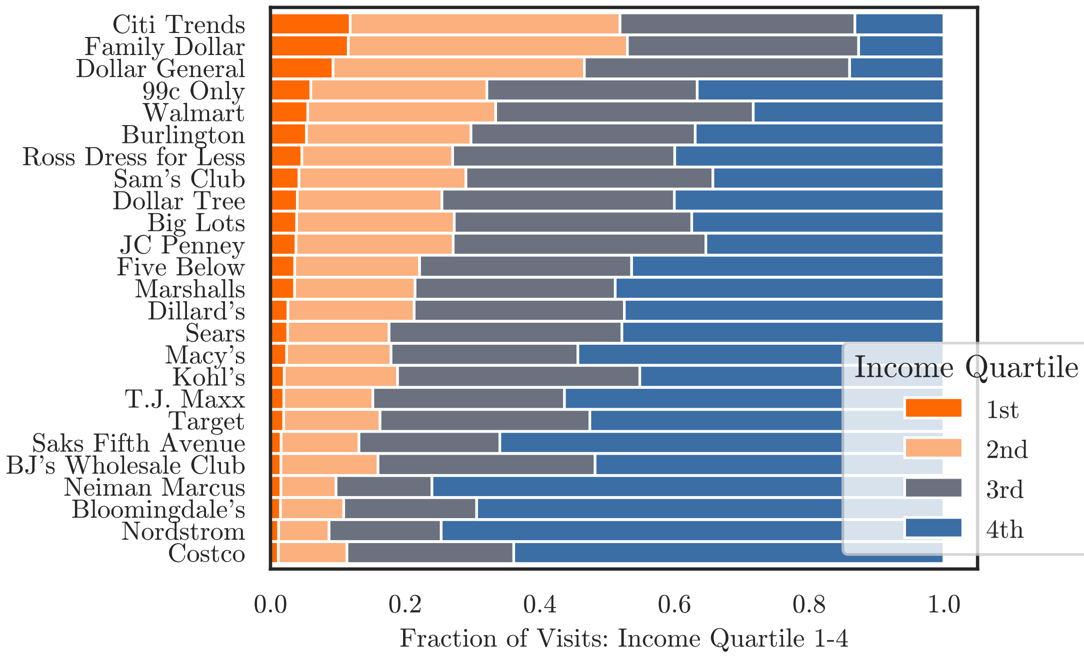
Note: These counterfactuals also take into account population changes from 2010 to 2019.

Table A.4: Additional Counterfactuals, Abstracting from Endogeneity

Income Quartile	1	2	3	4
ΔW, Actual	-0.433	0.788	-1.298	0.022
ΔW, No Moves	-0.512	-0.333	-0.441	0.006
ΔW, No Δ Fringe	0.561	1.579	-0.710	0.336
ΔW, No Δ Fringe nor Moves	0.471	0.350	0.296	0.340

Note: These counterfactuals also take into account population changes from 2010 to 2019.

Figure A.1: Household Shopping Patterns By Household Income Groups

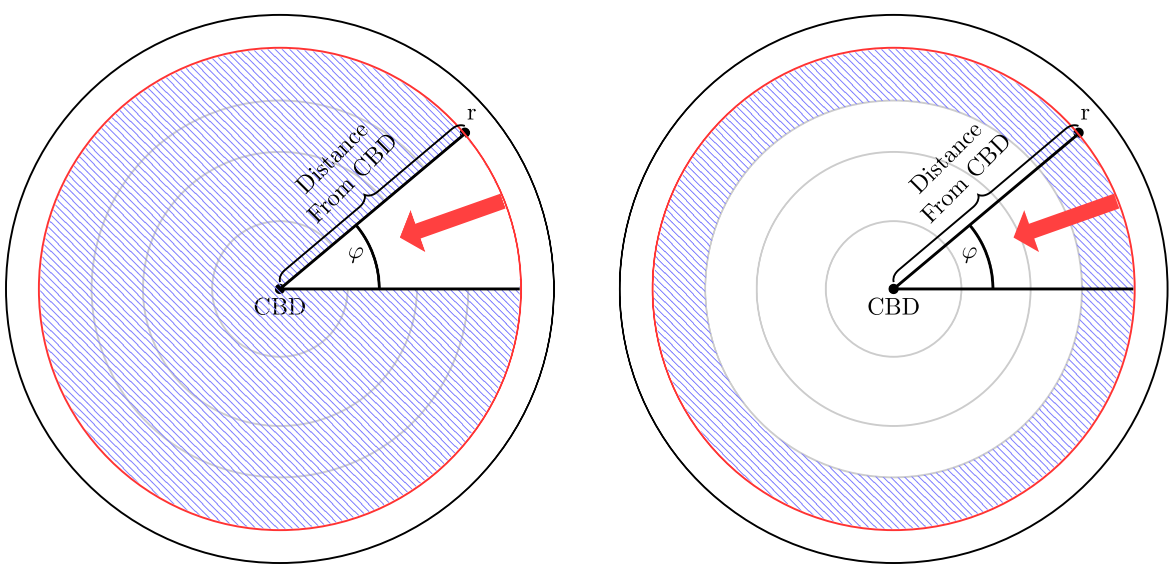


Note: The figure uses Precisely PlaceIQ data to show the share of 2019 visitors to each chain represented by members of each household income quartile. Chains are ordered from highest to lowest share of income quartile one visitors.

