Distributional Effects of Exclusive Dealing in Retail Real Estate

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Abstract

I study the welfare implications of exclusive dealing in U.S. retail. Using a novel dataset, I document widespread use of contracts that restrict local entry by rival stores. Stores with exclusives face fewer competitors and higher prices, suggesting anticompetitive effects, yet many grocers in under-served neighborhoods use them, implying potential entry benefits in low-demand markets. I estimate a structural model of household store choice and a landlord–retailer entry game to capture equilibrium pricing and entry. Exclusive dealing benefits landlords and large retailers. A ban raises welfare for some households but increases the number of households living in food deserts.

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1 Introduction

Restrictive covenants are exclusive dealing contracts in retail real estate that forbid specific retailers from operating on designated premises. For example, a Safeway in Chicago forbids its landlord from leasing nearby space to competing grocers, drug stores, liquor stores, and convenience stores. These private agreements, commonly embedded in commercial leases and deeds, are intended to protect the business interests of one or both parties. Since they mechanically limit competition, there is a long-standing concern that these contracts foreclose on competitor entry. For these reasons, Canada and several U.S. cities have attempted to limit this form of exclusive dealing.[1]

The economic impact of exclusive dealing contracts on market outcomes and welfare is theoretically ambiguous. While exclusive dealing can limit competition by restricting entry of new competitors (Aghion and Bolton, 1987; Bernheim and Whinston, 1998), it can also stimulate entry of stores into under-served neighborhoods and improve the quality of the consumer shopping experience (Klein and Murphy, 1988). Exclusive dealing in real estate may also be used to solve market failures resulting from shopping externalities (Brueckner, 1993) and landlord's imperfect information of retailer profitability (Katz, 1989).

This paper evaluates the welfare effects of exclusive dealing in Chicago. To do so, I manually build two novel datasets. First, I collect the complete set of retail real estate contracts, which determines where and when exclusive dealing has been implemented. Second, I build a novel database tracking "potential" retail locations, including already developed and planned locations. I combine these two new databases with Numerator data tracking households' retail store choices and shopping behavior.

Using these data, I document several novel patterns in the exclusive dealing retail space in Chicago. First, I show widespread and growing use of exclusive dealing in grocery and discount retail. Second, lease contracts with exclusives have 20% higher prices (rents) than lease contracts without exclusives, even after controlling for retail chain and surrounding demographics, consistent with landlord's need to be compensated for not renting to higher-profit tenants (Bork, 1978). Finally, within a shopping center radius, stores with exclusive dealing contracts tend to face fewer local competitors, even after controlling for chain, consistent with foreclosure.

The descriptive analysis above shows evidence that exclusive dealing is widespread and likely limits competition. While the descriptive analysis predicts further entry following a ban on exclusive dealing, it cannot account for equilibrium supply responses – price and entry decisions – from

[1] Both Chicago and Washington DC have limited exclusive dealing, and the Canada Competition Bureau is investigating potentially anticompetitive effects. In Chicago, the city limited stores that are greater than 7500 square feet from enforcing the exclusive dealing contract after the store exits. In DC, all exclusive dealing contracts are banned for grocery and all food retail stores.

retailers with these contracts. To assess the complete welfare implications, I conduct a structural analysis of the Chicago retail market. On the demand side, I model household store choice allowing for price sensitivity, distance sensitivity, and potential complementarities across retailers (Gentzkow, 2007) which generate shopping externalities across nearby retailers. On the supply side, I model the game between landlords and retailers allowing for location choices and rental prices to depend on expected profits, fixed cost of entry, and imperfect information on retailers' profitability. In a first stage, landlords post real estate prices and an incremental premium for exclusivity based on the expected profitability of retailers. In the second stage, competing retailers simultaneously select locations and contracts based on incomplete information about other retailer's entry probabilities. Once the retail entry game is realized, retailers set prices and households shop.

I estimate demand parameters with consumer panel data from Numerator, which includes detailed information on household purchases, shopping trips, and retailer locations. I construct a household shopping trip as the set of retailers shopped at within the same day, the price paid for the total bundle, and the total distance traveled. Price parameters are identified using an instrumental variable approach exploiting the fact that retailers' marginal costs are likely correlated across markets, but demand shocks for such retailers are likely not (Hausman et al., 1994). Distance parameters are identified from plausibly exogenous variation in the timing of retailer entry and exit, which provides exogenous variation in the household distances to retailer around the event. Retailer complementarities are identified from household's increased propensity to shop a certain retailers together, all else equal. On the supply side, I identify retailer marginal costs as the parameters that justify the observed shares and prices, assuming retailer maximize profits in Bertrand competition.

I find several empirical results. First, I find strong distaste for prices and distances. For small increases in price, households are only willing to travel marginally farther, implying that exclusive dealing can be effective even when implemented locally. Second, I find that large retailers have relatively higher qualities and heterogeneous retailer complementarities. Given these estimated complementarities, relatively low-quality retailers profit from locating next to higher-quality retailers. These benefits from co-location generate shopping externalities.

To externally validate my demand model, I compare the estimated complementarities with the information on blocking patterns provided in the exclusive dealing contracts. I find a strong correlation between the value of excluding rival retailers and the prevalence of exclusive dealing, providing external validation of both the estimated parameters and document contracts.

I estimate retail real estate parameters with retailer location choice panel data, which I construct from data on retailer potential locations, entry, prices (rents), exclusive dealing contracts, and expected retailer profitability (from the product market estimates). Fixed costs are identified from entry probabilities using variation in retailer choice sets and expected profitability at each location.

While the potential locations themselves may be endogenous and correlated with demand factors, the timing of when a location becomes a available depends on factors that create exogenous variation in the timing (such as delays or uncertainty due to permitting and development). I include a parameter to capture landlords' imperfect information of retailer profits, which is identified by additional observed use of exclusive dealing contracts past what is predicted by retailer complementarities. On the landlord side, marginal costs and unobserved prices (prices charged to non-entering retailers and prices of the non-chosen contract) are the parameters that justify observed prices, entry probabilities, and contracts, assuming retailer maximize profit in Bertrand competition.

I find low profit margins and large fixed costs of entry, particularly for large retailers. These estimates suggest that inducing entry is an important part of exclusive dealing contracts, indicating that exclusive dealing predominantly solves shopping externalities generated by large retailers.

I validate results of the real estate estimation with untargeted moments using detailed data from the exclusive contracts. Specifically, I show that model-implied high probability of entry with exclusive dealing is correlated with exclusive dealing contracts that block competitor entry, but is uncorrelated with exclusive dealing contracts that prohibit other types of use (e.g. contracts that prohibit the use of the space as a garbage dump or toxic waste facility).

Armed with estimated parameters, I move onto counterfactual simulations to isolate the effect of exclusive dealing. The first counterfactual compares the current world (with exclusive dealing) to a counterfactual world without explicit exclusive dealing. The landlord cannot commit to an explicit exclusive dealing contract and instead offers a single price to each large retailer. I then simulate the long-run effects of exclusive dealing by simulating retailer entry between 2001 and 2022. I find that in the long run an exclusive dealing ban would lead lower entry rates and lead to an increase in food deserts in Chicago.[2] A back of the envelope calculation suggests that a total ban on exclusive dealing would increase the percentage of people living in food deserts by 6.6% percentage points over the sample. However, the effects of exclusive dealing on consumers vary by consumer income and by neighborhood. When demand is high enough, a ban on exclusive dealing improves consumer welfare. In high-demand locations, smaller retailers such as dollar stores enter without preventing large retailer entry, and consumers benefit from lower prices and shorter distances.

The counterfactual suggests that exclusive dealing solves a hold-out problem wherein high-quality retailers do not enter unless lower-quality retailers are banned from entering nearby. Exclusive dealing and thus induce high-quality retailer entry and co-location of complementary store. These estimates suggest that the first order effect of exclusive dealing are higher prices for consumers but easier access to higher-quality and complementary retailers.

The counterfactual results are also heterogeneous in the upstream commercial real estate market.

[2]Food deserts are defined as zip codes without grocery stores (Allcott et al., 2019).

Under the counterfactual ban, profits decrease the most for the very largest retailers (big box retailers), decrease modestly for large retailers (grocery retailers), and increase for small retailers (dollar stores). I find that in high-demand neighborhoods, landlords and large retailers are able to extract additional surplus from an exclusive dealing, contract preventing small efficient entrants (Aghion and Bolton, 1987).

I test the externality validity of the model by studying a policy change in exclusive dealing in Washington DC.[3] In 2014, policymakers temporarily banned exclusive dealing in the grocery sector in Washington DC. Leveraging this policy change, I test the predictions of the model: benefits for high-income neighborhoods and harm for low-income neighborhoods. I study how the number of grocery retailers has changed across these two neighborhood types before and after the ban by employing a two-way fixed effect regression. I find that after the ban, lower-income neighborhoods have fewer grocery stores relative to higher-income neighborhoods, consistent with the results of the estimation and counterfactual.

Second, I simulate a counterfactual changing long-run trends in retail. Throughout the aughts and 2010s, technology shocks drove retailers like Blockbuster, Sears, and Borders Bookstore out of business (Cao et al., 2024). I simulate a counterfactual where demand for these brick-and-mortar businesses stays high and study the prevalence of exclusive dealing. I find less exclusive dealing and higher prices (rents) in this counterfactual, as the potential locations shrink and competition for real estate increases.

Related literature This is the first economics paper on these exclusive dealing contracts, with prior legal scholarship on their existence (Sturtevant, 1959; Lundberg, 1973), whether they encumber development (Stubblefield, 2019), and whether contracts signed at exit are anticompetitive (Ziff and Jiang, 2012; Leslie, 2021; Kang, 2022). The data collection and descriptive evidence parallel recent efforts to document government-imposed constraints such as zoning and residential restrictive covenants (see for example (Hughes and Turnbull, 1996; Plotkin, 2001; Glaeser and Gyourko, 2022; Trounstine, 2018). I also contribute demand-side estimates of retailer complementarities to understand the value of co-locating stores to consumers, particularly within the shopping center, adding to literatures on consumers preferences for specific retailers (Ellickson et al., 2020; Cao et al., 2024), trip-chaining and local spillovers (for demand side trip-chaining and multi-homing see (Thomassen et al., 2017; Rhodes and Zhou, 2019; Miyauchi et al., 2022; Relihan, 2022; Oh and Seo, 2023), for supply-side local spillovers see (Qian et al., 2023; Knight, 2023; Baum-Snow et al., 2024), and shopping center externalities (Benjamin et al., 1992; Brueckner, 1993),(Gatzlaff et al., 1994), (Pashigian and Gould, 1998; Konishi and Sandfort, 2003; Gould et al., 2005; Shoag and Veuger, 2018; Burayidi and Yoo, 2021; Evensen et al., 2024; Liu et al., 2024). Leveraging detailed

[3]To our knowledge, this is the only policy affecting this type of exclusive dealing in this time frame.

exclusive dealing contracts, I study how exclusive dealing changes the distribution of retailers, finding that exclusive dealing reduces food deserts. I contribute to the literature concerned with the supply-side provision of food across different neighborhoods (Bitler and Haider, 2011; Allcott et al., 2019; Handbury, 2021), grocery industry market structure (Ellickson, 2006, 2007; Jarmin et al., 2009), and how chain retailers choose locations (Jia, 2008; Holmes, 2011; Vitorino, 2012; Nishida, 2015; Vitali, 2022; Caoui et al., 2022; Beresteanu et al., 2024). This setting shows that exclusive dealing contracts should be considered alongside traditional factors like demand, agglomeration and scale, and government constraints in studying retailer location choice and consumer shopping behavior.[4]

This setting provides new opportunity to study exclusive dealing empirically. Due to difficulties obtaining detailed data from private exclusive dealing contracts, previous work either has devised empirical tests to detect foreclosure (Asker, 2016), assessed descriptively whether observed outcomes were consistent with efficiency enhancement or foreclosure (Sass, 2005; Ater, 2015; Chen and Shieh, 2016), and estimated structural models to compute whether exclusivity is profitable and firm's willingness to pay for it (Chipty, 2001; Sinkinson, 2020; Lee, 2013; Chen, 2014; Nurski and Verboven, 2016; Le, 2024; Yuan, 2025) (see (Lafontaine and Slade, 2007) for a summary of the literature). Typically, exclusivity is are narrowly defined and limited to a single industry (e.g. hamburgers, beers, and cable television). By contrast, the contracts studied here are complex, wide-ranging, and granular: they are employed by a wide range of retailers, limit products and retailers broadly, and vary across locations. Instead of presuming set of competing retailers and market geography, I leverage these details of the contracts to determine competitors and geographic markets. I then estimate the effect of exclusive dealing on welfare and profitability in the (upstream) commercial real estate market and (downstream) product market.

The welfare effect of exclusive dealing is theoretically ambiguous, as exclusive dealing contracts can be efficiency enhancing, correct for market failures, but also foreclose upon competitor entry.[5] Novel to this setting, shopping externalities created by consumer trip chaining are the main cause for the observed explicit exclusive dealing contracts. I also test for information asymmetry between

[4]For a long literature on grocery demand, see for example (Bell et al., 1998; Smith, 2004, 2005; Mehta, 2007; Song and Chintagunta, 2007; Hartmann and Nair, 2009; Smith and Øyvind Thomassen, 2012; Mehta and Ma, 2012a), (Mehta and Ma, 2012b), (Ellickson and Misra, 2012), (Leung and Li, 2021).

[5]The theoretical literature dates back to (Posner, 1976) and (Bork, 1978) who show that absent externalities, exclusive dealing is efficient. Following literature showed how exclusive dealing can be anticompetitive due to market failures or externalities, or procompetitive in some settings but anticompetitive in others (Katz, 1989; Hart and Tirole, 1990; Rasmusen et al., 1991; Besanko and Perry, 1993; Segal and Whinston, 2000; Fumagalli and Motta, 2006; Simpson and Wickelgren, 2007; Asker and Bar-Isaac, 2014). Exclusive dealing is considered pro-competitive when (a) it increases efficiency, for example by reducing double marginalization, (b) ensuring monopoly profits encourages investment and thus a higher-quality product and (c) ensuring monopoly profits allows for retailer entry in the first place. Exclusive dealing is considered anti-competitive when it partially or totally forecloses on another firm's entry, due to an externality.

landlords and retail tenants (Katz, 1989; Calzolari and Denicolò, 2013), finding a limited role for this hypothesized market failure. I find that these exclusive dealing contracts are largely procompetitive because the exclusive dealing contracts facilitate large retailer entry which improves the overall quality of the shopping mall (Marvel, 1982; Klein and Murphy, 1988), but depends on consumer demand. In high-demand neighborhoods where I find evidence of foreclosure, landlords and large retailers benefit from excluding small retailers like dollar stores which would have otherwise entered (Aghion and Bolton, 1987; Abito and Wright, 2006).

2 Data

I collect data to build and estimate a model of retailer location choice, which depends on where retailers can enter and the profitability at each potential location. I collect data on the potential locations each retailer can enter, retailer entry and exit at each location, and details of real estate contracts, specifically the rental prices and any exclusive dealing restrictions. To estimate this potential profitability at each potential location, as well as estimate consumer welfare, I estimate demand using data from a panel of consumer purchases. The paper focuses on Chicago to benefit from Chicago's large variety in neighborhood income, neighborhood density, and retail environments.

Potential Locations: I establish the set of potential locations a retailer can enter and define each retailers' potential locations by their latitude and longitude. To do so, I use novel data from Huxebo (formerly named Build Central and Planned Grocery), a startup which collects and sells planned retail locations to retailers so that retailers know where they and their competitors can enter. I observe the latitude, longitude, and square footage for new and existing builds. The observed square footage determines which retailers can feasibly enter and thus the set of potential locations is unique to each retailer. Importantly, I observe details of the timeline from initial proposal to completion: I observe the date the potential location becomes available, the date a retailer commits to entering the location, and the date the retailer enters the location, as well as locations which are never chosen. The time span is 2015-2024. I supplement these data with data from Historical Supplemental Nutrition Assistance Program (SNAP) Retailer Locator Data and InfoGroup Historical Datafile (Infogroup) to establish a longer time horizon (1990-present) and treat the set of potential locations that are eventually entered into as the consideration set.

Retailer locations, entry and exit: Store locations, entry, and exit dates are compiled from the SNAP Database and from Infogroup's Historical Database. The Infogroup historical data is similar to yellow pages: it provides a yearly directory U.S. companies, addresses, store name, and NAICS/SIC codes. The SNAP Retailer Location Data data spans 1990-2023 and records the date, location, and store name when each store enters and exits the SNAP database.

Lease Characteristics: Lease characteristics are obtained from CompStak. CompStak gathers its data from a network of brokers who report lease characteristics for the properties they rent to in exchange for characteristics of the leases for nearby properties, so that they can infer market prices and lease characteristics. I observe variables such as location, rent, square footage, lease length, and tenant industry. For market prices, I use net effective rent, the total amount of rent owed from the tenant to the landlord per year per square foot, deflated in 2016 U.S. Dollars. For lease characteristics, I use lease length, square footage, location (latitude and longitude), tenant industry, and lease type to focus on retail leases. I report moments from the raw data in Table 34 and Figure 15. Since the data comes from a network of brokers, the data may be selected. To ensure that the data is representative, I compare the time series of the net effective rent to other sources. Specifically, I compare this data series to mean asking rents from CBRE, a global real estate services company and with median asking rents from CoStar from Brooks and Meltzer (2024) by replicating Appendix Figure 1 from Brooks and Meltzer (2024) with our data. Figure 14 shows a comparison of these three time series and shows similar trends and orders of magnitudes, despite using different definitions of rent.

Exclusive dealing: Landlords and tenants record exclusive dealing contracts at the county recorder office in order to create a permanent record of transactions and restrictions. This official documentation ensures that future landlords and prospective tenants abide by the terms of the contract. Retailers and landlords are incentivized to report exclusive dealing contracts because third parties unaware of these restrictions are not bound by them.[6]

Exclusive dealing contracts are scraped from the Cook County Clerk's Office Record of Deeds Search, which records, stores and maintains land records and other official documents. The website and documents are publicly searchable. From this website, I scraped every deed, lease memorandum, lease, memorandum, termination, correction, incorporation, and reinstatement. I obtained a pdf of the document as well as the relevant parties (called grantor and grantee), which are the landlord and tenant in a lease and the buyer and seller in a deed, as well as the address, date, and parcel pin number. I extract the contents of the contracts (pdfs) with Optical Character Recognition, which gives us the text of the pdf documents. This gives us the universe of relevant official documents in Cook County, IL from 1980-present. From this data I create two datasets.

From the type of document (e.g. lease or deed) as well as the party name (e.g. landlord or tenant, buyer or seller), I establish whether a retailer owns or rents a property. Retailers that own properties have an implicit exclusive dealing contracts on the properties, because they can choose who to rent to and who to sell to. Retailers on rented properties may or may not have an exclusive dealing contract on the property.

I create the dataset of exclusive dealing contracts by identifying sections of the recorded docu-

[6]See, for example, a discussion by Baker McKenzie's digital library of legal content.

ments that include restrictions and extracting the relevant text. First, I read around 150 contracts manually and determine that (1) the contracts are standard and that (2) restrictions on use always include some combination of words "prohibited use", "restrictive covenant", "restriction", "exclusive use", "restrictions benefit" in the text, and (3) that there is often a designated section of the text dedicated to exclusive use or restrictions on the use of the property. Next, I confirmed with real estate professionals that these contracts tend to be standard and the method for identifying restrictions. I then extract the exclusive dealing contracts from the digitized document pdfs by (1) extracting the text that proceeds and follows the phrases "prohibited use", "restrictive covenant", "restriction", "exclusive use", and "restrictions benefit" (2) removing listed exceptions, which are specific retailers not subject to the restrictions (3) categorizing restrictions into types of retailers (such as grocery, drug, etc...). From this data, I learn the retailers and industries that use exclusive dealing, which properties have exclusive dealing restrictions, and the set of exclusive dealing restrictions and each property over time.

Panel on consumer purchases: I use a detailed household-level panel from Numerator with household trips and store purchases to pin down consumer preferences. The panel spans 2017-2019 and covers a broad range of consumer purchases from a broad range of stores, including grocery, discount, dollar, convenience, and other stores. Numerator reports retailer characteristics (e.g. store identity, store latitude, store longitude, retailer name, store identifier), consumer characteristics (e.g. household zip code and demographics), and consumer purchase information (e.g. purchase amount, product quantity, product descriptions, brand description, day and time of purchase).

With this data, I compute trips (the set of retailers shopped at in a day), distance traveled in each trip, and retailer prices. I consider bundles of one or two retailers, which accounts for 95% of trips in the data. Distances are defined as as-the-crow-flies distances that minimize the total distance between home and the retailers shopped at within a single trip. Prices are a relative price for each retailer and income group in each market. To compute bundle prices, retailer prices are weighted by the total retailer expenditure shares and summed (Thomassen et al., 2017). I discuss the data and variable construction used in estimation in Appendix B.2, showing distances are measured accurately and the estimation is robust to several alternate measures.

Geographic definition of the (downstream) product market: I define a market as a city-biweek-year, and estimate the parameters with data from 2017-2019 Chicago (Cook County). The model is estimated with retailer data (store latitude, longitude, address, retailer name), household purchase data (the bar codes scanned, and the price paid for each bar code, the stores traveled to and the time of day), and household demographic information (e.g. income, employment, education, and five digit zip code).

Geographic definition of the (upstream) commercial real estate market: Markets are defined yearly and by large and non-overlapping geographical areas shown in Figure 30. The model is estimated with retailer data (store latitude, longitude, address, retailer name), household information (location and demographics from the ACS, demand parameters estimated from consumer panel data), the set of potential locations (latitude, longitude and square footage from each landlord), and rents (prices) and exclusive dealing contracts.

The potential locations (including square footage, preexisting exclusive dealing contracts and preexisting retailers), dataset of entry and exit, lease characteristics (including rent), and exclusive dealing restrictions, along with the expected retailer profitability estimated from consumer panel data, provide enough data to write down the full retailer location choice problem, landlord price setting problem, and consumer shopping decisions. I consider the location choice for each retailer in Table 1 at the parent company level (e.g. Kroger chooses locations for both Mariano's and Food For Less).[7]

3 Stylized Facts about Exclusive Dealing

The exclusive dealing contracts studied in this paper are called restrictive covenants. These restrictive covenants contractually forbid specific retailers from operating at specific locations. Restrictive covenants are put in place to protect the business interests of one or both parties. For example, Figure 1 shows an excerpt from a Safeway restrictive covenant, which blocks the entry of retailers that sell similar or identical products to Safeway – retailers that sell food, drugs, and liquor – in a particular shopping center. As a result, these restrictions are important considerations for retailers choosing locations both because these contracts are an opportunity to limit the retailers' own competition, and because the set of locations they can consider may be limited by other retailers' restrictive covenants.

I document several new empirical facts about exclusive dealing in retail real estate in Cook County, IL. First, I find that the practice is extensive and has been growing over time. Second, I describe the types of retailers that employ these contracts. Third, I characterize the contents of the provisions and the retailers blocked by them. Finally, I analyze the radius at which the contracts bind and their (observed) effect on prices. I report additional stylized facts showing that exclusive dealing is uncorrelated with demographic factors, the timing and additional details of the contracts in Appendix A.

[7] I focus on entry because grocery chain and big box store exit is rare: as shown in Figure 13, 70% of grocery chain stores that have opened since 1990 have remained open to present day.

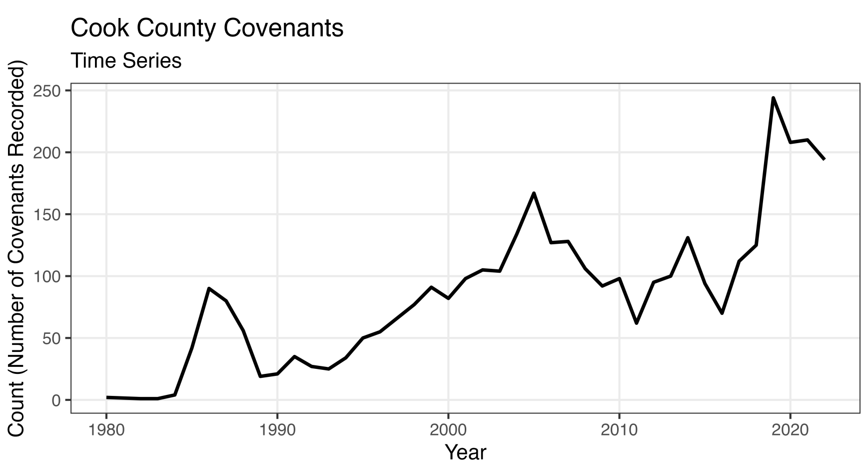
Figure 1: Example of an Exclusive Dealing Agreement

> The Lease provides, in part, that no premises (nor any part thereof) in the Shopping Center other than the Premises, shall be (i) used or occupied as a retail supermarket, drug store and combination thereof, nor (ii) used for the sale of any of the following: (a) fish or meat (except in prepared form sold by a permitted restaurant operation); (b) liquor and other alcoholic beverages in package form, including, but not limited to, beer, wine and ale; (c) produce; (d) baked goods; (e) floral items; (f)any combination of food items sufficient to be commonly known as a convenience food store or department; and (g) items requiring dispensation by or through a pharmacy or requiring dispensation by or through a registered pharmacist.

Source: Cook County Record of Deeds, Document Number 0010276527. This figure is an example of a restrictive covenant from Jewel Osco (whose parent company is Safeway) store in Chicago, 2001. The figure shows that at this location, Safeway's Jewel Osco and its landlord forbid the remaining portions of the shopping center for use as a grocer, drug store, liquor store, or convenience store.

Fact 1 – Exclusive Dealing is Common and Increasing: Figure 2 shows that the number of exclusive dealing contracts has grown steadily since the 1990s, peaking in 2005 and 2019. The persistent and growing prevalence underscores the importance of understanding the effects of the contracts.

Figure 2: Time Series of Exclusive Dealing Contracts in Cook County IL



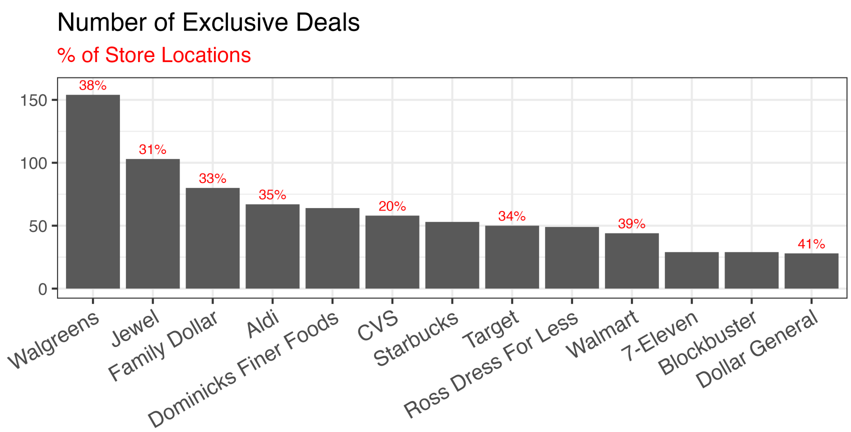
Source: Cook County Recorder Office. Figure plots a time series of exclusive dealing contracts recorded at the Cook County Recorder office, 1980-present.

Fact 2 – Exclusive Dealing Contracts are Most Prevalent for Grocery, Discount and Drug Stores: Figure 3 shows the retailers with the most exclusive dealing contracts in total (in gray) and on leased locations (in red).[8] The most common industries are grocery stores, drug stores, discount stores, and dollar stores. These retailers mostly sell consumer packaged goods and relatively similar

[8] A more expansive retailer list is found in Figure 9.

products to their direct competitors, while retailers that sell highly differentiated products do not use exclusive dealing contracts. This is consistent with retailers with low product differentiation benefiting more from higher spatial differentiation. As shown in red, I find that the extent to which stores have exclusive dealing contracts varies by location and retailer. In Appendix A, I show that variation in exclusive dealing contracts within retailers is uncorrelated with neighborhood demographics.

Figure 3: Retailers with the Most Number of Exclusive Dealing Contracts



Source: Cook County Recorder Office. Time span 1980-2023. Figure plots the retailers with the most recorded exclusive dealing contracts. The gray bars indicate the number of addresses with an exclusive dealing agreement. The red text specify the fraction of leased locations with these exclusive dealing contracts (these are only listed for stores that accept SNAP benefits).

Focusing on grocery, Table 7 lists the grocery chain retailers that operate in Chicago with at least one exclusive dealing contract. Importantly, all the grocers with the high market share use exclusive dealing contracts in their leases (such as Safeway's Jewel Osco and Alberston's Mariano's), and 48% of chain grocers have exclusive dealing contracts on premises (chains are defined as any retailer with more than four stores in the county). Table 8 shows the prevalence of exclusive dealing contracts in the grocery sector in Chicago. Of the 351 contracts that forbid retailers from selling groceries, 140 are found on grocery store locations, and the rest are found in similar industries such as discount stores and drug stores. Amongst rented grocery stores, exclusive dealing is particularly prevalent in low-income neighborhoods, suggesting that exclusive dealing may aid retailer entry.

Fact 3 – Retailers Blocked from Entering: The content of the contracts vary significantly across retailers and locations. Figure 10 shows the types of retail blocked by the largest grocery, big box, drug, and dollar stores. These contracts specify a limited square footage or total ban on specific products categories, which for the most part reflect the products sold by the blocking retailer. However, the contracts show significant asymmetry across retail locations and similar retailers. For example, Whole Foods blocks grocery products at all stores but blocks liquor at only 25% of stores, and, while both grocery stores sell liquor, Whole Foods limits liquor stores at many more locations than Safeway's Jewel Osco. This heterogeneity may indicate the retailer-specific and localized nature of competition in this market. Figure 11 shows the top 50 blocked categories for Whole Foods, Safeway's Jewel Osco, Aldi, Walmart, and Dollar General.[9] This broader list reveals a wide set of blocked product categories, reflecting direct competition (blocking retail and food), parking competition (blocking education and health services) and aesthetic curation (blocking garbage dumps, Marijuana, abortion centers, gun shops, etc...).

Fact 4 – Observationally, Exclusive Dealing Binds Locally: Consistent with the firm's presumed goal of limiting competition, retailers with exclusive dealing contracts have fewer competitors nearby. Figure 4 plots the relationship between exclusive dealing and number of competitors at different radii, showing that stores with exclusive dealing agreements have fewer competitors nearby but more competitors farther away. This relationship is determined by a regression of the number of competitors surrounding a store on whether a store has an exclusive dealing contract,

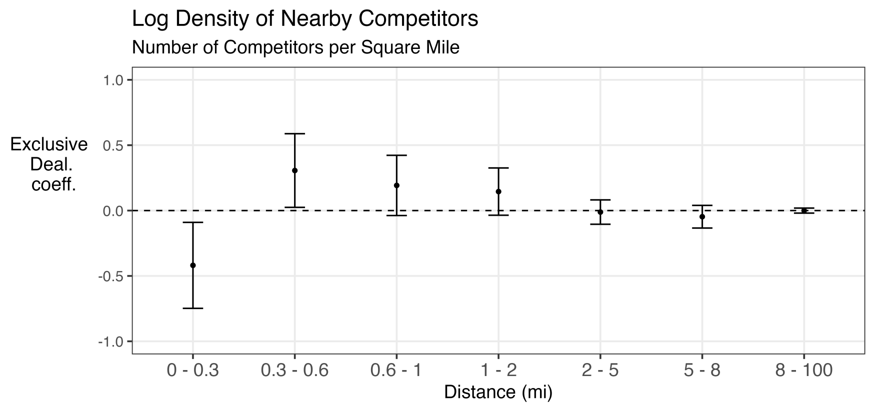
$$num\ stores_{r(i)t} = \beta exclusive\ deal_i + \sigma_i + \lambda_t + retailer_i + \epsilon_{it}$$

where num stores$_{r(i)t}$ are the number of dollar, grocery, drug, and big box stores surrounding a grocery or big box store (excluding the store itself) in a radius $r(i)$ in a year t, *exclusive deal*$_i$ indicates the presence of an exclusive dealing contract benefiting the property i, and σ_i, λ_t, and $retailer_i$ include zip, time, and retailer fixed effects. Importantly, the regression includes retailer fixed effects which allow us to control for retailer quality and allows us to leverage the variation in contracts across retailers, retailer locations, and time.

As shown in Figure 4, grocery stores and big box stores with exclusive dealing contracts have fewer competitors within a .3 mile radius of the store, which is approximately the radius of the shopping center. The result reverses between .3 and .6 miles, and there are more competitors surrounding stores with exclusive dealing contracts. These results are consistent with the hypothesis that exclusive dealing restricts competition by pushing competitors farther away. At a large radius, there is no difference between stores with and stores without exclusive dealing contracts. Tables 19 - 24 show the result is robust to similar specifications.

[9]Table 11 shows this asymmetric pattern for a wider set of retailers in the data.

Figure 4: Log Density of Nearby Competitors



Notes: Figure reports coefficients and 95% confidence interval from regression of number of competitors per square mile on whether or not the store has an exclusive deal, with year, zip5, and retailer fixed effects. I only use grocery chains and big box stores. Competitors are defined as grocery, big box, and drug stores. Data is based on the exclusive deal data from the Cook County recorder office and the retailer location, entry, and exit comes from the SNAP data.

The shopping center radius (0-.3 miles) is economically significant both because of the importance of foot-traffic externalities within shopping centers (Benjamin et al. (1992), Brueckner (1993),Gatzlaff et al. (1994), Pashigian and Gould (1998), Konishi and Sandfort (2003), Gould et al. (2005), Shoag and Veuger (2018), Burayidi and Yoo (2021), Evensen et al. (2024), Liu et al. (2024)) and because spillovers across retailers are localized to a small radius (Qian et al. (2023), Knight (2023), Baum-Snow et al. (2024) also find a small radius of .2 miles). Without imposing assumptions, I find that exclusive dealing contracts bind at the relevant radius determined by prior research.

Additionally, I confirm that exclusive dealing in large part is intended to bind locally by looking at the radius directly specified by the contracts. Table 9 shows the fraction of exclusive dealing contracts which specify a nearby radius, a more distant radius, and the fraction of documents that do not specify the radius at which the contract binds – 86% of contracts specify a nearby radius. The radius specified by the contracts for grocery stores and big box stores is in large part restricted to the shopping center or properties near the grocery or big box store. When shopping centers are owned by a single landlord, exclusive dealing contracts give retailers some control over the tenant mix.

Fact 5 – Rental Prices are Higher with Exclusive Dealing: Prices are higher in leases with exclusive dealing contracts. Looking within retailer and year, I find that rental prices are 20% higher when exclusive dealing is part of the contract when controlling for retailer. This is shown by regressing rents on the presence of exclusive dealing, controlling for demographics (such as income), lease characteristics (such as store size), and property characteristics (such as building quality). Additionally, the specification includes location, time, and retailer fixed effects.

$$\log y_{ijt} = \alpha_0 + \gamma \text{exclusive deal}_{ijt} + \sum_k \beta_k \log x_{kjt} + zip_j + year_t + retailer_i + \epsilon_{ijt}$$

Table 15 shows that prices per square foot per year are 8-30% higher in properties with exclusive dealing, conditional on demographics and lease characteristics. When focusing on grocery retailers and big box stores, (rental) prices are 20% higher in properties with exclusive dealing. Robustness checks which vary the demographics and lease characteristics included report estimates between 10% and 40% (see Tables 16 - 18).[10] The regressions indicate that the average lease prices would be 4$ higher per square foot per year for an exclusive dealing; for a typical grocery store, this translates to an additional 120,000$ per year for a lease with such a contract, or approximately .24% of average annual revenue.[11]

Figure 5: Rental Prices, Neighborhood Income, and Exclusive Dealing

Source: Cook County Recorder, ACS 2009-2023 and Census Demographic Data 1980, 1990, 2000, and CompStak lease characteristics data. Figure net effective rents in Cook County as a function of exclusive dealing status (covenant), census block group income, and size of the space. Net effective rent is the rent per square foot per year, averaged over the course of the lease.

[10]The tables vary on how demographic data is imputed when the data is not available, which controls are included in each regression, and what types of properties are included in the sample. Results are consistent across different methods of imputation. Table 16 does not impute any data. Table 15 imputes missing demographic data when the ACS and Census data are not available (1991-1999, 2001-2008) by interpolating the data when it is available. Table 17 interpolates the data by using earlier years when the data is available. Table 18 subsets to properties that where the retailers are most likely to have an exclusive dealing contract. Table 18 column (7) subsets to grocers and big box stores and includes retailer fixed effects and column (8) includes interaction between exclusive dealing and neighborhood income.

[11]Typical grocery stores in Chicago average 30,000 square feet and make around 50 million dollars in revenue each year.

Figure 5 shows how the exclusive dealing premium varies along two important dimensions: neighborhood income and store size. The literature shows that the higher the neighborhood income, the higher downstream retail prices (for example, Stroebel and Vavra (2019)); this plot shows prices are higher in the upstream [real estate] market as well. Rents with exclusive dealing contracts are higher in all neighborhoods but particularly more expensive in high-income neighborhoods. These findings are consistent both with higher demand from retailers and co-locating stores, as the landlord has to be compensated more to forgo potential profits from possible other retailers (as in Bork (1978)).

Rents with exclusive dealing contracts are inversely related to store size. When the store is very large, retailers with exclusive dealing contracts pay less (red line) than stores without exclusive dealing (black line). Two facts explain the low rent per square foot on the high end. First, since there are relatively few retailers that can fill such a large store size, there is less demand for such large space. Second, the large retailers that do exist likely drive demand for any nearby smaller stores. As a result, the landlords likely internalize this foot traffic externality, offer cheaper rent to large stores as an inducement to enter their locations, and charge higher rents to the co-locating stores. Rents with and without exclusive dealing are the same around 45,000 square feet – approximately the size of a supermarket. However, most retail store fronts are smaller than 45,000 square feet, and so most stores pay a premium for an exclusive dealing. When the store is smaller, retailers pay the highest premium for exclusive dealing (red line) relative to a similar-sized store without exclusive dealing (black line). At this end, high demand from retailers and co-locating stores are consistent with higher prices for exclusive dealing contracts, as the landlord has to be compensated more to forgo potential profits from possible other retailers.

These regressions demonstrate that exclusive dealing should be considered on par with the more traditional factors (like neighborhood demographics, state of the economy, interest rates, lease length) which are thought to determine prices in the commercial real estate market (Stanton and Wallace (2009), Gyourko (2009), Liu et al. (2018), Gupta et al. (2022), Moszkowski and Stackman (2022), Stackman and Moszkowski (2023)).

4 Model

Motivated by the stylized facts, I turn to a model to understand the role of exclusive dealing. In the model, prices and exclusive dealing contracts are endogenous and determined simultaneously in the commercial real estate market.

Agents: I consider the location choice problem of the retailers most frequented by consumers, which are listed in Table 1. These retailers are grouped into categories: large retailers, which comprise the most frequented big box stores and supermarkets, and small retailers, which comprise drug, dollar, liquor, smaller food, and all other stores.

Table 1: Most Frequented Retailers

Retailer	**Type**	**Size**	**Step (Timing)**
Jewel Osco (Safeway)	Supermarket	Large	2a, 2b
Mariano's (Kroger)	Supermarket	Large	2a, 2b
Whole Foods	Supermarket	Large	2a, 2b
Aldi	Specialty	Large	2a, 2b
Food 4 Less (Kroger)	Specialty	Large	2a, 2b
Trader Joe's (Aldi)	Specialty	Large	2a, 2b
Costco	Big Box	Large	2a, 2b
Meijer	Big Box	Large	2a, 2b
Sam's Club (Walmart)	Big Box	Large	2a, 2b
Target	Big Box	Large	2a, 2b
Walmart	Big Box	Large	2a, 2b
Drug	Drug Store	Small	3
Dollar	Dollar Store	Small	3
Liquor	Liquor	Small	3
Other Food	Other Food	Small	3
All Other	Outside Good	Both	2a, 2b, 3

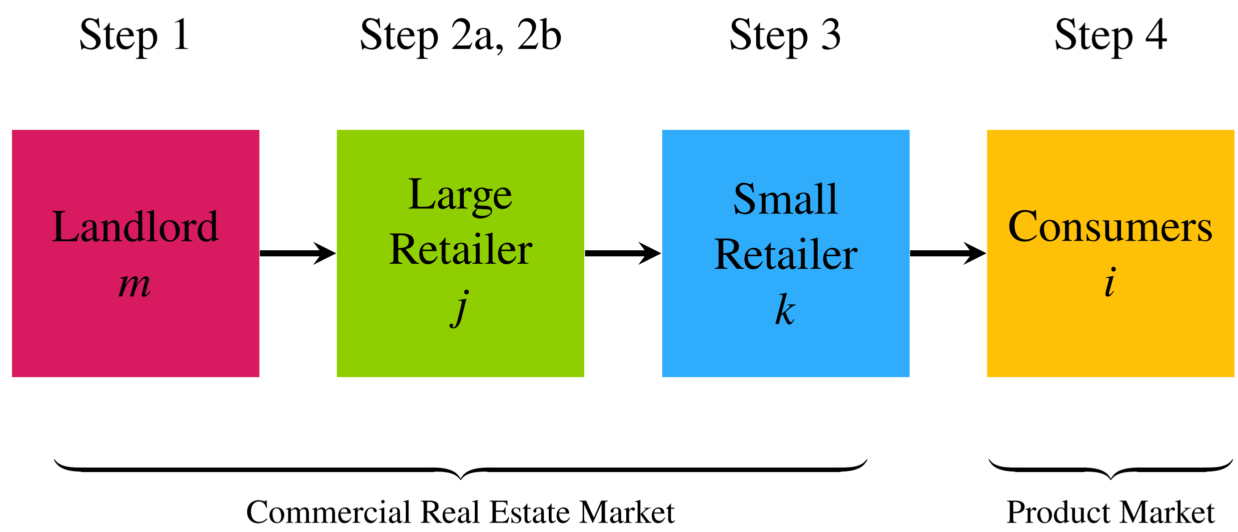
Notes: The retailers (and parent company, if retailers share a common parent company) included in the analysis are those with the largest market shares and most frequent trips.

Timing: Because large retailers facilitate smaller retailer entry by driving demand to nearby locations, landlords with multiple properties rent first to large retailers and next to smaller, co-locating retailers (Pashigian and Gould (1998), Benjamin et al. (1992), Brueckner (1993), Konishi and Sandfort (2003), Burayidi and Yoo (2021), Evensen et al. (2024), Liu et al. (2024)). The timing, shown in Figure 6, reflects this.

In step 1, each landlord offers two contracts to each retailer, each with a separate price, one for an exclusive contract and one for a non-exclusive contract. Landlord m offers retailer j contracts $a \in \{\text{exclusive, non-exclusive}\}$ at rental price r_{jma}. An exclusive dealing contract blocks all the competitors that decrease observed expected variable profits. The exclusive dealing contracts can vary across retailers and locations because the observed expected variable profits can vary across retailers and locations.

In 2a, each large retailer simultaneously choose intended locations and contracts. I focus on Bayesian Nash equilibra: retailers take landlords' prices as given but form beliefs over other retailer location choice strategies.

Figure 6: Model: Timing of Shopping Center



Notes: First, the landlord rents to the large retailers, second, the landlord rents to the small retailers, third, the retailers set prices in the product market, and fourth consumer shops for good. Landlords that own multiple properties – for example, in a strip mall – will rent to both large and small retailers.

In step 2b, large retailers entry is determined. Some firms will not enter as a result of capacity constraints or exclusive dealing contracts that their block their entry. In the case of such constraints, the highest-paying retailer enters.

In step 3, given large retailer entry, landlords set prices for smaller retailers whose entry is not foreclosed upon by an exclusive dealing contract. Smaller retailers choose locations and enter. Small retailers cannot make exclusive deals. The equilibrium is again Bayesian Nash.

In step 4, given entry decisions, all retailers set prices in the product market, consumers shop, and the product market clears.

Because large retailers make static, long-term decisions by signing leases that last for at least 10-25 years, and furthermore, because there is little exit for large retailers, the model is static.

The model is estimated in reverse order. Section 4.1 discuss the consumer problem, Section 4.2 discuss the firm problem in the product market, Section 4.3 discusses the retailer location choices, and Section 4.4 discusses the landlord price-setting problem. Additional details describing the data are Appendix B.4, and variable construction is discussed in Appendix B.2.

4.1 Consumer Demand for Retailers (Step 4)

I model household retail shopping choices at the level of aggregation of the exclusive dealing contracts. Households choose a maximum of two retailers to shop at in the same trip (ie, which retailers to shop at before returning home). Following McFadden (1978), Berry (1994), Berry et al. (1995), households make a discrete choice and receive indirect utility

$$u_{ib}^{g} = \alpha^{g} P_{b}^{g} + \gamma^{g} d_{ib} + \Gamma_{b} + \xi_{b}^{g} + u_{b} + \boldsymbol{\Sigma X_{b} y_{i}} + \epsilon_{ib} \tag{1}$$

where u_{ib}^{g} is the utility household i in income group g receives from shopping at one or two retailers $b \in \mathcal{B}$ (henceforth a bundle), which can include both large and small retailers, α^{g} is the price sensitivity, P_{b}^{g} is the total price paid, γ^{g} is the distance sensitivity, d_{ib} is the total distance traveled, Γ_{b} is bundle complementarity, ξ_{bt} and u_{b} are demand shocks, Σ captures the effect of the interaction between household demographic characteristics y_i and retailer characteristics X_b, and ϵ_{ib} is a household idiosyncratic preference for retailers b.

Households choose a maximum of two retailers from the most frequented retailers shown in Table 1. These retailers include national chain grocers, discount stores, club stores, as well as categories of retailers such as drug stores, dollar stores, and liquor stores. In this list, "Other Food" represents any other food store that isn't one of the listed retailers and is interpreted as the "best" non-listed grocery store for each household. "Other" represents any other non-food store that isn't one of the listed retailers or listed retail categories and is interpreted as the "best" other store to shop at (the same interpretation as in Cao et al. (2024)). "Other" retailers comprise the outside good and the outside good utility is normalized to zero: $P_{0}^{g} = 0, \Gamma_{0} = 0, -\alpha^{g} P_{0}^{g} + \Gamma_{0} + \xi_{0}^{g} + u_{0}^{g} = 0$, and so all prices and complementarities are interpreted relative to the outside good.

Prices and distances take into account total prices paid and total distances traveled. When shopping at a single retailer, households pay for the retailer's good and travel from home to the retailer and back (home $\longrightarrow$ retailer $\longrightarrow$ home). When multi-homing, households pay for the goods at both retailers and travel to both retailers before returning home (home $\longrightarrow$ retailer 1 $\longrightarrow$ retailer 2 $\longrightarrow$ home). In all cases, households take the shortest distance trip.[12]

I interpret Γ_{b}, ξ_{b}^{g} and u_{b}^{g} as aspects of bundle quality: Γ_{b} is fixed across markets, and ξ_{b}^{g} and u_{b}^{g} vary across markets. For multi-homing to be possible, households must receive additional utility to

[12] This implies that the consumer always shops at the closest store location within retailer, e.g. the closest Trader Joe's to home. This model of multi-homing or trip chaining is modeled this way in Relihan (2022) and departs from most grocery demand literature that assumes households pay the total trip costs to each retailer (for example Thomassen et al. (2017)).

justify increased prices and distances of shopping at multiple stores together. I interpret and refer to this additional utility, Γ_b, as the complementarity between two retailers (as in Gentzkow (2007)). When shopping at a single retailer, I interpret Γ_b as static, observable retailer quality. Bundle quality can additionally fluctuate over time and across locations, and I refer to this time-varying quality as demand shocks $\xi_b^g + u_b$. These demand shocks can affect prices, and I interpret ξ_b^g as the portion of the demand shock correlated with prices and u_b^g as the portion of the demand shock uncorrelated with prices.

I allow preferences to vary with household demographics x_i, which include information such as education and unemployment status, and bundle characteristics y_b. I include demographic characteristics that may be correlated with value of time and thus might change the disutility of distance or nearby shopping. y_{bt} are whether stores are located nearby one another.

Finally, consumer preferences have an idiosyncratic component, ϵ_{ib}. For example, ϵ_{ib} may represent daily preferences for a specific meal, which require a set of ingredients across retailers, and is modeled by an additive product-specific Type 1 Extreme Value shock.

Multi-homing is common in the data. As shown in Figures 19 - 22, 40% of expenditure-weighted trips are to multiple stores and 40% of expenditure-weighted trips to grocery stores include an additional retailer.

Multi-homing also changes the value of exclusive dealing contracts for retailers. Foreclosure of other retailers nearby (e.g. in a shopping mall) increases distances between retailers and decreases the likelihood that the stores are shopped at together. When limiting the entry of competitors, retailers mechanically increase the chances that complementary retailers will locate nearby. Complementary retailer co-location has two benefits for retailers: first, co-location of complementary stores lowers the total distance trip, raising the utility of the bundle can increase own demand, and second, complementarities can soften price competition within retailer pairs. Consumers benefit when the shorter-distance trip to complementary stores outweighs the welfare gains from price competition of (substitute) retailers.

Additionally, foreclosing on rival entry pushes competitors farther from certain consumers, which can further reduce entry and thus retail competition. As the disutility for distance, γ^g, becomes more negative, foreclosing on nearby rival entry becomes more profitable, and exclusive dealing becomes more effective.

4.2 Product market supply (Step 4)

I assume retailers set prices in Bertrand competition to maximize profits. Retailer j's variable profits are

$$\max_{p_j^g} \sum_g s_j^g (p_j^g - mc_j^g) \tag{2}$$

where p_j^g is the price retailer j sets at all store locations for income group g, s_j^g is retailer j's market share for income group g, and mc_j^g is the marginal cost retailer pays in the product market for income group g. Shares are computed by aggregating individual choice probabilities across bundles and household locations.[13] These marginal costs, mc_j^g, reference operating costs that can be adjusted after entry, such as wholesale prices of products and labor.

For large retailers, variable profits are determined by Equation 2. For small retailers, each location is assumed to be its own independent store, and households only shop at the store that is the closest within store type (e.g. households shop at the drug store closest to home). As a result, small retailer variable profits for small retailer k in location m are

$$\bar{\pi}_{km} = \sum_i \underbrace{s_{ik}^*\big(d(\boldsymbol{l}_{-k}), x, y; \phi\big)}_{\text{prob. hh } i \text{ picks k}} \left(p_k^{g(i)*}\big(d(\boldsymbol{l}_{-k}), x, y; \phi\big) - mc_k^{g(i)} \right) \tag{3}$$

where variable profits are summed over the profits from each household i and individual shares, s_{ik}^*, incorporates that small retailer k is only in household i's choice set if it is the closest store in that store type to the household, if $d_{ik} = \min_{\tilde{k}} d_{i\tilde{k}}$. As a result, the distances to consumers and the set of consumers that shop at a particular store are determined by the location of consumers and other retailers, $d(\boldsymbol{l_{-k}})$. Additionally, profits are determined by demographics, y, store characteristics, x, demand parameters, $\phi = \{\alpha, \gamma, \Gamma, \xi\}$, and marginal costs, mc_k^g.

Price setting in the product market has two main simplifications: retailers set a unique price for each income group in each market. Simply put, (1) a household cannot find lower prices at a different location of the same retailer and (2) households in the same income group purchase the same good from each retailer. First, consistent with the findings that different income groups purchase different types of food (Handbury (2021), Allcott et al. (2019)), retailers set different prices (ie. provide a different good) to households in different income groups g. Second, an extant literature has documented that retailers set prices mostly uniformly for the same products across stores (DellaVigna and Gentzkow (2019), Hitsch et al. (2021), Adams and Williams (2019), Brecko et al. (2025)), and Butters et al. (2022) document how price increases due to cost shocks are local to the region where the cost shock occurred. To incorporate this finding into the model, I assume that

[13]The shares and full equilibrium are written in Appendix B.1.

each chain retailer sells the same (representative) good at each store for the same price. A separate literature has also documented that households from different income groups pay different prices at the same retailers because they choose different product assortments (Handbury (2021)).[14] To allow retailers to internalize that different-income households will purchase different bundles but to continue modeling the retailer bundle choice problem at the retailer level (the aggregation level of for exclusive dealing), I assume that each retail chain can set a single price for each income group, and that consumers within an income group do not substitute between bundles meant for different income groups. Third, consistent with the timing in the data, I assume that each retailer chooses prices to maximize profits once all locations are determined.

For example, a Safeway sets three prices in Chicago – a price for the low-income group, a price for the middle-income group, and a price for the high-income group – and these prices are the same at all Safeways in Chicago. Since each Safeway is identical for all consumers, each consumer will buy the same representative product regardless of the Safeway shopped at; as a result, consumers shop at the store closest to home to minimize $\gamma^g d_{ib}$.

Prices are determined by the first order condition of the profit function in Equation 2. For large retailers, each retailer has a single price index and a unique store-wide marginal cost. For small retailers, a single price index is set for all drug stores, dollar stores, other food stores, and liquor stores, and the marginal costs are assumed to be the same for all stores within each store type.

$$p_j^g = mc_j^g + \left[\frac{\partial s_j^g}{\partial p_j^g}\right]^{-1} s_j^g \tag{4}$$

4.3 Retailer Location Choice (Stage 2a, 2b, 3)

Large retailers (Stage 2a, 2b): In the commercial real estate market, landlords set prices for contracts and entry occurs in stages 2a, 2b, and 3: large retailers choose and enter locations (choosing simultaneously and then entering simultaneously, following Seim (2006)), and then small retailers choose and enter locations (choosing simultaneously and then entering simultaneously). In stage 2a, a large retailer j, i.e., a retail chain with possible preexisting locations, may choose a new location m and contract $a \in \{\text{Exclusive } (E), \text{Non-Exclusive } (N)\}$ to maximize profits

[14] In the literature estimating grocery demand, demand is often estimated for separately for different income groups (Allcott et al. (2019), Atkin et al. (2018)). This reflects that in reality, the retailers internalize different elasticities across the income distribution and set prices accordingly. For example, Dominick's Finer Foods had higher priced stores and lower priced stores in different locations. Also, grocers sell a wider variety of similar products at different prices to price discriminate across consumers. In the model, this is approximated as three separate prices for different income groups at each retailer.

$$\max_{m,a} \quad E_{\boldsymbol{l}_{-j}}[\bar{\pi}_{jma}|\boldsymbol{a}_{jm}] + \bar{\mathbb{P}}_{jma}(\theta_j 1\{a_{jm} = E\}_{jma} - r_{jma} - F_m + \epsilon_{jm}) + (1 - \bar{\mathbb{P}}_{jma})\epsilon_{j0} \tag{5}$$

where $E_{\boldsymbol{l}_{-j}}[\bar{\pi}_{jma}|\boldsymbol{a}_{jm}]$ are the expected variable profits in the product market given that retailer j picks contract a_{jm} at location m, $\boldsymbol{l}_{-j}$ are the other large and small retailers' location choice strategies which are unknown in stage 2a, $\bar{\mathbb{P}}_{jma}$ is the probability the large retailer j enters given that it chooses to enter m (the entry is resolved in stage 2b), θ_j represents the information asymmetry regarding the profitability of exclusive dealing between landlords and large retailers, r_{jma} are the rents paid to landlord m for entering with contract a, F_m is the fixed cost of entry, and ϵ_{jm} is the idiosyncratic profitability of a location.[15] Retailers that choose to not enter (the outside good) collect variable profits from preexisting locations and a shock $E_{\boldsymbol{l}_{-j}}[\bar{\pi}_{j0}] + \epsilon_{j0}$.

Expected variable profits for large retailer j depend on the locations of consumers and all other store locations. Variable profits from adding a new location and contract (m, a) can be written as $E_{\boldsymbol{l}_{-j}}[\bar{\pi}_{jma}] = \prod_{j' \neq j} \left(\sum_{l'_{j'}=(m',a')} \mathbb{P}_{j'm'a'} \right) \bar{\pi}_{jma}(\boldsymbol{l}'_{j'})$, which is a function of large retailer j's location choice m, as well as possible preexisting locations, the simultaneous decisions of all other large retailers, and the future decisions of small retailers.[16] For large retailers with preexisting locations, adding a new store shortens the distance to some consumers, but in doing so, steals business from competitors and preexisting locations of j to the new one. Thus, in opening a new store, large retailer j balances the benefit from decreasing the distances to certain consumers with the traffic diverted from preexisting stores and entry costs. If the large retailer chooses not to add a store, expected variable profit comes entirely from preexising locations, $E_{\boldsymbol{l}_{-j}}[\pi_{j0}]$, but may change due to expected rival store entry.

For each retailer and potential location, I determine the set of retailers that would be blocked by an exclusive dealing agreement. I compute (1) observed expected variable profits for retailer j at location m and taking all other existing locations as given and (2) observed expected variable profits for retailer j are computed assuming retailer j enters location m and retailer k opens a nearby property owned by the same landlord. The set of retailers that could feasibly co-locate with retailer j in landlord m's property and for which profits under (1) are greater than profits under (2) are the set of retailers blocked by the exclusive dealing contract.

Exclusive contracts and capacity constraints limit which retailers can enter a particular location. Because of these conflicts, the probability of choosing a location is not the same as the probability of entry, and the retailer internalizes the probability of winning entry $\bar{\mathbb{P}}_{jma}$, when choosing locations.[17]

[15] The probability of winning entry is written in Appendix B.1.
[16] The probability the retailer chooses and then enters location m is written out in Appendix B.1.
[17] The probability the retailer chooses location m is written out in Appendix B.1.

If multiple retailers try to enter the same location, then the highest paying retailer enters. When a retailer does not enter due to a conflict, it loses the opportunity to enter that location but still collects variable profits from preexisting retailers and the idiosyncratic shock ϵ_{j0}. While conflicts block entry to a particular location, conflicts do not permanently block entry into a market because the retailer can choose enter the market in a different location the following year.

Mechanically, an exclusive dealing agreement affects a retailer's competitors (both large and small retailers) in two ways. First, the retailer pushes competitors away from certain consumers and towards other consumers. Second, exclusive dealing changes the total trip distance for trips to multiple retailers.[18] At any location m, a retailer will prefer an exclusive dealing contract (E) to non-exclusive contract (N) when

$$\underbrace{E_{l_{-j}}[\bar{\pi}_{jmE}] - E_{l_{-j}}[\bar{\pi}_{jmN}]}_{\text{commitment}} + \underbrace{\bar{\mathbb{P}}_{jmE}\theta_j}_{\substack{\text{info. asy.}\\ \text{excl. deal.}}} + \underbrace{(\bar{\mathbb{P}}_{jmE} - \bar{\mathbb{P}}_{jmN})}_{\text{entry prob.}} \underbrace{(-F_m + \epsilon_{jm} - \epsilon_{j0})}_{\substack{\text{info. asy.}\\ \text{location match}}} > \underbrace{\bar{\mathbb{P}}_{jmE}r_{jmE} - \bar{\mathbb{P}}_{jmN}r_{jmN}}_{\text{rents}} \tag{6}$$

$$\underbrace{E_{l_{-j}}[\bar{\pi}_{jmE}] - E_{l_{-j}}[\bar{\pi}_{jmN}]}_{\text{commitment}} + \underbrace{\theta_j}_{\substack{\text{info. asy.}\\ \text{excl. deal.}}} > \underbrace{r_{jmE} - r_{jmN}}_{\text{rents}} \tag{7}$$

where Inequality 6 is before entry and Inequality 7 assumes entry is guaranteed for retailer j.

Exclusive dealing solves two main problems between landlords and large retailers: a commitment (hold-out problem) and an information asymmetry. First, exclusive dealing safeguards retailer safeguards downstream profits. The higher the gap between exclusive and non-exclusive downstream profits, $E_{l_{-j}}[\bar{\pi}_{jmE}] - E_{l_{-j}}[\bar{\pi}_{jmN}] >> 0$, the greater the benefit of exclusive dealing.[19]

Second, conversations with industry professionals suggest that exclusive dealing exists in part to solves information asymmetry in the market. In the model, information asymmetry between large retailers and landlords arises from two sources: profitability from the location, ϵ_{jm}, and landlord misperception from the profitability of exclusive dealing, θ_j. The first, ϵ_{jm} captures elements such as layout or square footage whose effect on profitability are only known to the retailer. The second, θ_j captures landlord's and other retailer's misperception on the profitability of exclusive dealing

[18] Mechanically, paying higher prices (e.g. for exclusivity) can also lead to higher changes at entry.

[19] A landlord may not be able to credibly commit to not renting to competitors in stage 3 when there are large fixed costs of entry. When expected retailer profits are similar regardless of the exclusive dealing status, this indicates that the landlord does not to rent to nearby competitors that will significantly reduce observed variable profits. A landlord can credibly commit to a decision when it maximizes its own profits and there are no incentives to deviate once a large retailer enters.

for retailer j.[20] When misperception is small, $\mu_\theta \approx 0$, the benefits of exclusivity are sufficiently captured by the gain in expected surplus.[21] In the case of partially unobserved profits due to θ_j and ϵ_{jm}, landlords can use exclusive dealing as a screen to differentiate between retailers that are more or less sensitive to competition.[22]

Overall, the model pairs important aspects of the commercial real estate market (such as prices, exclusive dealing, landlords, and exact potential locations) with more traditional factors which are thought to determine the retailer entry game (such as business stealing, fixed costs of entry, variable profits) which are prevalent in a long literature in industrial organization on retailer entry and location choice.[23]

Small retailers (Stage 3): Once the large retailers have entered, the smaller and often co-locating retailers enter. These retailers are in the categories of other food, drug stores, liquor stores, dollar stores, and other stores. Landlords set a single price for all small retailers. There is no exclusive dealing, and when multiple retailers approach, entry is determined at random. These assumptions reflect the large number of potential locations available to these retailers and the few exclusive dealing contracts signed in this market.

In each market, potential entrants choose locations. Each small retailer k's location choice is determined by the probability that the firm will enter that location $\bar{\mathbb{P}}_{km}$ and the expected profits conditional on entry

$$\max_m \bar{\mathbb{P}}_{km}\Big(E[\bar{\pi}_{km}] - r_m^{small} - F_m^{small} + \epsilon_{km} - \epsilon_{k0}\Big) \tag{8}$$

where expected profits conditional on entry depend on expected variable profits, $E[\bar{\pi}_{km}]$ from

[20] Reducing information asymmetry is important to landlords: many landlords estimate demand for the shopping center by sitting in parking lot and counting customers, while more sophisticated landlords try to reduce information asymmetry by requesting sales data as part of the lease contract. Retailers, on the other hand, have access to more data on past performance of their stores.

[21] Estimating $(\mu_\theta, \sigma_\theta^2)$ provides an additional test of the model, whether estimating variable profits is sufficient in estimating the value of exclusive dealing. To test this, I hypothesize that $H_0 : \theta_j \approx 0$. Under the null, exclusive dealing is explained by the differential surplus. When $\theta_j \neq 0$, other factors are important for explaining the prevalence of exclusive dealing. This is discussed further in the estimation.

[22] Exclusive dealing may also benefit retailers as the higher-priced contract may increase the probability of entry to a location, $\bar{\mathbb{P}}_{jmE} - \bar{\mathbb{P}}_{jmN}$, which can be additionally be beneficial, for example, when the location is a particularly good match or for high draws of $\epsilon_{jm} - \epsilon_{j0}$.

[23] A long entry literature goes back to Hotelling (1929), Salop (1979), Bresnahan and Reiss (1990) and Bresnahan and Reiss (1991). This model incorporates agglomeration and business stealing aspects from the literature retailer chain location choice (Jia (2008), Holmes (2011), Vitorino (2012), Nishida (2015), Vitali (2022), Caoui et al. (2022)) and expicitly models the commercial real estate market (Moszkowski and Stackman (2022)) but instead focuses on retailer co-location driven by bundle complementarities, a commercial real estate market with retailer location choice, landlord price setting, and exclusive dealing, and entry decisions at a granular level (latitude and longitude).

Equation 3, the rents, r_m^{small}, the fixed cost of entry, F_m^{small}, and the probability of winning entry, $\bar{\mathbb{P}}_{km}$.[24] An exclusive dealing contract that forbids a type of retailer from entering a location limits the choice set of the retailer.

Due to complementarities, large, popular retailers can facilitate the entry of smaller retailers (Benjamin et al. (1992), Brueckner (1993), Konishi and Sandfort (2003), Burayidi and Yoo (2021), Evensen et al. (2024), Liu et al. (2024)) by effectively expand the market at nearby locations. Specifically, small retailer expected variable profits $\bar{\pi}_{km}$ depend on the actions of large retailers, $\boldsymbol{a}_{jm}$. When it is more profitable for small retailers to enter alongside large retailers, there is a positive "foot traffic externality" in retail.

The Bayesian Nash equilibrium from the smaller retailers is determined by the set of prices landlords set for each store type and the probability a location is chosen by each store type.

4.4 Landlord problem (Stage 1)

Each landlord has a limited amount of space (square footage) at its location (latitude, longitude). The landlord is assumed to be flexible in terms of which stores it can rent to but cannot add additional square footage to its lot. For example, the owner of a shopping mall (a typical landlord location) with 100,000 square feet can rent to one Walmart (which is also around 100,000 square feet), or a Safeway, a large other store, and a small other store (each 40,000 square feet, 40,000 square feet, and 20,000 square feet, respectively), or any other combination of retailers that sum to the total capacity of the space.

Each landlord m sets two prices – an exclusive (E) and a non-exclusive (N) price – for each large retailer j: r_{jma}. The landlord balances the probability of a retailer approaching (attempting to enter) with revenue from the entering retailer, including revenue from small retailers

$$\max_{r_{jma}} \sum_{j,a} \underbrace{\mathbb{P}_{jma}}_{\text{prob. choice}} \underbrace{\bar{\mathbb{P}}_{jma}}_{\text{prob. win}} \underbrace{(r_{jma} - mc_m)}_{\text{large retailer}} + \underbrace{E_{l_j}[\pi_m^{small}(\boldsymbol{a}_{jm})]}_{\substack{\text{exp. profits} \\ \text{small retailers}}}$$

where the landlord's profit are the probability-weighted sum of the profits from each retailer entering successfully with contract $a \in \{\text{exclusive, non-exclusive}\}$. The profit depends on the probability large retailer j approaches and wins entry with contract a, $\mathbb{P}_{jma}\bar{\mathbb{P}}_{jma}$, rents, r_{jma}, landlord marginal costs, mc_m, expected profits from the small retailer market, $\pi_m^{small}(a_j)$ which depend on large retailer entry and contracts $\boldsymbol{a}_{jm}$ from retailer j at location m. For example, without

[24] The probability of winning entry is 1 / the number of firms that approach.

any large retailer, the landlord profits $\pi_m^{small}(a = \emptyset)$, where $\vec{O}$ indicates that no large retailers entry.

The landlord has incentives to maximize demand for its property (often a shopping center), and seeks complementary retailers to enter to property. In a full information setting, the landlord can determine the combination of retailers that maximize total surplus and offer rents accordingly. Absent information on retailer profitability, the exclusive dealing contract mitigates some of the information asymmetry.

For the small retailers, landlords set prices balancing the probability of entry, s_m, with revenues given entry, $r_m^{small} - mc_m^{small}$. The landlord's profits from the small retailer market are

$$\max_{r_m^{small}} \underbrace{\left(s_m^{drug} + s_m^{dollar} + s_m^{liquor} + s_m^{\text{other food}} + s_m^{other}\right)\left(r_m^{small} - mc_m^{small}\right)}_{\pi_m^{small}}$$

Retailers limited from entering due to an exclusive dealing contract and retailers that are too large are not considered as potential entrants by the landlord.

Thus the full Bayesian Nash equilibrium is the set of prices, rents and contracts, shares in the product market, shares in the co-locating market, probability of choosing a location (in the real estate market) such that households maximize utility, retailers and landlords maximize profits. The rents and contracts are set to maximize profits; the first order conditions of the profit function for the retailers (in the product market) or the landlords (in the retail real estate market) are consistent with the demand and shares probabilities at these prices.

5 Estimation

5.1 Consumer Preferences

Let $b \in \mathcal{B}$ index the set of bundles available in county c during bi-week t and c_i denote the county household i lives. Under the model assumptions and with the constructed data, the likelihood household i in demographic group g chooses bundle b in county-year-bi-week t is

$$\mathcal{L}(b|\theta) = \prod_{i,b,t} \underbrace{\mathbb{1}\{b_i\}}_{i \text{ chooses } b} \underbrace{\frac{e^{\delta^g_{bt} + \lambda^g_{ibt}}}{\sum_{b'} e^{\delta^g_{b't} + \lambda^g_{ib't}}}}_{\text{prob. } i \text{ chooses } b} \tag{9}$$

where $\delta^g_{bt} = \alpha^g p^g_{bt} + \Gamma_b + \xi^g_{bt} + u^g_{bt}$ is the market-bundle-demographic group fixed effect, measured relative to the outside good $\delta_{0t}^{g} = 0$, and $\lambda_{ibt}^{g} = \gamma^{g} d_{ibt} + \gamma_1^{g} d_{1ibt} + \Sigma_{ib} x_{it} y_{bt}$ includes preferences for distance and shopping centers conditional on the household demographics and market fixed effects. Households can make multiple trips in the same bi-week, and each day of shopping is recorded as a separate trip. The distance parameter γ^{g} captures the disutility for traveling an additional log mile on a trip, which is measured as the distance from home → retailer → home when shopping at a single retailer or home → retailer 1 → retailer 2 → home when shopping at multiple retailers. The shopping center parameter γ_1^{g} represents the value of shopping at stores within the same shopping center, and captures the economies of scale of visiting nearby stores on the same trip. The complementarity parameter Γ_b captures utility of shopping at the different retailer bundles within the same trip.

In a first step, the maximum likelihood estimator gives consistent estimates for distance and shopping center parameters $\gamma^{g}, \gamma_1^{g}, \mathbf{\Sigma}$. In a second step, under the assumptions of the model, an instrumental variables regression gives consistent estimates for α^{g}, Γ_b (McFadden, 1978; Berry, 1994; Bayer et al., 2007).

Identification: The identifying assumption is that variation in bundle attributes (i.e., distance between households and retail bundles) is independent of any unobserved demand shocks. Plausibly exogenous variation in distances comes from timing of retailer entry and exit. While the event itself may be driven by changing demand, the exact event date is likely exogenous, creating within-household variation needed to estimate parameters. Additionally, conditioning on household observables mitigates the concern that time-varying demand shocks or price endogeneity biases these estimates. I condition on variables correlated with household value of time (income, unemployment, and education status), household locations (zip code), and market-bundle fixed effects, delta (including time). The average utility parameter δ_{bt}^{g} is identified from variation in bundle popularity (measured as retailer shares in the data) holding all other variables (such as distance) constant. The optimal parameters are chosen such that the model-implied shares match the observed shopping frequency in the data.

The marginal disutility for prices is determined by the extent to which average bundle popularity drops as (instrumented) prices rise. The intuition for the price instrument is as follows: assuming demand shocks are local but cost shocks are shared regionally, the average price from the same retailer in other cities is a valid supply shifter (Hausman et al., 1994). Since many prices are set irrespective of location (DellaVigna and Gentzkow, 2019; Hitsch et al., 2021) and costs shocks are passed through regionally (Butters et al., 2022), instrumenting for prices in this way will likely reflect variation from regional costs shocks. The complementarity parameters are identified by the relative popularity of the retailer bundle (measured in terms of average utility) holding instrumented prices fixed. Further details on the identification are detailed in Appendix B.3.

Results: Price and distance parameters are reported in Table 28. As expected, prices and distance coefficient are negative, and lower-income consumers are more price elastic than higher-income consumers. Estimates report a strong distaste for distance: a 1% increase in price is equivalent to a 1.2%, 1%, and .9% increase in distance for low, middle, and high income consumers, respectively. These results imply that households are unlikely to switch shopping centers for small price increases, indicating that limiting even local competition significantly softens price competition. These results are robust to alternate specifications, such as accounting for non-linearities in distance preferences or measuring distance in terms of travel time. Alternate specifications and the full set of parameter estimates are discussed in Appendix B.3.2.

Figure 24 reports the complementarity parameters, Γ_b, showing large heterogeneity across retailers. The excluded group is the outside good, interpreted as the "best" of the other stores for each household. Estimates of own quality are shown in Figure 23, showing that Costco, Sam's Club, Meijer, Trader Joe's and Whole Foods are high-quality stores and Liquor Stores, Drug Stores, Other Food Stores, Dollar Stores, and Aldi have lower qualities. Larger anchor stores that purportedly generate shopping externalities tend to have relatively higher quality, and smaller stores tend to have relatively lower quality (Pashigian and Gould, 1998).

The heterogenous complementarities generate externalities across retailers. High quality stores drive demand to their locations, incentivizing lower-quality retailers to enter. Depending on the complementarity values, co-location can either benefit both retailers, benefit the lower-quality retailer, or benefit neither retailer. Figure 27 illustrates the case when only the lower-quality retailer benefits from co-location, and Figure 28 shows a range of complementarities where in both stores, a single store, and neither store benefits from co-location. When only a single store benefits from co-location, these externalities create an incentive for exclusive dealing.

These externalities can create a hold-up problem when higher-quality retailers will not enter if its unprofitable to co-locate with a lower-quality retailer (e.g. Retailer 1 in Figure 27). This is especially salient when expected profits are lower. Contracts can solve this hold-up problem, resulting in entry of higher-quality retailers. Exclusives can also facilitate co-location of complementary retailers (or retailers where $\Gamma_{12} > \Gamma_1, \Gamma_2$), which can benefit both consumer welfare and retailer profitability. The exclusive comes at the cost of exclusive a more-efficient lower-quality entrant, whose entry could overall net-benefit consumers through increased price competition.

External validity: The demand estimates predict which retailers benefit the most from exclusive dealing. Figure 29 shows the correlation between the estimated profitability from excluding rival retailers and the prevalence of exclusive dealing for different retailers. As the computed profitability of excluding rival retailers increases, the prevalence of exclusive dealing increases as well, and the correlation is .72. For each retailer, the profitability of excluding a rival is computed as the percentage change in profits from a retailer co-locating or locating in a different shopping center, holding distances between retailers and consumers fixed: $\frac{\pi_j(dist_{jk}=d)}{\pi_j(dist_{jk}=0)} - 1$ for each retailer j and rival retailers k. Importantly, the expected profitability is computed with consumer panel data only. The prevalence of exclusive dealing is computed as the fraction of retailer locations that prohibit specific products (these products are grocery, drug/pharmacy, liquor, or dollar/convenience). The prevalence of exclusive dealing is computed with the exclusive dealing records from the Cook County recorder office.

This strong correlation result provides external validity to the estimation and documented exclusive dealing contracts. The product estimation captures the substitution patterns which are relevant for exclusive dealing. The exclusive dealing contracts are predictive of the estimates-implied profitabilities of foreclosure.

5.2 Retail Real Estate Market

Let $m \in M_t$ be the set of potential locations available in market t (year, geography). Under the model assumptions and constructed data, landlords set prices and retailers choose locations to enter in each market. The model is estimated in reverse order of entry: first small retailer parameters and then large retailer parameters. Further detail for the identification and estimation is included in Appendix B.3.3 and Appendix B.3.4.

Small retail real estate parameters: First, total costs of entry are computed for the small retail real estate market (total costs are tenant fixed costs of entry plus landlord marginal costs).

Identification: The expected variable profit at which a retailer enters a property pins down the total costs of entry. As expected variable profits increases, the probability of retailer entry increases as well; locations with lower fixed costs will be entered at lower expected variable profits. Over time, the retail landscape and household demographics change, creating variation in expected variable profits at each location. Similarly, over time, new developments and retailer exits generate variation in the amount of space available. The correlation between expected profit and observed entry rates over time identifies the total costs of entry in each location. Total costs are identified by equating probability and observed entry

$$g_{small}(TC) = s_m^{\text{data}} - \tilde{\mathbb{P}}_m(TC)$$

where s_m^{data} is the average fill rate across markets (here time) for each location m, $s_m^{data} = \frac{1}{T}\sum_{m \in t} \frac{\sum_j size_j 1\{j \in m_t\}}{tot.\ size\ avail._{mt}}$. Shares m is the fraction of available space that is filled in location m in market t, averaged across markets. The available space is defined as the minimum of the available space and the maximum space entrants could plausibly enter. $\tilde{\mathbb{P}}_{jmt}$ is the simulated probability retailer j enters location m in market t. The probability has two parts. First, retailer j has to choose to enter location m, taking into account expected variable profits from the new location, existing locations, and the simultaneous choices of other retailers. Second, conditional on choosing location m, retailer j has to win entry. Due to exclusivity and capacity constraints, entry is not guaranteed. For small retailers, entry is determined at random among the retailers that choose to enter. $\tilde{\mathbb{P}}_m$ are the location-level size-weighted entry shares implied by the model. $\tilde{\mathbb{P}}_m$ is the average across markets, $\tilde{\mathbb{P}}_m = \frac{1}{T}\sum_{j,m\in t}\tilde{\mathbb{P}}_{jmt}\frac{\text{size}_j}{\text{tot size avail}_{mt}}$.

Implementation: Total costs are estimated with the method of simulated moments (MSM). For each hypothesized parameter, $\hat{TC}$, I simulate S idiosyncratic entry shocks ϵ_{jms}. I then computed the optimal mixed strategy for each retailer. Each small retailer chooses to enter up to two small locations per market, where no entry is the outside option. I iterate across retailers until the entry probabilities converge. The estimator then chooses parameters $\hat{TC}_m$ to match observed and simulated entry rates (averaged over s).

Second, total costs are split into small retailer fixed costs and landlord marginal costs. First, assuming landlords profit maximize, marginal costs are computed from observed rents and estimated entry shares for each location, $\hat{mc} = r_{jmt} - 1/(1 - E[\hat{s}_{mt}])$. Then, marginal costs are subtracted from total costs to compute fixed costs, $\hat{F}_m = \hat{TC}_m - \hat{mc}_m$.

Large retail real estate parameters: The parameters in the large retail real estate market are the tenant fixed costs, F_m, landlord marginal costs, mc_m, and exclusive dealing parameters $\mu_\theta, \sigma_\theta$. Since rents for the contracts that are not chosen are unobserved in the model, large retailer entry decisions and landlord rents are estimated jointly.

Identification: The following moments are important in identifying these parameters.

$$g_F(\psi) = 1 - \frac{\tilde{\mathbb{P}}_m(\psi)}{s_m^{\text{data}}}$$
$$g_{mc}(\psi) = 1 - \frac{\tilde{r}_{jma}(\psi)}{r_{jma}^{data}}$$
$$g_{\mu_\theta}(\psi) = 1 - \frac{\tilde{\mathbb{P}}_{jE}}{s_{jE}^{data}}$$
$$g_{\sigma_\theta}(\psi) = 1 - \frac{\text{Var}_j(\tilde{\mathbb{P}}_{jE})}{\text{Var}_j(s_{jE}^{data})}$$

Fixed costs are primarily pinned down with g_F, which correlates observed entry probability with estimated profitability of entering each location. Higher estimated profitabilities but lower entry rates lead to higher estimated fixed costs. Similar to the small retailer total costs, the fixed costs are identified with the location-level entry shares and observed average entry share. In the case of entry conflicts, the most profitable large retailer enters (this differs from the small retail market, where all small retailers have the same size and pay the same rent).

Landlords set rents given marginal costs, other potential locations in the market, and expected variable profits for each retailers. Marginal costs are primarily identified from moment g_{mc}, equating simulated optimal rents, $\tilde{r}_{jma}(\psi) = \frac{1}{S}\sum_s \hat{r}_{jmas}(\psi)$ with observed rents, r^{data}_{jma}. Then, the fixed costs of entry are identified by subtracting marginal costs from the total costs. Without the observed rents marginal costs and fixed costs are not separately identified.

Exclusivity parameters are primarily identified from moments g_{μ_θ} and g_{σ_θ}. A higher μ_θ results in a higher rate in exclusive dealing across all retailers that cannot be explained by location fixed costs, landlord marginal costs, or expected retailer profitabilities. g_{σ_θ} pins down the dispersion across retailers. $\tilde{\mathbb{P}}_{jE}$ is the simulated probability retailer j enters market t with an exclusive dealing agreement, computed as an average across simualted draws S and markets T, $\tilde{\mathbb{P}}_{jE} = \frac{1}{TS}\sum_{t,s} 1\{a_j = E\}$. s^{data}_{jE} are the observed rates of exclusive dealing, computed as $s^{data}_{jE} = \frac{1}{T}\sum_t 1\{a_j = E\}$.

Implementation: The parameters are estimated with the simulated method of moments. For each hypothesized parameters $\psi = (F_m, mc_m, \mu_\theta, \sigma_\theta)$, and simulation s, I simulate values of idiosyncratic shocks ϵ_{jms} and θ_{js}. Then, retailers choose optimal mixed strategy and landlords choose optimal rents. Each large tenant chooses a probability of entering each location as well as no entry (the outside good) to maximize profits. Each landlord sets an exclusive and a non-exclusive rent for each retailer to maximize profits. I iterate over the best responses over all landlords and tenants until convergence. The estimator chooses parameters $\hat{TC}_m$ to match observed and simulated entry rates (averaged over s).

The location choice model has multiple equilibria since the probability of entry depends on the simultaneous choice of other large tenants. First, I test for multiple equilibria by trying forty starting points across a large range. I find multiple equilibria, but I also find similar results in terms of the probabilities of entry and the rents. I choose the estimate that delivers the lowest objective function. Further details on identification and estimation are in Appendix B.3.4.

Results: Figure 32 plots the density of fixed costs the small retailer must pay to enter, and maintenance costs the landlord pays to maintain the space for small retailers. Fixed costs are measured in 2016 dollars per square foot, scaling linearly with store size to capture the total cost of entry. The modal fixed cost of entry is 160 $ per square foot, but estimates span a wide range reflecting heterogeneity in tenant entry and responsibility (from replacing a similar vacant storefront to building a new store for the former and from paying base rent only to covering all operating expenses including taxes, maintenance costs, and rent). Marginal costs are measured in 2016 U.S. dollars per square foot per year. On average, marginal costs are half of rents.

Figure 33 plots the distribution of fixed costs and marginal costs in the large retailer market. Modal fixed costs are 92$ per square foot and modal marginal costs are 9$ per square foot per year, all in 2016 U.S. dollars. At a given location, costs for large and small retailers are similar in magnitude for both large and small retailers (measured in units of in 2016 U.S. dollars per square foot per year). With regard to exclusive dealing, the estimated high fixed costs of entry are consistent with the need for contracts to induce retailer entry.

Table 35 reports estimates for the exclusive dealing parameters, showing that μ_θ is small and insignificant and σ_θ is small. This shows that the information asymmetry between these retailers and landlords is small; landlords correctly estimate the value of exclusive dealing to retailers on average. Additionally, incorporating μ_θ and σ_θ allows a test of the model: when the parameters are small and insignificant, exclusivity is well-explained by the estimated surplus and the value of the exclusive dealing contract is primarily to protect entering retailers against future competitor entry.