Figure A.2: Alternative Instrument Constructions for Spatial Data

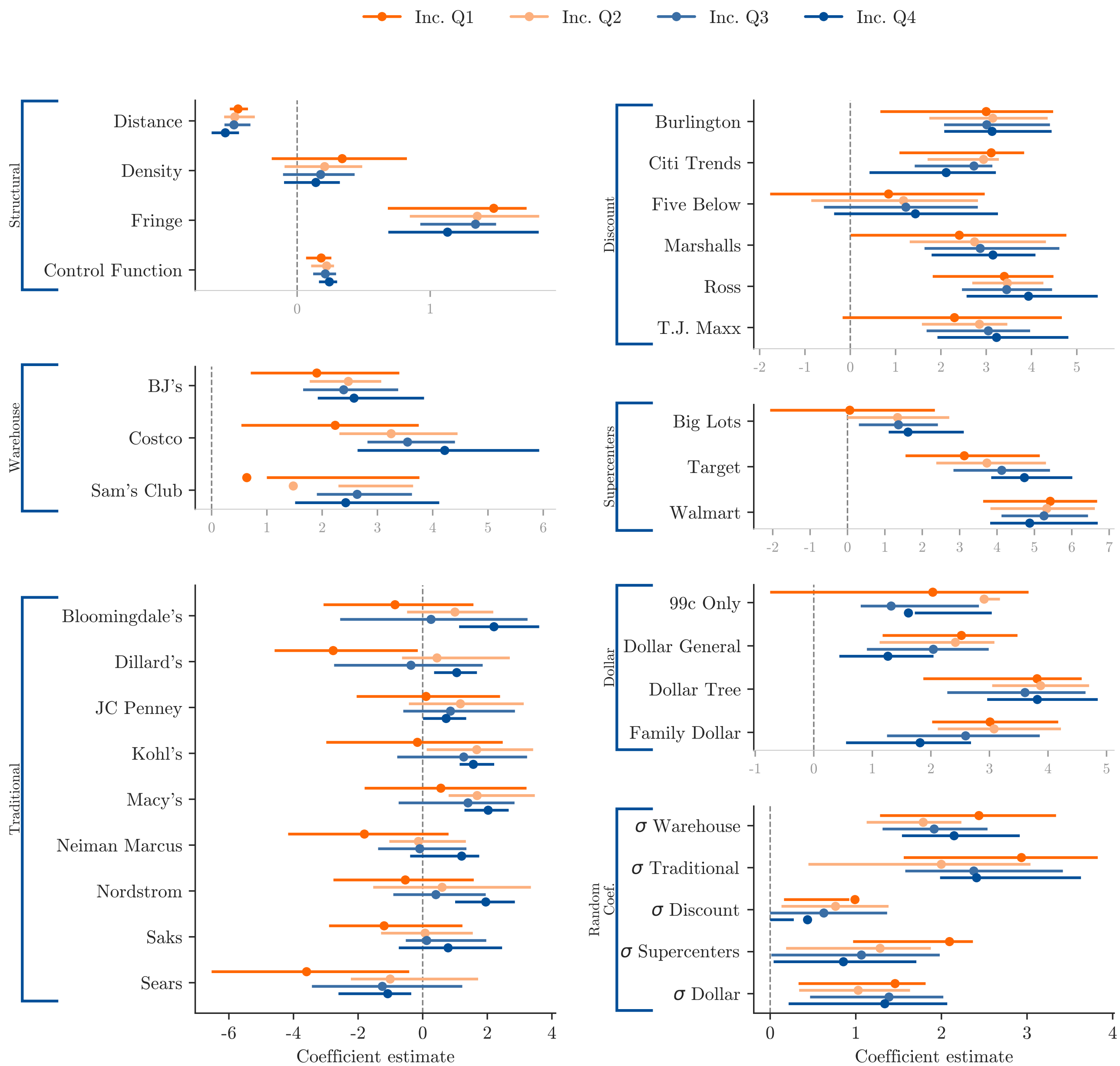
(a) Disc with Circular Sector Removed

(b) Annulus



Note: Panels (a) and (b) depict alternative spatial instruments that can be used depending on the application.

Figure A.3: Demand Parameters Range Plot – Endo. Dist (Disc) Groups



Note: Each line is the interquartile range of estimates for one parameter-income quartile across CBSAs.

B Monte Carlo Results

This appendix details the data-generating process, store location algorithm, estimation strategy, instrumental variable construction, and bias metrics used in the Monte Carlo simulations.

B.1 Demand Model

We consider a city of N consumers indexed by $i = 1, \ldots, N$ on a square grid of side length S. Each consumer is characterized by an income group $g_i \in \{1, 2, 3, 4\}$ and a consumer type $t_i \in \{1, 2, 3, 4\}$, both drawn uniformly at random.

A single retail store is located at position $\mathbf{s}^* \in [0, S]^2$. Let $d_i = \|\mathbf{x}_i - \mathbf{s}^*\|_2$ denote the Euclidean distance from consumer i's location $\mathbf{x}_i$ to the store. Consumer i chooses between purchasing at the store ($j = 1$) and an outside option ($j = 0$). The indirect utilities are

$$u_{i,1} = \nu_i + \varepsilon_{i1}, \tag{B.1}$$

$$u_{i,0} = \varepsilon_{i0}, \tag{B.2}$$

where ε_{i0} and ε_{i1} are i.i.d. T1EV shocks, and the deterministic component of purchase utility is

$$\nu_i = \alpha_{g_i} + \beta_i - \tau\, d_i. \tag{B.3}$$

Here α_{g_i} is an income-group-specific intercept, $\tau > 0$ is the distance cost parameter, and β_i is a consumer-specific preference given by

$$\beta_i = \bar{\beta}_{t_i} + \eta_i, \qquad \eta_i \overset{iid}{\sim} \mathcal{N}(0,\, \sigma_\beta^2), \tag{B.4}$$

with $\bar{\beta}_{t_i}$ a type-specific base preference and $\sigma_\beta = 0.3$. Consumer i purchases if $u_{i1} > u_{i0}$.

The individual purchase probability is

$$\Lambda_i = \frac{\exp(\nu_i)}{1 + \exp(\nu_i)}, \tag{B.5}$$

Purchase outcomes are realized as independent Bernoulli draws: $Y_i \sim \text{Bernoulli}(\Lambda_i)$.

Table B.1 reports the baseline parameter values used in the simulations.

Table B.1: Baseline Parameter Values

	Group 1	Group 2	Group 3	Group 4
Income preference α_g	0.5	1.0	0.0	0.5
Type base preference $\bar{\beta}_t$	0.5	0.5	1.0	1.0
Distance cost: $\tau = 3.0$				
Type preference noise: $\sigma_\beta = 0.3$				
Consumers per simulation: $N = 10{,}000$				
City size: $S = 10$				

B.2 Spatial Structure

Consumer locations are generated to produce realistic spatial sorting by income and type. Each consumer's position is determined in polar coordinates relative to the city center $\mathbf{c} = (S/2,\ S/2)$.

Angular placement. Each type t is assigned a wedge of the unit circle: $\Theta_1 = [0°, 30°]$, $\Theta_2 = [30°, 120°]$, $\Theta_3 = [120°, 240°]$, $\Theta_4 = [240°, 360°]$. With probability $1 - \theta_{\text{var}} = 0.7$, consumer i's angle θ_i is drawn uniformly from Θ_{t_i}; with probability $\theta_{\text{var}} = 0.3$, the angle is drawn uniformly from $[0, 2\pi)$.

Radial placement. The distance r_i from the city center depends on income group. For middle-income groups ($g \in \{2, 3\}$), distances are drawn from truncated normals concentrated at specific rings:

$$r_i \sim \mathcal{N}(\mu_g,\ \sigma_g^2), \quad \text{clipped to } [0, S], \tag{B.6}$$

with $(\mu_2, \sigma_2) = (0.35S,\ 0.2)$ and $(\mu_3, \sigma_3) = (0.50S,\ 0.2)$. For groups $g \in \{1, 4\}$, distances follow an exponential distribution:

$$r_i \sim \text{Exp}(\lambda_g), \qquad \lambda_1 = 0.2, \quad \lambda_4 = 1.5, \tag{B.7}$$

where λ_g is the rate parameter (mean distance $= 1/\lambda_g$). Cartesian coordinates are then computed as $x_i = S/2 + r_i \cos\theta_i$ and $y_i = S/2 + r_i \sin\theta_i$, clipped to $[0, S]$.

Type agglomeration. After initial placement, locations are pulled toward type-specific centroids with agglomeration parameter $\gamma = 0.3$:

$$\mathbf{x}_i \leftarrow (1-\gamma)\,\mathbf{x}_i + \gamma\,\bar{\mathbf{x}}_{t_i}, \tag{B.8}$$

where $\bar{\mathbf{x}}_{t_i}$ is the mean position of all consumers of type t_i.

B.3 Store Location Selection

The store location $\mathbf{s}^*$ is selected via grid search to maximize expected demand subject to a center-avoidance penalty, which we interpret as a cost of locating close to the city center. Specifically, an 80×80 grid of candidate locations is constructed over the interior of the city (excluding boundary cells). For each candidate $\mathbf{s}$, the expected demand is

$$D(\mathbf{s}) = \sum_{i=1}^{N} \Lambda\Big(\alpha_{g_i} + \beta_i - \tau\,\|\mathbf{x}_i - \mathbf{s}\|_2\Big). \tag{B.9}$$

The center-avoidance penalty term is given by:

$$\mathbf{s}^* = \arg\max_{\mathbf{s}} \left[D(\mathbf{s}) - \frac{w}{\max(\|\mathbf{s} - \mathbf{c}\|_2,\ 0.01)} \right], \tag{B.10}$$

where $w = 100$ is the punishment weight and $\mathbf{c} = (S/2, S/2)$ is the city center.

This setup generates endogeneity: the store locates to maximize demand, which depends on both observed income composition and unobserved type preferences. Consequently, distance d_i is correlated with the omitted variable β_i, biasing naive estimates of τ

toward zero.

B.4 Estimation Strategy

All models estimate the distance coefficient $\tau = -3.0$ via logit. We define the vectors $\mathbf{I}_i = (\mathbf{1}[g_i = 2], \mathbf{1}[g_i = 3], \mathbf{1}[g_i = 4])'$ denote the vector of income group dummies, with group 1 as the reference category.

Naive logit. The naive specification omits the unobserved type preference:

$$\Pr(Y_i = 1 \mid \mathbf{I}_i, d_i) = \Lambda\Big(\pi_0 + \boldsymbol{\pi}'_g \mathbf{I}_i + \tau_{\text{naive}}\, d_i\Big). \tag{B.11}$$

Because d_i is correlated with the omitted β_i, the estimate $\hat{\tau}_{\text{naive}}$ is biased.

Oracle logit. The oracle specification includes the true (unobserved in practice) type preference as a control:

$$\Pr(Y_i = 1 \mid \mathbf{I}_i, d_i, \beta_i) = \Lambda\Big(\pi_0 + \boldsymbol{\pi}'_g \mathbf{I}_i + \tau_{\text{oracle}}\, d_i + \pi_\beta\, \beta_i\Big). \tag{B.12}$$

This specification serves as a benchmark for the bias-corrected estimators.

Control function approach. To address the endogeneity of distance without observing β_i, we employ a two-step control function procedure in the spirit of Petrin and Train [2010]. The first stage estimates a linear model of distance on income controls and excluded instruments $\mathbf{Z}_i$:

$$d_i = \gamma_0 + \boldsymbol{\gamma}'_g \mathbf{I}_i + \boldsymbol{\delta}' \mathbf{Z}_i + v_i, \tag{B.13}$$

estimated by OLS. The residual $\hat{v}_i = d_i - \hat{d}_i$ captures the endogenous component of distance variation. The second stage augments the logit with $\hat{v}_i$:

$$\Pr(Y_i = 1 \mid \mathbf{I}_i, d_i, \hat{v}_i) = \Lambda\Big(\pi_0 + \boldsymbol{\pi}'_g \mathbf{I}_i + \tau_{\text{CF}}\, d_i + \pi_v\, \hat{v}_i\Big). \tag{B.14}$$

The coefficient $\hat{\tau}_{\text{CF}}$ provides a consistent estimate of the distance effect under the assumption that the instruments $\mathbf{Z}_i$ are relevant (correlated with d_i) and valid (uncorrelated with the structural error conditional on controls). A statistically significant $\hat{\pi}_v$ serves as a test of endogeneity.

B.5 Instrumental Variables

We construct two families of instruments, each producing four excluded instruments (one per income group $j \in \{1, 2, 3, 4\}$).

Disc instruments. For each consumer i and income group j, the disc instrument is defined as the empirical CDF of the distance-to-CBD distribution for group j, evaluated at consumer i's distance to the CBD:

$$Z_{j,i}^{\text{disc}} = \frac{\left|\left\{k : \ g_k = j,\ d_k^{\text{cbd}} \leq d_i^{\text{cbd}}\right\}\right|}{\left|\left\{k : \ g_k = j\right\}\right|}, \tag{B.15}$$

where $d_i^{\text{cbd}} = \|\mathbf{x}_i - \mathbf{c}\|_2$ is consumer i's distance to the city center. These instruments exploit the fact that a consumer's position within the income-group-specific distance distribution is predictive of store distance but, conditional on own income, should be independent of unobserved type preferences.

Neighborhood instruments. For a given radius $r > 0$, the neighborhood instrument for consumer i and income group j is the share of income-j consumers among i's spatial neighbors:

$$Z_{j,i}^{\text{nbhd}}(r) = \frac{\left|\{k : \ \|\mathbf{x}_k - \mathbf{x}_i\|_2 \leq r,\ g_k = j\}\right|}{|\{k : \ \|\mathbf{x}_k - \mathbf{x}_i\|_2 \leq r\}|}. \tag{B.16}$$

These instruments capture local income composition, which affects store distance through the store's location decision but should not directly affect purchase propensity conditional on own income. The radius r is specified as a fraction of the city size S, and the simulations test 60 values from $r/S = 0.01$ to $r/S = 0.60$.

In both cases, the first-stage instrument vector is $\mathbf{Z}_i = (Z_{1,i},\ Z_{2,i},\ Z_{3,i},\ Z_{4,i})'$, and the first-stage regression in equation (B.13) includes both the income dummies $\mathbf{I}_i$ and the four instruments $\mathbf{Z}_i$ as regressors, with a constant term added internally.

B.6 Bias Metrics

Let $\tau = -3.0$ denote the true distance coefficient. For each estimation method $m \in \{\text{naive}, \text{oracle}, \text{disc}, \text{neighborhood}\}$, the bias in simulation s is

$$\text{Bias}_{m,s} = \hat{\tau}_{m,s} - \tau^*. \tag{B.17}$$

Bias reduction relative to the naive estimator is

$$\text{BR}_{m,s} = \frac{|\text{Bias}_{\text{naive},s}| - |\text{Bias}_{m,s}|}{|\text{Bias}_{\text{naive},s}|} \times 100\%. \tag{B.18}$$

We report medians and means of both metrics across simulations.

First-stage strength is assessed via the R^2 of equation (B.13):

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \hat{v}_i^2}{\sum_{i=1}^{N} (d_i - \bar{d})^2}. \tag{B.19}$$

B.7 Monte Carlo Design

The simulation proceeds as follows for each of $M = 200$ replications:

1. Generate a city map of $N = 10{,}000$ consumers with the spatial structure described in Section B.2, using a replication-specific random seed, and construct instruments:
   (a) Disc instruments: $\{Z_{j,i}^{\text{disc}}\}_{j=1}^{4}$ per equation (B.15)
   (b) Neighborhood instruments: $\{Z_{j,i}^{\text{nbhd}}(r)\}_{j=1}^{4}$ per equation (B.16) for each of 60 radius values $r/S \in \{0.01, 0.02, \ldots, 0.60\}$.
2. Solve for the optimal store location $\mathbf{s}^*$ via equation (B.10) on an 80×80 grid.
3. Simulate purchase outcomes $\{Y_i\}$ from the logit model in equations (B.1)–(B.5).

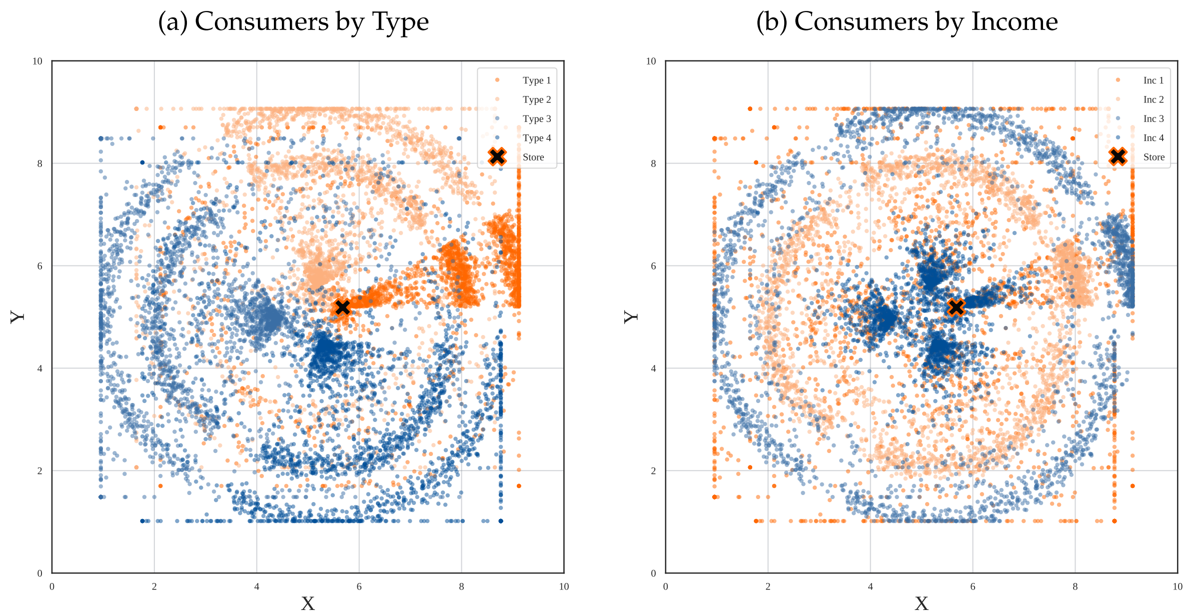
4. Estimate the naive and oracle models, and the disc and neighborhood IV control function models.