Two hypothesized externalities could have explained the observed explicit exclusive dealing contracts: shopping center externalities driven by differences in retailer quality (Marvel, 1982; Klein and Murphy, 1988), and information asymmetries between landlords and tenants (Katz, 1989; Calzolari and Denicolò, 2013). The combination of (a) heterogeneity in retailer quality, (b) high fixed entry costs, and (c) small estimated exclusive-dealing parameters suggests that shopping center externalities—rather than information asymmetry—are the primary driver of explicit exclusive dealing (Bernheim and Whinston, 1998).

Model fit: To assess model fit, I simulate the equilibrium in the small and large retailer market with the estimated parameters. Given potential locations, existing retailers, and estimated parameters, I simulate the landlord's problem (choosing prices), tenant problem (choosing locations and contracts for large) and the following small retailer problem (for large). Figure 34 reports the in-sample model fit, plotting observed entry rates in each large retailer market against the simulated entry rates. The simulated and observed rates are correlated but there are some markets where the model predicts higher entry rates than observed and there are there are other markets where the model predicts lower entry rates than observed.

External validity: I use industry reports, operating costs reported in CompStak, and detailed data on the exclusive dealing contracts to validate the model. These data are not used in the estimation and provide a test of the model.

With regard to fixed costs, industry reports publish a fixed costs between 37-580 per square foot, consistent with the estimates reported.[25] These reports also stress a wide range of estimates across different locations even in close geographic proximity, consistent with wide-ranging estimates. With regards to marginal costs, I compare model estimates with operating expenses reported in CompStak, which capture the cost of maintaing the property. The model marginal costs estimates are 13$ per square foot per year, closely matching the averaged observed operating expense in the data (12.77$ per square foot per year).

Because exclusive dealing enters only as a binary indicator, I use details of the exclusive dealing contracts – the set of blocked products – for out-of-sample validation. Specifically, I test whether the model predicts exclusive dealing provisions that foreclose product-market competition and, as a placebo, whether it fails to predict provisions unrelated to competition. The results support both predictions. To do so, I run the following regression

$$D_{jmtE} = \Phi(\alpha + \beta \Delta E[\pi_{jmta}] + \lambda_{year} + \phi_{geo} + \epsilon_{jmt})$$

where D_{jmE} is 1 if retailer j enters with an exclusive dealing agreement E at location m in market t and 0 if the retailer enters without an exclusive dealing agreement, $\Delta E[\pi_{jma}] = E[\pi_{jmtE}] - E[\pi_{jmtN}]$ is the expected profit premium of exclusivity, λ_{year} are year fixed effects and ϕ_{geo} are geographic fixed effects.

Estimates of β are reported in Table 36. The first column subsets to exclusive dealing contracts that block competition in the product market (i.e., at least one of the following retail types: grocers, drug stores, pharmacies, dollar stores, convenience stores, liquor stores, food stores, and retail). The first regression is therefore tests whether the estimates predicts exclusive dealing targeted at curbing product market competition. Results show that expected profitability is positively correlated with the observed relevant exclusive dealing contracts.

The second column of Table 36 subsets to non-relevant exclusive dealing contracts. These contracts do not block any of the relevant categories, and instead block at least one of the following categories: abortion clinics, animals, auditoriums, boats, bowling alleys, car repair, cinema, dance clubs, educational facilities, employment agencies, gyms, florists, funeral parlors, garbage dumps, gasoline, government offices, guns, hair salons, hazards, HIV clinics, illegal establishments, industrial facilities, karate, laboratories, laundromats, lodging, manufacturing, hospitals, monuments,

[25] In 2016 dollars, industry reports suggest tenant fixed cost of entry ranges from (a) 87.22-157 per square foot (these estimates report 92$ per square foot for large retailers and 160$ per square foot for large retailers). ; 370-580 for new construction or 275$ - 432$ in 2016 U.S. dollars; (b) 159.74$ per square foot for a 1,000 square foot store in the Chicago MSA or 122$ per square foot 2016 U.S. dollars; (c) 50-100 per square foot for simple stores and 150-250 per square foot high-cost retailers or 37$ - 190$ in 2016 U.S. dollars.

nail salons, offices, political parties, print shops, production, recreational centers, religious facilities, residential, shoe repair, skating rinks, sports, or veterinarians. These exclusive dealing contracts are put in place to limit competition for parking, or maintain a certain shopping mall aesthetic, not to limit product market competition. The estimates suggest that the gain in product market profits does not predict the presence of these non-relevant exclusive dealing contracts.

This suggests that model-implied high probability of entry with exclusive dealing is correlated with exclusive dealing contracts that block competitor entry, but is uncorrelated with exclusive dealing contracts that prohibit other types of use (e.g. contracts that prohibit the use of the space as a garbage dump or toxic waste facility).

6 Effects of Exclusive Dealing

6.1 Effect of Exclusive Dealing on Retailers and Landlords

With the estimated parameters, I simulate a counterfactual where landlords cannot explicitly contract on exclusivity. In this counterfactual, landlords now set a single price for each large retailer.

Table 2: Entry Probabilities by Geography for Large Food Retailers

Geographic Area	Observed (%) *Data*	Observed (%) *Estimated*	Counterfactual (%) *Simulated*	Difference (p.p.)
CBD	16.88	15.49	15.49	0.00
North Chicago	21.38	21.08	19.61	1.47
North Suburban	13.66	16.14	13.11	3.03
Northwest Suburban	12.03	14.94	14.80	.14
South Chicago	11.69	10.00	6.20	3.8
South Suburban	11.70	12.47	10.51	1.96
West Cook County	19.23	22.50	25.35	-2.85

Notes: Counterfactual: Average probability of a large food retailer in a market, in the data (Observed), with exclusive dealing (Estimated) and counterfactual ban on explicit exclusive dealing (Simulated).

Counterfactual results show that exclusive dealing contracts encourage entry in Chicago. Table 2 shows the difference in entry probabilities for retailers in each geographic area, averaged over retailers and over years. The results show that in all areas except West Cook County, exclusive dealing increases the probability of entry for large grocery retailers. The effect is most pronounced in the poorest and least population dense market, South Chicago, where probability of entry goes from 10% to 6% without exclusive dealing. The interpretation is that exclusive dealing contracts are necessary to ensure entry in the most under-served markets. Some suburban areas have the second largest drop in probability of entry in the counterfactual without exclusive dealing. This is likely explained by the retail environment of suburban neighborhoods: suburban areas tend to have a limited supply with fewer shopping malls surrounded by many houses. Without the exclusive contract, the probability of competitor entry decreases the probability of retailers entering in the first place. The central business district (CBD) and North Chicago have the lowest difference in entry without exclusive dealing. These neighborhoods are dense both in terms of retail and population, and retail often exists in stand alone locations. Finally, West Cook County and South Suburban have lots of land dedicated to commercial property, where exclusive dealing has little impact. As a result, the exclusive dealing contracts were least effective in these neighborhoods.

Table 3: Counterfactual Retailer Entry Rates and Profitability

Retailer	Entry Rates *Percentage Points*	Profits *Percent Change*
Costco	-2.31	-2.96
Walmart and Sam's Club	-1.93	-4.88
Target	-3.01	-13.1
Meijer	-2.74	-0.99
Whole Foods	-1.13	-7.24
Jewel Osco (Safeway)	-1.95	-5.71
Mariano's (Kroger)	-3.00	-4.62
Food 4 Less (Kroger)	-2.07	-1.44
Aldi	-2.15	-2.45
Trader Joe's	5.07	1.01
Liquor	2.26	.07
Drug	3.23	.03
Dollar	3.86	2.59

Notes: The first column lists the average change in entry rates across all market for each retailer. The column reports Counterfactual (%) - Observed (%). The second column lists the percent change in profits for retailers conditional on entry, averaged across each markets. The column reports Counterfactual ($/square foot /year) / Observed ($/square foot/ year) - 1. The second column compares counterfactual and estimated profits in a square foot of an actual store.

Relative to a world with explicit exclusive dealing, all major grocery stores except Trader Joe's reduce entry. Table 3 shows difference in entry rates for each large grocery retailer and small co-locating retailer. In the data, entry rates are computed as the number of entries divided by the number of locations available to each retailer. In the model, entry rates are computed by summing the probability of entry into each location divided by the number of locations a retailer can enter. Landlords have two ways to encourage entry: lower prices and exclusive contracts. Even with exclusive dealing, large retailers rents are already low, as shown in Figure 5. Without exclusive contracts, prices cannot go lower without landlord bankruptcy. Smaller retailers have slightly higher profits and increase their probability of entry when exclusive dealing is banned. These retailers benefit from a counterfactual world where landlords cannot contract on exclusivity. In the counterfactual, when large retailers still enter, small retailers follow. When large retailers no longer enter, there still may be some demand for small retailer entry.

Table 4: Counterfactual Profitability For Landlords (Percent)

Percentile	5th	25th	50th	75th	95th
	-8.50	-7.25	-3.51	-1.41	1.20

Notes: Counterfactual: average percent change in profits for landlords, averaged across landlords. A negative numbers indicates that banning exclusive dealing is unprofitable for landlords.

The percentage change in landlord profitability is shown in Table 4. The effects of a ban on exclusive dealing are heterogeneous across landlords, but most landlords benefit from exclusive dealing, with only 1% of landlord profit increasing as a result of a ban on exclusive dealing. Exclusivity allows landlords to further monetize their properties.

The counterfactual results speak to which part on the theory of exclusive dealing that apply in this setting. Landlords are paid to exclude rival retailers, consistent with the theory that an incumbent must pay for exclusivity (Posner, 1976; Bork, 1978). Landlords and large retailers profit from exclusive dealing, while small retailers like dollar stores would benefit from a ban: landlords and large retailers to contract to keep out small retailers like dollar stores. In doing so, landlords extract additional rents from large retailers and large retailers either enter more or extract additional profits from consumers. In the later case, exclusive dealing is consistent with foreclosure of an efficient entrant by an incumbent and the incumbent's contracting party (Aghion and Bolton, 1987; Abito and Wright, 2006).

6.2 Effect of Exclusive Dealing on Consumers

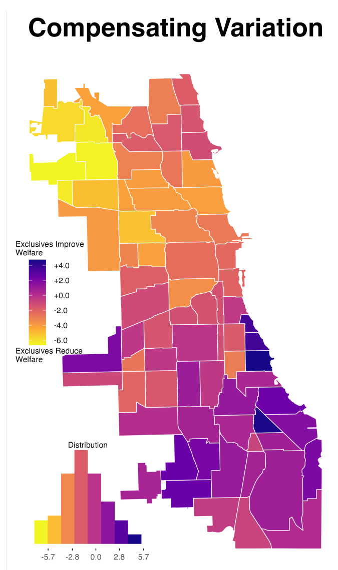
Finally, I study which consumers benefit from exclusive dealing. Consumer surplus is measured as the compensating variation, the compensation required for a household in the observable world to be indifferent with the distribution of retail locations and prices in the counterfactual world (no exclusive dealing), computed as

$$\mathbb{E}_{\epsilon_{ib}}\left[CV_i\right] = \frac{1}{I}\sum_i \left(\frac{1}{\alpha^g}\left[\ln\left(\sum_{b\in\mathcal{B}}\exp\left(u_{ib}(P_b^0, d_{ib}^0, \phi)\right)\right) - \ln\left(\sum_{b\in\mathcal{B}}\exp\left(u_{ib}(P_b^{cf}, d_{ib}^{cf}, \phi)\right)\right)\right]\right) \quad (10)$$

where u_{ib} is the utility from Equation 1 and ϕ are all the other non-price and non-distance parameters that are assumed to remain unchanged in the counterfactual. 0 denotes the observed world and cf denotes the counterfactual. $\mathcal{B}$ are the set of bundles computed in the demand estimation. The compensating variation is measured in terms of relative prices.

Table 7 shows the welfare effects of exclusive dealing in each market in Chicago. Positive values indicate that exclusives improve welfare and negative values indicate that exclusives reduced welfare. To compute the plot, I assume households live at the population-center of their census block group and then compute welfare for each household by census block group and income. I then compute the average welfare effect for each Chicago area (i.e., a large neighborhood).

Figure 7: Gain in Consumer Welfare From Exclusive Dealing



Notes: Plot shows the average welfare effects across households in different Chicago areas, plotting the observed - counterfactual. The map restricts to areas in the city of Chicago. The plot shows that exclusive dealing is welfare-improving in the lower-income areas (towards the bottom of the map), as well as directly far north of the central business district, and welfare.

Wealthier areas around downtown and the north side of Chicago would most benefit from an exclusive dealing ban, and under-served areas in south side Chicago most benefit from exclusive dealing. Key to the effect is that exclusives are necessary for entry when profit margins are low. Without exclusive dealing, large retailers creates demand for small retailers and small retailers enter. When the neighborhood cannot sustain both retailers, the large store does not enter in the first place. In these neighborhoods, exclusive dealing leads to increased availability of higher-quality retailers (the shopping centers preferred by consumers), consistent with the theory that exclusive dealing allows contracting parties to provide higher-quality products to consumers (Marvel, 1982; Klein and Murphy, 1988). When the neighborhood can sustain both retailers and both enter, consumers benefit from shorter distance trips to multiple stores.

Figure 35 shows the breakdown by price and distance. Exclusive dealing softens price competition, and prices would be lower for all consumers in the counterfactual. The counterfactual predicts that prices would be .6% higher without exclusive dealing. The distance effect mirrors the overall welfare effect.

Finally, I quantify the effect of exclusive dealing on the number of households living in food deserts, defined as the number of zip codes without a grocery stores (Allcott et al., 2019). I compute the expected number of grocery stores in each zip code in equilibrium with and without exclusive dealing between 2001 and 2022. Without exclusive dealing, 6.5% more households would be living in food deserts over the sample period.

6.3 Washington DC Temporary Ban on Exclusive Dealing in Grocery

In 2014, policymakers in Washington DC temporarily banned exclusive dealing in the grocery sector. I use this ban to test the implications of the model – which is estimated on data from Chicago, IL – in Washington DC. The model predicts that this policy should improve grocery count in higher-income neighborhoods and reduce grocery count in lower-income neighborhoods.[26] I therefore compare grocery chain counts in before and after the 2014 policy across high and low income neighborhoods. While both high-income and low-income neighborhoods are treated, the model predicts different treatment effects for the different neighborhoods.

The policy in DC specified a temporary ban on exclusive dealing in the grocery store sector. Motivated by a Safeway that would have closed and limited future grocery store entry, a bill was passed that temporarily banned exclusive dealing for grocery stores.[27] The policy was largely targeted towards exclusive contracts signed after grocery store exit, but is written broadly enough to cover the contracts signed at entry.[28]

> "To establish, on a temporary basis, that it shall be unlawful for the owner or operator of a grocery store to impose a restrictive land covenant or use restriction on the sale, or other transfer, or lease of real property used as a grocery store that prohibits the subsequent use of the property as a grocery store." - Grocery Store Restrictive Covenant

[26]The model affects count through lower expected variable profits in the downstream market.

[27]See news coverage here and the bill here.

[28]Consider, for example, a dollar store that wants to enter in the shopping mall ("the property") and argues it qualifies as a grocery store ("subsequent use as a grocery store"). This becomes legally contentious and subject to debate, see the legal discussion here: "The lack of a precise definition for a "sandwich" [here, "grocery"] is particularly important in the context of restrictive covenants, for example, exclusivity clauses and non-compete agreements. Food retailers may include such restrictive covenants on their leases; limiting the types of food establishments that can be built and operated in their vicinity. In fact, that was the issue in *White City Shopping Ctr., LP v. PR Restaurants, LLC*, where the decision hinged upon the definition of a sandwich."

Prohibition Temporary Act Of 2014, Passed December 5, 2014

I estimate a two-way fixed effect event study regression with data on grocery chain data from SNAP in Washington DC (county) from 2009-2019. I estimate the specification

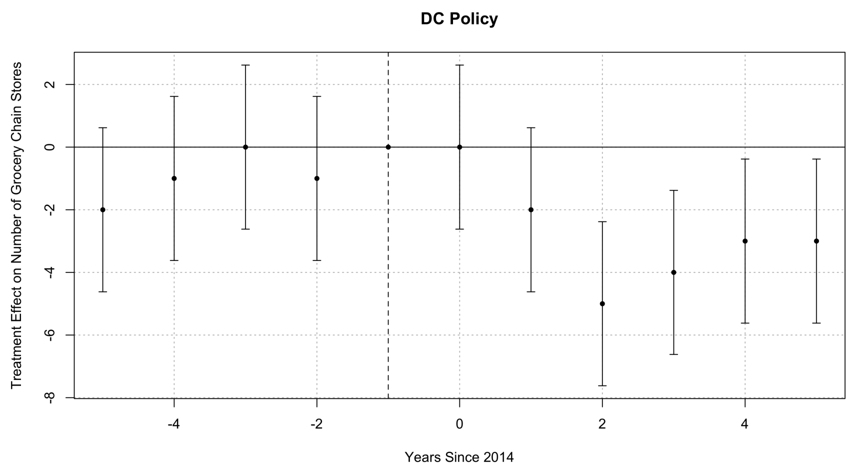
$$num\ stores_{it} = \alpha_i + \lambda_t + \sum_t \gamma_t D_{it} + \epsilon_{it}$$

where α_i is the income group fixed effect, λ_t is a year fixed effect, D_{it} is the years before or after the 2014 policy for the low income group. The parameter of interest is γ_t, differential amount by which the low-income neighborhoods experience a change in number of grocery stores upon the policy passing. I first classify census tracts into high- or income- rank neighborhoods. I (1) compute the income rank for each census tract by year between 2009 and 2019 (2) assign each tract their modal income rank over time as most tracts maintain the same income rank over time. Since this policy affected grocery stores only, and since chain grocery stores are the grocery stores with exclusive dealing contracts, I compute the outcome variable $num\ stores$ as the number of chain grocery stores in the high- or low-income neighborhoods i in year t.

I present results in Figure 8. The results compare high and low income neighborhoods before and after the policy. The lack of pre-trends show that before the policy, grocery count in high- and low-income DC neighborhoods followed the same trends. After the policy, the low-income neighborhood has 4 fewer chain grocery stores on average than high-income neighborhoods relative to the pre-period. The results are consistent with additional entry in high-income neighborhoods and additional closures in low-income neighborhoods. I note that the policy was implemented towards the end of 2014, consistent with a null result in the first year of the policy.

There are a few limitation to this external validity. First, any event that occurred simultaneously in 2014 that differentially changed grocery counts across high and low income areas in DC is not accounted for here. While I are unaware of any such event, results may nevertheless be driven by a different shock from the same year. Second, since I only have a single policy that curtailed exclusive dealing in the period where I have data, I am effectively limited to a single observation. Third, the policy is primarily targeting a different type of contract (contracts signed upon exit). However, the policy is relevant because it was written in general enough terms to apply to exclusive dealing contracts signed upon entry and because the policy reduces expected variable profits at entry by limiting contracts that raise chain retailer profits. Fourth, the time series is limited by two bookend events: before 2009, the great financial crisis likely had differential effects on grocers in high and low income locations, and after 2019, the COVID-19 pandemic likely had differential effects on grocery entry and exit in high and low income neighborhoods.

Figure 8: Effect of Exclusive Restriction Policy on Washington DC



Notes: Plot shows the differential effect of exclusive dealing policy on low-income versus high-income location in Washington DC. A negative value means fewer stores in low-income locations relative to high-income locations. *Source:* SNAP grocery chain stores in Washington DC counties. Estimated on data from 2009-2019.

Despite these limitations, this policy is important to study because it is the *only* policy change that affects exclusive dealing provisions during the study. I find that the results of the model predict the outcomes observed in the data.

6.4 Exclusive Dealing without the "Retail Apocalypse"

Throughout the aughts in and 2010s, online technologies lead to the closure of many brick and mortar stores (Cao et al., 2024). I study the extent to which this change in the retail landscape has affected exclusive dealing contracts. To do so, I compute a counterfactual Chicago where bankrupt retailers and closed storefronts remain open past their close dates. I then compute the rate of exclusive dealing in this market. This counterfactual partly captures the extent to which online shopping has affected commercial real estate contracts (Relihan, 2022, 2026).

Several factors can influence the rate of exclusive dealing. First, more brick and mortar retailers and fewer exits lead to increased demand for retail real estate and lower vacancies. Higher demand lessens the need for exclusive dealing as an inducement for entry. Second, greater presence of other retailers lowers the chances that a grocery store competitor will enter, lowering large retailer demand for exclusivity. On the other hand, as demand for exclusive dealing falls, the price of exclusive dealing falls as well. The net effect is determined by the counterfactual equilibrium.

To compute this counterfactual, I extend the tenure of stores that were supplanted by the internet or moved online: technology and department stores, shown in Table 37. Included are now-bankrupt retailers such as Borders, Bed Bath & Beyond, Blockbuster video, KB Toys and RadioShack. I then re-simulate the equilibrium counterfactual, with the estimated fixed costs and marginal costs.

Table 5: Retail Apocalypse Counterfactual

Variable	Model-Implied Entry	Counterfactual Entry	% Difference (Model vs CF)
Entry	0.491 %	0.592 %	20.57
Exclusive Dealing	.397 %	0.318 %	-19.90
Rents	$23.04/sqft/yr	$24.53/sqft/yr	6.33

Notes: Table presents results of a counterfactual analysis where now-defunct retailers are thriving. The counterfactual has higher entry rates, higher prices, and less exclusive dealing. Results present entry rates, exclusive dealing rates conditional on entry, and prices for large big box and grocery retailers (i.e. large retailers excluding "other stores" and "other food" stores). Note that here entry includes both "other" retailers and is now measured as number of locations with entries divided by number of locations available, instead of by number of square footage entered vs square footage available.

I report rates of exclusive dealing in Table 5. I find less exclusive dealing and higher prices (rents) in this counterfactual, as the potential locations shrink and competition for real estate increases. These results are consistent with the previous counterfactual, where exclusive dealing is being used to induce entry when there is less demand. Given the results of the counterfactual, the decline in brick and mortar stores may help explain some of the rising exclusive dealing rates in Figure 2. If more brick-and-mortar stores move online, the counterfactual suggests that exclusive dealing will be used increasingly as a way for landlords to induce large retailers to enter.

7 Conclusion

This paper is the first to establish the prevalence of these exclusive dealing contracts, their effects on consumer welfare and firm profitability, as well as their distributional effects on both consumers and firms. To do so, I document the prevalence of exclusive dealing contracts scraping data from publicly available leases and deeds. I then provide stylized facts for how exclusive dealing is correlated with prices, retail density, and neighborhood demographics. To quantify its importance, I endogenize exclusive dealing in a model with landlords, retailers, and consumers. This framework enables a counterfactual analysis where landlords and retailers cannot explicitly agree to an exclusive agreement. The counterfactual analysis allows us to understand how exclusive dealing contracts affect where retailers locate, how consumers shop, consumer welfare, and how goods and rental prices are set.

I find that exclusive dealing benefits most landlords, larger chain retailers, and consumers, while small chain retailers would benefit from an exclusive dealing ban. Exclusive contracts allow landlords and large retailers to internalize shopping center externalities. Relative to a counterfactual without exclusive dealing, landlord profitability is higher due to a higher probability of retailer entry and higher rents conditional on entry.Large retailers benefit from guaranteed limited local competition, in turn can enter less profitable locations. Consumers benefit from exclusive dealing when the benefit from increased large retailer entry outweighs the higher prices and longer distances to smaller retailers like drug stores and dollar stores. I find that the welfare effects are heterogeneous across locations, and is most beneficial for consumers living in sparse retail environments.

This paper makes three conceptual points that are relevant for policy. First, this paper highlights the role of exclusive dealing in limiting the creation of food deserts. Second, this paper contributes to the legal and policy debate on exclusive dealing, particularly in grocery.[29] Third, this paper studies a type of non-compete in the land market, highlighting the heterogeneous effects on welfare and profitability.[30]

[29] For example, in retail real estate, the Canada Competition Bureau has begun investigating these exact exclusive dealing contracts in grocery.

[30] This paper makes three conceptual points that are relevant for policy. First, this paper highlights the role of exclusive dealing in limiting the creation of food deserts. Second, this paper contributes to the legal and policy debate on exclusive dealing, particularly in grocery.[31] Third, this paper studies a type of non-compete in the land market, highlighting the heterogeneous effects on welfare and profitability.

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A Exclusive Dealing In Retail Real Estate: Stylized Facts

Prohibited use: Terms vary across retailers, products prohibited, timing, and radius. The language of the exclusive dealing contracts vary from blocking specific retailers (see Figure 37), narrowly-defined product assortments (see Figure 38), and broadly-defined product assortments (see Figure 36). In each case, the contracts (partially) reflect the retailer' perceived competition. For example, Figure 36 shows an excerpt where Safeway prohibits direct competition (grocers, drug stores, liquor stores), competition for parking space (offices, educational facilities), and retailers with different aesthetics (thrift stores, funeral homes).

Duration: The duration of the restriction varies greatly, from only valid while the retailer operates at the premises (see Figure 37), to while the lease is in effect (see Figure 36), to many years after the retailer has left the premises (see Figure 38).

Radius: The radius varies as well, from the exact premises of the store (see Figure 38), to the shopping center (see Figure 36), to specifying a radius (see Figure 37, which specifies a 1 mile radius wherever the landlord or an affiliate owns property).

Neighborhood demographics: Figure 12 reports a histogram of exclusive dealing, neighborhood income, and population density. Table 14 reports regressions of exclusive dealing status on neighborhood demographics or socioeconomic status, finding that exclusive dealing status is uncorrelated with neighborhood demographic characteristics. The table reports

$$\text{excl. deal}_{it} = \boldsymbol{\beta} \boldsymbol{X}_{it} + \sigma_i + \lambda_t + \epsilon_{it}$$

where excl. deal is a binary indicator that is one if a (tract,year) has a contract i with an exclusive dealing contract and zero otherwise. Exclusive dealing in a (tract,year) is then regressed on demographic factors in the census tract, including variables such as median income, population density, travel time to work, ownership of homes, vacancy status, unemployment, share of the population by gender, share of the population by race, census tract fixed effects, and year fixed effects. Since exclusive dealing is present throughout Cook County, Chicago, no clear trends emerge.

Timing: Most contracts are signed upon entry (57%), as shown in Table 10. These are typically signed between a retailer leasing a property and the landlord that owns additional land parcels. Exclusive dealing contracts that are recorder after the retailer enters a location ("during") are often re-leases. Exclusive dealing contract signed as the retailer leaves the property ("exit") are rare (8% or affecting 20 in grocery and big box store in Cook County since the 1980s). For this reason, the analysis focuses on the entry decisions of retailers.

Legal challenges: Challenges to these contracts are largely litigated in court. Typically, restrictive covenants usually holds when the provision is negotiated as a legitimate business interest and are struck down then they are deemed not in the public interest[32]. However, there is a growing concern that restrictive covenants cause food deserts by displacing and foreclosing upon rivals (Leslie, 2021; Kang, 2022; Frerick, 2024; Adeel, 2026). In line with this thinking, several cities have attempted to limit exclusive dealing contracts[33].

Details from Manually-Read Contracts: Tables 12 and 13 show details of several contracts. These details are produced by manually reading a subset (196) of the restrictive covenants and exclusive use contracts for grocery chains in Cook county and documenting patterns observed in the data. This manually collected data illustrates the range of contracts and the types of documents the contracts can be found in.

Own vs lease: Exclusive dealing is found in both rented and purchased properties. For rented properties, the landlord covenants to not rent to certain retailers. For purchased properties, the buyer covenants to not rent to certain retailers for a certain number of years after the sale. Amongst purchased properties within this manual subset, the retailer is imposing restrictions on 30 properties, and buying 8 properties with restrictions. As is the case with the full dataset, the majority of agreements are rented (e.g. in Memorandum instead of Deeds in Table 6), are signed within three years of the grocery store entering the property (i.e. "Entry Timing"), and the restriction only applies locally (i.e. Property or Adjacent Property).

Radius: When the restriction specifies a distance, the distance is small (e.g. the median is .5 miles in the manually recorded data). As a result, the model focuses on the retailer entry decisions on rented properties, and on the effects of exclusive dealing contracts on the local tenant mix.

[32]E.g. of a restrictive covenant holding up: in *Child World, Inc. v. South Towne Centre (1986)* Child World, Inc wanted to vacate the property early but had signed a restrictive covenant limiting competitors, and the "restrictive provision was negotiated as an inducement to enter the lease and in return tenant agreed to 20 years of continuous operation." As a result, the restrictive covenant held up in the court, and as a result Child World could not vacate the premises. E.g. of a restrictive covenant being struck down: a court struck down a restrictive covenant that forbid the operation of a grocery store on a vacant property (similar to the termination restriction in Figure 38), arguing that the covenant was not in the public interest and contributed to food deserts by limiting the availability of grocery stores (*Davidson Bros., Inc. v. D. Katz & Sons, Inc. (1994)*).

[33]In 2005, Chicago attempted to ban restrictive covenants after a Dominick's Finer Foods put a restrictive covenant forbidding future grocery entry on a property in what became a food desert. At first, the Chicago City Council proposed an ordinance to ban restrictive covenants completely. However, the proposal was met by opposition from the Chicagoland Chamber of Commerce and the Illinois Retail Merchants Association. After some negotiation, a measure was passed that bans restrictive covenants put in place on larger (greater than 7500 square feet) when a retailer leaves the community.

B Model and Estimation

B.1 Equilibrium

The equilibrium is characterized by the prices set by landlords in the commercial real estate market, the probability retailers will choose each location, and the prices and share in the product market.

Shares for large retailers in the product market:

$$s_j = \underbrace{\sum_i \omega_i}_{\substack{\text{CBG,}\\ \text{demographics}}} \underbrace{\sum_{j'=1}^{J}}_{\text{retailers}} \underbrace{\frac{e^{-\alpha P_{jj'}+\xi_{jj'}+\Gamma_{jj'}+\gamma d_{ijj'}+\sum \sigma X_{jj'} y_i}}{1+\sum_{j,j'} e^{-\alpha P_{jj'}+\xi_{jj'}+\Gamma_{jj'}+\gamma d_{ijj'}+\sum \sigma X_{jj'} y_i}}}_{\substack{i'\text{s share of shopping at } j \text{ and } j' \text{ together}\\ \text{for } j'=j,\, i \text{ shops at } j \text{ alone}}}$$

$$s_j^g = \underbrace{\sum_{i' \in g} \omega_{i'}^g}_{\text{CBG}} \underbrace{\sum_{j'=1}^{J}}_{\text{retailers}} \underbrace{\frac{e^{-\alpha P_{jj'}+\xi_{jj'}+\Gamma_{jj'}+\gamma d_{i'jj'}+\sum \sigma X_{jj'} y_{i'}}}{1+\sum_{j,j'} e^{-\alpha P_{jj'}+\xi_{jj'}+\Gamma_{jj'}+\gamma d_{i'jj'}+\sum \sigma X_{jj'} y_{i'}}}}_{\substack{i'\text{s share of shopping at } j \text{ and } j' \text{ together}\\ \text{for } j'=j,\, i \text{ shops at } j \text{ alone}}}$$

where s_j is the share of retailer j and s_j^g is the share of retailer j within income group g. Households are assumed to live in the center of a census block group cbg with demographics g, indexed by $i = (cbg, demographics_i)$. Then, ω_i is the fraction of the total population of Chicago who live in i's census block group with a specific income group. Retailer j's share is weighted sum of each household's total probability of shopping at any bundle that includes retailer j. $P_{jj'}$ is the expenditure-weighted sum of prices from both stores, $P_{jj'} = \phi_{jj'}P_j + (1 - \phi_{jj'})P_{j'}$, where $\phi_{jj'}$ is the fraction of expenditure spent on store j across all trips to j and j' together. When a household shops at a single store, $P_{jj'} = P_j, \phi_{jj'} = 1$. $\Gamma_{jj'}$ are the within-trip complementarities of shopping at jj' together or when $j = j'$, shopping at j alone, relative to the outside good. $d_{ijj'}$ is the minimum distance from a household located at i to travel from home to retailer j, retailer j', and back to home. $X_{jj'}y_i$ are the remaining terms, the interaction terms between retailer characteristics and household characteristics. For household characteristics, I use employment status, household size, ethnicity, education. For store characteristics, I use distance to the retailer and both distance and price as robustness. Additionally, household zip5 is included as a control for household heterogeneity across zip5. The assumption is that within zip5, sorting is random with respect to distance to retailers. $\xi_{jj'}$ is a market-level demand shock or quality of shopping at j and j' together. Coefficients α, γ, σ are the coefficients on their respective shocks. The functional form for the shares result form the T1EV assumption of the ϵ_{ib} shock.

The total shares for small retailer store types in the product market:

$$s_j = \underbrace{\sum_i \omega_i}_{\substack{\text{CBG,}\\ \text{demographics}}} \underbrace{\sum_{j'=1}^{J}}_{\text{retailers}} \underbrace{\frac{e^{-\alpha P_{jj'} + \xi_{jj'} + \Gamma_{jj'} + \gamma d_{ijj'} + \sum \boldsymbol{\sigma} X_{jj'} y_i}}{1 + \sum_{j,j'} e^{-\alpha P_{jj'} + \xi_{jj'} + \Gamma_{jj'} + \gamma d_{ijj'} + \sum \boldsymbol{\sigma} X_{jj'} y_i}}}_{\substack{i'\text{s share of shopping at } j \text{ and } j' \text{ together}\\ \text{for } j'=j,\, i \text{ shops at } j \text{ alone}}}$$

$$s_j^g = \underbrace{\sum_{i' \in g} \omega_{i'}^g}_{\text{CBG}} \underbrace{\sum_{j'=1}^{J}}_{\text{retailers}} \underbrace{\frac{e^{-\alpha P_{jj'} + \xi_{jj'} + \Gamma_{jj'} + \gamma d_{i'jj'} + \sum \boldsymbol{\sigma} X_{jj'} y_{i'}}}{1 + \sum_{j,j'} e^{-\alpha P_{jj'} + \xi_{jj'} + \Gamma_{jj'} + \gamma d_{i'jj'} + \sum \boldsymbol{\sigma} X_{jj'} y_{i'}}}}_{\substack{i'\text{s share of shopping at } j \text{ and } j' \text{ together}\\ \text{for } j'=j,\, i \text{ shops at } j \text{ alone}}}$$

The total share for smaller retailers, s_j, is the total share summed over all dollar stores (when j are dollar stores), or all drug stores (when j are drug stores), or all liquor stores (when j are liquor stores), or all other food stores (when j are other food stores), or all other stores (when j are other stores). The total shares is the sum of shares over each location from that store type.

The share for each small retailer in the product market:

$$s_k = \underbrace{\sum_i \omega_i}_{\substack{\text{CBG,}\\ \text{demographics}}} \underbrace{\sum_{j'=1}^{J}}_{\text{retailers}} 1\{d_{ik} = \min_{\tilde{k} \in j} d_{i\tilde{k}j'}\} \underbrace{\frac{e^{-\alpha P_{jj'} + \xi_{jj'} + \Gamma_{jj'} + \gamma d_{ijj'} + \sum \boldsymbol{\sigma} X_{jj'} y_i}}{1 + \sum_{j,j'} e^{-\alpha P_{jj'} + \xi_{jj'} + \Gamma_{jj'} + \gamma d_{ijj'} + \sum \boldsymbol{\sigma} X_{jj'} y_i}}}_{\substack{i'\text{s share of shopping at } j \text{ and } j' \text{ together}\\ \text{for } j'=j,\, i \text{ shops at } j \text{ alone}}}$$

The share for an individual smaller store is s_k, where k is an individual store and j is the retailer or store type (e.g. k is a liquor store and j is the liquor store category). $\tilde{k}$ are the stores that comprise retailer j. Since households take the shortest distance trip, store k's customers are the set of households whose shortest distance trips include store k.

Prices in the product market for large and small retailers:

$$p_j^g = mc_j^g + \left[\frac{\partial s_j^g}{\partial p_j^g}\right]^{-1} s_j^g - \frac{\partial s_j^g}{\partial p_j^g}$$

Both large and small retailers j listed in Table 1 set a unique price for each income group g taking into account total shares and marginal costs. For example, Safeway sets prices $p^g_{safeway}$ for income group g based on a marginal cost $mc^g_{safeway}$ and the share equation $s^g_{safeway}$. Similarly, all dollar stores set the same price p^g_{dollar} as a function of the total shares to all dollar stores s^g_{dollar}

and the marginal costs which are assumed to be common to all dollar stores mc^g_{dollar}.

The small retailer variable profits are computed at the store level while demand parameters are estimated at the store type level. Therefore, the model is misspecified both because prices for individual stores vary within store type which can lead to incorrect prices and demand estimates, and because the misspecification of within-store type competition biases retailer marginal costs. On the former point, the current measured prices capture the average price for each store type relative to other retailers in the market. For the consumers, the model is well specified when the variation in prices within store type does not affect consumer choices. Indeed, when consumers shop at the closest store in the store type to home and when variation in prices within store type is small compared to variation across stores types (or if stores of the same store type have similar price indices to average price index), consumer choices are unlikely to be unaffected by variations in prices within store type. These assumptions are in line with the data. Furthermore, estimated parameters suggest that consumers' disutility for distance dominates the disutility for price at the observed prices and distances, or that consumers are not willing to travel long distances to reduce prices.

For the retailer's marginal costs, the model is well specified when entry decisions are the same whether the retailer sets individual prices or the average price across store types. The first concern is that using an average price across all retailers of the same time is a bad approximation to the original price. This assumption can be corroborated in the data. The second assumption is that misspecification of the small retailer profit function leads to misspecification of the marginal costs, counterfactual prices, and variable profits. Specifically, since the profit equations assumes a single retailer per store type instead of many retailers per store type, this form of misspecification will overestimate marginal costs and overestimate prices. The assumption makes it easier for smaller retailers to enter, regardless of the other locations of retailers.

The probability of choosing location m for large and small retailers in the real estate market:

While the estimation restricts large retailers to choose a single location indexed by m, the model allows for large retailers to choose multiple locations and for small retailers to choose a single location. The equilibrium thus allows large retailer j to choose a strategy profile $\boldsymbol{l}_j$, which can be a discrete choice over multiple locations.

The probability the retailer chooses strategy profile $\boldsymbol{l}_j$ to maximize

$$\max_{\boldsymbol{l}_j} \quad E_{\boldsymbol{l}_{-j}}[\bar{\pi}_{j\boldsymbol{l}_j}] + \sum_{(m,a)\in\boldsymbol{l}_j} \bar{\mathbb{P}}_{jma}(\theta_j 1\{excl.\ deal.\}_{jma} - r_{jma} - F_m + \epsilon_{jm}) + (1 - \sum_{(m,a)\in\boldsymbol{l}_j} \bar{\mathbb{P}}_{jma})\epsilon_{j0}$$

where $\boldsymbol{l}_j \in \mathcal{L}_j$ is a set of landlords m and contracts a retailer j chooses to enter. Let $(m, a) \in \boldsymbol{l}_j$. For large retailers, the contract can be explicitly exclusive or not, $a = \{\text{exclusive, non-exclusive}\}$, and for small retailers, the contract can only be non-exclusive, $a = \{\text{non-exclusive}\}$. If the large retailer chooses a non-exclusive contract, the landlord can still rent to the large retailer exclusively, and the resulting entry would be characterized as non-explicit exclusive dealing. The outside good is choosing no entry.

Expected profits from the outside good are

$$E_{l_{-j}}[\pi_{j0}] + \epsilon_{j0}$$

Expected variable profits are determine by preexisting locations of own and other retailers, the strategy profile $\boldsymbol{l}_j$, and the strategy profile of all other retailers, $\boldsymbol{l}_{-j}$. For large retailers, entry decisions occur simultaneously with other large retailers. For small retailers, location decisions occur after large retailer entry and simultaneously with other small retailers. Variable profits from the product market are determined after all retailer entry.

$$\begin{aligned} E_{l_{-j}}[\bar{\pi}_{j\boldsymbol{l}_j}] &= \sum_{\boldsymbol{l}_{-j}} \mathbb{P}(\boldsymbol{l}_{-j}) \bar{\pi}(\boldsymbol{l}_j, \boldsymbol{l}_{-j}) \\ &= \prod_{j' \neq j} \left(\sum_{\boldsymbol{l}_{j'}} \mathbb{P}_{j'\boldsymbol{l}_{j'}} \right) \bar{\pi}(\boldsymbol{l}_j, \boldsymbol{l}_{-j}) \end{aligned}$$

The expected variable profits depend on the variable profits under each possible combination of other retailer location choice, $\boldsymbol{l}_{-j}$, the probability of each strategy profile from all other retailers, $\mathbb{P}(\boldsymbol{l}_{-j})$, and the realized observed variable profits, $\bar{\pi}(\boldsymbol{l}_j, \boldsymbol{l}_{-j})$, given all retailer decisions $(\boldsymbol{l}_j, \boldsymbol{l}_{-j})$.

When multiple large retailers approach the same location but there are exclusivity or capacity constraints, a limited number of retailers can enter. When there are conflicts, the higher paying large retailer(s) enter.

$$\bar{\mathbb{P}}_{jma} = 1 - \underbrace{\sum_{\boldsymbol{l}'_{-j}} \mathbb{P}(\boldsymbol{l}'_{-j})}_{\text{conflict and no entry}}$$

where $\bar{\mathbb{P}}_{jma}$ is the probability retailer j enters location m with contract a given that it chooses $\boldsymbol{l}_j$ and $(m, a) \in \boldsymbol{l}_j$. $\boldsymbol{l'}_{-j} \in \boldsymbol{l}_{-j}$ is a permutation of other retailer, $-j$, strategy profiles such that a higher-paying combination of retailers will enter and there is an entry conflict where j no longer wins entry. For example, if both retailer j and j' choose location m with contracts (m, a) and (m, a') where $r_{jma} < r_{j'ma'}$ and a' is an exclusive dealing contract that also blocks retailer j, then retailer j would not enter. Capacity constraints are dictated by the landlord's total square footage, and the set of retailers that could feasibly enter and pay the highest total rent to the landlord enter.