5. Record $\hat{\tau}$, bias, bias reduction, first-stage R^2, and purchase rate.

Neighbor queries in step 6(a) use a KD-tree built once per replication for efficiency, effectively changing computation to roughly $O(N \log N)$ time instead of $O(N^2)$. The 200 replications are parallelized across 115 CPU cores. GPU support is also built in to the simulator.

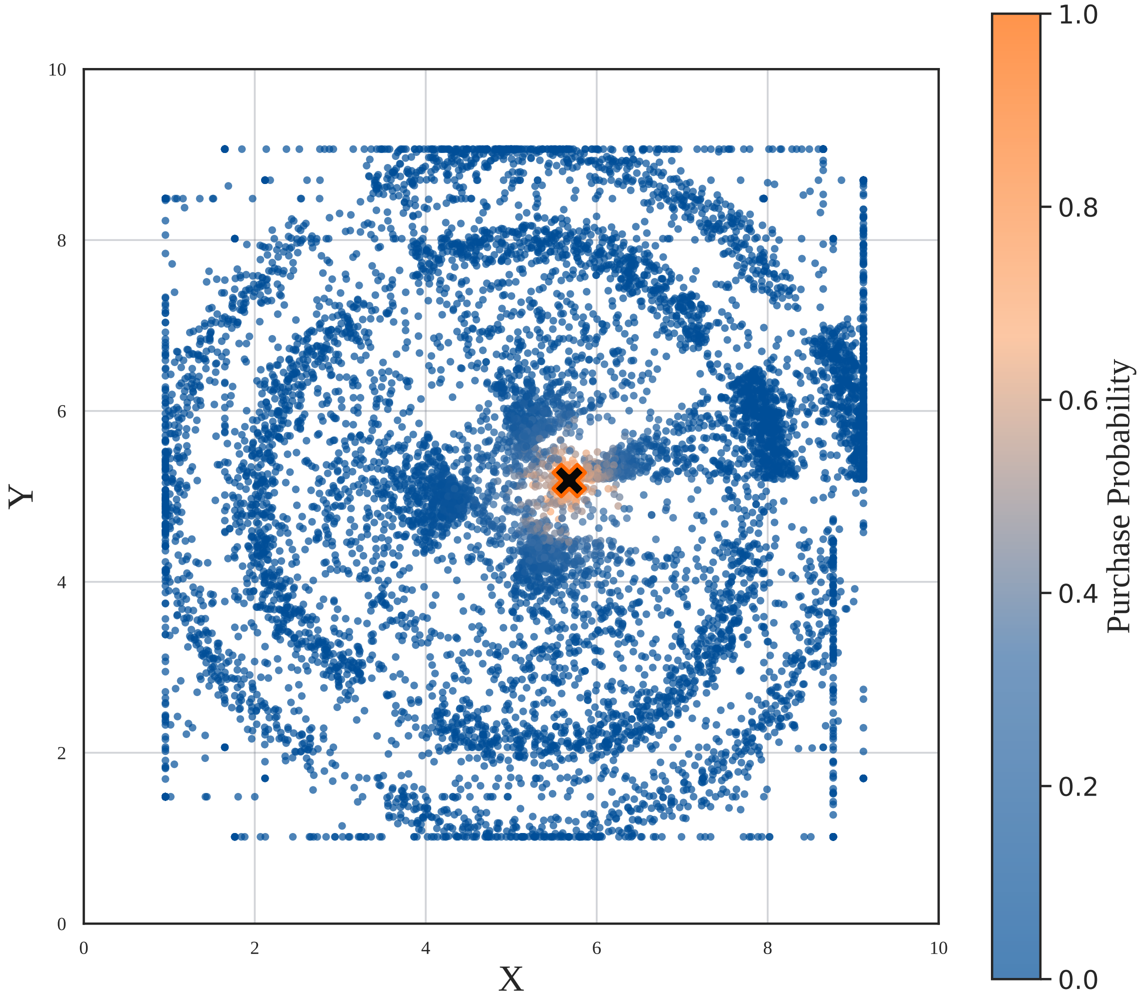
B.8 Monte Carlo Results

Figure B.1: Alternative Instrument Constructions for Spatial Data



Note: Panels (a) and (b) the spatial location of consumers based on income and type.

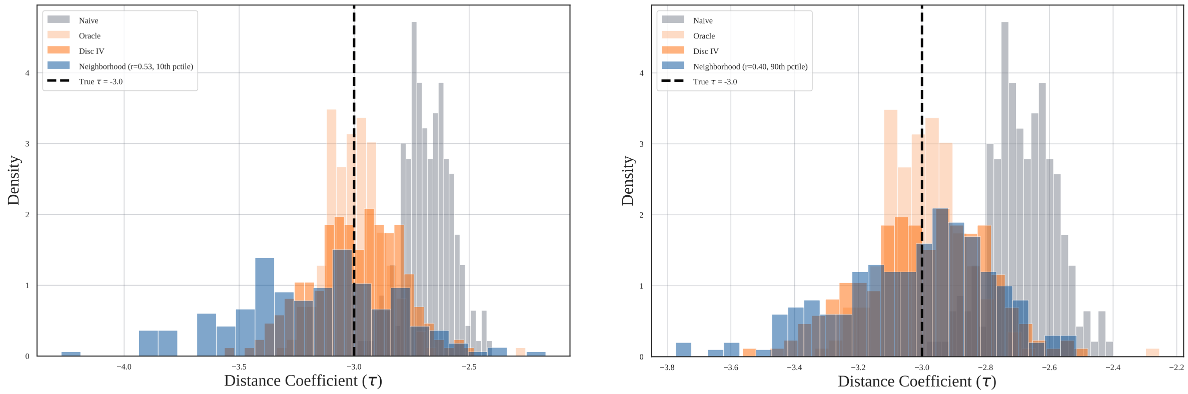
Figure B.2: Consumer Choice Probabilities



Note: Depicted are the consumer choice probabilities for consumers in the city.

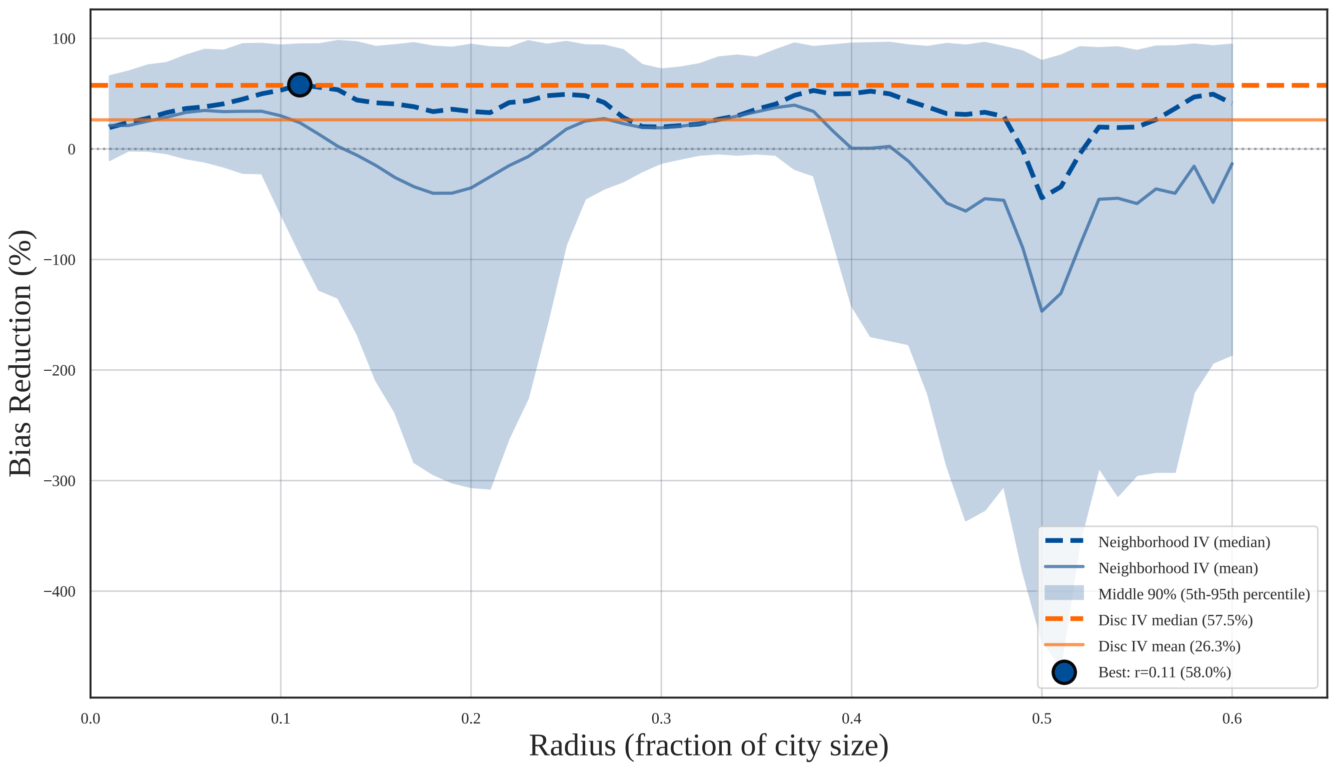
Figure B.3: Neighborhood Instrument Bias, 10th and 90th Percentiles

(a) Neighborhood Instrument Bias, 10th pctile　　(b) Neighborhood Instrument Bias, 90th pctile



Note: Panels (a) and (b) depict the bias in neighborhood instruments. For the 10th percentile, we select the radius that results in the 10th percentile among all radii examined. Depicted is the histogram of results for the 10th percentile. Similarly, the 90th percentile selects the radius with the 90th percentile of bias.

Figure B.4: Instrument Bias across All Neighborhood Instruments



Note: Depicted are the biases for the neighborhood instruments by radius. Also included are the disc instrument bias, which does not vary across radius.

C Additional Demand Estimates

Table C.1: Summary of Demand Estimates, Distance Endogenous (Neighborhood)

Income Quartile		Income Quartile 1	Income Quartile 2	Income Quartile 3	Income Quartile 4
Parameter					
Distance	β^{d1}	-0.450	-0.448	-0.445	-0.495
Density	β^{d2}	0.316	0.197	0.156	0.127
Fringe	ω	1.446	1.381	1.366	1.123
Control Function	ρ	0.211	0.220	0.201	0.218
Chain Preferences					
BJ's Wholesale Club		1.980	2.526	2.603	2.755
Costco		2.504	3.257	3.728	4.144
Sam's Club		0.709	1.343	2.819	2.358
Bloomingdale's		-1.482	0.902	0.614	2.319
Dillard's		-3.852	-0.363	-0.224	1.314
JC Penney		-0.172	0.753	0.927	0.855
Kohl's		-0.378	1.262	1.313	1.704
Macy's		0.322	1.344	1.486	2.103
Neiman Marcus		-2.290	-0.628	-0.007	1.341
Nordstrom		-0.838	0.151	0.411	2.042
Saks Fifth Avenue		-1.542	-0.476	-0.057	0.919
Sears		-3.955	-1.402	-1.134	-1.016
Burlington		3.354	3.214	3.157	3.258
Citi Trends		3.218	2.886	2.756	2.335
Five Below		1.288	1.330	1.461	1.667
Marshalls		2.795	2.817	3.034	3.318
Ross Dress for Less		3.621	3.546	3.604	3.865
T.J. Maxx		2.711	2.873	3.144	3.593
Big Lots		0.189	1.513	1.456	1.633
Target		3.237	3.846	4.172	4.680
Walmart		5.406	5.323	5.188	4.819
99c Only		1.332	2.752	1.752	1.747
Dollar General		2.461	2.314	1.906	1.091
Dollar Tree		3.783	3.822	3.576	3.702
Family Dollar		2.902	2.985	2.443	1.633
Random Coefficients	σ_k				
Warehouse Stores		2.254	1.761	1.670	2.011
Traditional Stores		3.039	2.286	2.264	2.196
Discount Stores		0.730	0.539	0.347	0.187
Supercenters		1.941	1.090	0.917	0.611
Dollar Stores		1.527	1.087	1.404	1.291
Summary					
Number of Visits		1,476,820	7,737,705	11,797,999	13,796,397
Number of Devices		130,157	605,128	886,500	1,132,056
Avg. First Stage Partial R^2		31.5%	27.2%	25.5%	25.7%
Avg. First Stage Partial F-stat		290.8	1094.3	1426.3	2078.4

Note: Demand estimation parameters, summary over all CBSAs. Each column represents an income quartile, with 1 being the lowest income group. This version of the model treats distance as exogenous.

Table C.2: Summary of Demand Estimates, Dist. & Fringe Endogenous (Disc)

Income Quartile		Income Quartile 1	Income Quartile 2	Income Quartile 3	Income Quartile 4
Parameter					
Distance	β^{d1}	-0.446	-0.467	-0.462	-0.535
Density	β^{d2}	0.252	0.182	0.151	0.075
Fringe	ω	1.409	1.460	1.466	0.899
Control Function	ρ_1	0.182	0.220	0.201	0.238
Control Function	ρ_2	-0.213	0.038	0.149	-0.198
Chain Preferences					
BJ's Wholesale Club		2.000	3.118	2.324	1.565
Costco		2.152	3.468	3.731	3.768
Sam's Club		0.562	1.592	2.770	1.963
Bloomingdale's		-1.035	0.428	0.439	1.814
Dillard's		-2.676	-0.334	-0.263	0.264
JC Penney		0.073	0.724	1.010	0.360
Kohl's		-0.147	1.347	1.446	1.210
Macy's		0.503	1.389	1.535	1.623
Neiman Marcus		-2.015	-0.615	-0.022	0.853
Nordstrom		-0.612	0.139	0.548	1.593
Saks Fifth Avenue		-1.506	-0.545	0.137	0.485
Sears		-3.761	-1.456	-1.135	-1.539
Burlington		3.085	3.385	3.236	2.713
Citi Trends		3.043	3.198	2.980	1.638
Five Below		0.919	1.301	1.172	1.017
Marshalls		2.554	2.971	3.094	2.755
Ross Dress for Less		3.485	3.813	3.841	3.572
T.J. Maxx		2.440	3.074	3.280	2.833
Big Lots		0.033	1.576	1.584	1.198
Target		3.091	3.966	4.303	4.280
Walmart		5.376	5.556	5.419	4.420
99c Only		2.213	3.147	1.965	1.752
Dollar General		2.450	2.685	2.082	0.759
Dollar Tree		3.775	4.166	3.837	3.389
Family Dollar		2.829	3.223	2.467	1.291
Random Coefficients	σ_k				
Warehouse Stores		2.437	1.765	1.858	2.124
Traditional Stores		2.926	2.302	2.333	2.351
Discount Stores		0.949	0.716	0.496	0.407
Supercenters		2.110	1.300	1.030	0.857
Dollar Stores		1.506	0.919	1.312	1.323
Summary					
Number of Visits		1,476,820	7,737,705	11,797,999	13,796,397
Number of Devices		130,157	605,128	886,500	1,132,056
Avg. First Stage Partial R^2		18.4%	13.1%	11.0%	12.2%
Avg. First Stage Partial F-stat		222.7	669.6	773.0	1344.2

Note: Demand estimation parameters, summary over all CBSAs. Each column represents an income quartile, with 1 being the lowest income group. This version of the model treats distance as exogenous.