Given location choices, entry decisions are deterministic for large retailers. In practice, for each set of location choices $(\boldsymbol{l}_j, \boldsymbol{l}_{-j})$, I first compute if there are possible entry conflicts due to exclusive dealing or capacity. If there are conflicts, the set of possible feasible entry decisions are computed, as are the associated expected landlord profits (expectations are formed over the small retailer location choices). The retailer entry combination that maximizes expected landlord profits is (are) the retailer(s) that enter.

When multiple small retailers approach the same location but there are capacity constraints, a limited number of small retailers can enter. Since small retailer prices are the same for each landlord, the retailer entry is determined randomly with equal probability (e.g. with a coin flip).

$$\begin{aligned}
\bar{\mathbb{P}}_{km}(\boldsymbol{l'}_{-k}) &= \frac{N_{allowed}(\boldsymbol{l'}_{-k})}{N_{total}(\boldsymbol{l'}_{-k})} \\
\bar{\mathbb{P}}_{km} &= \underbrace{1 - \sum_{\boldsymbol{l'}_{-k}} \mathbb{P}(\boldsymbol{l'}_{-k})}_{\text{no conflict and entry}} + \underbrace{\sum_{\boldsymbol{l'}_{-k}} \mathbb{P}(\boldsymbol{l'}_{-k}) \bar{\mathbb{P}}_{km}(\boldsymbol{l'}_{-k})}_{\text{conflict and entry}}
\end{aligned}$$

where $\bar{\mathbb{P}}_{km}$ is the probability small retailer k enters location m given that it chooses location m. $\bar{\mathbb{P}}_{km}(\boldsymbol{l'}_{-k})$ is the probability of winning entry given that small retailer k chooses location m and the other small retailers choose locations $\boldsymbol{l'}_{-k}$, $\mathbb{P}(\boldsymbol{l'}_{-k})$ is the probability other small retailers choose $\boldsymbol{l'}_{-k}$, and $\boldsymbol{l'}_{-k} \in \boldsymbol{l}_k$ are the set of other small retailer location choices that cause capacity conflicts at m. $N_{allowed}(\boldsymbol{l'}_{-k})$ are the set of combinations where small retailer k enters location m given the set of other small retailers that approach determined by $\boldsymbol{l'}_{-k}$, and $N_{total}(\boldsymbol{l'}_{-k})$ are the total number of entry possibilities. If N small retailers approach and there is capacity for one small retailer only, the probability of entry is $1/N$.

In sum, the entry decision for large and small retailers can be re-written as

$$\max_{\boldsymbol{l}_j} \quad A_{\boldsymbol{l}_j} + \vec{B}'_{\boldsymbol{l}_j} \vec{E}_{j\boldsymbol{l}_j}$$

where $A_{\boldsymbol{l}_j}$ is the scalar, observable component of expected profits, $A_{\boldsymbol{l}_j} = E_{\boldsymbol{l}_{-j}}[\bar{\pi}_{j\boldsymbol{l}_j}] - \sum_{(m,a)\in \boldsymbol{l}_j} \bar{\mathbb{P}}_{jma}(r_{jma} + F_m)$, and $\vec{E}_{j\boldsymbol{l}_j}$ is a vector of unobserved retailer-specific profitabilities, which include the idiosyncratic location-specific profitability shocks, ϵ_{jm} and the idiosyncratic exclusivity-specific profitability shocks, θ_j: $\vec{E}_{j\boldsymbol{l}_j} = (\epsilon_{j1}, \epsilon_{j2}, ..., \epsilon_{jm}, ..., \epsilon_{jM}, \theta_j)$. Each draw is independent and identically distributed following the normal distribution, $\epsilon_{jm}, \theta_j \sim N(\mu_\theta, \sigma_\theta^2)$. $\vec{B}'_{\boldsymbol{l}_j}$ is a row vector so that $\vec{B}'_{\boldsymbol{l}_j} \vec{E}_{j\boldsymbol{l}_j} = \sum_{(m,a)\in \boldsymbol{l}_j} \bar{\mathbb{P}}_{jma}(\theta_j 1\{excl.\ deal.\}_{jma} + \epsilon_{jm}) + (1 - \sum_{(m,a)\in \boldsymbol{l}_j} \bar{\mathbb{P}}_{jma})\epsilon_{j0}$. Then $A_{\boldsymbol{l}_j} + \vec{B}'_{\boldsymbol{l}_j} \vec{E}_{j\boldsymbol{l}_j} \sim N(A_{\boldsymbol{l}_j}, \vec{B}'_{\boldsymbol{l}_j} \vec{B}_{\boldsymbol{l}_j})$.

The probability retailer j picks entry strategy $\boldsymbol{l}_j$ is the probability that row $\boldsymbol{l}_j$ gives the highest value of a vector $\vec{A} + \boldsymbol{B}\vec{E}$ where A is an $|\mathcal{L}_j|$ x 1 vector of all the possible location choice strategies $\boldsymbol{l}_j \in \mathcal{L}_j$, $\boldsymbol{B}$ is a $L = |\mathcal{L}_j|$ x (M+1) matrix that scales the M+1 x 1 vector of idiosyncratic shocks (ϵ_j, θ_j), $\vec{E}$, by the appropriate probabilities to determine expected profits. Written, the probability $\boldsymbol{l}_j$ is chosen is equivalent to the probability that it offers higher profits than all other alteratives, or

$$\mathbb{P}\left(\begin{pmatrix} A_1 + \sum B_{1a} E_a \\ A_2 + \sum B_{2a} E_a \\ \dots \\ A_L + \sum_a B_{La} E_a \end{pmatrix} \leq \begin{pmatrix} A_{\boldsymbol{l}_j} + \sum_a B_{\boldsymbol{l}_j a} E_a \\ A_{\boldsymbol{l}_j} + \sum_a B_{\boldsymbol{l}_j a} E_a \\ \dots \\ A_{\boldsymbol{l}_j} + \sum_a B_{\boldsymbol{l}_j a} E_a \end{pmatrix}\right)$$

Or, alternatively

$$\mathbb{P}\left(\begin{pmatrix} A_{\boldsymbol{l}_j} + \sum_a B_{\boldsymbol{l}_j a} E_a \\ A_{\boldsymbol{l}_j} + \sum_a B_{\boldsymbol{l}_j a} E_a \\ \dots \\ A_{\boldsymbol{l}_j} + \sum_a B_{\boldsymbol{l}_j a} E_a \end{pmatrix} - \begin{pmatrix} A_1 + \sum B_{1a} E_a \\ A_2 + \sum B_{2a} E_a \\ \dots \\ A_L + \sum_a B_{La} E_a \end{pmatrix} \geq \begin{pmatrix} 0 \\ 0 \\ \dots \\ 0 \end{pmatrix}\right) \tag{11}$$

and

$$\mathbb{P}\left(\boldsymbol{\Omega}^{\boldsymbol{l}_j}(\vec{A} + \boldsymbol{B}\vec{E}) \geq 0\right)$$

where $\boldsymbol{\Omega}^{\boldsymbol{l}_j}$ is the $L-1$ x L matrix that transform L x 1 vector $\vec{A}+\boldsymbol{B}\vec{E}$ into Equation 11. That is, $\boldsymbol{\Omega}^{\boldsymbol{l}_j}$ multiplies the expected profits such that the expected profits from the chosen locations $\boldsymbol{l}_j$ are subtracted by a vector of the remaining expected profits. Then $\boldsymbol{\Omega}^{\boldsymbol{l}_j}(\vec{A}+\boldsymbol{B}\vec{E}) \sim N(\vec{A}, \boldsymbol{\Omega}^{\boldsymbol{l}_j}\boldsymbol{B}\boldsymbol{B}'\boldsymbol{\Omega}^{\boldsymbol{l}_j}{}')$.

Therefore, $\mathbb{P}_{j\boldsymbol{l}_j}$ is the multivariate normal distribution evaluated at $\boldsymbol{x}=\boldsymbol{0}$ with mean $\boldsymbol{\mu}^{\boldsymbol{l}_j}$ and variance-covariance matrix $\boldsymbol{\Sigma}^{\boldsymbol{l}_j}$ where

$$\boldsymbol{\mu}_i^{\boldsymbol{l}_j} = \sum_l \Omega_{il}^{\boldsymbol{l}_j} \underbrace{\left(E_{\boldsymbol{l}_{-j}}[\bar{\pi}_{jl}] - \sum_{(m,a)\in l} \bar{\mathbb{P}}_{jma}(r_{jma}+F_m) \right)}_{\text{Lx1 vector, each row for each } l\in\mathcal{L}_j}$$

$$\boldsymbol{\Sigma}_{ii'}^{\boldsymbol{l}_j} = \sum_{l,l',(m,a)} \Omega_{il}^{\boldsymbol{l}_j}\Omega_{i'l'}^{\boldsymbol{l}_j} \underbrace{\bar{\mathbb{P}}_{jma}(l)\bar{\mathbb{P}}_{jma}(l')}_{\substack{\text{prob. retailer } j \text{ enters } m\\ \text{with contract } a\\ \text{with strategy } l \text{ or } l'\in\mathcal{L}_j}} \left(1+\underbrace{\theta_j 1\{excl.\ deal.\}_{jma}(l)}_{\substack{\text{excl. deal at } m\\ \text{with strategy } l}} \right)\left(1+\underbrace{\theta_j 1\{excl.\ deal.\}_{jma}(l')}_{\substack{\text{excl. deal at } m\\ \text{with strategy } l'}} \right)$$

and

$$\boldsymbol{\Omega}_{ll'}^{\boldsymbol{l}_j} = \begin{cases} 1 & l=\boldsymbol{l}_j \\ -1 & l=l' \underbrace{\left[\boldsymbol{\Omega}_{\boldsymbol{l}_j}/\{\boldsymbol{l}_j\}\right]_{ll'}}_{\substack{-\text{identity matrix}\\ \boldsymbol{l}_j \text{ col. removed}\\ \mathcal{L}\text{x}\mathcal{L}}} \\ 0 & l\neq l' \underbrace{\left[\boldsymbol{\Omega}_{\boldsymbol{l}_j}/\{\boldsymbol{l}_j\}\right]_{ll'}}_{\text{off-diagonal}} \end{cases}$$

The price landlords set for large retailers in the real estate market:

Each landlord sets two prices for each large retailer that could be feasibly enter to maximize total expected profits

$$\max_{r_{jma}} \sum_{j,a} \underbrace{\mathbb{P}_{jma}}_{\text{prob. choice}} \underbrace{\bar{\mathbb{P}}_{jma}}_{\text{prob. win}} \underbrace{(r_{jma}-mc_m)}_{\text{large retailer}} + \underbrace{E_{\boldsymbol{l}_j}[\pi_m^{small}(\boldsymbol{l}_j)]}_{\substack{\text{exp. profits}\\ \text{small retailers}}}$$

where the first term are the expected profits from large retailer entry, and the second term are expected profits from small retailer entry. Profits from large retailers are a function of the probability of each retailer j chooses location m with contract a, $\mathbb{P}_{jma}$, and the corresponding probability of entry, $\bar{\mathbb{P}}_{jma}$, as well as the profits conditional on entry, $r_{jma} - mc_m$. Profits from small retailers depend on the location choices of all large retailers, and can be written as

$$E_{\boldsymbol{l}_j}[\pi_m^{small}(a_j)] = \prod_j \left(\sum_{\boldsymbol{l}_j} \mathbb{P}_{j\boldsymbol{l}_j} \right) \pi_m^{small}(\boldsymbol{l}_j) \tag{12}$$

$$= \prod_j \left(\sum_{\tilde{a}} \mathbb{P}_{jm\tilde{a}} \right) \pi_m^{small}(\tilde{\boldsymbol{a}}_j) \tag{13}$$

$$= \sum_\rho \mathbb{P}_\rho \pi_m^{small}(\rho) \tag{14}$$

which depends on all permutations of large retailer choices at location m. At location m, large retailers can choose between an exclusive contract, a non-exclusive contract, and non-entry. Thus, $\tilde{a} \in \{\text{exclusivity (E)}, \text{ non-exclusivity (N)}, \text{ non-entry (O)}\}$. For example, with two retailers expected profits from the smaller retailers are $\sum_{\tilde{a}_{j=1}} \sum_{\tilde{a}_{j=2}} \mathbb{P}_{1m\tilde{a}_1} \mathbb{P}_{2m\tilde{a}_2} \pi_m^{small}(\tilde{a}_1, \tilde{a}_2)$. As a second example, if no retailers enter, the expected profitability to the landlord from the small retailers is $\left(1 - \sum_{j,a} \bar{\mathbb{P}}_{jma} \mathbb{P}_{jma}\right) \pi_m^{small}(O)$. In equation 12, the first line shows the expected profits written as all possible entry combinations, the second line shows the expected profits written out as all possible entry combinations at location m, and the third line shows the expected landlord profits where ρ is a permutaion of all the possible location choices.

The landlords prices according to

$$[\text{foc } r_{kmb}] : \mathbb{P}_{kmb} \bar{\mathbb{P}}_{kmb} + \sum_{j,a} \left(\frac{d\bar{\mathbb{P}}_{jma}}{dr_{kmb}} + \frac{\mathbb{P}_{jma}}{dr_{kmb}} \left(r_{jma} - mc_m \right) \right) + \sum_\rho \frac{d\mathbb{P}_\rho}{dr_{kmb}} \pi_m^{small}(\rho) = 0$$

The price landlords set for small retailers in the real estate market:

Each landlord sets a single price for all small retailers

$$\max_{r_m^{small}} \underbrace{\left(s_m^{drug} + s_m^{dollar} + s_m^{liquor} + s_m^{\text{other food}} + s_m^{other} \right) \left(r_m^{small} - mc_m^{small} \right)}_{\pi_m^{small}}$$

where $s_m^{drug}, s_m^{dollar}, s_m^{liquor}, s_m^{\text{other food}}, s_m^{other}$ are the probability of entry for drug, dollar, other food, and other stores, respectively. $r_m^{small} - mc_m^{small}$ is the profits conditional on retailer entry. Then, $s_m^k = \mathbb{P}_{km}\bar{\mathbb{P}}_{km}$ where $k \in$ {drug, dollar, liquor, other food, other}, $\mathbb{P}_{km}$ is the probability small retailer k chooses location m and $\bar{\mathbb{P}}_{km}$ is the probability of entry conditional on choosing location m.

When a large retailer has an exclusive dealing contract that blocks a subset of small retailers – drug, dollar, liquor, and other food – the retailers no longer consider m as part of the choice set.

B.2 Variable Construction and Discussion

B.2.1 Variables – Product Market (Step 4)

Markets: A market is defined as a county x year x bi-week x income group. The assumption is that prices p_{bt}^g and demand shocks ξ_{bt}^g in county x year x bi-week t for income group g vary across retailers j and therefore across bundles b. Households are categorized in three income groups according to numerator.

Choices: Given the decision to shop, consumers choose to shop at one of the 136 bundle options from the most frequented 15 stores, an outside option, or a two-store combination of these retailers. The outside option is any non-food store shopped at that and is interpreted as the most-preferred other store a consumer could shop at.

Prices: Retailer prices are aggregated from bar code to the retailer-income group level. This level of aggregation has several benefits. First, the aggregation is done at the level of the exclusive dealing contracts. Second, this level of aggregation incorporates several features of this market documented in the literature, such as uniform pricing across stores (DellaVigna and Gentzkow, 2019; Hitsch et al., 2021), different price elasticities across different income groups (Thomassen et al., 2017; Atkin et al., 2018; Allcott et al., 2019), and different bundles of goods across different income groups (Handbury, 2021; Brecko et al., 2025).

Bar-code price data is aggregated to the level of retailer. In the data, the bar codes are ITEM IDs in the Numerator data set and unit prices are computed by dividing the price of the good by the number of ounces in that good. I construct a price for each retailer × income group by regressing expenditure-weighted log bar code prices on retailer fixed effects and bar code fixed effects separately for each income group × market (Atkin et al., 2018). Retailer prices are the retailer fixed effects in this regression. The regression includes bar code fixed effects to hold product quality fixed, so that retailer prices are interpreted as the component of prices explained by retailers. Each retailer price represents a relative price in each market × income group, measured in log dollars. Bundle prices of two retailers is the sum of the prices, weighted by the expenditure shares for each retailer (expenditure shares are fixed across the whole sample).

Household Locations: Household locations are placed at the center of their most likely census block group (CBG) using household zip code and demographic information. First, household ZCTA is established using a ZCTA-zip5 crosswalk. Next, household are assigned a probability of living in a census block group condition on their ZCTA, using the ZCTA-to-Block Group allocation factor from the Missouri Census Data Center. Each household is thus has a probability of living in each census block group that overlaps with its zip code. Next, this probability is updated using household characteristics and demographic data from the ACS. Given the household's demographic information, I compute the probability that a household with that demographic feature lives in a certain census block group among the set of block groups it potentially lives in. The original household probability is treated as a prior and updated using Bayes rule with probabilities computed from the ACS. I assigned a household to its most likely census block group, after incorporating the information from the household demographic characteristics and ACS.

Retailer Locations: I compute two measures of retailer locations. First, I have direct data on store locations (latitude and longitude) from Numerator. Second, I compute a measure of "retailer access", or the closest stores to the center of the census block group.

Distances: Distances are computed as the shortest distance trip from home as the crow flies. For trips to one retailer I compute distances as a trip from home → retailer → home. For trips to two retailers I compute distances as: home → retailer 1 → retailer 2 → home.

I find that this is the relevant measure of distance for retailers and policymakers. First, retailers reportedly measure catchment areas by drawing a radius around a potential stores location, and determine the population and local retail competition. This suggests that when forecasting future demand, retailers measure distance from consumer homes as opposed to other consumer locations. Second, policymakers who care about food access also measure distances from consumers' homes to food-providing retailers.

Further, I find that this is a relevant measure of distance in the data. First, I find that consumers shop close to home, and shown in Figure 17, and so access to home is both the accurate and relevant. Second, in Figure 17 I show similar distances between homes and retailers (computed using the store latitude and longitude provided in the data) and the imputed distance between homes and retailers (computed using the closest store to home), with a maximum difference of .111 miles as the crow flies. Third, in Figure 18, I show the correlation between as crow flies distances, which are measured in miles, and OSRM travel times, which are measured in car-driving minutes and find that they are highly correlated but in different numeric units.

Demographics: Demographic characteristics are reported for each household and year. Household preferences are allowed to vary by household income, education, unemployment status, and ethnicity. Preferences for bundles, distances, prices, and shopping at nearby stores are allowed to vary with individual household demographic characteristics.

B.2.2 Variables – Commercial Real Estate Market (Steps 1-3)

Overview: In each market, I observe the set of potential locations, eventual entry, rent and exclusive dealing status. I also observe current retailer locations and household locations. To estimate retailer location choice, I compute the expected variable profits for each possible entry combination. To do so, I merge the data on potential locations (using data from Hubexo, SNAP and Infogroup), eventual entry (using data from SNAP and Infogroup), rents (using data from CompStak), exclusive dealing contracts (using data from the Cook County Recorder) current retailer locations (using data from SNAP and Infogroup) and expected variable profits (using data from the ACS, Census, and our demand estimates, and other retailer locations).

Retailer list: I consider the entry decisions of retailers in Table 6, which are the set of retailers used throughout the analysis.

Markets (large retailers): Chicago is split into geographic areas: the Central Business District (CBD), North Chicago, South Chicago, and surrounding suburbs North Suburban, Northwest Suburban, South Suburban, and West Cook County. Each market is defined as a year x geographic area. Figure 30 shows the geographic boundaries.

Markets (small retailers): Markets for small retailers are zip5 x year.

This yields a total of 4090 markets in the data.

For each market, I compute all possible entry combinations for all retailers as well expected variable profits for each retailer and entry combination. This is not possible for markets with many potential locations. When there are more than 6 potential locations (2% of all markets), I use a k means to cluster locations into smaller markets (market - groups) for tractability. I treat these market-groups as independent markets. I show an example in Figure 31, which shows potential locations in different markets (2018 North Chicago and 2001 North Chicago). On the left, there are only six potential locations large retailers can enter. Here, 2018 North Chicago is treated as a single market. On the right, there are fifteen potential locations large retailers can enter. I split these into three sub-markets, 2001 North Chicago 1, 2001 North Chicago 2 and 2001 North Chicago 3.

Entry Decisions: Large retailers can enter each market at most once and small retailers can enter each market twice. Retailers make separate entry decisions across markets. This limitation on entry is made for tractability to limit the number of entry combinations in each market. However, the limitation is consistent with data. For large retailers: 88% of large retailers have at most one entry per market; 10% of large retailers entering twice or more in a market are "other food" and "other" retailers (i.e. driven by different firms that are lumped together in the same category). 92%

of small retailers have at most two entries per market.

Potential locations: Potential locations are defined by year, latitude and longitude location, and size. For the Hubexo data, I observe when the landlord starts to look for tenants, when the tenants agree to enter the property, and when they actually do enter the property. I used detailed notes on entry dates to determine the entry timeline. For example, I observe: "*(1)* $\underline{\mathrm{mm}_1/\mathrm{dd}_1/\mathrm{yyyy}_1}$: *Landlord* A *at latitude* x *and longitude* y *is looking for a grocery tenant. (2)* $\underline{\mathrm{mm}_2/\mathrm{dd}_2/\mathrm{yyyy}_2}$: *Tenant* B *is set to enter* (x,y) *on* $mm_3/dd_3/yyyy_3$. *(3)* $\underline{\mathrm{mm}_4/\mathrm{dd}_4/\mathrm{yyyy}_4}$: *Tenant* B *has entered the space."* In this case, location A becomes a potential location on *(1)* $\mathrm{mm}_1/\mathrm{dd}_1/\mathrm{yyyy}_1$, stops being a potential location on *(2)* $\mathrm{mm}_2/\mathrm{dd}_2/\mathrm{yyyy}_2$, and Tenant B pays the entry fixed cost, starts paying rent and starts collecting variable profits on *(3)* $\mathrm{mm}_4/\mathrm{dd}_4/\mathrm{yyyy}_4$.

For entry before the Hubexo sample, I do not observe the same timeline and I cannot necessarily determine which properties are never entered. Using the Hubexo data as a guide, I conservatively assume that retailers are aware of a potential location two years before observed entry. Potential locations that are never entered but continue to look for tenants should appear in our Hubexo Dataset. Potential locations that are never entered but stopped looking for tenants are not observed. I assume that these locations – if they exist – were never part of the choice set and the fixed costs were too high to justify entry.

For locations (latitude, longitude, available space) with retailers that are not included in the (relatively) new Hubexo sample, I construct a history of store entry at each locations. From the maximum capacity entered at each location (across time), I infer the amount of empty space in each location any given year as well as the set of existing locations.

While each location is defined by a latitude and longitude, each location needs to capture the contiguous square foot owned by the same landlord. The goal is to group retailers where exclusive dealing binds, separating locations where the exclusive dealing contracts applies from locations where exclusive dealing contracts would not apply. To do so, I measure a radius around each large retailer and group retailers within this radius to the same location, i.e., I assign these retailers the same latitude and longitude.[34] I use .05 miles for large retailers in Chicago. For suburban locations, I use a radius of .2 miles for very large retailers and .1 miles for large retailers. I use a radius of 0 mi for small retailers. These radii should lead to a conservative estimate for the value of exclusive dealing, because I use a small radius where exclusive dealing could bind, when in practice it appears to bind on average for approximately .3 miles. This leads to a set of locations where within locations, exclusive dealing binds, but out side of the location (i.e. nearby even),

[34] A standard method of using the street grid to divide retailer locations doesn't work because many of the latitude and longitudes observed are located on the street in front of the retailer. This latitude and longitude location is another reason why I include such a small radius when grouping retailers.

there is free entry of retailers.

Size categories: I discretize retailer sizes into four categories: small, medium, large, and very large. Small store locations are typically 15,000 square feet (dollar, drug, liquor, and other small stores). Medium stores correspond are typically 15,000-30,000 square feet (Aldi, Trader Joe's), large stores are typically above 30,000 square feet (large grocers such as Jewel Osco) and very large stores are larger than 100,000 square feet (big box stores like Walmart). In any given year, I compute which retailers can plausibly enter each potential location using these broad category definitions. For example, a potential location that is $70,000$ square feet can fit one big box store can fit a big box store and a small store, two grocery-sized stores and a small store, etc...

Retailer choice set: The retailer choice set is determined by the potential locations available that the retailer can plausibly enter into in each market. The outside option is no entry. I focus on leasing decisions.

Observed Entry and Exit: I obtain the set of retailer locations by merging data from SNAP and Infogroup.

The USDA Historical Supplemental Nutrition Assistance Program (SNAP) Retailer Locator Data (SNAP data) provides location, store name, date of entry into SNAP, and date of exit from SNAP of all SNAP-accepting stores. The dataset spans 1990 to present. I subset the data to Cook County, IL and clean the data according to the following steps:

First, missing grocer locations are added to ensure I account for the full consumer choice set and retailer location choices. Missing stores are found by cross checking the SNAP stores with the county recorder's office (discussed here) and Infogroup (discussed later). With data from the county recorder office, I obtain a set of locations (address, latitude, longitude) where stores should be located. For locations missing from the SNAP data set, I investigate whether the store ever existed with news articles confirming opening dates and possible store exit dates. From this search, I add Jewel Osco at 8721 S Stony Island, 60617, Chicago, Whole Foods at 9600 S Western Ave, 60805, Evergreen Park, Dominick's Finer Food at 4636 S Damen Ave, 60609, Chicago and Pete's Fresh Market at 4233 Lincoln Hwy, 60443, Matteson and other mising stores to the data set.

I additionally correct minor mistakes in the SNAP dataset such as modifying the city of record id 856052 (the store identifier in the dataset) to be Dixmoor or modifying the address of record id 571844 as 7515 Cermak Rd.

Second, I identify chains and clean the store names to establish consistent retailer names. Chains are defined as stores that have at least four locations. I identify chains by looking for store names that appear at least four times in the data set, checking the accuracy against lists of major chains historically present in Chicago.

Third, duplicates are combined and removed. Store entry and exit is defined by first entry and last exit into the SNAP dataset. Duplicates due to multiple entries and exits into SNAP are combined into a single store. Stores with the (almost) same name, latitude, and longitude but slightly different addresses are considered to be the same store. Stores with near-identical store name or address or latitude and longitude but are otherwise identical are considered to be the same stores and are combined into a single retailer. Particular attention is paid to ensure different stores are not combined, even when they have similar names and locations.

Fourth, I establish the retailer name as one of the retailer names in the analysis. Large retailers are classified by their chain name (e.g. Safeway's Jewel Osco and Kroger's Mariano's). Small retailers – dollar stores, drug stores, liquor stores, other food – are classified with the following steps: stores calling themselves dollar stores or 99-cent stores (e.g. Dollar General, Dollar Tree, Family Dollar or 99-cent) are classified as dollar stores. Drug Stores are comprised of Phar Mor, CVS, Osco Drug, Walgreens, Rite Aid, Duane Reade, Eckerd or any other store name that calls itself a pharmacy or drug store directly. Stores are classified as liquor stores if the store name explicitly mentions liquor, wine, beer, or spirits but does not mention grocery, market, supermarket, food, or deli. The remaining chain stores are classified into "other food" or "other" category based on their description. The remaining stores are classified into "other food" and "other". Other food stores are comprised of independent grocery stores and smaller retailer chains such as Patel Brother's and Cermak produce.

Fifth, I geocode the address using the Census geocoder to establish a standard latitude and longitude for each location.

Next, I clean the Infogroup (called the InfoGroup Historical Datafile, access through UChicago libraries) dataset. I subset to stores in Cook County, IL, in retail trade (NAICS codes that start with 44 or 45). The cleaning steps are very similar to the SNAP data. First, I clean store names, creating a single store name for each chain. Second, I establish a first and last opening (by year) for each store. Third, I eliminate duplicates from address, latitude, and longitude. Fourth, I classify each retailer as a store in Table 1. Fifth, I geocode addresses. Finally, I combine the SNAP and Infogroup datasets to get the full list of retailer locations.

Excluding owned stores: For the retailer location choice model, I focus on entry of rented stores. I determine which stores are rented and which stores are owned by each retailer using deed records from the Cook County recorder office. Both rented and owned storefronts comprise the set of retailer locations.

Retailer expected variable profits: Variable profits for each retailer are computed with model-implied retailer profitability and depend on retailer locations, population demographics, and future entry of retailers. First, for each market, I compute the set of possible entry decisions for each retailer. I assume that large retailers will not enter the same location twice and small retailers will split the expected surplus at each location. I also limit entry to feasible locations (i.e. options without exclusive dealing or capacity constraints). Second, for each possible entry combination, I compute expected variable profits over the next several years. These next several years represent the number of years required to re-coup the fixed costs: following industry reports, I use 6 years for large retailers and 3 years for small retailers. I use the product market estimates to compute shares at each retailer for households in each census block group and income group g, assuming households live at the center of a census block group and each household only shops at the nearest retailer to home. In this computation, I also include all the existing retailer locations and a buffer of existing retailers in a 2 mile radius around the geographic market to correctly capture which households shop at the new locations.[35] I also need to make assumptions on the future path of demand shocks, marginal cost shocks, and demographic trends. I assume marginal costs, mc_j^g and demand shocks, ξ_{bt}^g, and population are constant and use estimated average value for each retailer and bundle across for marginal costs and demand shocks, and use population from that year. Following the data, I assume household shop on average 2.2 times per week. Third, I compute expected surplus for large retailers with or without an exclusive dealing arrangement, where the exclusive dealing contract limits entry of all competitors within the same location (latitude, longitude).

Rental prices and exclusive contracts: I then merge rental price data and exclusive dealing data onto retailer entry decisions so that for each location I have: (retailer name(s), size(s), latitude, longitude, rental prices, exclusive dealing contracts, available space). At each location, I track the set of existing retailers and exclusive dealing contracts over time. Prior exclusive dealing contracts can limit future retailer entry.

B.3 Identification and Estimation

B.3.1 Identification – Product Market (Step 4)

With our consumer panel data, the likelihood of households (i) choosing bundle b in county x year x bi-week t is

$$\mathcal{L}(b|\theta) = \prod_i \prod_b \underbrace{1\{b_i\}}_{i \text{ chooses } b} \underbrace{\frac{e^{\delta_{bt}^g + \lambda_{ibt}^g}}{\sum_{b'} e^{\delta_{b't}^g + \lambda_{ib't}^g}}}_{\text{prob. } i \text{ chooses } b}$$

[35]This buffer comprises a large geographic area of existing stores and is important because it ensures that the households go to the correct retail location. Households far away go the preexisting retailers.

where δ^g_{bt} is the average utility a household in income group g receives from shopping at retailers b in the same day (henceforth bundle b) in the household's county in year and bi-week t (henceforth market t). The average utility of the outside good is set to zero, $\delta_{0t} = 0$, and the remaining average utilities are relative to the outside good.

Average utility is composed of a price element, a bundle fixed effect, and two error terms

$$\delta^g_{bt} = \alpha^g p^g_{bt} + \Gamma_b + \xi^g_{bt} + u^g_{bt}$$

where α^g is the marginal disutility of a higher relative price index (henceforth prices) for income group g, Γ_b is the utility for bundle b. I interpret Γ_b as the quality of a bundle. When b corresponds to multiple stores, households must receive additional utility for shopping at these stores together during the same day (henceforth trip chaining) to justify the increased prices and distances. When households shop at multiple stores, I interpret Γ_b as the complementarity between two retailers in b (henceforth Γ_b is referred to as a complementarity, and own-complementarity is retailer quality). ξ^g_{bt} is the common demand shock for that bundle in that time period. For example, a trend might increase the demand for goods at a particular set of retailers b and might cause higher utility for a particular bundle in that time period. Demand shocks are likely correlated with prices. Let ξ^g_{bt} represent the portion of the demand shock correlated with prices and let u^g_{bt} is the portion of the demand shock uncorrelated with prices. For example, road closures near retailers b may temporarily decrease demand for bundle b in market t.

I interpret the average utility, price index and complementarity relative to the outside good, so that

$$\begin{aligned} \delta^g_{0b} &= 0 \\ p^g_{0t} &= 0 \\ \Gamma_{0t} &= 0 \end{aligned}$$

The individual term λ^g_{ibt} depends on total distances traveled, whether the stores are nearby, and interactions between household demographics and bundle characteristics

$$\lambda^g_{ibt} = \gamma^g d_{ibt} + \gamma_1 d_{1ibt} + \Sigma_{ib} x_{it} y_{bt}$$

where γ^g is the marginal disutility of distance for income group g. Here, distance is defined as either as-the-crow-flies distance in miles for the total distance trip, or as the OSRM-computed travel time distance in minutes when driving a car. γ_1 is the utility from shopping at stores that are located close together, either within .2 miles (as the crow flies) or within a 5 minute drive (travel time). x_{it} are household demographics such as education and unemployment status. I include demographic characteristics that may be correlated with value of time and thus might change the disutility of distance or nearby shopping. y_{bt} are whether stores are nearby.

The log-likelihood of observing the data under the model is

$$\log \mathcal{L}(b) = \sum_i \left(\delta^g_{b^*t} + \lambda^g_{ib^*t} - \log \left(\sum_{b'} e^{\delta^g_{b't} + \lambda^g_{ib't}} \right) \right)$$

where household i chooses bundle b^*.

In a first step, the maximum likelihood estimator gives consistent estimates for $\delta^g_{bt}, \gamma^g, \gamma_1, \mathbf{\Sigma}$. Variation across household choices identifies the parameters.

The average utility parameter δ^g_{bt} is identified off of variation in bundle popularity (measured as counts in the data) holding all other variables (such as distance) equal. The optimal δ^g_{bt} is chosen such that the model-implied shares match the observed shopping frequency in the data.

At optimum, the distance that is actually traveled should reflect the predicted distance traveled by the model, which is the share-weighted distance a household travels to each bundle. Variation in household distances to bundles identifies the marginal disutility for distance. As distances increase for consumers, the decreases in the model-implied probability of shopping at the bundle determines the disutility. Distance parameters are identified by within-household changes in choice set, as distances change when retailer enter and exit the sample. This within-household variation identifies both the marginal disutility of a longer trip, γ^b, and the utility of shopping at nearby stores, $\gamma^b_1, \mathbf{\Sigma}$. Additionally, cross-section variation across households further identifies the disutility for distance. I condition on observables such as bundle, time, market, demographic, and household zip code fixed effects to control for household preferences that vary across different observable groups.

Disutility for distance is decomposed into a zip-code specific fixed effect and a residual distaste for distance, partially out any household-zip effects.

$$\underbrace{\hat{\gamma}^g_{bt} d_{ibt}}_{\substack{\text{disutility attributed} \\ \text{to dist.}}} = \underbrace{\sigma_i}_{\text{zip FE}} + \underbrace{\tilde{\gamma}^g_{bt} d_{ibt}}_{\text{est. net of zip FE}} + \tilde{\epsilon}_{ibt}$$

where σ_i is a zip code fixed effect. If household select into the zip code or if retailer location correlates with household zip code, σ_i should explain a significant portion of the variation in distance and the remaining residual $\tilde{\gamma}^g_{bt} d_{ibt}$ should be small.

For shopping to nearby stores, γ_1 is be chosen to match the fraction of trips to nearby stores with the model-implied fraction of trips to nearby stores. Variation in co-locating stores, e.g. due to changes within a shopping center or differences in shopping centers across space, identifies the marginal utility for shopping at nearby stores, or the value of the shopping center holding fixed the total distance trip. As with the distance parameters, retailer entry and exit generates within-household variation in which bundles are located in shopping centers to pin down the parameter, and cross-sectional variation (conditional on covariates) provides additional variation.

In a second step, an instrumental variables regression gives consistent estimates for α^g, Γ_b. The marginal disutility for prices is determined by the extent to which average bundle popularity drops as (instrumented) prices rise. The instrument that isolates supply-side price shifts identifies the demand parameters. The instrument here is the average price of the same retailer in other markets, assuming that cost shocks are common to all markets (given that retailers set prices more uniformly) while demand shocks are unique to each market and uncorrelated with national demand (Hausman et al. (1994)). The complementarity parameters is determined by the average utility of the bundle partialing out the effect of prices and individual parameters.

With estimated parameters $\hat{\delta}^g_{bt}, \hat{\alpha}^g p^g_{bt}, \hat{\Gamma}_{bt}$, I compute the biweekly demand shock, ξ^g_{bt} as

$$\xi^g_{bt} = \hat{\delta}^g_{bt} - \hat{\alpha}^g p^g_{bt} - \hat{\Gamma}_{bt}$$

With these parameters estimated, I compute marginal costs for each retailer x income group x county x year x biweek:

$$mc^g_{jt} = p^g_{jt} - \left[\frac{\partial s^g_{jt}}{\partial p^g_{jt}}\right]^{-1} s^g_{jt} + \frac{\partial s^g_{jt}}{\partial p^g_{jt}}$$

B.3.2 Estimation - Product Market (Step 4)

In the first step, I estimate the average bundle utility, δ^g_{bt}, the distance parameter, γ^g, the shopping center parameter, γ_1, and interaction parameters Σ. I estimate the following with maximum likelihood:

$$\underbrace{(\hat{\delta}^g_{bt}, \hat{\gamma}^g, \hat{\gamma}_1, \hat{\Sigma})}_{\hat{\theta}} = \arg\max_{\theta} \sum_i \sum_b \left(D_{ibt} + \delta^g_{bt} + \lambda^g_{ibt} - \log \left(\sum_{b'} e^{\delta^g_{b't} + \lambda^g_{ib't}} \right) \right)$$

where D_{ibt} indicates the observe choice (household i chooses bundle b), δ^g_{bt} represents the average utility, distance for each income group, γ^g, preference for shopping within a shopping center, γ_1, preference for shopping within a shopping center for different education groups and when unemployed, Σ. These shopping center terms capture the value of shopping at nearby stores, for example, capturing the value of price shopping, comparing different products in the same place, and allowing for different values of time across different demographic groups.

I report the distance estimates in Table 28. I find strong distaste for distance. For a 1% increase in distance, household utility declines by 1.79% for low income, 1.62% for mid income, and 1.58% for high income consumers.

Distaste for distances varies little with household locations, conditional on household income. To show this, I regress estimated utility from distance, $\hat{\gamma}^g d^g_{ibt}$, on distances and household zip code to control for selection into zip code and to isolate the disutility of distance.

$$\hat{\gamma}^g d^g_{ibt} = \beta_0 + \beta^g_1 d^g_{ibt} + \sigma_i + \epsilon_{ibt}$$

where σ_i is household zip code.

I report results in Table 31. I find that the baseline distance estimates, $\hat{\gamma}^g$, are identical to the distance estimates net of household zip, $\hat{\beta}^g_1$, indicating that income effectively captures the disutility of distance.

I also conduct robustness around two other measures of distance: distance measured with travel time and non-linearities in distances traveled. I report the estimates in Table 30. First, I measure distance using travel time, specifically, in log OSRM-measured driving time in minutes. This measure should account for traffic and the city street layout. I find find disutility of travel times to range from 3.5 (high income) to 3.7 (low income), or roughly double the disutility as measured in log as-the-crow-flies distance. These estimates are consistent with the correlation between as the crow flies distance and travel timed documented in Figure 18. To account for nonlinearities, I allow for both linear and square terms in distance: $\gamma^g_a d^g_{ibt} + (\gamma^g_a)^2 d^g_{ibt}$. I find a strong negative squared coefficient, indicating a strong preference to shop close to home.

Shopping center parameters are reported in Table 29. I find that conditional on distance and bundle, there is no additional utility to shop at stores nearby. That is, in this setting, the shopping plaza is primarily used to shorten the distance between trips to retailers.

In a second step, I estimate the price coefficient, bundle coefficients, and unobserved demand shocks, $\alpha^g, \Gamma_b, \xi^g_{bt}$ with an instrumental variables regression to correct for endogeneity in prices. I run the following instrument variable regressions:

$$\delta^g_{bt} = \alpha^g p^g_{bt} + \Gamma_{bt} + \xi^g_{bt} + \phi_t + u^g_{bt}$$

Price estimates are reported in Table 28. OLS price estimates are reported in Table 33 and the first stage and F-test estimates in Table 32. I find that the price instrument strongly predicts prices, and that prices and average income utility are positively correlated if not instrumented.

Retailer quality estimates - singleton Γ_b are reported in Figure 23 and all complementarity estimates in Figure 24.

Demand shocks ξ^g_{bt} are computed as the residual $\xi^g_{bt} = \delta^g_{bt} - \alpha p^g_{bt} - \Gamma_b$ and are reported in Table 25. I report the histogram and distribution of demand shocks ξ^g_{bt} implied by the estimates. I also report confidence intervals for ξ^g_{bt}. The confidence intervals are computed by compounding the standard errors from the maximum likelihood estimation and the instrumental variables regression, and are computed as $se_{\xi^g_{bt}} = \left(se^2_{mle} + se^2_{iv}\right)^{1/2}$. These confidence intervals are reported in light gray horizontal lines and are computed as $\xi^g_{bt} \pm 1.96 se_{\xi^g_{bt}}$.

Finally, I estimate firm marginal costs. Marginal costs are a residual parameter, computed assuming retailers maximize profits and compete over prices. Marginal costs are computed as

$$mc^g_{jt} = p^g_{jt} + \frac{1}{\alpha^g(1 - s^g_{jt})}$$

Marginal costs are reported in Figure 26. The top plot reports the histogram and density of marginal costs computed from the estimated parameters. The bottom plot additionally includes the marginal costs computed assuming parameters from the 95% confidence interval. These marginal costs are computed as $\hat{mc}^g_{jt} \pm 1.96 se_{mc}$, where se_{mc} are computed by compounding standard errors from the maximum likelihood estimation and instrumental variables regressions, $se_{mc} = \left(se^2_{mle} + se^2_{iv}\right)^{1/2}$.

B.3.3 Identification – Retail Real Estate Market (Steps 1-3)

Small retailers: I identify the fixed costs of tenant entry and marginal costs of landlord maintenance. The total costs (tenant fixed costs plus landlord marginal costs) determines the profitability at which retailers enter. Since fixed costs are assumed to be constant over time, fixed costs are pinned down from variation in vacancy rates and expected profitability over time.[36] Each time a potential location becomes available at location m over the time period (2000-2023), the retail landscape, household demographics, and therefore the expected profitability at m have changed. The minimum expected surplus required for entry determines the expected total costs of entry.

Total costs are estimated first and fixed costs and marginal costs are computed second. To estimate total costs, I include the following moments in estimation

$$g_{1,m}(TC) = s_m^{\text{data}} - \tilde{\mathbb{P}}_m(TC) \tag{15}$$

$$g_{2,t}(TC) = s_t^{\text{data}} - \tilde{\mathbb{P}}_t(TC) \tag{16}$$

$$\hat{TC}_m^{small} = \arg\min_{TC} g_1(TC)^\top W_1 g_1(TC) \ + \ g_2(TC)^\top W_2 g_2(TC) \tag{17}$$

where j are retailers, m are locations and t are markets.

The first moment corresponds to the location-level entry shares. This moment equates the simulated and observed average entry probability, averaging over time. The second moment matches the simulated and observed average market share, averaged across locations within the same geography and time. The first moment is included to identify the fixed costs. The second moment is included to ensure that market-level shares are measured correctly as well.

s_m^{data} is the average fill rate across markets (here time) for each location m. Shares are computed by summing the store sizes that exist in a particular location m in market t divided by the total size available in location m. The total size is the minimum of the available space and the maximum space entrants could plausibly enter.

$$s_m^{data} = \frac{1}{T}\sum_{m\in t}\frac{\sum_j size_j 1\{j \in m_t\}}{tot.\ size_m}$$

s_t^{data} is the average fill rate within each market t across locations $m \in t$. Shares are computed by summing the store sizes that exist in a particular location m in market t and then averaged over

[36] Costs are measured in real terms to net out inflation.

across all locations within a market.

$$s_t^{data} = \frac{1}{M}\sum_{m\in t}\frac{\sum_j size_j 1\{j\in m_t\}}{\sum_{m\in t} tot\ size_m}$$

$\tilde{\mathbb{P}}_{jmt}$ is the simulated probability retailer j enters location m in market t. The probability has two parts. First, retailer j has to choose to enter location m, taking into account expected surplus from the new location, existing locations, and the simultaneous choices of other retailers. Second, conditional on choosing location m, retailer j has to win entry. Due to exclusivity and capacity constraints, entry is not guaranteed. For small retailers, entry is determined at random among the retailers that choose to enter.

$\tilde{\mathbb{P}}_m$ are the location-level size-weighted entry shares implied by the model, $\tilde{\mathbb{P}}_m = \frac{1}{T}\sum_{j,t}\tilde{\mathbb{P}}_{jmt}\frac{\text{size}_j}{\text{tot size avail}_{mt}}$.

$\tilde{\mathbb{P}}_t$ are the market-level size-weighted entry shares implied by the model, $\tilde{\mathbb{P}}_t = \frac{1}{M}\sum_{j,m\in t}\tilde{\mathbb{P}}_{jmt}\frac{\text{size}_j}{\text{tot size avail.}_{mt}}$.

Each retailer plays a mixed-strategy game choosing the probability of entry for each location, $\boldsymbol{p}_j = (p_{j1}, ..., p_{jm}, ..., p_{jM})$ and maximizes the total expected probability.

$$\max_{\boldsymbol{p}_j}\sum_x \pi_{jx}P_x - \sum_m (F_m + r_m)1\{j\in m\}_x + \sum_m \epsilon_{jm}1\{j\in m\}_x$$

where x indicates each possible observed entry outcome, P_x is the probability that this outcome occurs, π_{jx} are product market profits for retailer j in outcome x, F_m are fixed costs of the location m, r_m are landlord rents for small retailers at location m, $1\{j\in m\}_x$ indicates whether j enters m in state x and ϵ_{jm} are the idiosyncratic profitabilities, which can be from the outside good.[37]

Landlord rents are determined from profit maximization

$$r_m = mc_m + \frac{1}{1 - E_x[s_{mx}]}$$

where $E_x[s_m]$ are the expected share at location m, or the probability of each state x times the fraction of the newly-filled space in state x.

To estimate total costs, fixed costs + rents are replaced with total costs plus the second term involving landlord shares. Estimating total costs is important in identifying barriers to enter a location when rental prices are unobserved; rental prices are unobserved for 50% of locations.

Large retailers: I identify the fixed costs of tenant entry, marginal costs of landlord maintenance,

[37] For example, when there are two firms and one location and no exclusive dealing the observed entry outcomes are $x\in\{(EE),(EO),(OE),(OO)\}$.

and additional benefits of exclusivity net of estimated surplus: F_m^{small}, mc_m^{small}, F_m^{large}, mc_m^{large}, μ_θ, σ_θ. Identification of large retailer total costs is similar to the identification of the small retailers.

$$g_{1,m}(\psi) = 1 - \frac{\tilde{\mathbb{P}}_m(\psi)}{s_m^{\text{data}}} \tag{18}$$

$$g_{2,t}(\psi) = 1 - \frac{\tilde{\mathbb{P}}_t(\psi)}{s_t^{\text{data}}} \tag{19}$$

$$g_{3,m}(\psi) = 1 - \frac{\tilde{r}_{jma}(\psi)}{r_{jma}^{data}} \tag{20}$$

$$g_{4,j}(\psi) = 1 - \frac{\tilde{\mathbb{P}}_{jE}}{s_{jE}^{data}} \tag{21}$$

$$g_5(\psi) = 1 - \frac{\text{Var}_j(\tilde{\mathbb{P}}_{jE})}{\text{Var}_j(s_{jE}^{data})} \tag{22}$$

$$\hat{\psi} = \arg\min_{\psi} \; g(\psi)^\top W \, g(\psi) \tag{23}$$

where $\psi = (F, mc, \mu_\theta, \sigma_\theta)$ are the parameters for fixed costs, marginal costs, and exclusivity. The first moment, Equation 18, corresponds to the location-level entry shares and the second moment, Equation 19, corresponds to the market-level entry shares, which are similar (but not identical) to the small retailer moments. Here, correlation between estimated expected surplus minutes rents and entry rates identifies the fixed costs of entry. The third moment, Equation 20, matches the model-implies simulated rents with the observed rents at each location and market. The fourth and fifth moment, Equation 21 and Equation 22, match the model-implied observed rates of exclusive dealing with the data.

s_m^{data} is the average fill rate across markets (here time) for each location m, computed by summing the store sizes that exist in a particular location m in market t divided by the total space available in location m: $s_m^{data} = \frac{1}{T}\sum_{m\in t} \frac{\sum_j size_j 1\{j\in m_t\}}{tot.\ size_m}$. s_t^{data} is the average fill rate within each market t across locations $m \in t$, computed by summing the store sizes that exist in a particular location m in market t and then averaged over across all locations within a market: $s_t^{data} = \frac{1}{M}\sum_{m\in t} \frac{\sum_j size_j 1\{j\in m_t\}}{\sum_{m\in t} tot\ size_m}$.

$\tilde{\mathbb{P}}_{jmt}$ is the simulated probability retailer j enters location m in market t. The probability has the same two parts as the small retailer. First, retailer j has to choose to enter location m, taking into account expected surplus from the new location, existing locations, and the simultaneous choices of other retailers. Second, conditional on choosing location m, retailer j has to win entry. Due to exclusivity and capacity constraints, entry is not guaranteed. For large retailers, entry is determined by the highest-paying entrant among the retailers that choose to enter. $\tilde{\mathbb{P}}_m$ are the location-level size-weighted entry shares implied by the model, $\tilde{\mathbb{P}}_m = \frac{1}{T}\sum_{j,t}\tilde{\mathbb{P}}_{jmt}\frac{\text{size}_j}{\text{tot size avail}_{mt}}$. $\tilde{\mathbb{P}}_t$ are the market-level size-weighted entry shares implied by the model, $\tilde{\mathbb{P}}_t = \frac{1}{M}\sum_{j,m\in t}\tilde{\mathbb{P}}_{jmt}\frac{\text{size}_j}{\text{tot size avail.}_{mt}}$.

Each large retailer plays a mixed-strategy game choosing the probability of entry for each location, $\boldsymbol{p}_j = (p_{j1}, ..., p_{jm}, ..., p_{jM})$ and maximizes the total expected profitability

$$\max_{\boldsymbol{p}_j} \sum_x \pi_{jx} P_x - \sum_m (F_m + r_m) 1\{j \in m\}_x + \sum_m \theta_j 1\{j \in (m, excl.)\}_x + \sum_m \epsilon_{jm} 1\{j \in m\}_x$$

where x indicates each possible observed entry outcome, P_x is the probability that this outcome occurs, π_{jx} are product market profits for retailer j in outcome x, F_m are fixed costs of the location m, r_m are landlord rents for small retailers at location m, θ_j is the additional profitability from an exclusive contract, $1\{j \in m\}_x$ indicates whether j enters m in state x and ϵ_{jm} are the idiosyncratic profitabilities, which can be from the outside good.

Each landlord sets two prices (exclusive, non-exclusive) for each large retailer to maximize total expected profitability, taking into account retailer entry probabilities, expected profits from the small retailers, and other landlord's rental prices (in the same market). In practice, this amounts to taking into account rental prices charged by the surrounding 2-6 potential locations. The landlord sets prices $\boldsymbol{r}_{jma} = (r_{1mE}, r_{1mN}, r_{2mE}, ..., r_{jma}, r_{JmE}, r_{JmN}))$ for all retailers j with can feasibly enter the space and are not restricted by a previous exclusivity agreement. Rents can be set at infinity, indicating that the landlord would never allow the retailer to enter.

$$0 = \frac{d}{dr_{jma}}\left[\sum_{j,a}\left(\underbrace{\mathbb{P}^1_{jma}}_{prob.\,choice}\ \underbrace{\mathbb{P}^2_{jma}}_{prob.\,win}\ (r_{jma} - mc_m^{large}) + E[\pi_m^{small}(j,a)]\right)\right]$$

Since most of the rents are unobserved (all but the one that is selected), the landlord problem is estimated jointly with the large tenant, and target the observed rents as an additional moment in the model, matching model-simulated rents, $\tilde{r}_{jma}(\psi) = \frac{1}{S}\sum_s r_{jmas}(\psi)$, with observed ones.

To identify the exclusive dealing parameters parameters $\mu_\theta, \sigma_\theta$, I match the rates of exclusive dealing in the model with the data. Conditional on fixed costs and expected surplus, the extent to which exclusive dealing is observed is explained by μ_θ and the spread across retailers is explained by σ_θ. μ_θ and σ_θ have two interpretations: either, they represent the extent to which there is asymmetric information between retailers and landlords/rival retailers or they represent the extent to which the demand side model is misspecified and the estimates cannot explain exclusivity rates.

$\tilde{\mathbb{P}}_{jE}$ is the simulated probability retailer j enters market t with an exclusive dealing agreement, computed as an average across simualted draws S and markets T, $\tilde{\mathbb{P}}_{jE} = \frac{1}{TS}\sum_{t,s} 1\{a_j = E\}$. s_{jE}^{data} are the observed rates of exclusive dealing, computed as $s_{jE}^{data} = \frac{1}{T}\sum_t 1\{a_j = E\}$. Moment 21 targets the average and Moment 22 targets the variance.

B.3.4 Estimation – Retail Real Estate Market (Steps 1-3)

Small retailers and landlords: First, I estimate fixed costs of entry for small retailers. I construct moments matching entry decisions and the likelihood of entry. Estimation proceeds in two steps: first I estimate $(g_1(TC)\, g_2(TC))' W (g_1(TC)\, g_2(TC))$ where W is the identity matrix. In the second step, I re-estimate fixed costs setting W to the inverse variance-covariance matrix. I estimate the total costs with simulated method of moments. For each market, I simulate S draws of ϵ_{jms} and compute the tenant optimization problem (choosing locations) iterating over different tenants optimization and best response until the probabilities converge. This gives the location choice probability for each small retailer j and simulation s, where small retailers can choose to not enter (the outside option), enter one location, or enter two locations: P_{jms}. I average over the S draws to construct each model-simulated moment. The optimal total costs are chosen to minimize the distance between the observed shares (entry rates) and the simulated probabilities. When rental prices are observable, I compute tenant fixed costs of entry and landlord marginal costs from the rents and estimated total costs.

The objective function is non-convex and I find multiple equilibria. To ensure that the global minima is recovered, I start the optimization at 40 different starting points and check that the optimization recovers the original parameters across multiple starting points. In a few instance, the optimization yields different estimates, indicating that the optimizer has converged to local minima. In this case, I pick the lowest objective function and report those results.

I compute standard errors with the parametric bootstrap, re-drawing the simulated shocks ϵ and θ and re-estimating for each new set of draws.

Large retailers and landlords: Large retailer estimation is similar to the small retailer estimation with the following exception. First, I estimate the landlord and tenant problem simultaneously, and additionally loop over the different landlords setting optimal rents given marginal costs and the other parameters. Second, I simulate over both ϵ and $\theta_j \sim N(\mu_\theta, \sigma_\theta)$.

B.4 Descriptive Statistics

B.4.1 Descriptives – Product market (Step 4)

Table 26 shows summary statistics of trips in the data. The first column shows the retailers in the demand estimation. The second column counts the number of visits to each retailer (trips). The third column counts the total expenditure at that retailer. The fourth and fifth column rank the retailers by expenditure and and visits. The data shows that the majority of the market share is spent at the inside good, and the market is dominated by Big Box stores like Walmart and Target and by popular grocery stores like Jewel Osco (Safeway).

Table 27 shows the counts and shares for each bundle. The estimation matches the observed shares to the estimate-implied model shares.

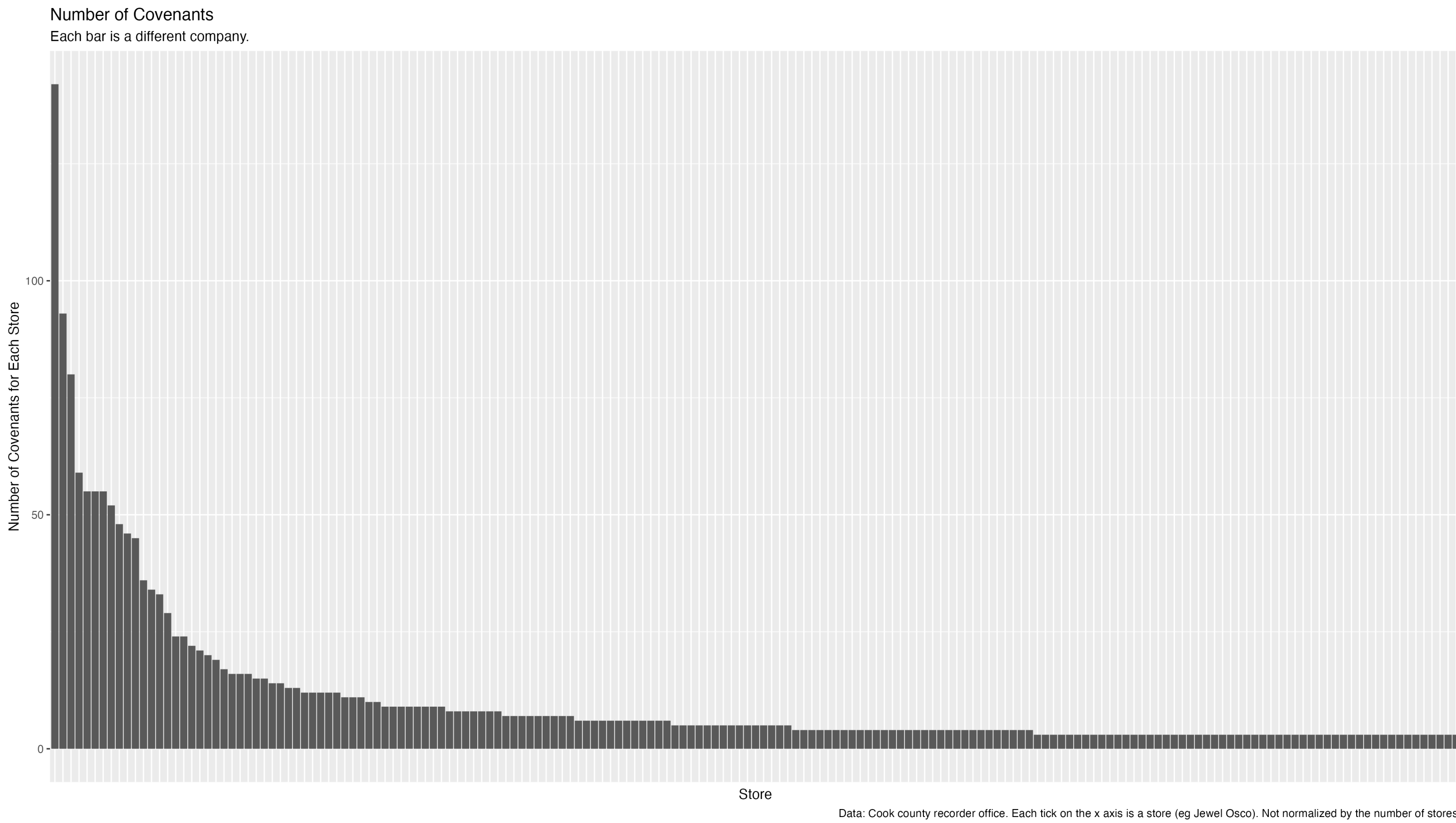
40% of trips to the grocery stores are multi-homing trips, and that percentage increases when there is a chain grocer or the chain grocer is co-located with another retailer. I report additional descriptive statistics about multi-homing and the types of trips consumers take in Figure 19, Figure 20, Figure 21, and Figure 22. An emerging literature has highlighted the importance of trip-chaining in consumer shopping ((Rhodes and Zhou, 2019; Miyauchi et al., 2022; Relihan, 2022; Oh and Seo, 2023)).

B.4.2 Descriptives – Commercial Real Estate market (Steps 1-3)

I focus on retailer entry for two reasons. First, most exclusive dealing contracts are signed at entry. Second, large retailer sign long leases upwards of 10 years (commonly 10-65 years) and rarely exit, as show in in Figure 13. The the vast majority of big box stores, chain drug stores, grocery chain stores, and dollar stores have remained open to present, as shown by the vertical bar to the left of zero.

B.5 Exclusive Dealing

Figure 9: Distribution of Exclusive Dealing Contracts

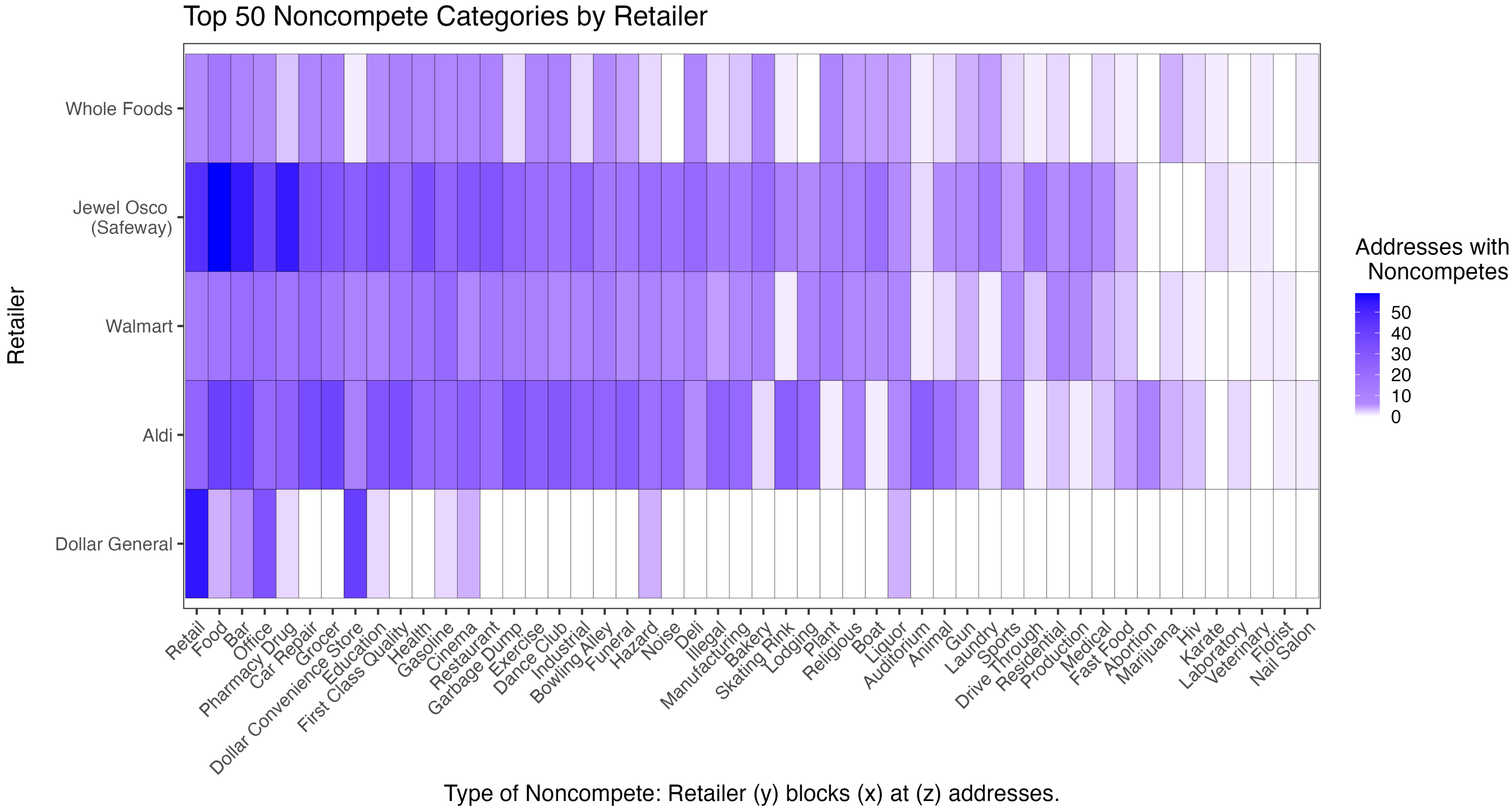


Notes: Figure plots the top retailers with exclusive dealing contracts. Each observation is a different address that records exclusive dealing agreements. *Source:* Cook County Recorder Office. Time span 1980-2023.

Figure 10: Contents of Exclusive Dealing Contracts Across Select Retailers and Restrictions

Notes: Source: Cook County Recorder Office. Figure shows the details of the exclusive dealing contracts for nine retailers: Jewel Osco (Safeway), Whole Foods (Amazon), Aldi, Walmart, Walgreens, CVS, Target, Dollar General and Family Dollar. The plot shows the fraction of addresses where each retailer has blocked a certain type of retailer: dollar stores and convenience stores (in light blue), grocery stores (in blue), liquor stores (in red), and pharmacy or drug stores (in purple).

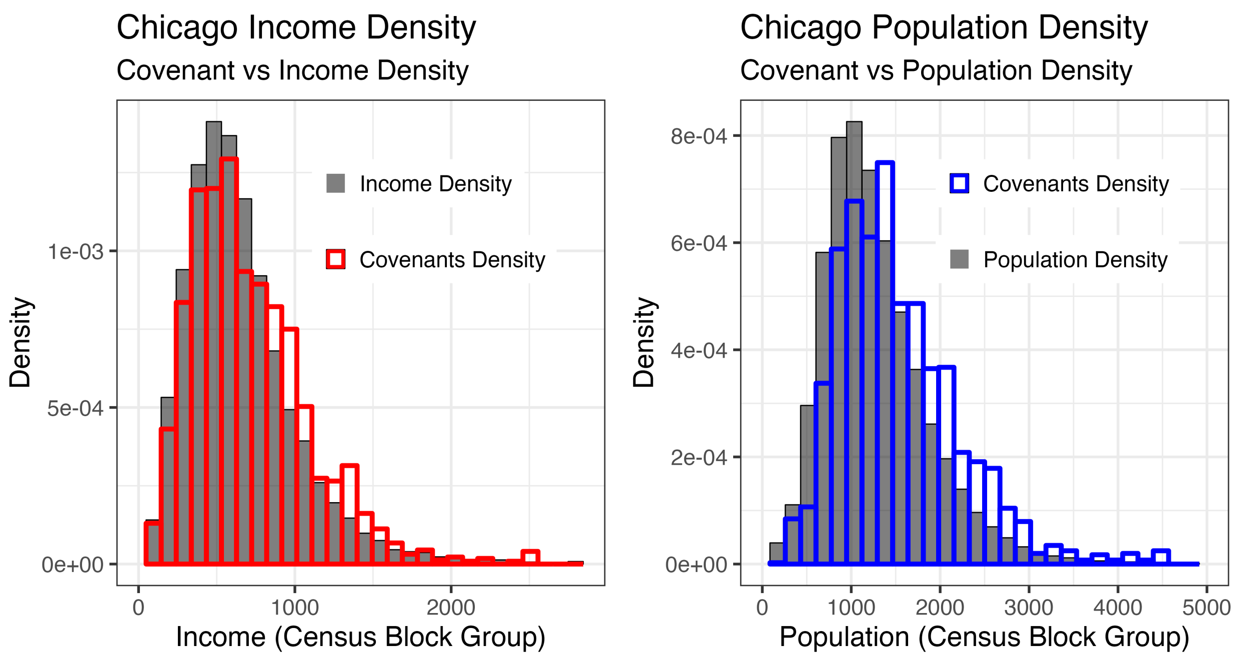
Figure 11: Contents of the Exclusive Dealing Contracts Across Select Retailers



Notes: Source: Cook County Recorder Office. Figure shows the top 50 categories of restrictions (non-competes) for Whole Foods (Amazon), Jewel Osco (Safeway), Walmart, Aldi, and Dollar General. The retailers are chosen to show a mix of retailers at different price points. The color intensity shows the number of addresses that impose a particular restriction. For example Jewel Osco blocks food retailers at over fifty addresses and does not block nail salons at any address. The top fifty restrictions (noncompetes) can be classified into direct competition (retail, food), competition for parking spots (education, health), and curation of the aesthetics of the shopping center (garbage dump, gun, abortion, Marijuana, etc...).

B.6 Exclusive Dealing and Demographics

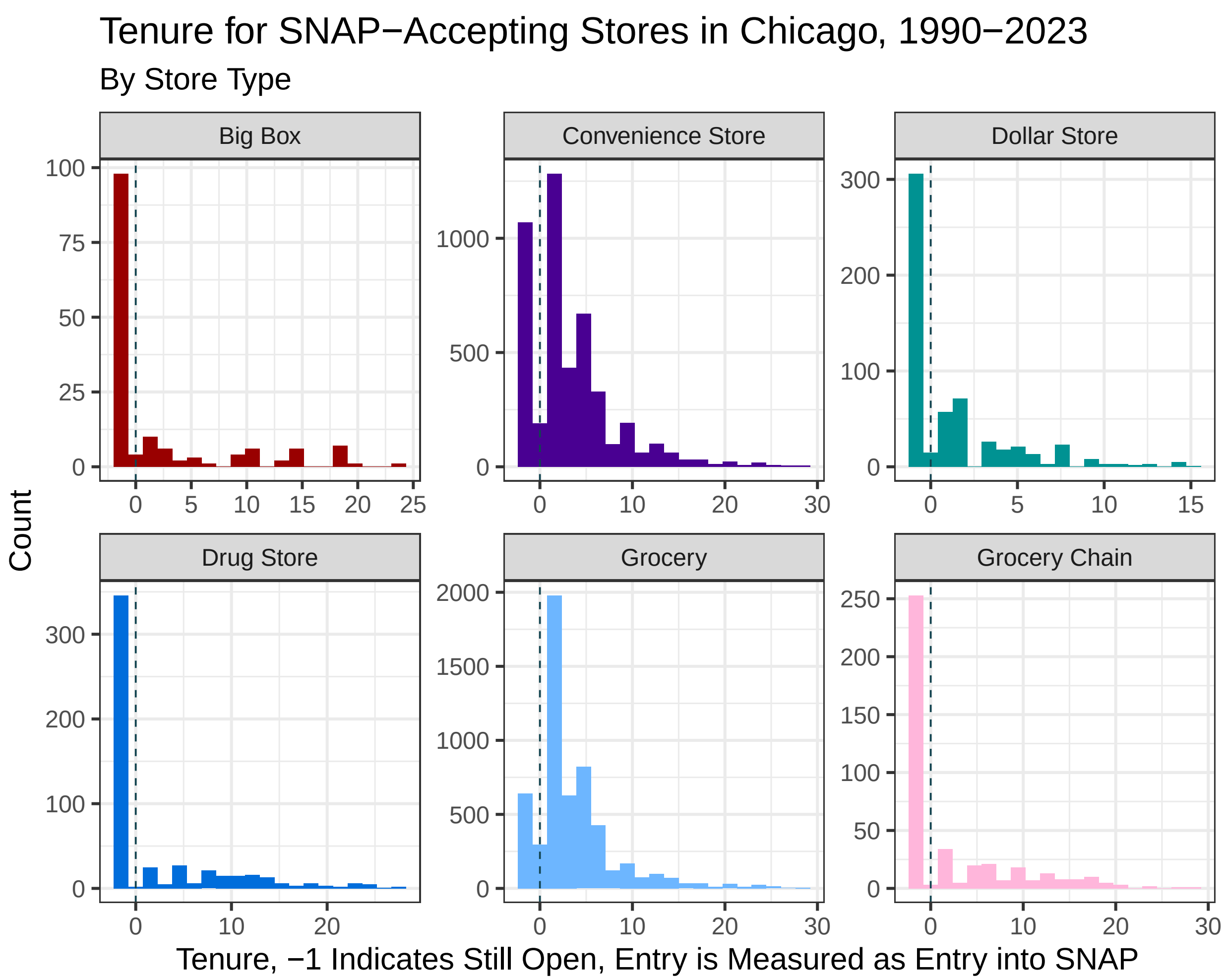
Figure 12: Exclusive Dealing Contracts (Covenants), Income and Population Density



Notes: Figure plots histograms of income density (left) and population density (right) in Cook County, Illinois, and overlays the density of exclusive dealing contracts in red (left) and blue (right). *Source:* Cook County Recorder, ACS 2009-2023 and Census Demographic Data 1980, 1990, 2000.

B.7 Retailer Churn

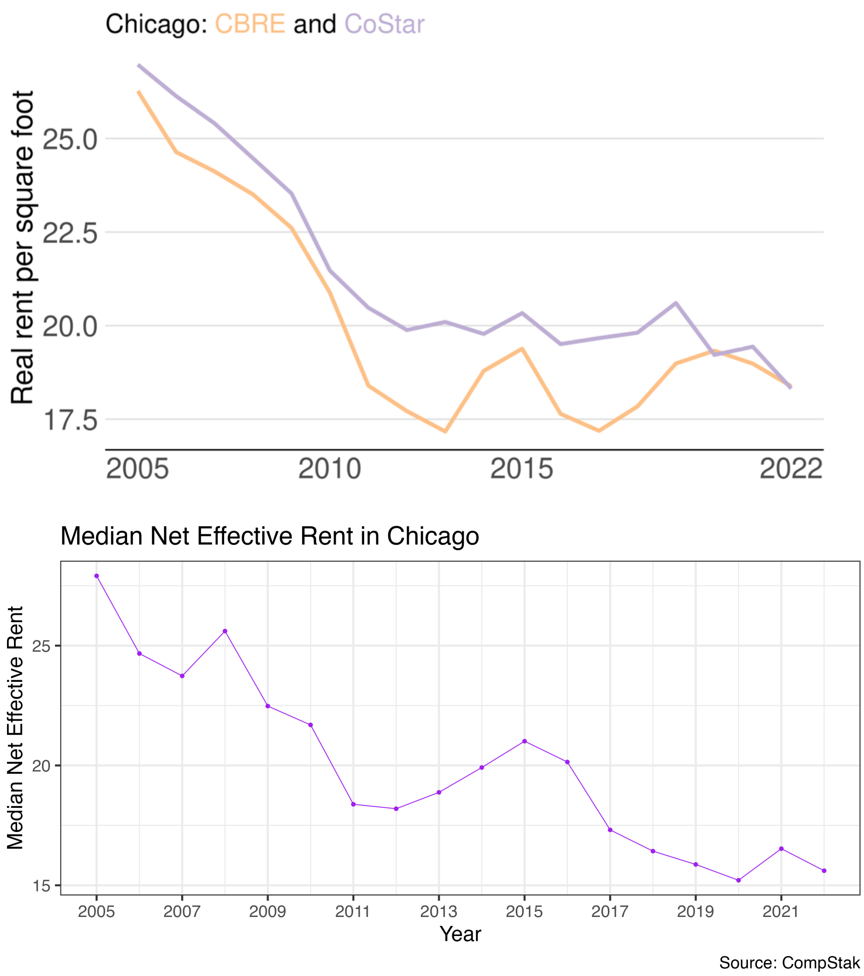
Figure 13: Exit is Rare for Big Box Stores, Chain Drug Stores, and Chain Grocery Stores: Number of Years a Retailer Stays Open by Store Type



Notes: Figure plots the number of years each store stays open by store type. At $x = -1$ is the mass of stores that has not yet closed. At $x > 0$ number of years open for stores that have closed. The plot shows that exit is rare for big box stores, chain drug stores (drug stores), and chain grocery stores. *Source:* SNAP Retailer Database.

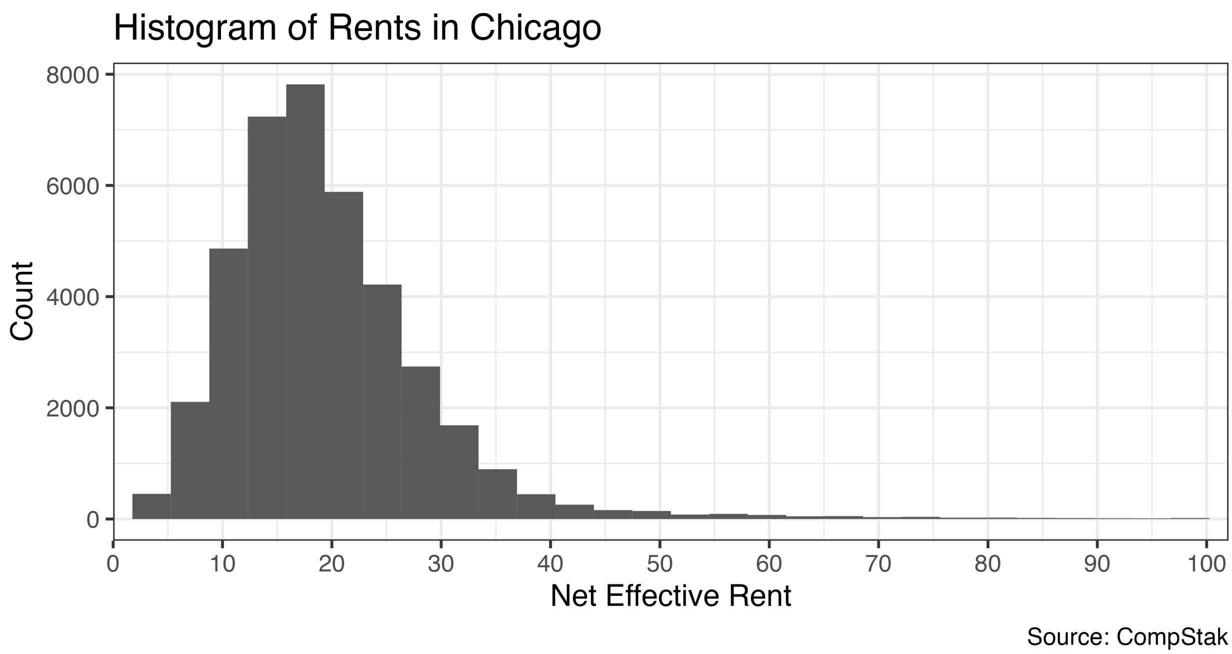
B.8 Real Estate Prices (Rents)

Figure 14: Time Series of Rental Prices



Notes: Top: Appendix Figure 1 from Brooks and Meltzer (2024) which shows median CoStar rents per square foot (largely asking rent, but in some cases effective or starting rent) in orange and CBRE mean retail gross asking rent per square foot in purple. CoStar is the data source used by Brooks and Meltzer (2024), and CBRE is a global real estate services company that collects data on retail leases. The data is in 2022 dollars. The levels are different between CoStar and CBRE likely use different sources or definitions of asking rent (Brooks and Meltzer (2024)). Bottom: Median net effective rents in Chicago over time in CompStak data used in this paper. The data is in 2022 dollars. This measure is different than the asking rent (top) and is measured as net effective rent (the total rent owed to the landlord per year per square foot). *Source:* CompStak.

Figure 15: Rental Prices in the Data



Notes: Histogram of rental prices in the CompStak data. Rents are computed as net effective rent, the total amount owed to the landlord per square foot per year, in 2016 USD. *Source:* CompStak.

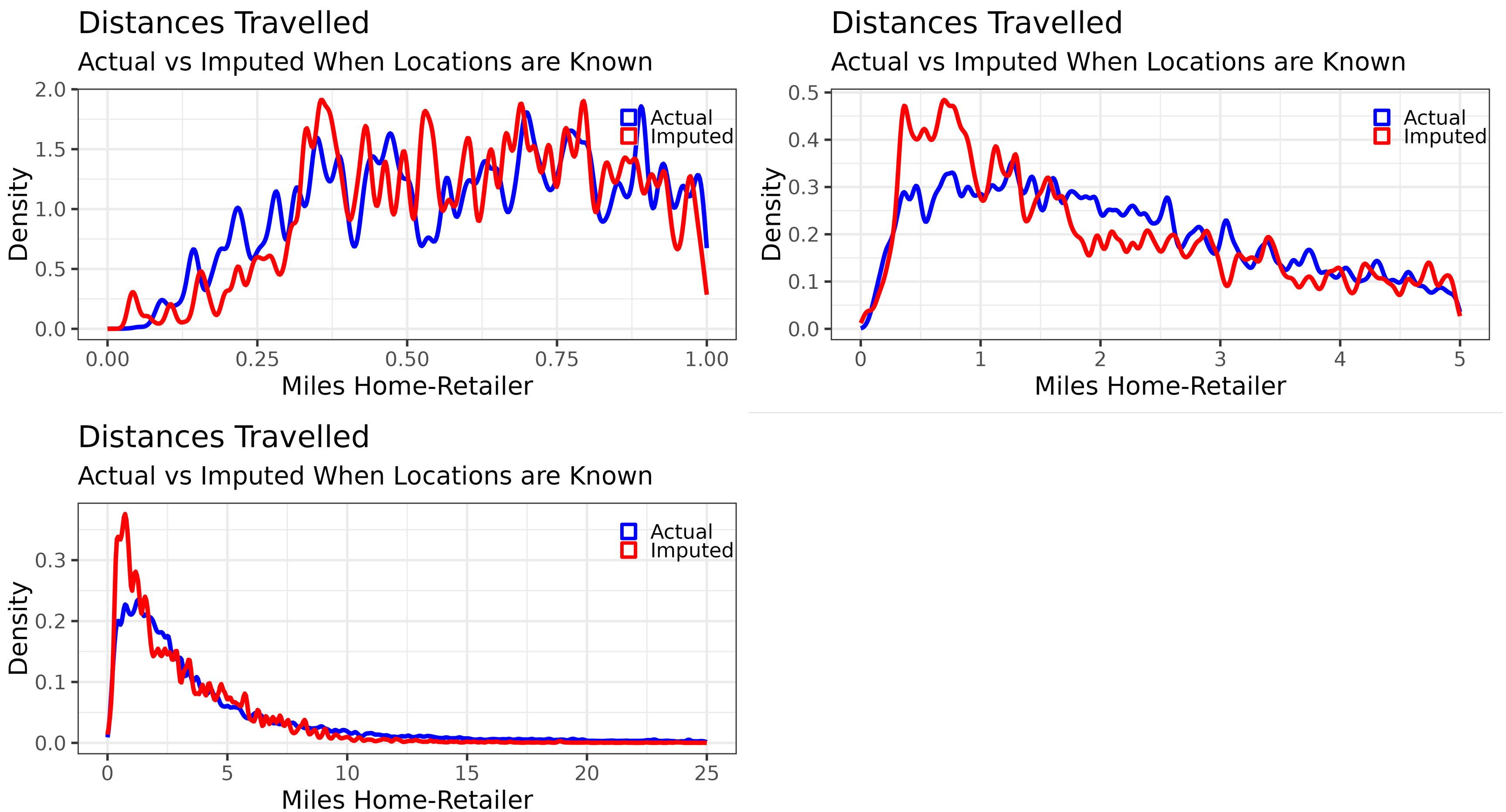
B.9 Consumer Shopping Patterns

Figure 16: Numerator Definitions

Item ID		Department		Sector
(ex: French's Crispy Fried Jalapenos 5 oz)	$\subset$	(ex: Condiments)	$\subset$	(ex: Grocery)
n = 13,589,708		n = 312		n = 23

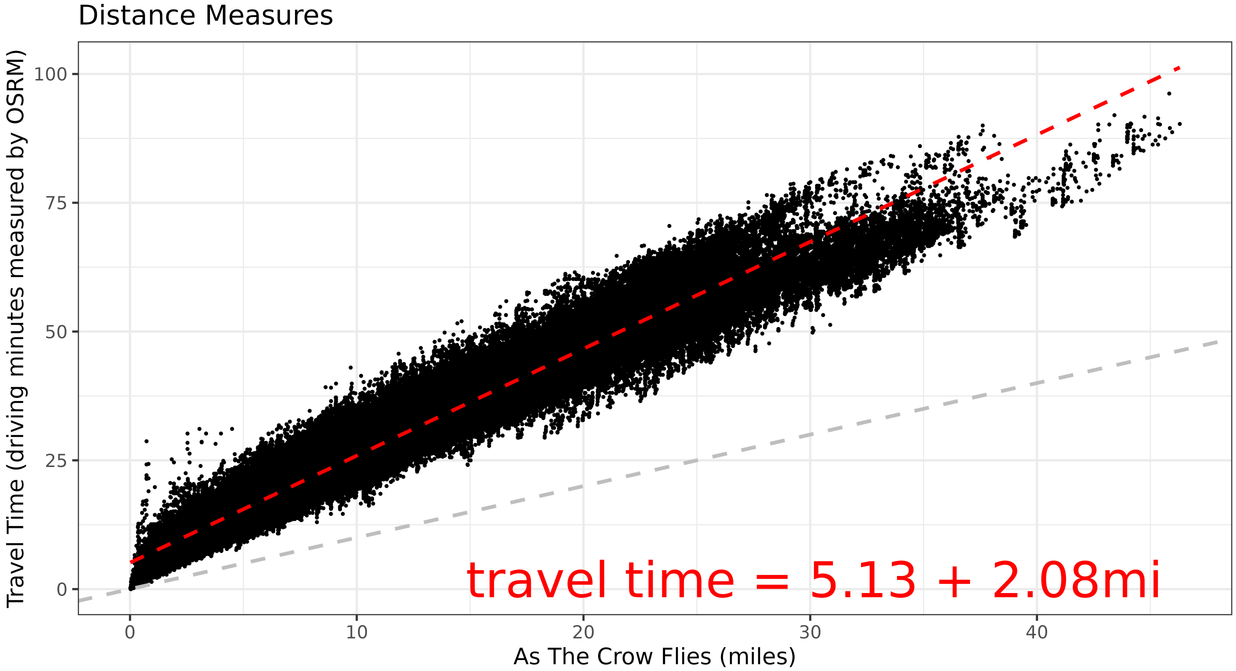
Notes: Figure shows three of the levels of aggregation in the Numerator data. This figure follows a similar figure in Handbury (2021). On a trip, a consumer purchases a set of individual items recorded at the barcode level, called Item ID's, that comprise the individual's basket of purchases for that trip. Numerator data classifies items in to several categories, broader and broader categories. Figure 16 shows these categories. For example, a single item "French's Crispy Fried Jalapenos 5oz", belongs to a larger category of goods that are similar to the consumer but might be quite different in terms of content. These categories are then grouped into larger departments, which are itself grouped into larger sectors, such as grocery and home goods.