C.1 CBSA-Specific Parameter Estimates

Table C.3: Atlanta-Sandy Springs-Alpharetta, GA Metro Area — Endo. Dist (Disc)

Income Quartile		Inc. 1	Inc. 1 SE	Inc. 2	Inc. 2 SE	Inc. 3	Inc. 3 SE	Inc 4.	Inc. 4 SE
Parameter									
Distance	β^{d1}	-0.532	(0.074)	-0.606	(0.057)	-0.623	(0.037)	-0.587	(0.031)
Density	β^{d2}	0.036	(0.075)	0.119	(0.034)	0.184	(0.027)	-0.075	(0.025)
Fringe	ω	1.092	(0.126)	1.045	(0.074)	1.225	(0.052)	1.075	(0.038)
Control Function	ρ	0.302	(0.060)	0.405	(0.045)	0.377	(0.027)	0.312	(0.020)
Chain Preferences									
BJ's Wholesale Club		1.231	(2.147)	1.832	(3.721)	0.888	(1.557)	0.560	(0.941)
Costco		1.586	(2.454)	2.470	(2.644)	1.920	(3.754)	2.974	(1.114)
Sam's Club		2.112	(5.352)	3.043	(4.211)	1.904	(3.845)	1.511	(2.678)
Bloomingdale's		-3.076	(5.573)	-0.483	(3.024)	-2.555	(2.728)	1.331	(2.289)
Dillard's		-3.908	(5.767)	0.306	(2.577)	-2.448	(3.335)	0.356	(1.525)
JC Penney		-2.718	(2.352)	0.158	(3.040)	-1.777	(2.084)	0.472	(1.247)
Kohl's		-3.329	(3.071)	0.398	(2.952)	-1.689	(3.002)	1.419	(1.632)
Macy's		-0.040	(2.737)	1.681	(2.375)	-2.012	(2.866)	2.004	(1.786)
Neiman Marcus		-4.418	(4.357)	0.290	(2.695)	-1.082	(2.484)	1.378	(2.961)
Nordstrom		-2.084	(4.183)	-0.706	(3.860)	-2.008	(3.600)	1.238	(2.054)
Saks Fifth Avenue		-1.110	(4.702)	2.112	(3.169)	-0.098	(3.319)	3.199	(4.374)
Sears		-7.756	(5.683)	-3.403	(4.098)	-7.365	(3.640)	-5.211	(2.778)
Burlington		0.029	(2.111)	2.976	(1.946)	2.085	(1.199)	2.516	(1.152)
Citi Trends		0.800	(2.409)	3.285	(1.578)	2.523	(1.899)	3.291	(0.565)
Five Below		-3.211	(2.085)	0.544	(2.208)	-0.375	(2.303)	0.563	(0.990)
Marshalls		-1.690	(4.311)	2.140	(3.390)	2.057	(2.402)	3.631	(1.447)
Ross Dress for Less		0.136	(6.285)	3.198	(3.956)	2.460	(2.624)	3.661	(1.154)
T.J. Maxx		-1.649	(5.157)	2.579	(3.798)	1.844	(3.253)	3.233	(2.407)
Big Lots		-5.014	(2.680)	0.264	(0.852)	0.934	(0.530)	2.075	(0.349)
Target		-1.260	(5.982)	2.364	(3.991)	3.115	(3.085)	4.273	(2.424)
Walmart		4.524	(5.578)	5.076	(3.899)	4.979	(3.088)	4.589	(1.336)
99c Only		–	–	–	–	–	–	–	–
Dollar General		2.703	(2.946)	2.902	(2.682)	2.914	(2.414)	2.006	(0.740)
Dollar Tree		3.369	(2.405)	3.699	(2.334)	3.818	(2.180)	3.731	(0.841)
Family Dollar		2.671	(2.227)	2.884	(2.555)	2.892	(2.205)	2.216	(1.175)
Random Coefficients	σ_k								
Warehouse Stores		3.902	(1.330)	2.418	(1.309)	4.109	(1.269)	2.238	(0.638)
Traditional Stores		4.432	(1.042)	1.984	(0.420)	1.988	(0.365)	0.000	(0.474)
Discount Stores		0.000	(0.324)	0.000	(0.139)	0.409	(0.195)	0.000	(0.346)
Supercenters		3.154	(1.057)	0.912	(1.016)	1.804	(0.721)	0.000	(0.121)
Dollar Stores		2.335	(1.089)	1.905	(0.836)	2.794	(0.381)	2.734	(0.254)
Summary									
Log Likelihood		-183084.4		-1442782.1		-2829354.4		-2369548.1	
Number of Visits		93,187		710,037		1,356,299		1,081,661	
Number of Devices		9,257		58,953		101,608		88,523	
First Stage Partial R^2		15.5%		10.4%		9.2%		16.0%	
First Stage Partial F-stat		251.4		949.4		1435.9		2509.3	

Note: Demand estimates using simulated maximum likelihood with 100 Halton draws per random coefficient. Standard errors computed using block bootstrap.

Table C.4: Tampa-St. Petersburg-Clearwater, FL Metro Area — Endo. Dist (Disc)

Income Quartile		Inc. 1	Inc. 1 SE	Inc. 2	Inc. 2 SE	Inc. 3	Inc. 3 SE	Inc 4.	Inc. 4 SE
Parameter									
Distance	β^{d1}	-0.142	(0.043)	-0.235	(0.021)	-0.241	(0.018)	-0.431	(0.031)
Density	β^{d2}	0.866	(0.090)	0.763	(0.053)	0.825	(0.036)	0.710	(0.050)
Fringe	ω	0.601	(0.128)	1.106	(0.072)	1.375	(0.059)	2.146	(0.105)
Control Function	ρ	-0.099	(0.044)	-0.048	(0.022)	-0.052	(0.016)	0.136	(0.021)
Chain Preferences									
BJ's Wholesale Club		0.185	(2.773)	1.719	(0.434)	2.423	(0.540)	5.335	(0.810)
Costco		0.285	(2.938)	2.259	(1.782)	3.035	(1.645)	6.579	(2.073)
Sam's Club		1.193	(3.100)	2.708	(2.610)	3.315	(2.518)	5.890	(3.072)
Bloomingdale's		–	–	–	–	–	–	–	–
Dillard's		-4.346	(3.506)	-3.959	(1.968)	-3.625	(2.036)	0.344	(1.523)
JC Penney		-2.684	(2.388)	-3.043	(2.443)	-3.223	(2.151)	-1.785	(2.059)
Kohl's		-3.343	(3.428)	-1.616	(1.831)	-1.237	(1.671)	1.375	(1.448)
Macy's		-2.447	(3.718)	-2.104	(2.114)	-1.894	(2.189)	1.041	(2.211)
Neiman Marcus		-5.137	(4.576)	-5.754	(3.334)	-6.012	(3.528)	-1.443	(3.320)
Nordstrom		-3.638	(3.229)	-4.884	(2.959)	-4.910	(3.201)	-0.009	(2.500)
Saks Fifth Avenue		–	–	–	–	–	–	–	–
Sears		-6.423	(4.778)	-5.837	(3.304)	-6.349	(3.580)	-3.187	(3.398)
Burlington		0.014	(3.886)	1.476	(1.182)	2.066	(1.656)	4.737	(1.492)
Citi Trends		-0.325	(3.895)	0.492	(0.988)	0.299	(1.535)	2.982	(1.736)
Five Below		-3.166	(2.317)	-2.053	(2.075)	-1.200	(1.756)	0.949	(1.441)
Marshalls		-0.170	(3.258)	1.215	(2.608)	1.936	(2.654)	4.547	(2.152)
Ross Dress for Less		0.091	(4.456)	1.468	(2.000)	2.232	(2.268)	5.018	(2.572)
T.J. Maxx		-0.516	(3.617)	0.865	(2.270)	1.631	(2.746)	4.938	(2.372)
Big Lots		-2.973	(1.736)	-2.322	(0.620)	-0.815	(0.438)	3.154	(0.478)
Target		-0.554	(2.699)	0.206	(2.581)	1.986	(2.739)	5.302	(2.385)
Walmart		2.558	(2.893)	3.680	(2.446)	4.108	(3.097)	5.948	(2.626)
99c Only		–	–	–	–	–	–	–	–
Dollar General		1.203	(0.602)	-0.425	(1.346)	-0.033	(1.711)	-0.946	(1.931)
Dollar Tree		1.625	(2.404)	1.374	(1.401)	2.056	(1.563)	3.200	(1.460)
Family Dollar		1.184	(1.722)	-0.676	(1.561)	-0.153	(1.528)	-0.597	(1.216)
Random Coefficients	σ_k								
Warehouse Stores		2.560	(1.674)	3.260	(1.305)	3.543	(0.853)	3.761	(0.652)
Traditional Stores		2.375	(0.958)	2.768	(0.342)	2.208	(0.238)	1.750	(0.692)
Discount Stores		0.000	(0.792)	2.823	(0.373)	2.613	(0.275)	3.899	(0.475)
Supercenters		0.000	(0.582)	0.247	(0.328)	0.175	(0.266)	0.000	(0.312)
Dollar Stores		0.379	(0.679)	0.000	(0.495)	0.000	(0.523)	0.000	(0.726)
Summary									
Log Likelihood		-138062.6		-969245.5		-1416054.9		-949616.4	
Number of Visits		67,770		456,269		642,900		403,343	
Number of Devices		5,978		33,858		43,222		29,075	
First Stage Partial R^2		10.7%		8.7%		7.6%		13.3%	
First Stage Partial F-stat		119.4		547.0		625.2		850.9	