Figure 17: Households Shop Close To Home: Comparing Observed and Imputed Distances Traveled to Retailers



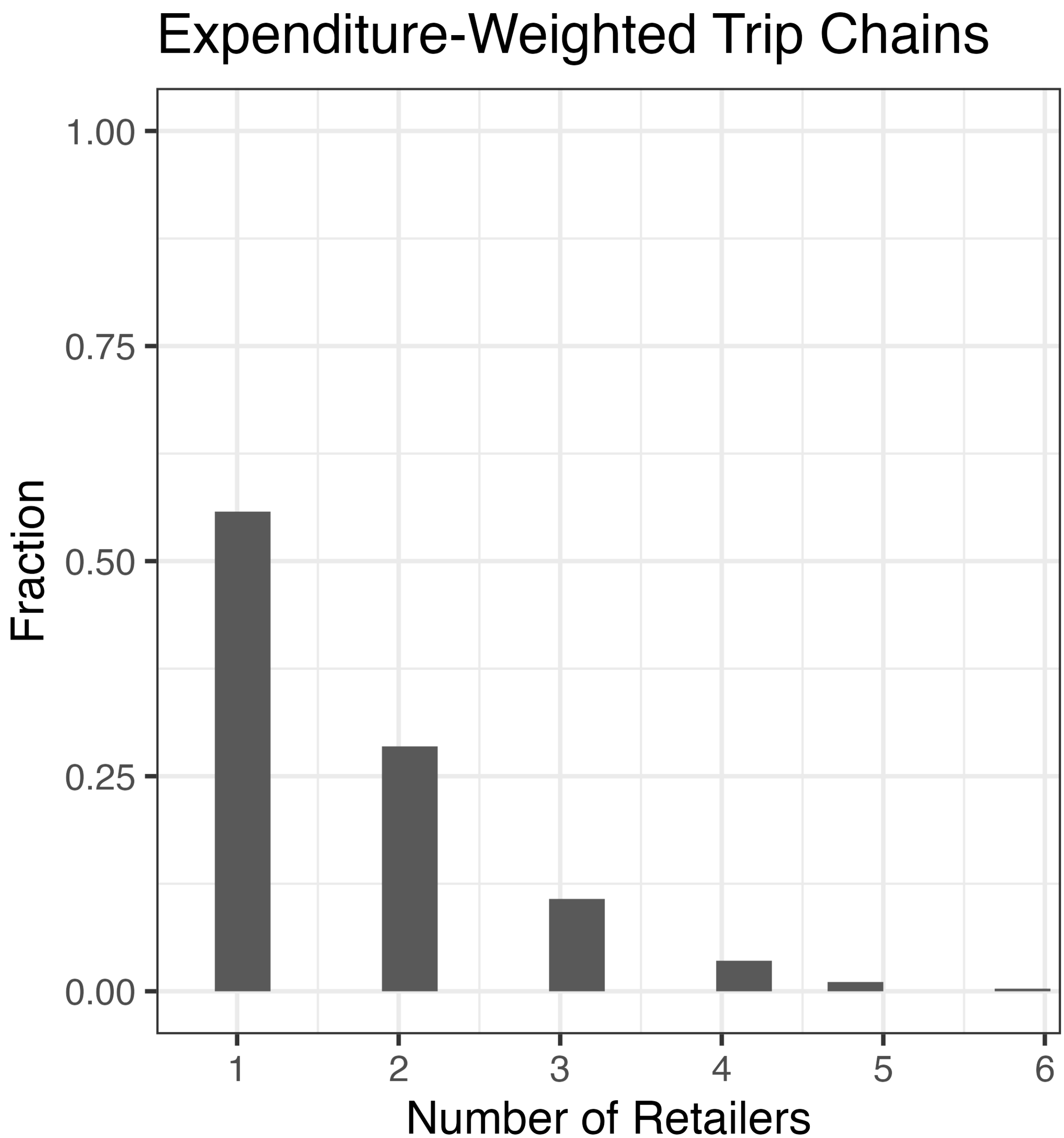
Notes: Comparison of actual distances traveled versus imputed distance traveled when the data on store locations are available for distances between (a) 0-1 miles, (b) 0-5 miles and (c) 0-25 miles. This tests whether consumers are shopping at stores close to home. The Kolmogorov–Smirnov test to determine whether the distributions (imputed and observed) are the same, finding a D = 0.111 and a p-value $< 2.2e - 16$. The distance, D, indicates that the maximum distance in as-the-crow-flies miles between the actual and imputed distributions is 0.111 miles. *Source:* Numerator.

Figure 18: Distances and Travel Times are Correlated



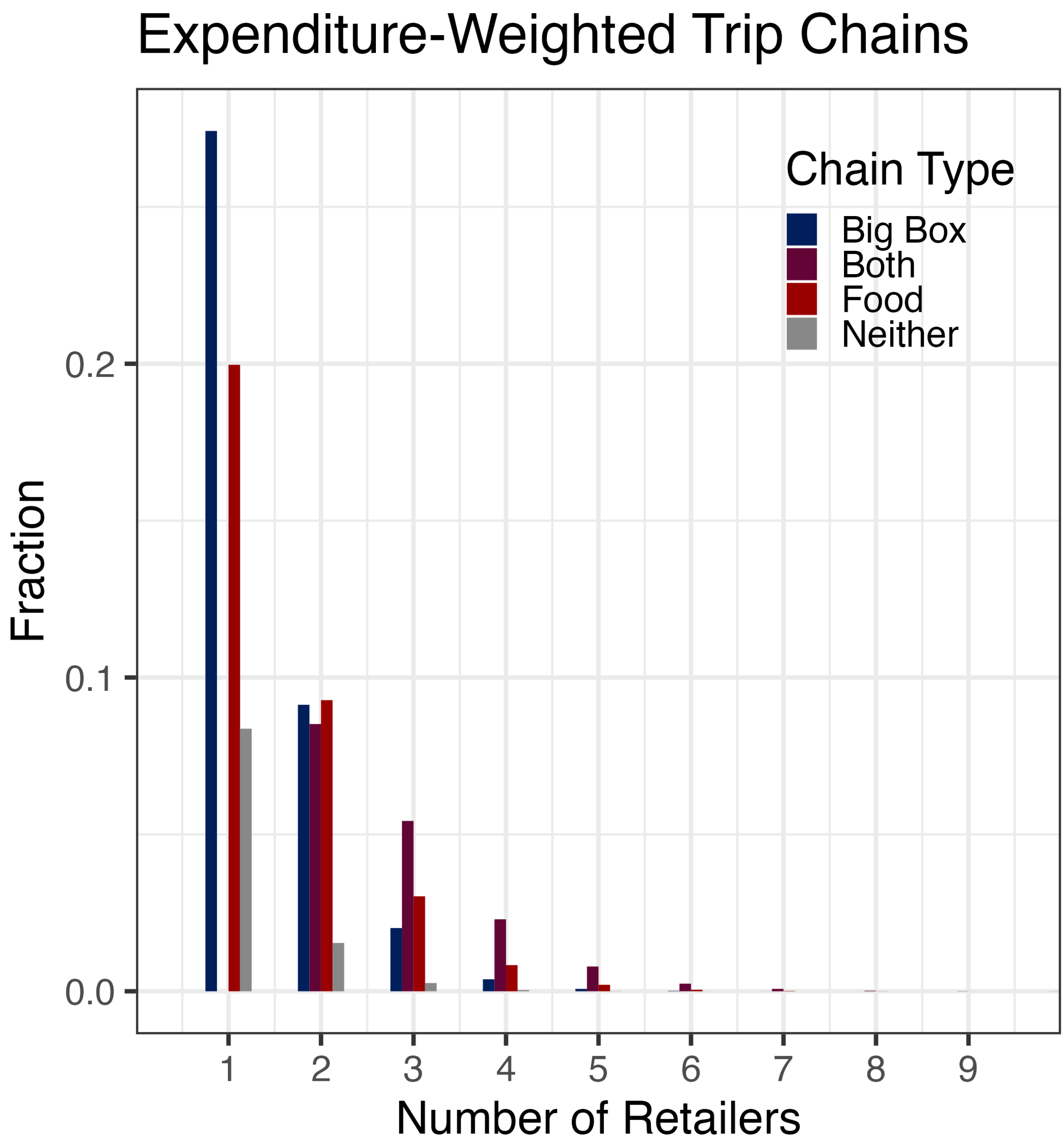
Notes: Figure shows total trip distance in miles and total travel time. Distances are measured in miles and travel times are measured in minutes in the car as reported by OSRM. The red dashed line reports the best fit, and the grey line reports the 45 degree line where travel times and distances are the same. *Source:* Numerator, Chicago, 2017-2019.

Figure 19: Histogram of Trips with Different Numbers of Retailers



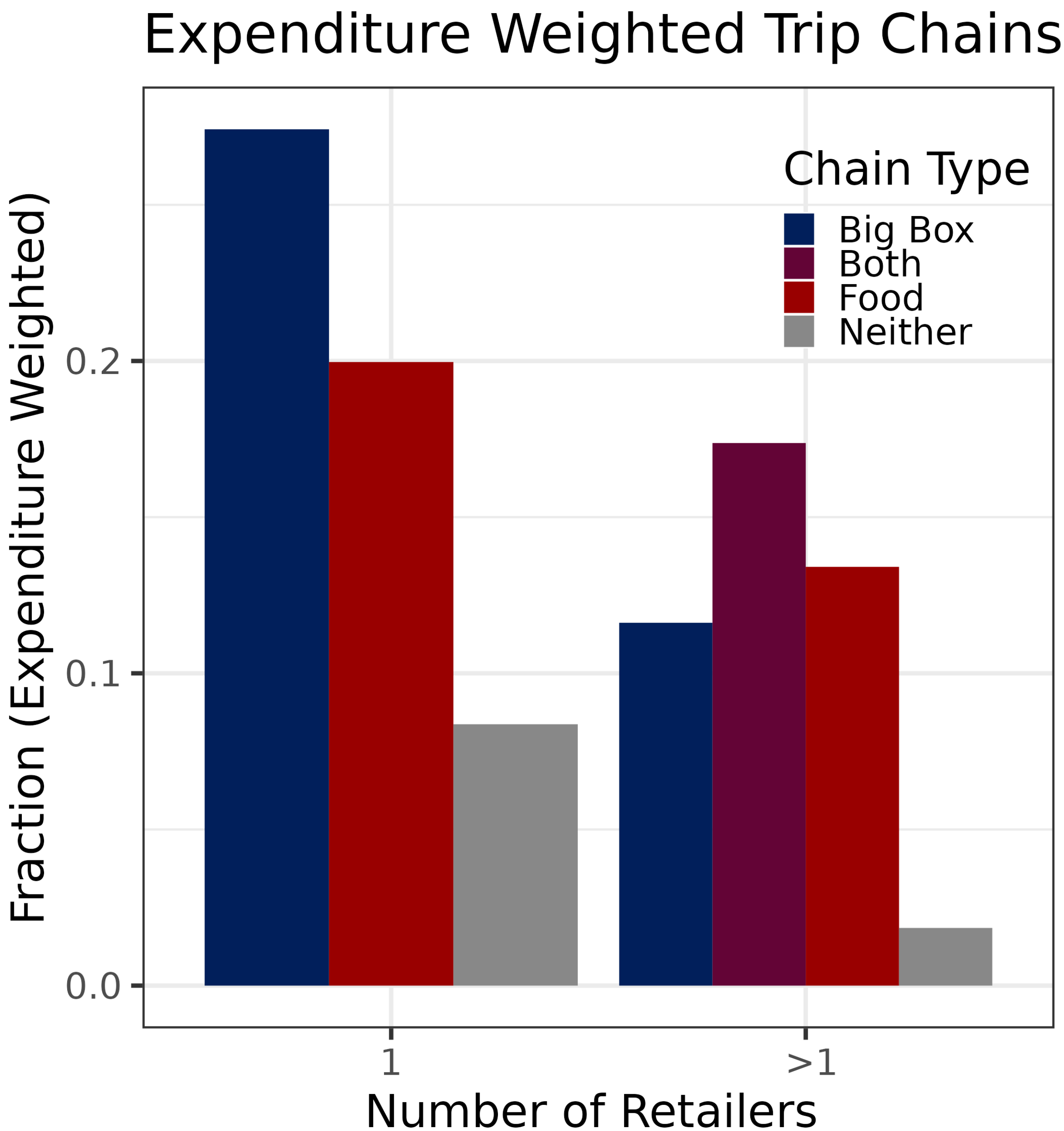
Notes: Figure shows prevalence of multi-homing or shopping at more than one store in the same day. *Source:* Numerator, Chicago, 2017-2019.

Figure 20: Multi-Homing: Histogram of Number of Retailers Shopped at Per Trip by Store Type



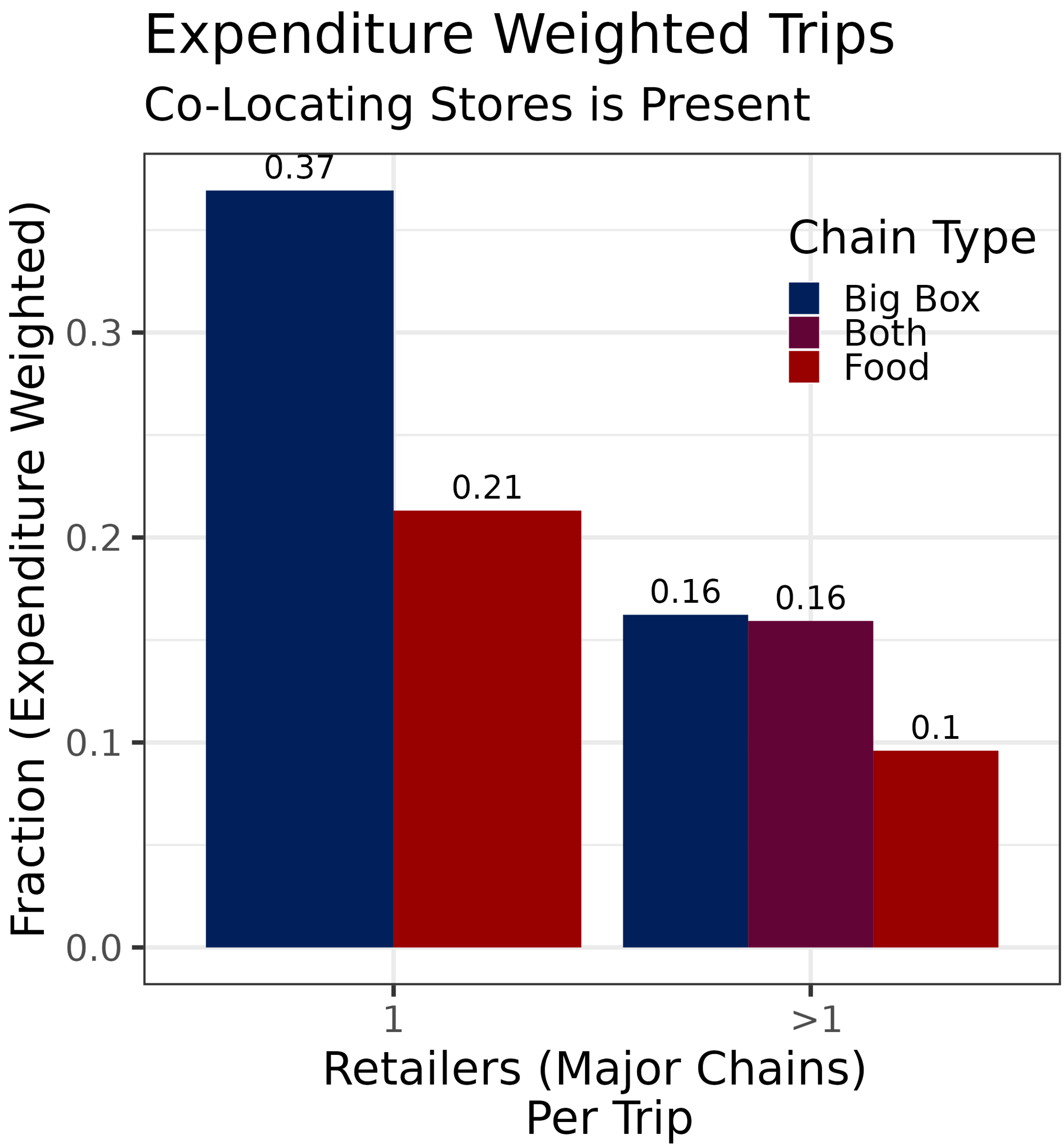
Notes: Figure shows prevalence of multi-homing or shopping at more than one store in the same day, broken down into store type categories. *Source:* Numerator, Chicago, 2017-2019.

Figure 21: Multi-Homing



Notes: Figure shows prevalence of multi-homing or shopping at more than one store in the same day, broken down into store type categories. *Source:* Numerator, Chicago, 2017-2019.

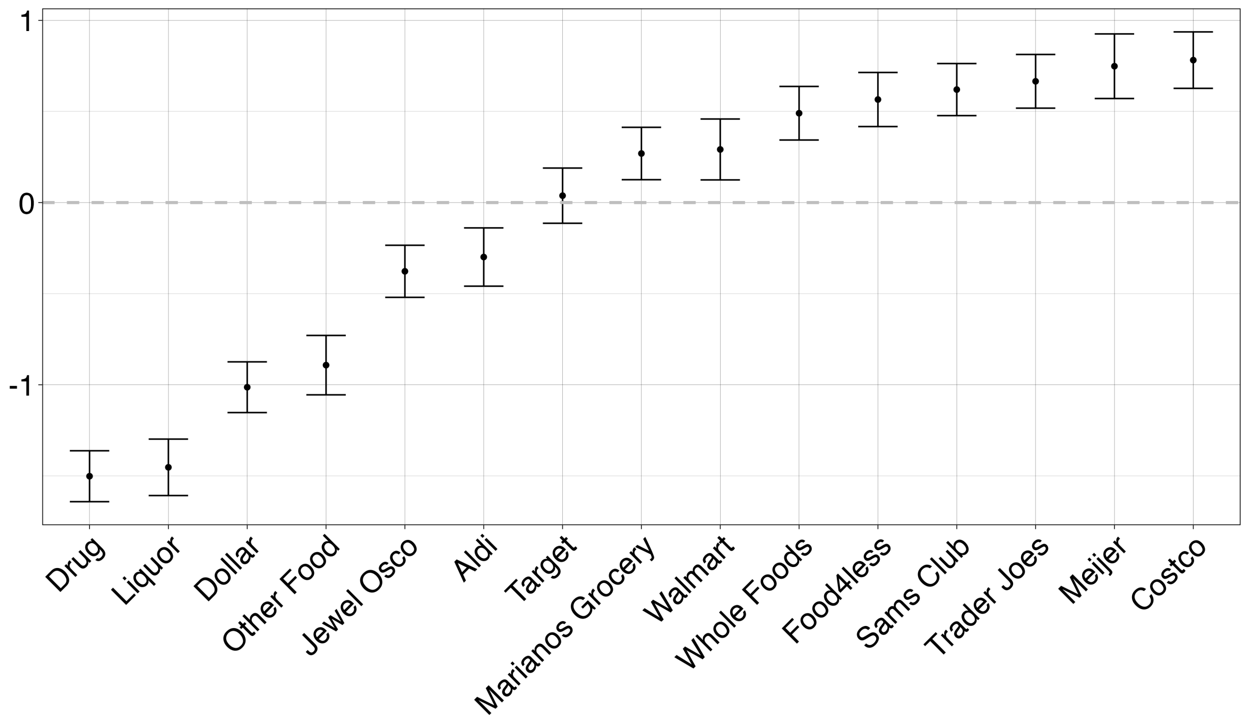
Figure 22: Multi-Homing with Large Retail Chains when Co-Locating Stores Are Present



Notes: Figure shows number of retailers per trip conditional on (1) a household shops at a large grocery or big box store (2) another store is present within .2 miles of the large grocery store or big box store. We call this second store present a co-locating store. Therefore, this plot shows the frequency of trips to a single store versus multiple stores when it is easy for the household to shop at a second store. *Source:* Numerator, Chicago, 2017-2019.

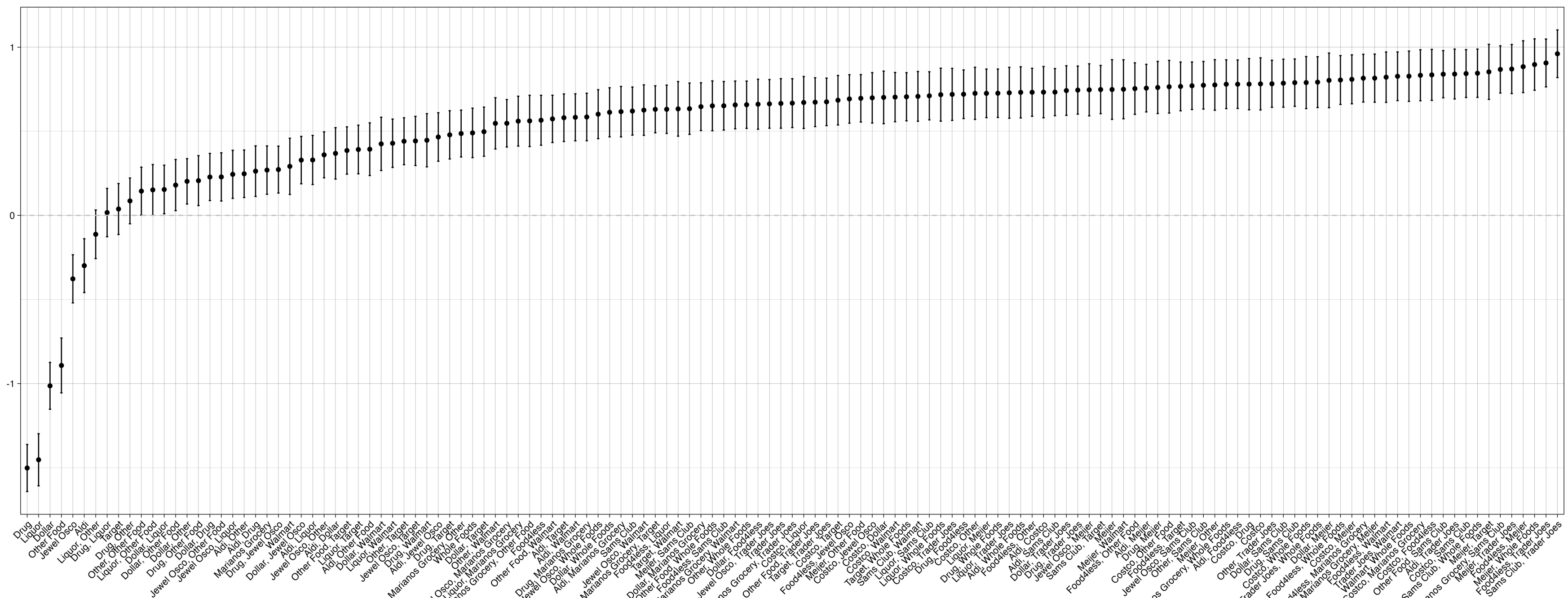
B.10 Product Market Estimates

Figure 23: Complementarity Estimates: Own Quality



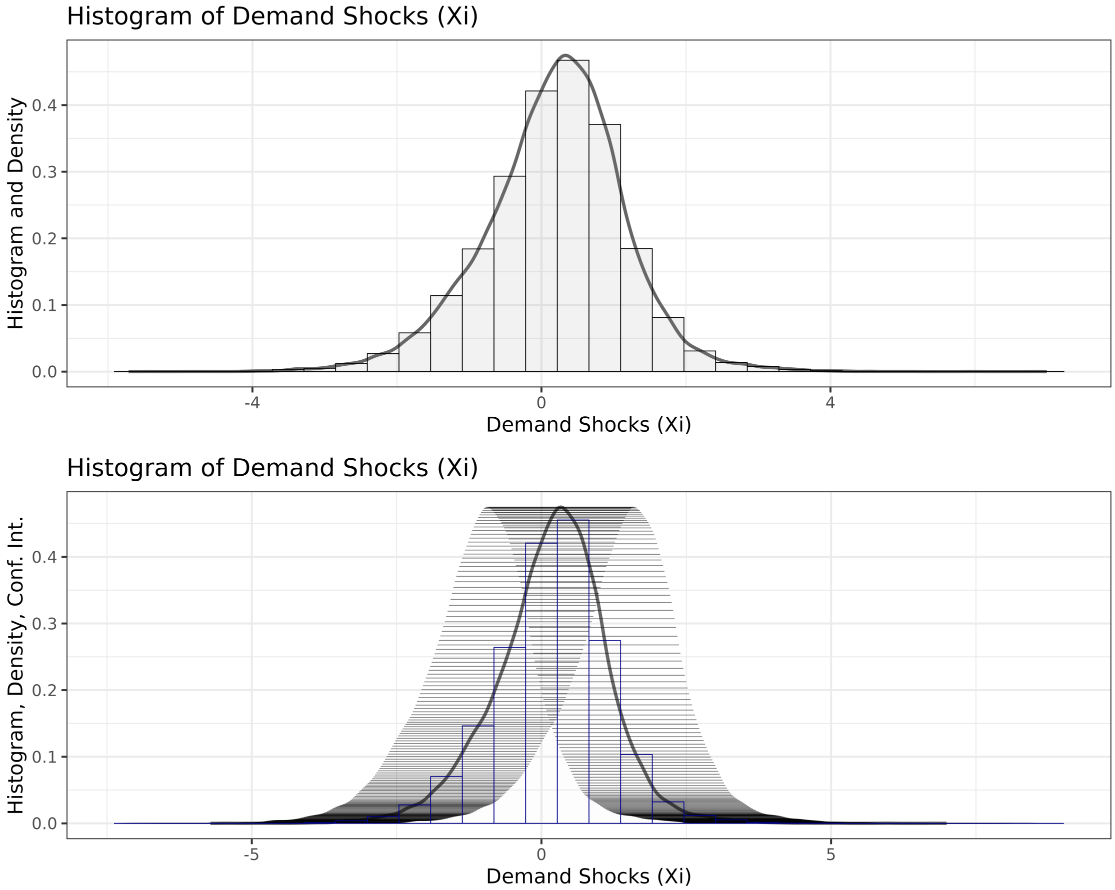
Notes: Estimates of own quality, Γ_b, for each retailer in the estimation. The omitted group is the outside good $\Gamma_{outside} = 0$. *Source:* Numerator 2017-2019.

Figure 24: Complementarity Estimates



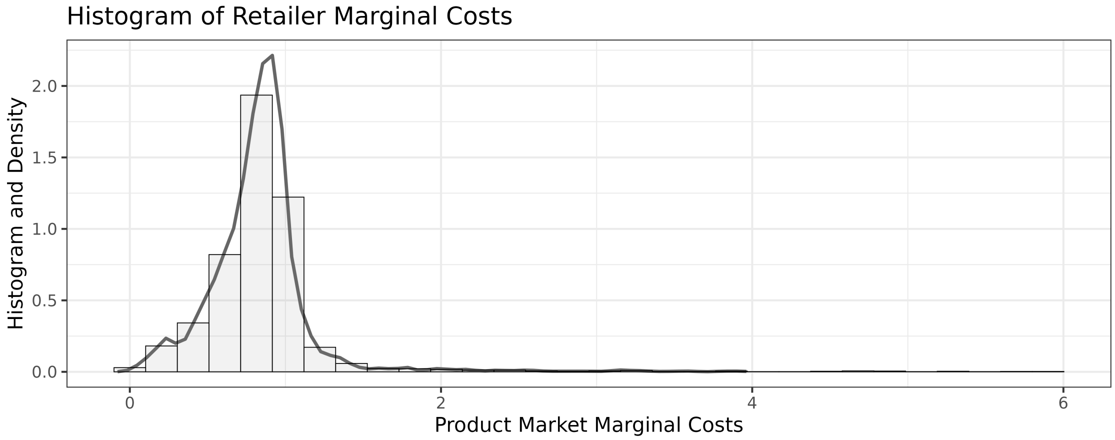
Notes: All estimates of Γ_b, the store complementarities and own-store quality estimates. *Source:* Numerator 2017-2019.

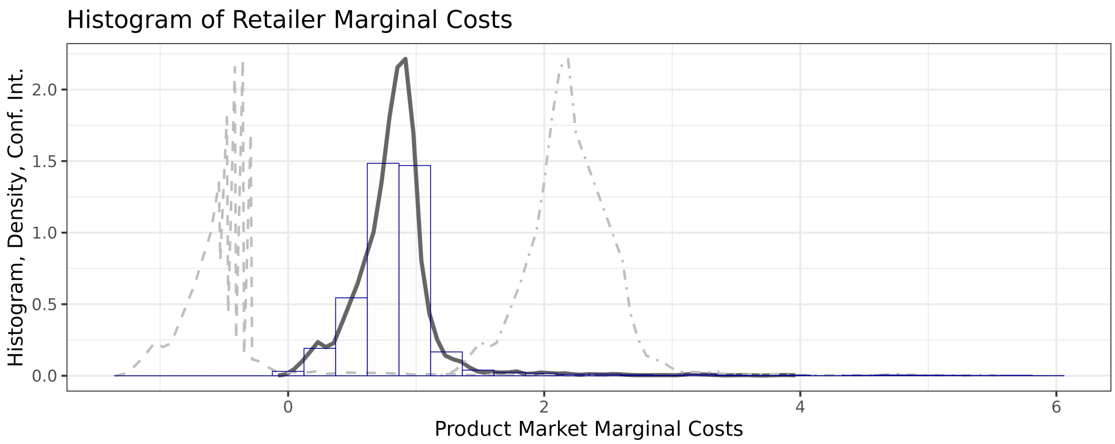
Figure 25: Demand Shocks in the Product Market



Notes: The top plot shows the histogram and density of demand costs, ξ^g_{bt} for the estimated parameters. The bottom plot shows the histogram and density of demand shocks for the estimated parameters (dark grey line), and the 95th confidence interval for each estimate around the density (horizonal light grey lines). The confidence interval are computed using estimates implied by the 95% confidence level for the estimates used to compute marginal costs, $\delta^g_{bt}, p^g_{bt}, \Gamma_b$. Standard errors from the maximum likelihood estimation and instrumental variables regression are compounded, $(se^2_{mle} + se^2_{iv})^{1/2}$ to compute a standard error for marginal costs. *Source:* Numerator 2017-2019.

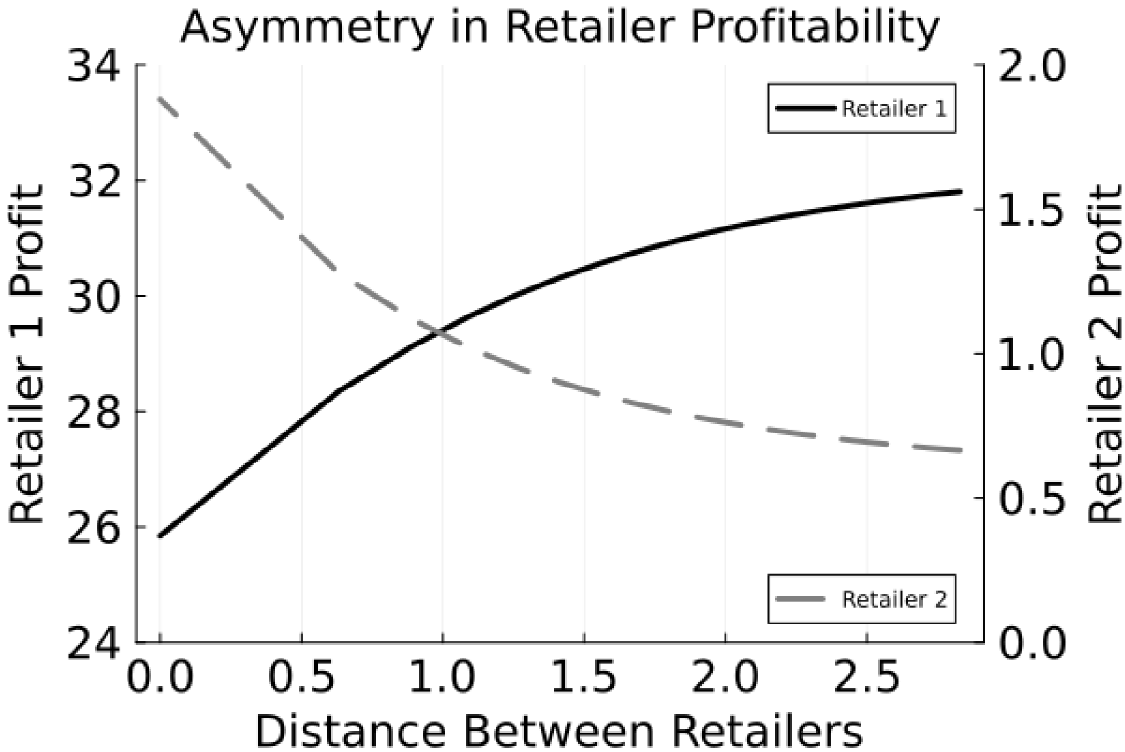
Figure 26: Marginal Costs in the Product Market





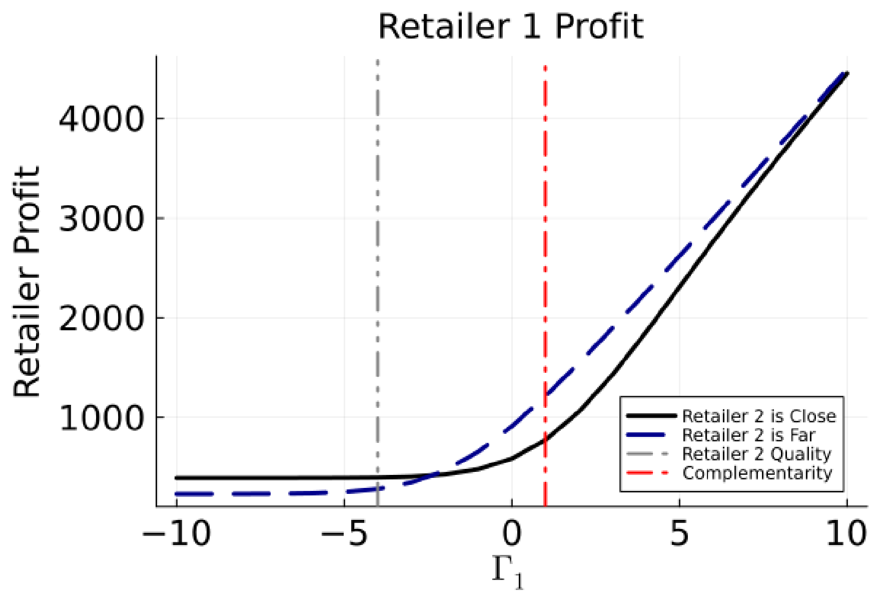
Notes: The top plot shows the histogram and density of marginal costs for the estimated parameters. The bottom plot shows the histogram and density of marginal costs implied by the 95% confidence interval (dashed line, shifted left and dash-dotted line, shifted right). The 5th and 95th percentile parameters are computed using standard errors from the maximum likelihood estimation and instrumental variables regression are compounded, $(se_{mle}^2 + se_{iv}^2)^{1/2}$ to compute a standard error for marginal costs. *Source:* Numerator 2017-2019.

Figure 27: Complementarity Estimates Γ_b Lead to Asymmetric Profitabilities



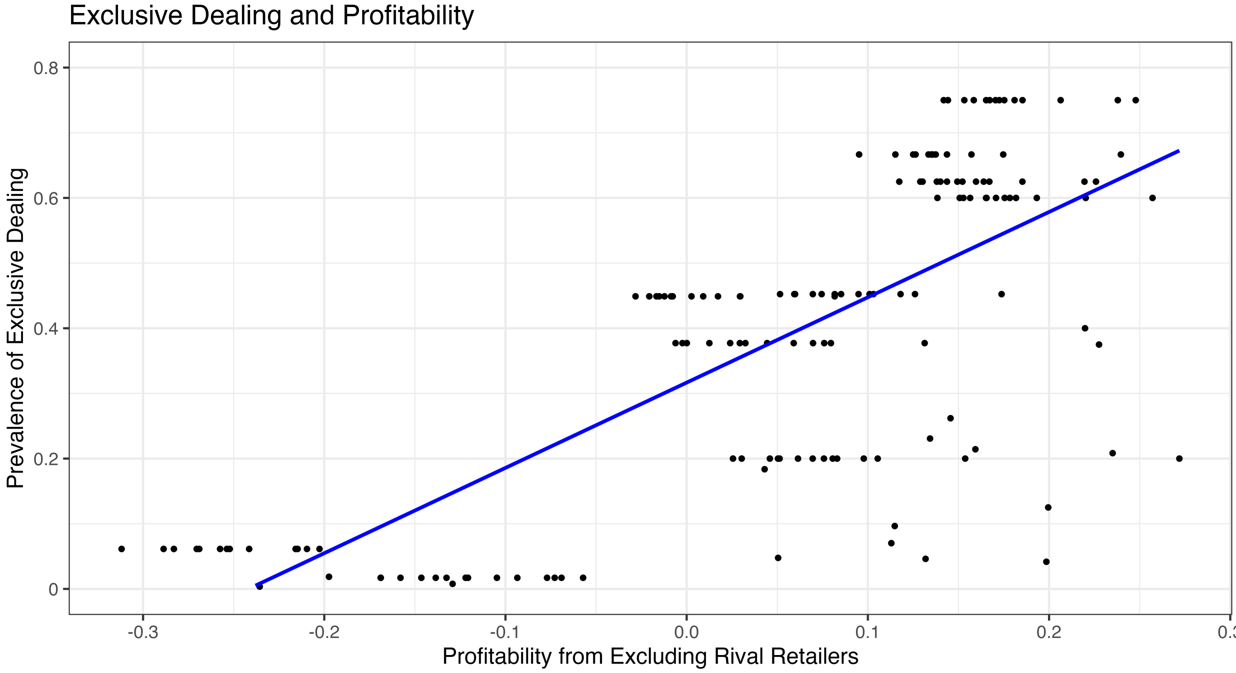
Notes: Figure shows expected profitability of two retailers to illustrate how asymmetry in complementarity estimates, Γ_b, result in asymmetric profitability. In this illustrative example, households prefer Retailer 1 to Retailer 2, and prefer shopping at both stores to shopping at Retailer 2 alone: $\Gamma_1 > \Gamma_{12} > \Gamma_2$. Distances between households and each retailer alone is kept constant, but the distance between retailers is increased (x axis). The Figure shows that Retailer 2 profits from being close to Retailer 1. Retailer 1 benefits when the retailers are far apart, incentivizing Retailer 1 to sign an exclusive dealing agreement with their landlord.