Note: Demand estimates using simulated maximum likelihood with 100 Halton draws per random coefficient. Standard errors computed using block bootstrap.

D Travel Time in place of Travel Distance

Table D.1: Summary of Demand Estimates, Time Endogenous (Disc)

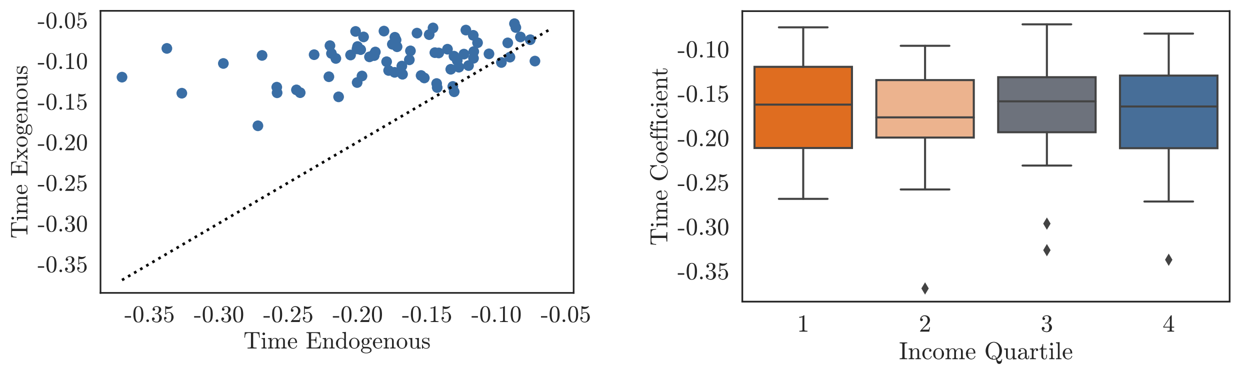
Income Quartile		Inc. 1	Inc. 1 SE	Inc. 2	Inc. 2 SE	Inc. 3	Inc. 3 SE	Inc 4.	Inc. 4 SE
Parameter									
Distance	β^{d1}	-0.165	(0.009)	-0.179	(0.005)	-0.170	(0.004)	-0.173	(0.004)
Density	β^{d2}	0.353	(0.090)	0.234	(0.020)	0.195	(0.015)	0.109	(0.016)
Fringe	ω	1.428	(0.708)	1.240	(0.050)	1.155	(0.024)	0.925	(0.018)
Control Function	ρ	0.070	(0.007)	0.089	(0.004)	0.080	(0.003)	0.077	(0.002)
Chain Preferences									
BJ's Wholesale Club		2.542	(1.331)	3.070	(0.543)	2.745	(0.566)	3.040	(0.438)
Costco		3.158	(0.823)	3.667	(0.307)	3.924	(0.462)	4.199	(0.395)
Sam's Club		1.337	(1.340)	1.064	(1.014)	3.017	(0.714)	2.480	(0.736)
Bloomingdale's		0.025	(1.329)	1.250	(0.766)	0.462	(0.700)	2.473	(0.546)
Dillard's		-1.615	(1.645)	0.369	(0.662)	-0.181	(0.859)	1.463	(0.517)
JC Penney		1.245	(0.729)	1.805	(0.502)	1.195	(0.457)	1.145	(0.436)
Kohl's		1.076	(0.712)	2.229	(0.382)	1.747	(0.512)	2.226	(0.334)
Macy's		1.483	(0.873)	2.136	(0.507)	1.719	(0.499)	2.459	(0.383)
Neiman Marcus		-0.995	(1.222)	0.242	(0.677)	-0.102	(0.708)	1.462	(0.490)
Nordstrom		0.370	(0.940)	1.071	(0.679)	0.652	(0.668)	2.279	(0.449)
Saks Fifth Avenue		-0.632	(1.187)	0.523	(0.723)	0.316	(0.719)	1.372	(0.637)
Sears		-3.047	(1.185)	-0.518	(0.620)	-0.937	(0.731)	-0.573	(0.537)
Burlington		3.724	(0.802)	3.435	(0.407)	3.229	(0.317)	2.682	(0.312)
Citi Trends		3.728	(1.481)	3.273	(0.415)	2.971	(0.813)	1.421	(0.582)
Five Below		1.696	(0.862)	1.523	(0.403)	1.495	(0.422)	1.166	(0.401)
Marshalls		3.225	(0.748)	3.001	(0.436)	3.010	(0.586)	2.651	(0.334)
Ross Dress for Less		4.130	(0.930)	3.754	(0.696)	3.797	(0.756)	3.768	(0.410)
T.J. Maxx		3.136	(0.929)	3.069	(0.642)	3.317	(0.646)	2.830	(0.516)
Big Lots		-0.015	(0.778)	1.109	(0.416)	0.921	(0.295)	1.121	(0.298)
Target		3.254	(0.882)	3.826	(0.610)	4.022	(0.713)	4.649	(0.451)
Walmart		5.740	(1.085)	5.663	(0.601)	5.284	(0.590)	4.778	(0.471)
99c Only		1.835	(0.969)	2.821	(0.563)	0.894	(0.501)	0.859	(0.347)
Dollar General		2.383	(0.873)	2.492	(0.428)	2.045	(0.505)	1.085	(0.450)
Dollar Tree		3.952	(0.734)	4.086	(0.349)	3.746	(0.442)	3.780	(0.336)
Family Dollar		3.138	(0.775)	3.312	(0.379)	2.599	(0.455)	1.557	(0.405)
Random Coefficients	σ_k								
Warehouse Stores		1.858	(0.297)	1.735	(0.198)	1.557	(0.179)	1.825	(0.152)
Traditional Stores		2.335	(0.331)	1.797	(0.221)	2.067	(0.191)	1.816	(0.186)
Discount Stores		0.663	(0.267)	0.772	(0.161)	0.487	(0.148)	0.708	(0.150)
Supercenters		2.168	(0.287)	1.709	(0.147)	1.520	(0.115)	1.096	(0.137)
Dollar Stores		1.927	(0.230)	1.277	(0.144)	1.409	(0.127)	1.355	(0.127)
Summary									
Number of Visits		1,476,820		7,737,705		11,797,999		13,796,397	
Number of Devices		130,157		605,128		886,500		1,132,056	
Avg. First Stage Partial R^2		15.6%		11.9%		10.2%		10.5%	
Avg. First Stage Partial F-stat		186.3		677.1		837.7		1266.9	

Table D.2: Summary of Demand Estimates, Time Exogenous

Income Quartile		Inc. 1	Inc. 1 SE	Inc. 2	Inc. 2 SE	Inc. 3	Inc. 3 SE	Inc 4.	Inc. 4 SE
Parameter									
Distance	β^{d1}	-0.101	(0.007)	-0.099	(0.003)	-0.095	(0.002)	-0.101	(0.002)
Density	β^{d2}	0.351	(0.072)	0.252	(0.021)	0.191	(0.015)	0.133	(0.015)
Fringe	ω	1.395	(0.778)	1.240	(0.065)	1.152	(0.024)	0.895	(0.017)
Chain Preferences									
BJ's Wholesale Club		1.825	(1.592)	2.018	(0.513)	1.750	(0.535)	1.886	(0.411)
Costco		2.283	(0.943)	2.422	(0.313)	2.908	(0.447)	3.186	(0.410)
Sam's Club		0.478	(1.479)	0.263	(0.950)	2.023	(0.680)	1.452	(0.909)
Bloomingdale's		-0.996	(1.471)	-0.126	(0.792)	-0.517	(0.644)	1.548	(0.549)
Dillard's		-2.798	(1.777)	-1.165	(0.699)	-0.562	(0.792)	0.627	(0.542)
JC Penney		0.432	(0.806)	0.437	(0.572)	0.330	(0.434)	0.268	(0.438)
Kohl's		0.314	(0.836)	1.023	(0.377)	0.952	(0.486)	1.421	(0.336)
Macy's		0.614	(0.968)	0.729	(0.516)	0.800	(0.492)	1.516	(0.359)
Neiman Marcus		-1.924	(1.374)	-1.153	(0.687)	-0.927	(0.669)	0.536	(0.478)
Nordstrom		-0.470	(1.036)	-0.395	(0.699)	-0.235	(0.643)	1.360	(0.444)
Saks Fifth Avenue		-1.442	(1.250)	-0.935	(0.725)	-0.862	(0.703)	0.472	(0.647)
Sears		-3.286	(1.311)	-1.876	(0.630)	-1.789	(0.708)	-1.567	(0.564)
Burlington		2.685	(0.898)	2.160	(0.408)	2.080	(0.309)	1.449	(0.324)
Citi Trends		2.792	(1.760)	2.057	(0.428)	1.730	(0.914)	0.011	(0.635)
Five Below		0.543	(1.020)	0.161	(0.421)	0.425	(0.404)	-0.001	(0.386)
Marshalls		2.199	(0.843)	1.753	(0.445)	1.875	(0.551)	1.518	(0.315)
Ross Dress for Less		3.099	(1.080)	2.551	(0.674)	2.656	(0.706)	2.567	(0.434)
T.J. Maxx		2.056	(0.980)	1.826	(0.662)	2.170	(0.616)	1.692	(0.523)
Big Lots		-1.124	(0.867)	-0.440	(0.428)	-0.270	(0.312)	-0.298	(0.314)
Target		2.242	(0.960)	2.510	(0.627)	2.990	(0.688)	3.565	(0.462)
Walmart		4.840	(1.079)	4.581	(0.593)	4.322	(0.562)	3.660	(0.477)
99c Only		0.683	(1.047)	1.738	(0.572)	-0.073	(0.501)	0.209	(0.343)
Dollar General		1.502	(0.991)	1.233	(0.439)	0.574	(0.505)	-0.360	(0.504)
Dollar Tree		3.069	(0.818)	3.010	(0.362)	2.642	(0.421)	2.649	(0.362)
Family Dollar		2.317	(0.878)	2.112	(0.384)	1.408	(0.427)	0.001	(0.422)
Random Coefficients	σ_k								
Warehouse Stores		1.642	(0.302)	1.725	(0.199)	1.359	(0.177)	1.628	(0.152)
Traditional Stores		2.041	(0.351)	1.847	(0.230)	1.821	(0.187)	1.409	(0.195)
Discount Stores		0.641	(0.265)	0.785	(0.147)	0.453	(0.140)	0.632	(0.147)
Supercenters		2.181	(0.291)	1.902	(0.147)	1.561	(0.118)	1.260	(0.129)
Dollar Stores		1.974	(0.239)	1.479	(0.138)	1.640	(0.119)	1.495	(0.136)
Summary									
Number of Visits		1,476,820		7,737,705		11,797,999		13,796,397	
Number of Devices		130,157		605,128		886,500		1,132,056	

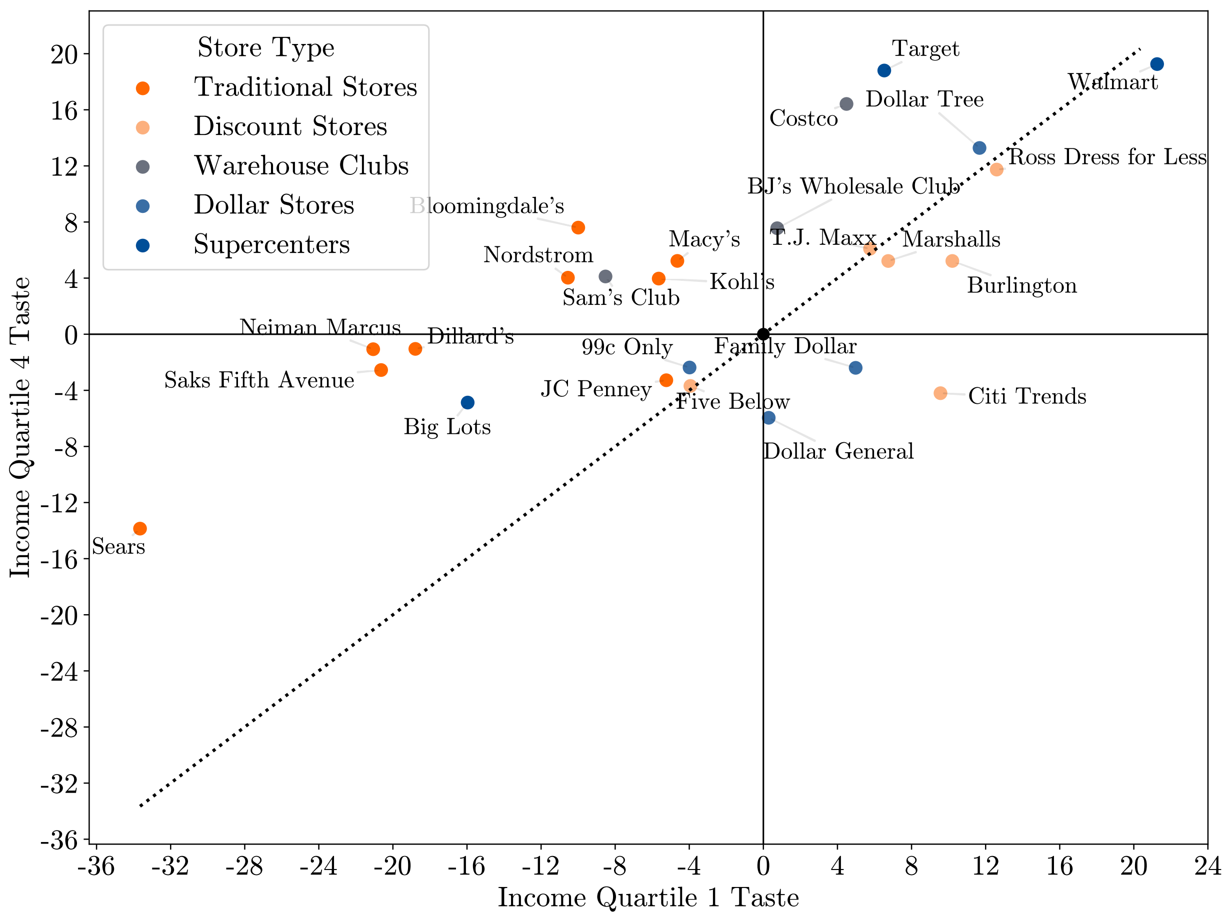
Figure D.1: Time Coefficients

(a) Time as Endogenous vs. Exogenous (b) Time Across CBSA and Inc. Quartile



Note: These figures report the same information as Figure 7, except the endogenous variable is measured as travel times (in minutes) between Census block groups instead of distance (in miles).

Figure D.2: Distance Normalized Chain Taste Parameters with Time



Note: This figure reports the same information as Figure 8, except the endogenous variable is measured as travel times (in minutes) between Census block groups instead of distance (in miles).