Figure 28: Complementarity Estimates Γ_b Lead to Asymmetric Profitabilities



Notes: Figure illustrates when two retailers prefer to locate close vs far away from each other, depending on the values of complementarity Γ. The figure plots Retailer 1 profits when Retailer 2 is close (solid black line) and far (dashed blue line) as a function of Retailer 1 quality (x axis). Households choose between Retailer 1, Retailer 2, Both 1 and 2, and Retailer 3; Retailer 3 is relatively low quality outside good. Below the gray line, Retailer 1 quality is worse than Retailer 2, and Retailer 1 profits from co-locating near Retailer 2. Between the gray line and the red line, Retailer 1 quality is higher than Retailer 2, but positive complementarities (red dash-dotted line) make it profitable for co-location. For high enough values of own quality, Retailer 1 profits from locating farther from Retailer 2. The key parameters are own quality and complementarity: $\Gamma_1, \Gamma_2, \Gamma_{12}, \Gamma_3$.

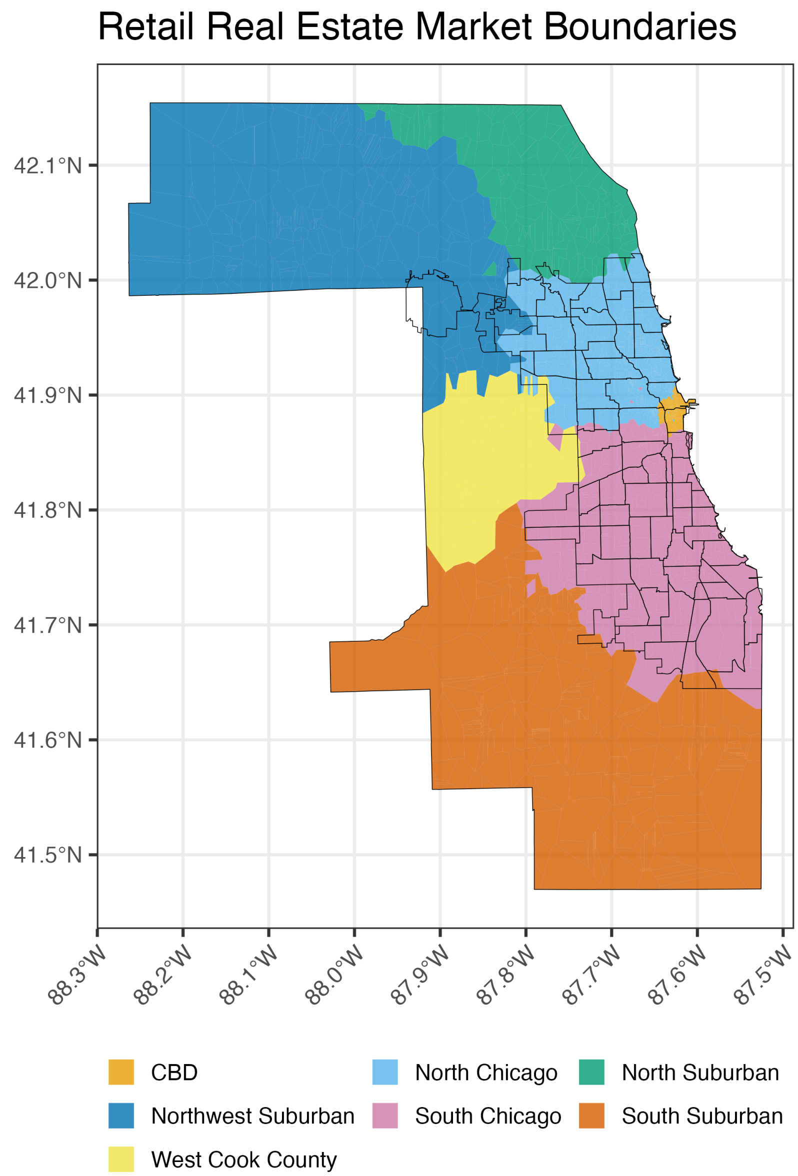
Figure 29: Profitability and Profitability of of Rival Exclusion



Notes: This figure shows the correlation between the profitability from excluding rival retailers and the prevalence of exclusive dealing. *x* axis: The profitability of excluding rival retailers is estimated with consumer panel data. Each observation plots the percent change in profits from displacing a rival retailer from the same shopping center to a nearby shopping center. The set of retailers are: Aldi, Costco, Dollar, Drug, Food 4 Less, Jewel, Liquor, Mariano's, Meijer, Sam's Club, Target, Trader Joe's, Walmart, Whole Foods. *y* axis: The prevalence of exclusive dealing is computed with data on store locations and exclusive dealing contracts at each location. Each observation represents the fraction of stores that block a particular product: for example, the fraction of Costco's that forbid food sales. The set of retailers are: Aldi, Costco, Dollar (comprised of Dollar General, Family Tree and Family Dollar), Drug (comprised of CVS, Walgreens and Phar-Mor), Food 4 Less, Jewel, Liquor, Mariano's, Meijer, Sam's Club, Target, Trader Joe's, Walmart, and Whole Foods. The set of categories blocked are: Food, Drug/Pharmacy, Dollar Store/Convenience Store Products, and Liquor. Exclusive dealing is more common as the profitability of exclusion increases. *Source:* Numerator 2017-2019 and Cook County Recorder Office 1980-2023.

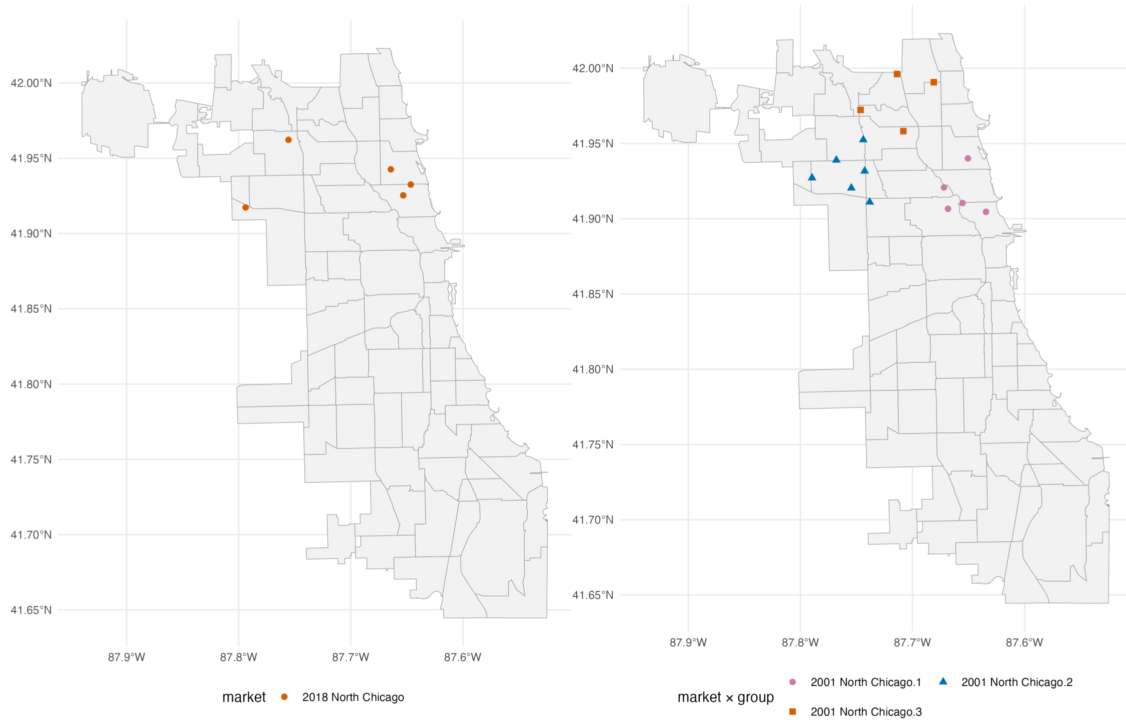
B.11 Retail Real Estate Market Definition

Figure 30: Market Definition



Notes: Figure shows geographic areas for different retail real estate in Cook County, Chicago. the total potential locations for all retailers (retailers and co-locating stores) in the analysis. The boundaries are defined to minimize the probability a consumer shops across boundaries, from data and conversations industry professionals. The colors are plotted computing Voronoi polygons to fill in the colors across points.

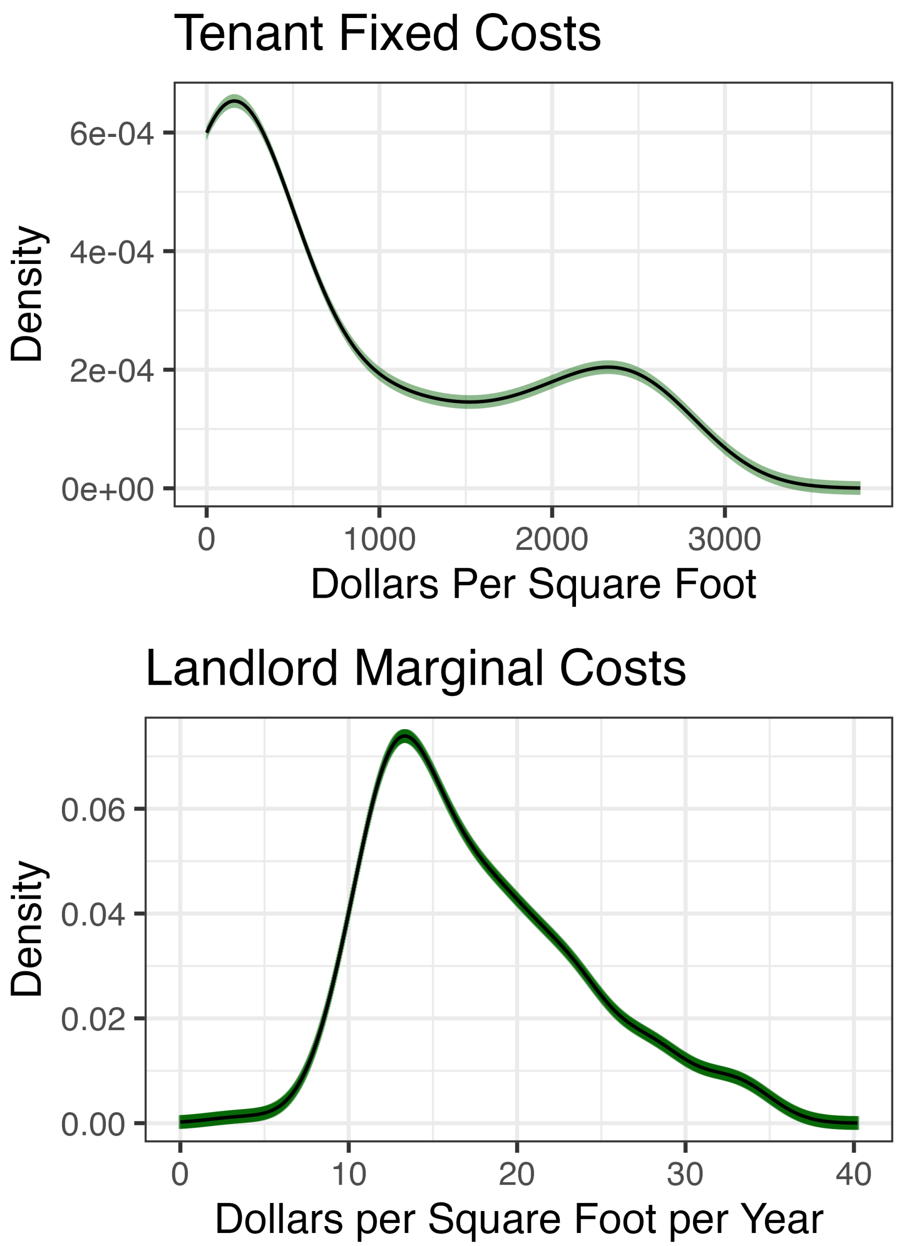
Figure 31: Potential Locations for Large Retailers in a Market: Example



Notes: Figure shows potential locations in markets for large retailers in North Chicago in 2001 and 2018. On the left hand side, potential locations (orange dots) are plotted for 2018 North Chicago. On the right hand side, potential locations are plotted for 2001 North Chicago. 2001 North Chicago is further split into groups 1, 2, and 3 for tractability. The groups are determined by clustering geographically close points together with k-means.

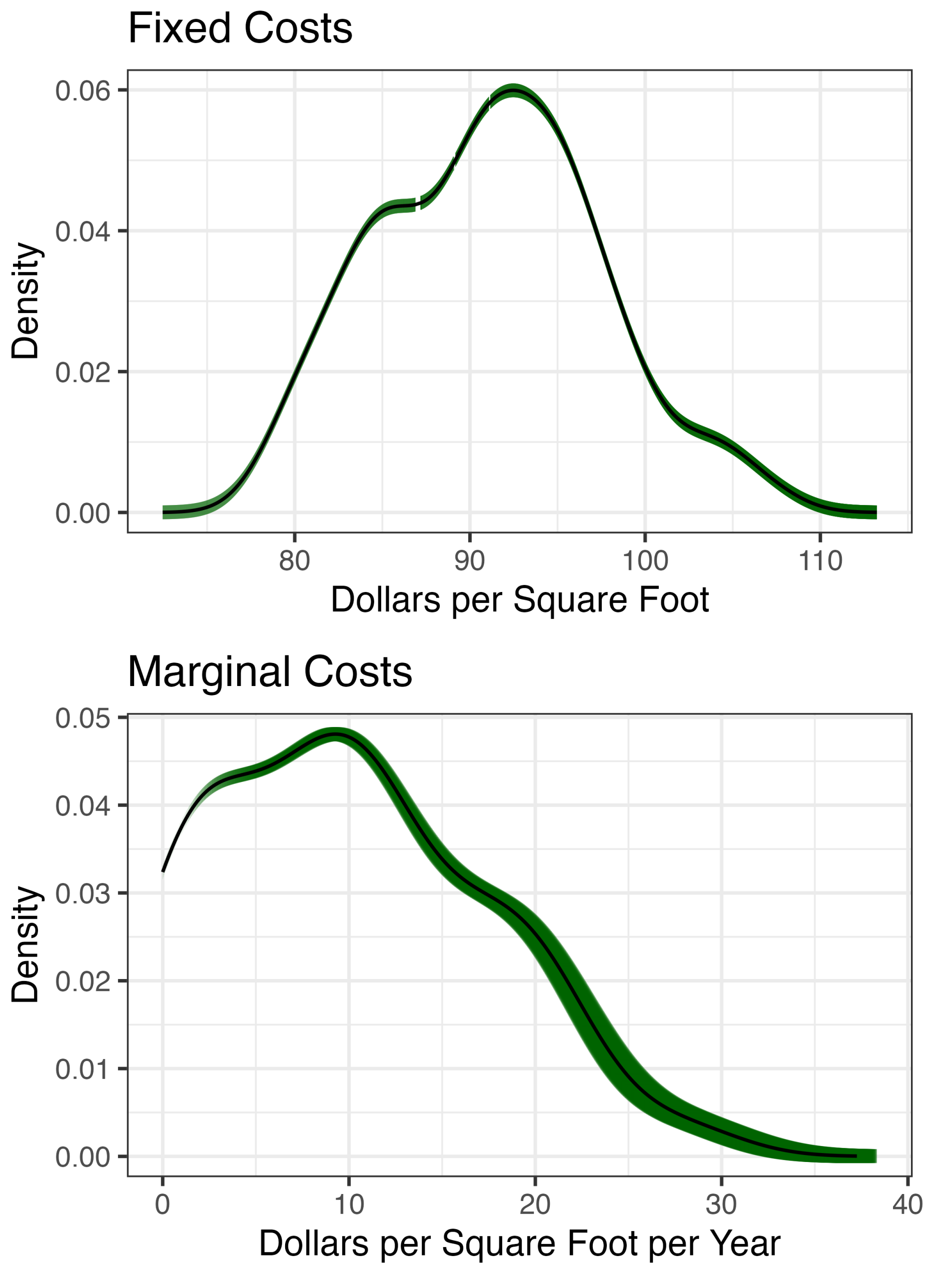
B.12 Retail Real Estate Market Estimates

Figure 32: Small Retailer and Landlord Costs



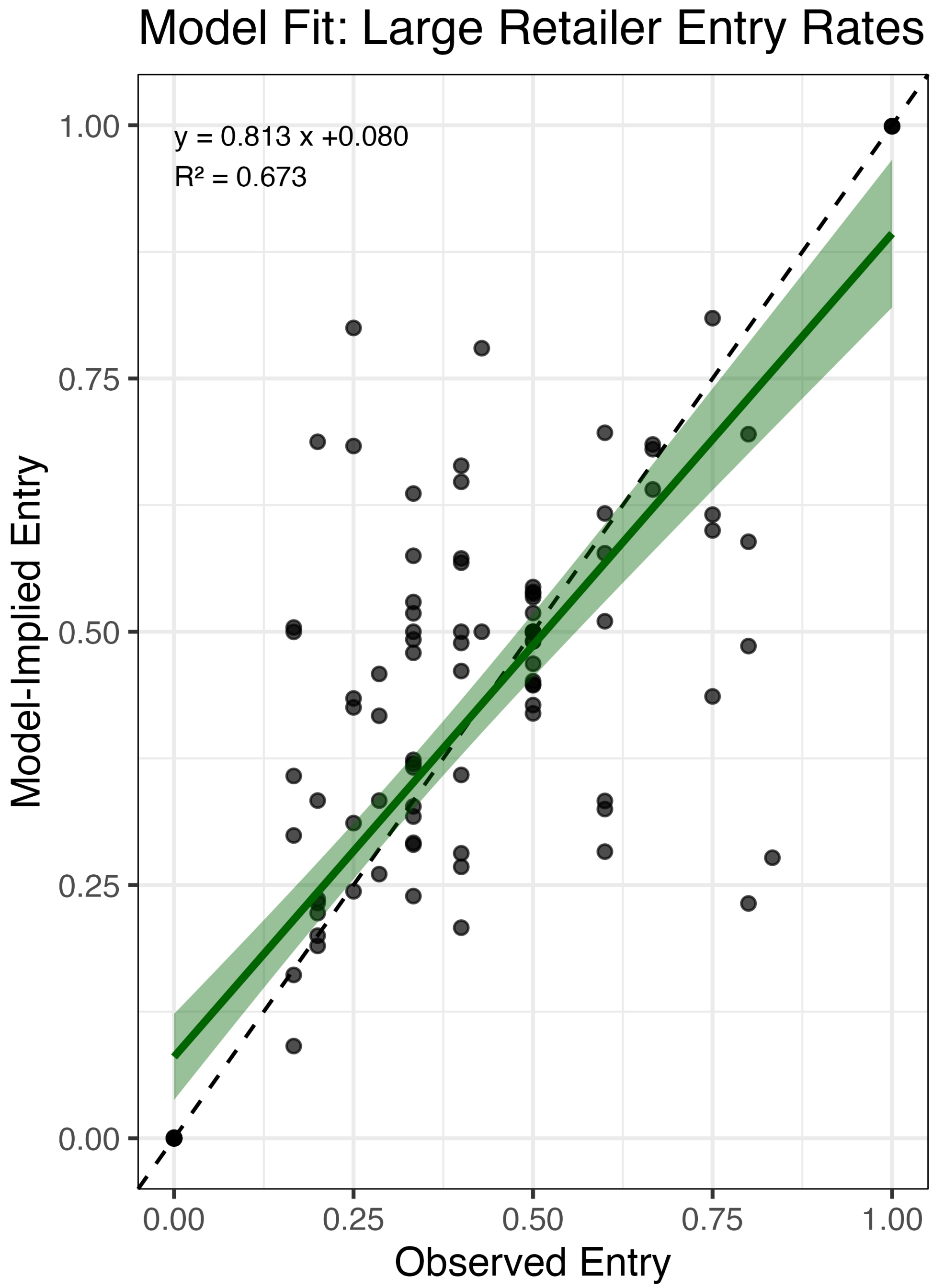
Notes: Estimates of the tenant fixed costs of entry, and landlord marginal costs in the small retailer real estate market. Fixed costs are measured in 2016 US dollars per square foot and marginal costs are measured in 2016 US dollars per square foot per year. Estimates assume that large retailers have 3 years to recoup the fixed costs of entry. Standard errors are computed with 200 draws from the parametric bootstrap. The shaded band around each estimate shows the 95th confidence interval.

Figure 33: Large Retailer and Landlord Costs



Notes: Estimates of the tenant fixed costs of entry, and landlord marginal costs in the small retailer real estate market. Fixed costs are measured in 2016 US dollars per square foot and marginal costs are measured in 2016 US dollars per square foot per year. Estimates assume that large retailers have 6 years to recoup the fixed costs of entry. Standard errors are computed with 200 draws from the parametric bootstrap. The shaded band around each estimates shows the 95th confidence interval.

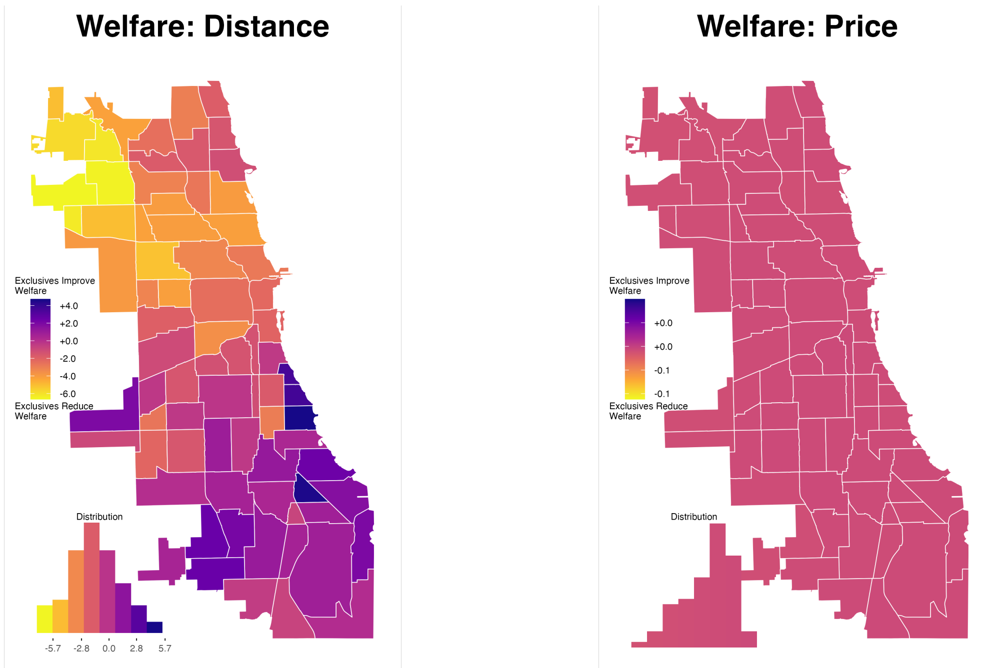
Figure 34: Model Fit: Observed Entry Rates in Model and Data



Notes: Figure plots observed entry rates in the data in each market for large and small retailers (x) axis and the predicted model entry rates for large retailers in each market (y) axis. Estimates and data match exactly on the 45 degree line (the black dashed line). The linear fit line, 95% confidence interval is reported with the green solid line.

B.13 Counterfactuals

Figure 35: Consumer Welfare Estimates



Notes: Figure plots the compensating variation comparing the equilibrium with exclusive dealing to the equilibrium without exclusive dealing. The left side shows the welfare changes from distance and the right hand side shows the changes from prices.

C Tables

C.1 Retailers

Table 6: Most Frequented Retailers by Size and Parent Company

Parent	Retailer	Size
Amazon	Whole Foods	Large
Safeway	Jewel Osco	Large
Kroger	Mariano's (Kroger)	Large
Kroger	Food 4 Less	Large
Aldi	Aldi	Medium
Trader Joe's	Trader Joe's	Medium
Costco	Costco	Very Large
Meijer	Meijer	Very Large
Walmart	Sam's Club	Very Large
Walmart	Walmart	Very Large
Target	Target	Large
	Drug Store	Small
	Dollar	Small
	Liquor	Small
	Other Food	Large
	Other	Small, Large, and Very Large

Notes The retailers (and parent company, if retailers share a common parent company) included in the analysis are those with the largest market share and most frequent trips. Retailers and potential locations are categorized into coarse location size groups. Aldi and Trader Joe's are opearted separately, and so are assumed to perate sparately.

C.2 Exclusive Dealing: Summary Statistics and Descriptive Analysis

Table 7: Chicago Grocery Chains with Exclusive Dealing Contracts

Aldi	Jewel Osco (Safeway)	Trader Joe's
Delray Farms	Mariano's (Kroger)	Whole Foods
Dominicks Finer Foods (Safeway)	Meijer	
Food 4 Less (Kroger)	Save a Lot	
Gordon Food Service Store	Tony's Fresh Market	

Notes: Table reports retailers in Chicago which have exclusive contracts. Data is for Cook County, IL. Data comes from the Cook County office recorder and the SNAP database.

Table 8: Prevalence of Exclusive Dealing in the Grocery Industry

	Total	*Total on a Grocer Location*	*Fraction on a Grocer Location*
Exclusive Dealing Contracts Blocking Grocers	351	140	0.40
	Total	*Total with Contracts*	*Fraction with Contracts*
Grocery Chains (Retailers)	23	12	0.52
Grocery Chain Stores	389	110	0.28
Fraction of Grocery Chain Stores with Exclusive Dealing by Neighborhood Income	*Rank*	*All Chains*	*Most-Frequented Chains*
Lowest Income Rank	1	.58	.71
	2	.34	.36
	3	.42	.50
Highest Income Rank	4	.63	.61

Notes: Table reports the prevalence of exclusive dealing contracts among grocery chains. The first block (row 1) reports the total number of locations with exclusive dealing contracts that block the sale of groceries. The first column (row 1 column 1) reports the total number of contracts at unique addresses that prohibit or limit the sale of groceries, the second column (row 1 column 2) enumerates the number of grocery stores that employ such contracts, and the third column (row 1 column 3) enumerates the fraction of grocery stores that employ such contracts. The second block shows the number of grocery chain retailers that have exclusive dealing contracts at at least one property, by chain (row 2) and by store (row 3). The grocery chains operating in Chicago are defined as retailers that have had at least 5 different store locations between 1990 and 2023 in Cook County, IL. The third block shows the fraction of rented grocery chain stores in low, middle, and high income neighborhoods that have exclusive dealing contracts. Most stores in low-income neighborhood (income rank 1 in row 4) have exclusive dealing contracts associated with the property. *Source:* Cook County Recorder Office and SNAP database.

Table 9: Summary of Radius Restrictions for Grocery and Big Box Stores

Radius Type	Count	Fraction
Adjacent Property or Shopping Center	140	.86
Radius (mi)	12	.08
Unknown	10	.06

Notes: Source: Cook County Recorder and SNAP. The table first subsets to grocery stores and big box store locations in Cook County that are (a) rented and have (b) an exclusive dealing contract. This table characterizes whether or not there is a particular radius at which the contract binds. Documents that specify the restriction holds on adjacent, nearby, or the shopping center are counted in the "Adjacent Property or Shopping Center" radius type; restrictions that specify a radius in miles or kilometers are counted in "Radius (mi)" and documents that specify an exclusive use clause or a restrictive covenant but do not provide details are categorized as "Unknown."

Table 10: Summary of Timing Restrictions for Grocery and Big Box Stores

Description of Retailer and Contract	Total	Fraction
Chain Grocery and Big Box Stores	647	
Chain Grocery and Big Box Stores with Exclusive Dealing Contracts	234	0.36
Entry	134	0.57
During including Re-Leases	99	0.42
Exit	20	0.09

Notes: Source: Cook County Recorder and SNAP. The table first subsets to grocery stores and big box store locations in Cook County that have an exclusive dealing contract. The total number is thus the total number of grocery chain and big box stores with exclusive dealing contracts (Row 1). Retailers can write exclusive dealing contracts with landlords of nearby property when the retailer enters ("entry"), while the retailer is on the property ("during"), and when the retailer exits the property ("exit"). Documents signed during tenure include releases.

Table 11: Blocking Patterns of Retailers with Most Exclusive Dealing Agreements

Retailer	Locations	Abortion	Bakery	Bowling Alley	Car Repair	Cinema	Dance Club	Deli	Convenience or Dollar Store	Drive Through	Exercise	Fast Food	Florist	Food	Grocer	Hair Salon	Karate	Liquor	Marijuana	Nail Salon	Drug	Restaurant	Retail	Shoe Repair	Skating Rink	Sports	Veterinary
Walgreens	154	0	1	57	87	58	15	3	14	6	53	11	0	102	8	5	0	4	8	1	145	60	18	0	65	4	3
Jewel Osco (Safeway)	103	0	19	15	33	30	17	21	27	16	20	4	0	66	33	0	2	7	0	0	53	33	47	1	10	5	1
Family Dollar	80	0	0	1	9	1	1	0	66	0	2	0	0	4	1	0	0	1	0	0	0	1	36	0	0	0	0
Aldi	67	10	2	24	36	26	29	6	11	1	27	5	1	43	40	1	0	8	4	1	26	20	24	1	27	7	0
Dominicks Finer Foods	64	0	5	20	27	9	14	10	7	3	24	11	0	54	36	1	0	27	0	0	33	27	23	0	22	1	0
CVS	58	0	1	8	21	9	2	2	23	3	4	0	0	20	4	0	0	3	1	0	38	3	22	0	8	1	0
Ross Dress For Less	56	0	2	34	53	15	33	2	10	0	37	0	0	3	9	0	0	3	0	1	2	18	24	0	41	23	31
Dollar General	55	0	0	0	0	4	0	0	41	0	0	0	0	4	0	0	0	4	0	0	2	0	55	0	0	0	0
Starbucks	53	0	2	2	5	3	2	1	4	23	4	3	0	15	11	0	0	39	0	0	3	41	49	0	2	0	1
Target	50	0	3	13	17	11	12	3	15	5	10	4	0	13	5	0	0	3	3	0	11	18	18	1	12	5	11
Walmart	44	0	11	13	24	9	8	10	11	3	11	3	1	19	16	0	0	9	2	0	17	14	14	0	1	8	1
Blockbuster	43	0	4	30	37	38	36	2	2	0	33	2	0	12	4	0	19	4	0	0	2	34	40	0	35	0	0
Autozone	36	0	0	17	31	20	21	0	2	0	12	0	0	1	19	0	0	0	0	0	19	13	8	0	18	0	0
7-Eleven	32	0	2	0	1	1	0	5	19	0	0	0	0	20	21	0	0	21	0	0	1	8	23	0	0	1	0
Marianos	26	0	17	2	5	8	0	17	4	2	2	2	2	21	26	0	0	21	0	0	8	10	22	0	2	0	0
Tonys Fresh Market	22	0	0	1	4	1	0	0	3	0	1	0	0	2	0	0	0	0	0	0	0	2	2	0	0	0	0
Kmart	20	0	0	1	6	1	1	0	4	1	4	0	0	6	5	0	0	2	0	0	6	3	13	0	1	1	0
Burlington Coat Factory	19	11	2	16	16	14	7	2	5	0	16	0	0	15	9	0	2	4	11	2	10	15	9	0	11	3	1
Food 4 Less	18	0	5	3	9	5	5	4	2	2	5	3	0	10	11	0	0	6	0	0	8	4	7	0	7	1	1
Staples	17	0	0	11	14	1	12	0	0	0	12	1	0	10	2	0	0	0	0	0	1	13	6	0	9	11	0
Fitness Intl	16	0	0	1	6	1	12	0	2	0	15	0	0	16	1	0	1	0	1	0	2	10	5	2	0	11	0
Whole Foods	16	0	10	6	9	9	10	9	1	1	9	1	0	16	10	0	1	5	4	1	3	10	7	0	1	2	1
Home Depot	14	0	1	3	7	4	4	1	4	4	4	1	0	4	3	0	0	1	0	0	2	4	10	1	3	1	0
Costco	13	0	0	3	6	3	3	1	4	4	3	2	0	6	4	0	0	2	0	0	1	5	7	0	2	0	1
Meijer	13	0	4	6	9	5	1	2	5	1	3	0	0	6	7	0	0	6	1	0	5	3	7	0	4	0	4
Panera	13	0	5	0	0	0	0	7	0	1	2	1	0	5	2	0	0	0	0	0	0	8	4	0	0	0	0
Dunkin Donuts	12	0	11	1	8	1	1	7	3	1	1	1	0	3	9	0	0	0	0	0	1	11	10	0	1	0	0
Burger King	11	0	0	1	1	1	1	0	0	0	0	1	0	10	0	0	0	0	0	0	1	11	0	0	1	0	0
Gas Depot	11	0	0	0	3	0	0	0	3	0	2	0	0	4	0	0	0	0	0	0	0	0	3	0	0	0	0
Office Depot	11	0	0	9	11	8	8	0	0	0	10	0	0	0	0	0	6	1	0	0	0	1	1	0	10	10	0
McDonalds	10	0	1	0	1	0	0	4	1	0	0	1	0	5	1	0	0	1	0	0	1	4	2	0	0	0	0
Blazin Wings	9	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	1	0	0	0	8	3	0	0	2	0
Delray Farms	9	0	0	0	3	0	0	0	4	0	2	0	0	6	4	0	0	0	0	0	2	1	2	0	0	0	0
Supervalu	9	0	4	3	5	4	4	4	2	0	1	1	0	8	4	0	0	5	0	0	4	2	1	0	0	3	4
Chick-Fil-A	7	0	0	2	5	2	2	0	1	0	2	0	0	5	0	0	0	1	3	0	3	4	1	0	1	1	0
Petsmart	7	0	0	6	7	6	1	0	1	5	5	1	0	7	1	0	1	1	0	0	1	5	1	0	6	2	6
Gordon Food Service Store	6	0	0	3	3	3	3	1	2	0	2	1	0	5	1	0	0	0	0	0	2	4	2	0	3	0	0
Hobby Lobby Stores	6	4	0	3	6	6	1	0	1	0	2	0	0	1	3	0	0	6	5	0	2	1	5	0	0	4	0
HomeGoods	6	0	0	4	2	6	6	0	0	0	0	0	0	5	2	0	0	2	3	1	2	2	6	0	6	5	0
Kohls	6	0	1	3	4	3	3	1	1	2	3	1	0	3	0	0	0	1	1	0	3	3	1	0	3	0	1
Trader Joes	6	0	3	3	4	3	2	4	1	0	3	1	0	5	5	3	3	3	2	2	3	4	3	0	3	0	0
Dicks Sporting Goods	5	0	0	1	0	2	0	0	0	0	1	0	0	2	0	1	0	0	0	1	0	1	1	0	0	4	0
Lou Malnatis Pizzeria	5	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	3	3	0	0	1	0
Menard	5	0	1	0	0	1	0	1	0	0	1	0	0	3	2	0	0	1	0	0	0	0	3	0	0	0	0
Moran Foods	5	0	3	0	0	0	1	3	1	0	1	0	0	5	3	0	0	0	0	0	0	0	0	0	0	0	0
Wendys	5	0	0	0	0	0	0	1	0	0	1	1	0	2	0	0	0	0	0	0	0	4	0	0	0	0	0
Borders	4	0	2	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	4	0	0	0	0
Raising Canes Restaurants	4	0	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	4	0	0	0	0	0
Save A Lot	4	0	3	0	0	0	1	3	0	0	1	0	0	4	3	0	0	0	0	0	0	0	0	0	0	0	0
Sears	4	0	0	0	1	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	3	0	0	0	0
Shoe Carnival	4	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	4	0	1	1	0

Notes: Source: Cook County Recorder.Table shows the retailers with the most number of exclusive dealing contracts by locations in Cook County. Retailers are ranked by the most number of locations with exclusive dealing contracts, denoted by the "Locations" column. The remaining columns enumerate the number of locations that block a specific type of retailer or storefront. For example, the first column "Grocer" indicates the number of retailer locations that block grocery stores, or the number of retailer locations that put restrictions on the extent to which groceries can be sold on nearby properties.

Table 12: Subset of Exclusive Dealing Data

			Num	*Frac*
Total	→		196	
Own/Lease	→	Own	64	0.33
		Lease	131	0.67
Buy/Sell	→	Buy	8	0.21
		Sell	30	0.79
Document Type	→	Deed	28	0.19
		Agreement	27	0.19
		Memorandum	77	0.53
		Restriction	11	0.08
		Termination	2	0.01
Grocery Grantor	→	Yes	80	0.5
		No	72	0.54
Timing	→	Entry	94	0.48
		During Lease	74	0.38
		Exit	13	0.07
		Not Grocery	15	0.08

Notes: Source: Cook County Recorder and SNAP. Subsetting to 196 grocery covenants in Chicago, and characterizing the restrictions. The majority of the covenants from leasing agreements between a landlord and a grocery store tenant, the majority of which are entry covenants (half of the covenants overall are entry covenants). Amongst the covenants for properties that are owned by the grocery store, 80% are established when the property is sold: after the grocery store presence is gone from that specific location (whether there was a grocery store to begin with is unclear). These covenants are found in a variety of legal documents: lease memoranda, deeds, agreements, restrictions, easements, and terminations.

Table 13: Exclusive Dealing Observed in Chicago: Subset of Data

			Num	*Frac*
Total	→		196	
Text Length	→	Short	72	0.39
		Long	113	0.61
Radius	→	Property	104	0.58
		Adjacent Property	44	0.25
		Miles (median 0.5)	30	0.17
Duration After	→	Years (median 8)	62	0.46
		No	72	0.54
Covenant Timing	→	Enter	94	0.48
		During	74	0.38
		Exit	13	0.07
		Not Grocery	15	0.08

Notes: Source: Cook County Recorder. Detail of the extent to which the covenants might restrict competition. Covenants that are longer restrict more store types, and constitutes 60% of the observed covenants. Shorter covenants typically only block the same store type. Next, the covenant can bind at a variety of different radii: the property (typically the shopping center), within a certain mile radius (the median is .5), and the adjacent property. The vast majority of covenants bind at that specific shopping center. Finally, covenants can last even when a grocery store is not present at that location. The median duration is 8 years, and 62 explicitly detail a duration after exit.

Table 14: Regression of Exclusive Dealing Status on Demographics

	Has Exclusive Balance			
	(1)	(2)	(3)	(4)
log(Real Income)	0.0196**	-0.0068	0.0027	-0.0087
	(0.0086)	(0.0061)	(0.0054)	(0.0214)
Share Unemployed	0.0559	-0.0203	0.0020	-0.0770
	(0.0518)	(0.0506)	(0.0513)	(0.1332)
Share Black	-0.0164	0.0309**	0.0221	0.0482*
	(0.0610)	(0.0143)	(0.0136)	(0.0292)
Share White	0.0376	0.0469**	0.0135	0.0375
	(0.0523)	(0.0215)	(0.0170)	(0.0379)
Share Hispanic	0.0237	0.0340***	0.0213*	0.0812
	(0.0213)	(0.0095)	(0.0106)	(0.0834)
Share Asian	0.0173	0.0953***	0.0469**	0.0130
	(0.0552)	(0.0266)	(0.0216)	(0.0580)
Poverty		-0.0657**	-0.0035	0.0425
		(0.0268)	(0.0264)	(0.0706)
Share Travel 30-60min		5.6×10^{-6}	$-3.92 \times 10^{-5***}$	7.26×10^{-6}
		(5.1×10^{-6})	(1.15×10^{-5})	(2.16×10^{-5})
Share Age 25-60		-0.0343	-0.0173	0.0035
		(0.0219)	(0.0231)	(0.0746)
Share College		0.0094	0.0352	-0.0217
		(0.0486)	(0.0470)	(0.0823)
Housing Rent		2.28×10^{-5}		
		(1.39×10^{-5})		
Housing Vacant		0.0001***	2.91×10^{-5}	-8.66×10^{-6}
		(3.44×10^{-5})	(2.77×10^{-5})	(6.47×10^{-5})
Share Women			-0.3167	-0.6338
			(0.2853)	(0.4698)
Share Travel Less 30 min			$2.65 \times 10^{-5***}$	$5.28 \times 10^{-5***}$
			(5.9×10^{-6})	(1.54×10^{-5})
Share Travel 60-90 min			-9.59×10^{-6}	0.0001**
			(3.42×10^{-5})	(4.61×10^{-5})
log(Housing Rent)			0.0081	0.0433***
			(0.0079)	(0.0166)
Housing Occupied			$2.02 \times 10^{-5**}$	$-3.28 \times 10^{-5*}$
			(8.14×10^{-6})	(1.7×10^{-5})
Standard-Errors		year		IID
Observations	16,268	16,267	16,242	1,351
R^2	0.11131	0.02839	0.03232	0.03974
Year fixed effects	✓	✓	✓	✓
Tract fixed effects	✓			

Notes: Table regresses presence of an exclusive dealing contract on demographic characteristics. The demographic characteristics vary across the columns. Each observation is a (year,tract,has exclusive), where has exclusive is 1 if there is a new contract with an exclusive use clause in that (year,tract). All demographics are included as a lagged term from the previous year. *Sources:* ACS 2009-2023, Census 1990, 2000, SNAP, Cook County Recorder Office.

Table 15: Hedonic Price Regression

	log(Net Effective Rent) Hedonics Price Regressions					
	(1)	(2)	(3)	(4)	(5)	(6)
Has Exclusive	0.1019***	0.0858**	0.3723***	0.3263***	0.1121***	0.0905**
	(0.0311)	(0.0382)	(0.0313)	(0.0356)	(0.0348)	(0.0420)
log(Real Income)				-0.0309	-0.0345	-0.0004
				(0.0390)	(0.0373)	(0.0841)
log Pop				-0.0102	-0.0053	-0.0731**
				(0.0144)	(0.0138)	(0.0322)
Share Female				0.0645	0.0481	-0.2880
				(0.1314)	(0.1253)	(0.3401)
Share Vacant				-0.1536	-0.1913**	0.2331
				(0.0978)	(0.0934)	(0.2498)
Share Renter				0.1778***	0.2578***	0.4941***
				(0.0467)	(0.0446)	(0.1229)
Share Unemployed				0.1280	0.3204**	0.3731
				(0.1675)	(0.1601)	(0.3738)
Share Poverty				0.0141	-0.0158	-0.4566*
				(0.1253)	(0.1200)	(0.2693)
Share Black				-0.2214***	-0.3432***	-0.4020***
				(0.0756)	(0.0723)	(0.1467)
Share Hispanic				-0.1014	-0.1813***	-0.2878*
				(0.0709)	(0.0677)	(0.1507)
Share Asian				-0.2813***	-0.2287***	-0.1300
				(0.0702)	(0.0670)	(0.2104)
Share College				0.3444***	0.3324***	0.4537*
				(0.1063)	(0.1014)	(0.2597)
logHousingValue				0.0416	0.0190	-0.0029
				(0.0256)	(0.0245)	(0.0601)
logHousingRent				0.0829**	0.1194***	0.1313*
				(0.0351)	(0.0335)	(0.0725)
log(TransactionSqft)					-0.0700***	-0.1769***
					(0.0034)	(0.0117)
log(LeaseTerm)					0.0465***	0.3083***
					(0.0053)	(0.0175)
Observations	28,489	3,187	28,489	15,080	15,055	2,308
R^2	0.25815	0.46112	0.21285	0.21772	0.28844	0.52299
year fixed effects	✓	✓	✓	✓	✓	✓
zip code fixed effects	✓	✓	✓	✓	✓	✓
space type fixed effects	✓				✓	

Notes: Table regresses log(net effective rent) on exclusive dealing, other lease characteristics, and demographics. Each column includes further controls or subsets on the data. Column (1) regresses rents on only exclusivity holding fixed year, zip code, and space type. Column (2) additionally subsets to the retailers that most commonly use exclusive dealing agreements. Column (3) includes only year and zip code fixed effects. Columns (4-6) include controls for time-varying demographics. Column (4) uses the same fixed effects as column (3), column (5) uses the same controls as column (1), and column (6) uses the same data as column (2). Missing demographics data from years 1991-1998 and 2001-2008 are imputed by interpolating observed data within tract. *Sources:* ACS 2009-present, Census 1990, 2000, SNAP, Cook County Recorder Office, and Compstak.

Table 16: Hedonic Price Regression: Robustness with Different Demographic Variables

	log(Net Effective Rent) Hedonics						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Has Exclusive	0.3723***	0.3138***	0.3012***	0.3387***	0.3361***	0.3155***	0.2459***
	(0.0469)	(0.0472)	(0.0467)	(0.0540)	(0.0408)	(0.0404)	(0.0100)
log(Real Income)		-0.0004	0.0027	-0.0125	0.0178	0.0137	2.681***
		(0.0873)	(0.0810)	(0.0789)	(0.0274)	(0.0295)	(0.0464)
log(Transaction Sqft)			-0.0723***			-0.0799***	
			(0.0064)			(0.0063)	
log(Lease Term)			0.0770***			0.0923***	
			(0.0066)			(0.0043)	
log(Pop Density)				0.0450*	0.0391***	0.0307**	0.2644***
				(0.0228)	(0.0103)	(0.0104)	(0.0055)
Share Unemployed				0.3978	0.6385**	0.7341***	15.69***
				(0.2264)	(0.2161)	(0.2141)	(0.2508)
Share Black				-0.6897**	-0.1059	-0.1911**	
				(0.3017)	(0.0716)	(0.0803)	
Share Hispanic				0.0253	-0.2506	-0.2916*	
				(0.2429)	(0.1453)	(0.1466)	
Observations	28,627	14,373	14,340	11,908	11,908	11,885	24
R^2	0.14403	0.27648	0.29891	0.29698	0.19983	0.23132	0.99500
Year Lease Starts FE	✓	✓	✓	✓	✓	✓	✓
Zip code FE	✓				✓	✓	
Tract FE		✓	✓	✓			
Store Name FE							✓

Notes: Table regresses log(net effective rent) on exclusive dealing, other lease characteristics, and demographics. Each column includes further controls. Column (1) regresses rents on only exclusivity. Column (2) additionally controls for tract income of the store. Column (3) includes controls for lease characteristics. Columns (4-5) include controls for time-varying demographics. Column (6) controls for both lease characteristics and demographics. Column (7) subsets to grocery stores and big box stores, and controls for the identity of the retailer. *Sources:* ACS 2009-present, Census 1990, 2000, SNAP, Cook County Recorder Office, and Compstak.

Table 17: Hedonic Price Regression: Robustness

	log(Net Effective Rent)							
	Hedonics							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Has Exclusive	0.3723***	0.3153***	0.3077***	0.2744***	0.2438***	0.2292***	0.1949**	-0.7444
	(0.0469)	(0.0373)	(0.0370)	(0.0636)	(0.0620)	(0.0596)	(0.0855)	(0.6954)
log(Real Income)		0.0971**	0.0995**	-0.1204	-0.0083	-0.0222	2.317***	0.0669**
		(0.0379)	(0.0376)	(0.0815)	(0.0441)	(0.0425)	(0.6767)	(0.0249)
log(Transaction Sqft)			-0.0722***			-0.0894***		-0.0538***
			(0.0057)			(0.0058)		(0.0053)
log(Lease Term)			0.0636***			0.0869***		
			(0.0078)			(0.0108)		
log(Pop Density)				0.0431**	0.0564***	0.0482***	0.2177**	
				(0.0177)	(0.0130)	(0.0108)	(0.0760)	
Share Unemployed				0.1424	0.3495*	0.3701*	13.94***	0.0374
				(0.1893)	(0.1723)	(0.1853)	(3.834)	(0.2287)
Share Black				-0.7733***	-0.1177	-0.1745		
				(0.2001)	(0.1168)	(0.1178)		
Share Hispanic				0.0804	-0.1135	-0.1289*		
				(0.0942)	(0.0670)	(0.0690)		
Poverty					0.6169**	0.6192**		
					(0.2846)	(0.2803)		
Share Women					2.981	3.590*		
					(2.427)	(2.086)		
Share Age 25-60					0.5548***	0.5924***		
					(0.1898)	(0.1814)		
Share College					0.7424***	0.5382**		
					(0.2251)	(0.2211)		
Share Travel Time to Work < 30 min					-6.14×10^{-6}	9.93×10^{-6}		
					(3.6×10^{-5})	(3.42×10^{-5})		
Share Travel Time to Work 30-60 min					-0.0001**	-0.0002***		
					(5.36×10^{-5})	(5.33×10^{-5})		
Share Vacant					1.175	1.516*		
					(0.7822)	(0.8036)		
log(Housing Tenure)					0.0877	0.1008		
					(0.0897)	(0.0880)		
log(Housing Own Value)					0.0264	0.0390		
					(0.0406)	(0.0357)		
log(Housing Rent)					0.0815**	0.0882**		
					(0.0392)	(0.0385)		
Housing Vacant					-0.0005	-0.0007		
					(0.0004)	(0.0004)		
Has Exclusive × log(Real Income)								0.2616***
								(0.0668)
Has Exclusive × log(Transaction Sqft)								-0.0780*
								(0.0442)
Observations	28,627	20,668	20,631	8,228	8,228	8,207	34	19,331
R^2	0.14403	0.25208	0.27383	0.39148	0.29505	0.33066	0.98401	0.19617
Year Start fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Zip Code fixed effects	✓				✓	✓		✓
Tract fixed effects		✓	✓	✓				
Store name fixed effects							✓	

Notes: Table regresses log(net effective rent) on exclusive dealing, other lease characteristics, and demographics. Each column includes further controls. Column (1) regresses rents on only exclusivity. Column (2) additionally controls for tract income of the store. Column (3) includes controls for lease characteristics. Columns (4-5) include controls for time-varying demographics. Column (6) controls for both lease characteristics and demographics. Column (7) subsets to grocery stores and big box stores, and controls for the identity of the retailer. Column (8) includes interaction terms between exclusive dealing and demographics. All demographics are included as a lagged term from the previous year. ACS values are imputed from previous years when the data is unavailable. *Sources:* ACS 2009-present, Census 1990, 2000, SNAP, Cook County Recorder Office, and Compstak.

Table 18: Hedonic Price Regression: Robustness

	log(Net Effective Rent) Hedonics							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Has Exclusive	0.1019**	0.0689	0.0869*	0.2744***	0.1263**	0.1357**	0.1949**	-0.2487
	(0.0488)	(0.0452)	(0.0438)	(0.0636)	(0.0596)	(0.0571)	(0.0855)	(0.7082)
log(Real Income)		0.1064***	0.1080***	-0.1204	-0.0187	-0.0292	2.317***	0.0710***
		(0.0345)	(0.0348)	(0.0815)	(0.0415)	(0.0405)	(0.6767)	(0.0253)
log(Transaction Sqft)			-0.0593***			-0.0845***		-0.0502***
			(0.0053)			(0.0063)		(0.0056)
log(Lease Term)			0.0356***			0.0675***		
			(0.0052)			(0.0109)		
log(Pop Density)				0.0431**	0.0454***	0.0391***	0.2177**	
				(0.0177)	(0.0106)	(0.0088)	(0.0760)	
Share Unemployed				0.1424	0.3889**	0.4152**	13.94***	0.1412
				(0.1893)	(0.1770)	(0.1885)	(3.834)	(0.2332)
Share Black				-0.7733***	-0.1412	-0.1969*		
				(0.2001)	(0.1004)	(0.1050)		
Share Hispanic				0.0804	-0.0838	-0.1066		
				(0.0942)	(0.0692)	(0.0709)		
Poverty					0.6107*	0.6191*		
					(0.3151)	(0.3085)		
Share Women					1.482	2.280		
					(1.990)	(1.757)		
Share Age 25-60					0.5600***	0.5976***		
					(0.1869)	(0.1823)		
Share College					0.8446***	0.6248***		
					(0.2159)	(0.2123)		
Share Travel Time to Work <30min					-1.59×10^{-6}	1.52×10^{-5}		
					(3.25×10^{-5})	(3.17×10^{-5})		
Share Travel Time to Work 30-60min					-0.0002***	-0.0002***		
					(5.59×10^{-5})	(5.61×10^{-5})		
Share Vacant					1.311*	1.656**		
					(0.7255)	(0.7668)		
log(Housing Tenure)					0.1188	0.1297		
					(0.0867)	(0.0867)		
log(Housing Own Value)					0.0182	0.0303		
					(0.0402)	(0.0355)		
log(Housing Rent)					0.0733*	0.0830**		
					(0.0384)	(0.0378)		
Housing Vacant					-0.0006	-0.0008*		
					(0.0004)	(0.0004)		
Has Exclusive × log(Real Income)								0.1558**
								(0.0699)
Has Exclusive × log(Transaction Sqft)								-0.0809*
								(0.0444)
Observations	28,627	20,668	20,631	8,228	8,228	8,207	34	19,331
R^2	0.19330	0.29667	0.31097	0.39148	0.31270	0.34334	0.98401	0.24075
Year Start Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Zip Code Fixed Effects	✓				✓	✓		✓
Space Type Fixed Effects	✓	✓	✓		✓	✓		✓
Tract Fixed Effects		✓	✓	✓				
Store Name Fixed Effects							✓	

Notes: Table regresses log(net effective rent) on exclusive dealing, other lease characteristics, and demographics. Each column includes further controls. Column (1) regresses rents on only exclusivity. Column (2) additionally controls for tract income of the store. Column (3) includes controls for lease characteristics. Columns (4-5) include controls for time-varying demographics. Column (6) controls for both lease characteristics and demographics. Column (7) subsets to grocery stores and big box stores, and controls for the identity of the retailer. Column (8) includes interaction terms between exclusive dealing and demographics. All demographics are included as a lagged term from the previous year. ACS values are imputed from previous years when the data is unavailable. This robustness check additionally controls for space type. *Sources:* ACS 2009-present, Census 1990, 2000, SNAP, Cook County Recorder Office, and Compstak.

Table 19: Log Density of Nearby Competitors with Chain Fixed Effects

	log(density)						
	0 - .3 mi	.3 - .6 mi	.6 - 1 mi	1 - 2 mi	2 - 5 mi	5 - 8 mi	8 - all mi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
exclusive dealing	-0.3724**	0.3715***	0.2130*	0.2127**	0.0272	-0.0081	0.0397
	(0.1566)	(0.1375)	(0.1241)	(0.0915)	(0.0625)	(0.0567)	(0.0408)
Observations	2,172	2,193	2,583	3,079	3,180	3,180	3,180
R^2	0.69880	0.67632	0.76780	0.84330	0.85209	0.82288	0.44236
zip5 fixed effects	✓	✓	✓	✓	✓	✓	✓
year open fixed effects	✓	✓	✓	✓	✓	✓	✓
store name fixed effects	✓	✓	✓	✓	✓	✓	✓

Notes: Table reports coefficients and 95% confidence interval from regression of number of competitors per square mile on whether or not the store has an exclusive deal, with year, zip5, and retailer fixed effects. We only use grocery chains and big box stores. Competitors are defined as grocery, big box, and drug stores. Data is based on the exclusive deal data from the Cook County recorder office and the retailer location, entry, and exit comes from the SNAP data.

Table 20: Log Density of Nearby Competitors without Chain Fixed Effects

	log(density)						
	0 - .3 mi	.3 - .6 mi	.6 - 1 mi	1 - 2 mi	2 - 5 mi	5 - 8 mi	8 - all mi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
exclusive dealing	-0.3275***	0.4067***	0.1254	0.0483	0.0262	-0.0375	0.0113
	(0.1110)	(0.1249)	(0.1654)	(0.0875)	(0.0579)	(0.0473)	(0.0338)
Observations	2,172	2,193	2,583	3,079	3,180	3,180	3,180
R^2	0.65640	0.63287	0.74549	0.83430	0.84872	0.81915	0.43479
zip5 fixed effects	✓	✓	✓	✓	✓	✓	✓
year open fixed effects	✓	✓	✓	✓	✓	✓	✓

Notes: Table reports coefficients and 95% confidence interval from regression of number of competitors per square mile on whether or not the store has an exclusive deal, with year and zip5 fixed effects. We only use grocery chains and big box stores. Competitors are defined as grocery, big box, and drug stores. Data is based on the exclusive deal data from the Cook County recorder office and the retailer location, entry, and exit comes from the SNAP data.

Table 21: Density of Nearby Competitors with Chain Fixed Effects

	density						
	0 - .3 mi	.3 - .6 mi	.6 - 1 mi	1 - 2 mi	2 - 5 mi	5 - 8 mi	8 - all mi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
exclusive dealing	-2.859**	2.174***	0.5902	0.5537	0.1868	0.0691	0.0009
	(1.363)	(0.6568)	(0.6468)	(0.3623)	(0.2298)	(0.1264)	(0.0015)
Observations	2,172	2,193	2,583	3,079	3,180	3,180	3,180
R^2	0.77518	0.71105	0.73597	0.78789	0.79745	0.76057	0.47046
zip5 fixed effects	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓
store name fixed effects	✓	✓	✓	✓	✓	✓	✓

Notes: Table reports coefficients and 95% confidence interval from regression of number of competitors per square mile on whether or not the store has an exclusive deal, with year, zip5, and retailer fixed effects. We only use grocery chains and big box stores. Competitors are defined as grocery, big box, and drug stores. Data is based on the exclusive deal data from the Cook County recorder office and the retailer location, entry, and exit comes from the SNAP data.

Table 22: Density of Nearby Competitors without Chain Fixed Effects

	density						
	0 - .3 mi	.3 - .6 mi	.6 - 1 mi	1 - 2 mi	2 - 5 mi	5 - 8 mi	8 - all mi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
exclusive dealing	-2.271**	2.164***	0.5425	0.3800	0.1618	0.0356	-0.0001
	(0.9760)	(0.7753)	(0.6960)	(0.3916)	(0.2055)	(0.1470)	(0.0012)
Observations	2,172	2,193	2,583	3,079	3,180	3,180	3,180
R^2	0.71599	0.65015	0.70456	0.77524	0.78962	0.75074	0.45939
zip5 fixed effects	✓	✓	✓	✓	✓	✓	✓
year open fixed effects	✓	✓	✓	✓	✓	✓	✓

Notes: Table reports coefficients and 95% confidence interval from regression of number of competitors per square mile on whether or not the store has an exclusive deal, with year and zip5 fixed effects. We only use grocery chains and big box stores. Competitors are defined as grocery, big box, and drug stores. Data is based on the exclusive deal data from the Cook County recorder office and the retailer location, entry, and exit comes from the SNAP data.

Table 23: Count of Nearby Competitors with Chain Fixed Effects

	count						
	0 - .3 mi	.3 - .6 mi	.6 - 1 mi	1 - 2 mi	2 - 5 mi	5 - 8 mi	8 - all mi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
exclusive dealing	-0.9220**	1.627***	1.047	3.772	7.509	1.428	-15.15
	(0.4291)	(0.5723)	(1.206)	(3.119)	(12.69)	(13.76)	(24.61)
Observations	2,172	2,193	2,583	3,079	3,180	3,180	3,180
R^2	0.83004	0.79461	0.83180	0.88401	0.91325	0.92687	0.97402
zip5 fixed effects	✓	✓	✓	✓	✓	✓	✓
year open fixed effects	✓	✓	✓	✓	✓	✓	✓
store name fixed effects	✓	✓	✓	✓	✓	✓	✓
year fixed effects	✓	✓	✓	✓	✓	✓	✓

Notes: Table reports coefficients and 95% confidence interval from regression of number of competitors per square mile on whether or not the store has an exclusive deal, with year and zip5 fixed effects. We only use grocery chains and big box stores. Competitors are defined as grocery, big box, and drug stores. Data is based on the exclusive deal data from the Cook County recorder office and the retailer location, entry, and exit comes from the SNAP data.

Table 24: Count of Nearby Competitors without Chain Fixed Effects

	count						
	0 - .3 mi	.3 - .6 mi	.6 - 1 mi	1 - 2 mi	2 - 5 mi	5 - 8 mi	8 - all mi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
exclusive dealing	-0.6423**	1.836***	1.091	3.582	10.67	4.365	-4.368
	(0.2760)	(0.6577)	(1.400)	(3.691)	(13.56)	(18.01)	(36.33)
Observations	2,172	2,193	2,583	3,079	3,180	3,180	3,180
R^2	0.71599	0.65015	0.70456	0.77524	0.78962	0.75074	0.45939
zip5 fixed effects	✓	✓	✓	✓	✓	✓	✓
year open fixed effects	✓	✓	✓	✓	✓	✓	✓

Notes: Table reports coefficients and 95% confidence interval from regression of number of competitors per square mile on whether or not the store has an exclusive deal, with year and zip5 fixed effects. We only use grocery chains and big box stores. Competitors are defined as grocery, big box, and drug stores. Data is based on the exclusive deal data from the Cook County recorder office and the retailer location, entry, and exit comes from the SNAP data.

C.3 Summary Statistics: Shopping Patterns

Table 25: Household Shopping

Number of Grocers a Household Shops at

Variable	Quantile				
	5th	25th	Median	75th	90th
All	1	1	3	6	14
More than 5 times in a year	1	1	2	4	6
More than 10 times in a year	1	1	2	3	5
More than 15 times in a year	1	1	2	3	5

Notes: Source: Numerator. Number of grocers households shop at.

Table 26: Trips to Each Retailer

Retailer	Counts (Total)	Expend (Total)	Counts (Fraction)	Expend (Fraction)
Walmart	221886	12641556.62	0.14	0.18
Target	175570	9454001.43	0.11	0.13
Jewel Osco	192179	7818518.36	0.12	0.11
Costco	59331	6602305.32	0.04	0.09
Other	191448	6476655.52	0.12	0.09
Drug	230634	5287421.61	0.14	0.07
Other Food	122336	4393988.07	0.07	0.06
Aldi	96170	3998455.58	0.06	0.06
Mariano's	83842	3850563.52	0.05	0.05
Sam's Club	30950	3227499.07	0.02	0.04
Meijer	31445	1904166.68	0.02	0.03
Dollar	111165	1546703.80	0.07	0.02
Whole Foods	33775	1521076.70	0.02	0.02
Trader Joe's	28471	1130818.71	0.02	0.02
Food 4 Less	25629	1093974.88	0.02	0.01
Liquor	13936	593054.73	0.01	0.01

Source: Numerator, Chicago, 2017-2019. Each count is a unique visit to a retailer. The total number of visits and expenditure to each retailer is reported.

Table 27: Trips to each Bundle

Bundle	Count	Bundle	Count	Bundle	Count
Drug	160436	Walmart	154773	Jewel Osco	129048
Other	124488	Target	120742	Other Food	73601
Dollar	67511	Mariano's Grocery	58252	Aldi	57062
Costco	37638	Whole Foods	22494	Meijer	21463
Trader Joe's	18111	Sam's Club	17801	Food 4 Less	15920
Drug, Jewel Osco	10475	Drug, Other	10313	Other, Walmart	10104
Jewel Osco, Other	9487	Drug, Walmart	8547	Dollar, Walmart	8360
Drug, Target	8059	Other, Other Food	7705	Liquor	7597
Drug, Other Food	7313	Jewel Osco, Target	7035	Target, Walmart	6970
Other, Target	6703	Jewel Osco, Other Food	6651	Aldi, Walmart	6542
Dollar, Drug	6451	Jewel Osco, Walmart	6448	Dollar, Other	5711
Other Food, Walmart	5479	Aldi, Jewel Osco	4628	Dollar, Jewel Osco	4597
Aldi, Drug	4536	Aldi, Other Food	4200	Dollar, Target	4185
Drug, Mariano's Grocery	4069	Aldi, Dollar	4021	Other Food, Target	3971
Dollar, Other Food	3851	Aldi, Target	3838	Sam's Club, Walmart	3574
Aldi, Other	3529	Mariano's Grocery, Target	3482	Costco, Target	3215
Mariano's Grocery, Other	3192	Jewel Osco, Mariano's Grocery	3026	Costco, Jewel Osco	2755
Costco, Walmart	2465	Mariano's Grocery, Walmart	2161	Costco, Other	2140
Costco, Other Food	2119	Costco, Drug	1987	Mariano's Grocery, Other Food	1921
Aldi, Costco	1730	Drug, Whole Foods	1722	Meijer, Walmart	1672
Costco, Mariano's Grocery	1557	Target, Whole Foods	1520	Food 4 Less, Walmart	1519
Target, Trader Joe's	1468	Drug, Food 4 Less	1393	Jewel Osco, Whole Foods	1378
Dollar, Mariano's Grocery	1347	Dollar, Food 4 Less	1285	Jewel Osco, Trader Joe's	1277
Jewel Osco, Sam's Club	1264	Aldi, Mariano's Grocery	1263	Other, Whole Foods	1228
Liquor, Other	1222	Other, Trader Joe's	1195	Meijer, Other	1183
Drug, Trader Joe's	1155	Other, Sam's Club	1133	Drug, Sam's Club	1120
Sam's Club, Target	1120	Other Food, Sam's Club	1115	Jewel Osco, Meijer	1087
Drug, Meijer	1056	Meijer, Target	1034	Trader Joe's, Whole Foods	1034
Aldi, Sam's Club	996	Food 4 Less, Other	992	Mariano's Grocery, Whole Foods	942
Food 4 Less, Jewel Osco	941	Aldi, Food 4 Less	893	Jewel Osco, Liquor	872
Costco, Dollar	826	Food 4 Less, Other Food	813	Other Food, Whole Foods	796
Trader Joe's, Walmart	795	Aldi, Meijer	790	Liquor, Other Food	790
Drug, Liquor	764	Mariano's Grocery, Trader Joe's	760	Dollar, Sam's Club	753
Costco, Trader Joe's	721	Dollar, Meijer	684	Costco, Whole Foods	651
Food 4 Less, Target	641	Liquor, Walmart	612	Aldi, Trader Joe's	608
Aldi, Whole Foods	568	Costco, Meijer	564	Walmart, Whole Foods	559
Meijer, Other Food	546	Other Food, Trader Joe's	525	Food 4 Less, Sam's Club	522
Dollar, Liquor	433	Mariano's Grocery, Sam's Club	391	Liquor, Target	371
Mariano's Grocery, Meijer	367	Costco, Sam's Club	355	Meijer, Sam's Club	354
Dollar, Whole Foods	293	Dollar, Trader Joe's	260	Liquor, Mariano's Grocery	252
Aldi, Liquor	246	Liquor, Whole Foods	155	Food 4 Less, Mariano's Grocery	143
Liquor, Trader Joe's	139	Costco, Liquor	134	Food 4 Less, Meijer	132
Costco, Food 4 Less	126	Meijer, Trader Joe's	120	Meijer, Whole Foods	110
Sam's Club, Trader Joe's	100	Liquor, Meijer	81	Sam's Club, Whole Foods	66
Food 4 Less, Liquor	61	Liquor, Sam's Club	56	Food 4 Less, Whole Foods	32
Food 4 Less, Trader Joe's	23				

Source: Numerator, Chicago, 2017-2019. Each count is the set of retailers traveled to in each day. The total number of visits and expenditure to each retailer is reported.

C.4 Parameter Estimates: Product Market

Table 28: Price and Distance Product Market Demand Estimates

	Estimates by Income Group		
Variable	Low	Middle	High
α^g (log price)	−2.215	−1.782	−1.487
	(0.997)	(0.815)	(0.745)
γ^g (distance) (log mi)	−1.870	−1.780	−1.690
	(0.052)	(0.069)	(0.042)

Distance and price coefficient estimates. Distance standard errors are computed withed heteroscedasticity-robust standard errors. *Source:* Numerator, Chicago, 2017-2019.

Table 29: Shopping Center Product Market Demand Estimates

Shopping Center Variable	Estimates
All	−1.316
	(8.752)
Education: Advanced Degree	-2.306
	(30.6858)
Education: College	-0.738
	(12.6859)
Education: High School	-4.245
	(563.4304)
Employed	1.968
	(289.6705)

Shopping center coefficient estimates. The excluded groups are no high school and unemployed. Standard errors are computed with heteroscedasticity-robust standard errors. *Source:* Numerator, Chicago, 2017-2019.

Table 30: Product Market Estimates: Different Distance Estimates

Variable			
	Income: Low	*Income: Middle*	*Income: High*
γ^g log Driving Mins (OSRM)	-3.776	-3.675	-3.516
	(0.016)	(0.018)	((0.014)
log Distance (Crow Flies)	-0.470	4.751	1.376
	(.019)	(.026)	(0.020)
log Distance^2 (Crow Flies)	-1.824	-6.761	-3.396
	(.065)	(.031)	(.025)

Distance parameter estimates for different alternative measures of distance. In the first row, distances are computed with OSRM travel times, which measures travel time from origin to destination in driving minutes. In the second and third row, we include both distance and distance squared to allow for nonlinearities in preferences. Standard errors are computed withed heteroscedasticity-robust standard errors. *Source:* Numerator, Chicago, 2017-2019.

Table 31: Further Distance Estimates

Dependent Variable:	Distance Estimates
Variables	
Distance x Income Group Low	-1.1785
	(.054)
Distance x Income Group Mid	-1.621
	(.069)
Distance x Income Group High	-1.576
	(.042)
zip code x Income Group Fixed Effects	Yes
Observations	185,307,208
R^2	1

Regression of estimated utility from distance ($\hat{\gamma}^g d^g_{ibt}$) on distance and zip code fixed effects, to partial out the effect due to household zip. Standard errors compound regression standard errors with the standard error on $\hat{\gamma}^g$ from the first stage maximum likelihood estimation. *Source:* Numerator, Chicago, 2017-2019.

Table 32: First Stage Estimates

Dependent Variables:	*Price, High Inc.*	*Price, Low Inc.*	*Price, Mid Inc.*
Model:	(1)	(2)	(3)
Variables			
Instrument $\times$ High Inc.	0.4607***	-0.1371***	-0.0922***
	(0.0223)	(0.0235)	(0.0279)
Instrument $\times$ Low Inc.	-0.1893***	0.4628***	-0.0965***
	(0.0225)	(0.0236)	(0.0281)
Instrument $\times$ Mid Inc.	-0.1894***	-0.1375***	0.3933***
	(0.0223)	(0.0235)	(0.0279)
Fixed-effects			
Time	Yes	Yes	Yes
Fit statistics			
Observations	27,960	27,960	27,960
R^2	0.35490	0.30101	0.28887
F-test (1st stage)	2,238.2	1,658.2	799.16

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

First stage estimates from the instrumental variables regression of average market-level estimated utility δ_{bt}^{g} on instrumented prices and bundles, including time fixed effects. *Source:* Numerator, Chicago, 2017-2019.

Table 33: OLS Estimates

	Average Bundle Utility δ^g_{bt}
Variables	
Price × Inc. Low	0.6461***
	(0.0277)
Price × Inc. Mid	0.7116***
	(0.0242)
Price × Inc. High	0.5892***
	(0.0283)
Fixed-effects	
idx_bundle	Yes
idx_time	Yes
Fit statistics	
Observations	27,960
R^2	0.31519

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table reports OLS estimates regressing average market-level estimated utility δ^g_{bt} on prices, bundles fixed effects, and time fixed effects. *Source:* Numerator, Chicago, 2017-2019.

C.5 Summary Statistics: Prices (Rents)

Table 34: Summary statistics of the rental data

Rents (Dollars/sqft/month)	
Mean Rents	20.01
Minimum	0.00
5th percentile	8.07
25th percentile	13.65
Median	18.08
75th percentile	23.81
95th percentile	35.31
Maximum	585.37

Notes: Source: Compstak. Summary statistics of the rental data.

C.6 Retail Real Estate Market Estimates

Table 35: Exclusive Dealing Parameters: Mean μ_θ and Standard Deviation σ_θ

Mean μ_θ	-0.655
	(0.620)
Variance σ_θ	0.725
	(0.136)

Notes: Table reports exclusive dealing parameter estimates in the large retail real estate markets with standard errors in parentheses. Standard errors are computed using 200 bootstrapped samples. The μ_θ and σ_θ represent the mean and standard deviation of the average non-surplus value of an exclusive dealing agreement across large retailers.

C.7 Model Validation

Table 36: Estimates Predict Relevant Exclusive Dealing Contracts and Not Irrelevant Exclusive Dealing Contracts

	Relevant Block	Non-relevant Block (Placebo)
$E_{-j}[\pi_{jmE}] - E_{-j}[\pi_{jmN}]$	0.061	0.000
	(0.021)	(0.028)
Year FE	✓	✓
Geography FE	✓	✓
Observations	171	171
Pseudo R^2	0.152	0.032

Notes: Table reports probit regression estimates with standard errors in parentheses. The independent variable is the exclusive dealing premium: the change in expected product market profits for an exclusive dealing contract relative to no exclusive dealing contract. The dependent variable is whether or not an exclusive dealing contract is observed. The first column subsets to relevant exclusive dealing contracts, contracts that block at least one of the following retail types: grocers, drug stores, pharmacies, dollar stores, convenience stores, liquor stores, food stores or retail. The second column subsets to exclusive dealing contracts that are irrelevant to product market competition, contracts that do not block any of the relevant categories and instead block at least one non-relevant category such as industrial, guns, schools, or skating rinks. Each observation is the entry of a large retail (excluding other and other food) in Cook County between 2000 and 2023.

C.8 Counterfactual: Retail Apocalypse

Table 37: NAICS Codes in the "Retail Apocalypse" Counterfactual

NAICS Code	Industry Title
441310	Automotive Parts and Accessories Stores
442110	Furniture Stores
442299	All Other Home Furnishings Stores
443141	Household Appliance Stores
443142	Electronics Stores
444190	Other Building Material Dealers
448120	Women's Clothing Stores
448130	Children's and Infants' Clothing Stores
448140	Family Clothing Stores
448150	Clothing Accessories Stores
448190	Other Clothing Stores
451110	Sporting Goods Stores
451120	Hobby, Toy, and Game Stores
451211	Book Stores
452111	Department Stores (except Discount Department Stores)

Notes: In the counterfactual, retailers in these NAICS categories do not exit in bankruptcy.

D Examples of Exclusive Dealing

Figure 36: Restrictive Covenant in a Safeway Lease Memorandum

2. Restrictions. By virtue of the Lease, Tenant, its subtenants, invitees, customers and employees and parties holding possessory rights in the Premises shall have, and are hereby granted, the use in common with Landlord and other tenants of Landlord and their respective invitees, customers, employees and parties holding possessory rights in the Shopping Center, of "Building Areas" and those portions of Building Areas upon which buildings are not constructed (all of which are referred to as the "Common Areas"). "Building Areas" shall refer to the areas designated as "Jewel/Osco", "Retail Bld'g A", Retail Bld'g B", "Retail Bld'g C" and "Bank" on the Site Plan. The Common Areas are required by the terms of the Lease to be devoted to the purposes of driving and parking motor vehicles, loading and unloading of motor vehicles and vehicular and pedestrian ingress and egress to and from and within the Shopping Center. Additional rights are granted by the Lease to such parties in connection with the construction and maintenance of utility facilities necessary to the Shopping Center. All buildings constructed in the Shopping Center shall be located wholly within the "Building Areas". Additional use and development restrictions and maintenance, development and performance obligations with regard to the Premises and the Shopping Center are specified in the Lease.

In addition to other restrictions and obligations set forth in the Lease, the Lease provides that the types of uses permitted in the Shopping Center shall be of a retail and/or commercial nature found in shopping centers of a similar size and quality in the metropolitan marketing area in which the Shopping Center is located.

The Lease provides, in part, that no premises (nor any part thereof) in the Shopping Center other than the Premises, shall be (i) used or occupied as a retail supermarket, drug store and combination thereof, nor (ii) used for the sale of any of the following: (a) fish or meat (except in prepared form sold by a permitted restaurant operation); (b) liquor and other alcoholic beverages in package form, including, but not limited to, beer, wine and ale; (c) produce; (d) baked goods; (e) floral items; (f)any combination of food items sufficient to be commonly known as a convenience food store or department; and (g) items requiring dispensation by or through a pharmacy or requiring dispensation by or through a registered pharmacist.

In addition, except as expressly permitted in the Lease, none of the following uses shall be conducted in the Shopping Center: (a) offices; (b) funeral homes; (c) any production, manufacturing, industrial, or storage use of any kind or nature; (d) entertainment or recreational facilities; (e) training or educational facilities; (f) restaurants; (g) car washes, gasoline or service stations, or the displaying, repairing, renting, leasing, or sale of any motor vehicle, boat or trailer; (b) dry cleaner with on-premises cleaning; (i) any use which creates a nuisance or materially increases noise or the emission of dust, odor, smoke, gases, or materially increases fire, explosion or radioactive hazards in the Shopping Center; (i) any business with drive-up or drive-through lanes; (k) second-hand or thrift stores, or flea markets; and (1) any use involving any Hazardous Material (as defined in the Lease).

Source: Cook County Record of Deeds, Document Number 0010276527. This figure is an example of a restrictive covenant. Here, Jewel Osco (parent company Safeway) in Chicago at the Intersection of Ashland and Roosevelt in 2001 limits the competitors in the shopping center. At this location, this portion of the lease memorandums shows Safeway is blocking (a) stores that sell similar products: grocers, drug stores, and liquor stores, (b) stores that also compete for food: restaurants and gas stations, (c) stores that compete for parking: offices, educational facilities, and (d) stores that would bring a different aesthetic to the shopping center: funeral homes, second-hand or thrift stores, stores that create a nuissance or materially increase noise.

Figure 37: Restrictive Covenant in a Dollar General Lease Memorandum

4. So long as the Demised Premises is being operated as a Dollar General store, Landlord covenants and agrees not to lease, rent or occupy, or allow to be leased, rented or occupied, any property now or hereafter owned by Landlord or an affiliate of Landlord, or developed by Landlord or an affiliate of Landlord (for a third party), within a one (1) mile radius of the boundaries of the Demised Premises for the purpose of conducting business as, or for use as, a Family Dollar Store, Bill's Dollar Store, Fred's, Dollar Tree, Dollar Zone, Variety Wholesale, Ninety-Nine Cents Only, Deals, Dollar Bills, Bonus Dollar, Maxway, Super Ten, McCory's, McCory's Dollar, Planet Dollar, Big Lots, Odd Lots, Walgreens, CVS, Rite Aid, or Wal-Mart Supercenter.

This covenant shall run with the land and shall be binding upon Landlord and its affiliates and their respective successors, assigns and successors in title to the Demised Premises and to any such land owned, developed or acquired in the future within a one (1) mile radius. As of the Effective Date, Landlord does not own land within a one (1) mile radius of the Demised Premises. So long as the Demised Premises is being operated as a Dollar General store, Landlord agrees (for itself and its affiliates) not to accept any engagement as a developer for such purposes in violation of the foregoing restrictive covenants within such one (1) mile radius.

Source: Cook County Record of Deeds, Document Number 1532115028. This figure is an example of a restrictive covenant from a Dollar General Lease Memorandum in 2015, for a store at the intersection of 79th and Marquette Avenue. This restrictive covenant limits the landlord and affiliates from leasing to competitors within a mile radius for as long as the Dollar General is in operation on the premises. The restrictive covenant runs with the land, which means that it binds even if the landlord stays the same. The competitors are listed explicitly, and are largely other dollar stores, but also include discount stores and drug stores that sell similar snacks: Family Dollar Store, Bill's Dollar Store, Fred's, Dollar Tree, Dollar Zone, Variety Wholesale, Ninty-Nine Cents Only, Deals, Dollar Bills, Bonus Dollar, Maxway, Super Ten, McCory's Dollar, Planet Dollar, Big Lots, Odd Lots, Walgreens, CVS, Rite Aid, or Wal-Mart Supercenter.

Figure 38: Restrictive Covenant upon Termination of Dominick's Finer Foods Lease

USE RESTRICTION AGREEMENT

THIS USE RESTRICTION AGREEMENT ("Agreement") is dated as of ~~September~~ October 1, 2015, and is made and entered into by and between RAMCO-GERSHENSON PROPERTIES, L.P., a Delaware limited partnership ("Landlord"), and DOMINICK'S FINER FOODS, LLC, a Delaware limited liability company ("Tenant").

C. On the date hereof, Tenant operates one or more grocery supermarkets within a radius of five (5) miles of the Property. The properties within such radius on which Tenant, any "Affiliate" (defined later) of Tenant, and/or its or their respective successors and assigns may in the future sell "Grocery Merchandise" (defined later), and/or "Prescription Pharmacy Merchandise" (defined later) are together called the "Benefited Properties." "Affiliate" of a named legal person or entity shall mean any legal person or entity that controls, is controlled by, or is under common control with the named legal person or entity.

D. Landlord acknowledges that (i) Tenant or its Affiliate has made a considerable investment in the Benefited Properties, (ii) Tenant or its Affiliate has invested its business reputation in the Benefited Properties, which reputation will be adversely affected if the sales volume of Tenant is negatively impacted, (iii) the addition of other businesses to the Property that may violate the "Restrictions" (defined later) will result in a reduction of Tenant's sales volume and thus impair the benefit of the bargain for which Tenant negotiated in entering into the Termination Agreement, and (iv) Tenant's agreement to terminate the Lease is predicated upon Landlord's acknowledgement of all of the foregoing, and Landlord's agreement to the terms of this Agreement.

1. USE RESTRICTION. Landlord agrees, on behalf of itself and its successors and assigns, that for the "Restriction Period" (defined later) (collectively the "Restriction Periods"), the Property will not be used in violation of the "Restrictions" (defined later). The "Restrictions" are the "Supermarket Restriction" (defined later) and the "Prescription Pharmacy Restriction" (defined later).

1.1. Supermarket Restriction. No portion of the Property shall be used or occupied for a general food market, supermarket, grocery store, meat market, fish market, fruit store, vegetable store, convenience store, or any combination of the foregoing ("Supermarket Restriction"). Notwithstanding the Supermarket Restriction, stores on the Property may devote up to, but not more than, the lesser of (i) five thousand (5,000) square feet of sales area (including aisle space adjacent thereto), or (ii) sales area (including aisle space adjacent thereto) of up to fifteen percent (15%) of the total square footage of the store, to the sale of Grocery Merchandise. "Grocery Merchandise" means, for off premises consumption, baked goods, fish, poultry or meat, liquor or other alcoholic beverages, fruits and vegetables, produce, floral items, pet food, greeting cards, photo processing services, health and beauty aids. Notwithstanding anything to the contrary contained herein, the Supermarket Restriction shall not apply to: (i) a restaurant-bakery, such as Panera or Atlanta Bread Company, of not more than 2,500 square feet in size; (ii) a retailer selling arts and craft supplies, including party supplies and dried floral arrangements; (iii) a beauty supply retailer that specializes in the sale of beauty and/or body care products, cosmetics, health care items, and/or beauty aids; (iv) a retailer selling greeting cards, giftware, stationary and/or keepsake ornaments; or (v) a retailer selling live animals as pets and pet food and related accessories.

Source: Cook County Record of Deeds, Document Number 1527955057. This figure is an excerpt from a Dominick's Finer Foods Lease Termination in 2015. In 1998, Safeway purchases Dominick's Finer Foods. In 2013, Safeway is in the process of closing all of Dominick's Finer Foods stores. Then, in 2015, Safeway acquires Jewel Osco. At this Dominick's location in 2015, Safeway and landlord agree to put a restrictive covenant on the property to prevent the entry of a grocery store for five years after Safeway leaves the premises ("no portion of the property shall be used as a grocery store"). The restrictive covenant specifies the motivation for the restrictive covenants: the tenant made investments to the property which benefited the landlord ("landlord acknowledges tenant has made considerable investment in the property"), and the tenant would stand to lose business if a competitor opened ("tenant operates a grocery store within 5 miles of the property").