# The Evolution of U.S. Retail Concentration*

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January 21, 2022

**Abstract**

Increases in national concentration have been a salient feature of industry dynamics in the U.S. and have contributed to concerns about increasing market power. Yet, local trends may be more informative about market power, particularly in the retail sector where consumers have traditionally shopped at nearby stores. We find that local concentration has increased almost in parallel with national concentration using novel Census data on product-level revenue for all U.S. retail stores. The increases in concentration are broad based, affecting most markets, products, and retail industries. We implement a new decomposition of the national Herfindahl-Hirschman Index and show that despite similar trends, national and local concentration reflect different changes in the retail sector. The increase in national concentration comes from consumers in different markets increasingly buying from the same firms and does not reflect changes in local market power. We estimate a model of retail competition which links local concentration to markups. The model implies that the increase in local concentration explains one-third of the observed increase in markups.

JEL: L8
Keywords: Retail, Local Markets, Concentration, Herfindahl-Hirschman Index

*Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau's Disclosure Review Board and Disclosure Avoidance Officers have reviewed this information product for unauthorized disclosure of confidential information and have approved the disclosure avoidance practices applied to this release. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1975 (CBDRB-FY20-P1975-R8604).
We gratefully acknowledge advice from Thomas Holmes, Teresa Fort, Amil Petrin, Joel Waldfogel, Emek Basker, Brian Adams, Fatih Guvenen, Juan Herreño, Emily Moschini, Jeff Thurk, and Nicholas Trachter. We also thank participants of seminars at various institutions as well as participants at the 2021 NBER SI CRIW, 2021 CEA, 2021 IIOC, and 2019 SED meetings and the 2018 FSRDC conference. This paper is based upon work supported by the Doctoral Dissertation Fellowship at the University of Minnesota.

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# 1 Introduction

There is an economy-wide trend toward greater ownership concentration and an increase in the dominance of large, established firms. These trends have been accompanied by rising markups, which raises concerns about increasing market power.[1] The increase in concentration has been particularly strong in the retail sector, where both the share of sales going to the largest firms and the national Herfindahl-Hirschman Index (HHI) have been increasing steadily for decades across retail industries (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020; Hortaçsu and Syverson, 2015). However, local product-based concentration is more informative than national industry-based concentration about the degree of competition and the evolution of markups in retail, because consumers in the retail sector primarily choose between local stores selling a given product. This raises the need for new measures of retail concentration that reflect the evolution of retail markets.

In this paper, we use novel U.S. Census data covering all retail establishments to show that both national and local concentration have increased. The data come from the Census of Retail Trade (CRT) and span 1992 to 2012, allowing us to measure the distribution of changes in local and national concentration over 20 years. Our data allow us not only to measure industry-based concentration, but also to construct sales by product for individual retail stores with which we compute new measures of concentration for local product markets, handling retailers that sell multiple products by assigning their sales to the appropriate markets. We consistently find increases across these measures.

Our data show that the national and local HHI increased almost in parallel between 1992 and 2012. We show that the HHI measures the probability that two dollars spent at random are spent at the same firm. We use this fact to interpret changes in the HHI. The national HHI increased from 1.3 to 4.3, indicating that the probability that two random dollars spent on a product anywhere in the U.S. are spent at the same firm has increased

[1] See Autor, Dorn, Katz, Patterson, and Van Reenen (2020) for evidence of increased concentration in retail and other sectors, and Decker, Haltiwanger, Jarmin, and Miranda (2014, 2020) for the dominance of large firms. Hall (2018); De Loecker, Eeckhout, and Unger (2020) document increasing markups.

by 3 percentage points. Local (commuting zone) concentration increased by 2.1 percentage points, from 6.4 to 8.5. Moreover, we find that the increases in local retail concentration hold and are often larger when looking at an extended sample dating back to 1982, when changing the geographical definition of local markets, or when concentration is measured using the sales share of the largest firms.

We find that the increases in local concentration were widespread, with a majority of markets and product categories experience increasing concentration. The local HHI increased in 57 percent of commuting zones between 2002 and 2012; the increases were even more widespread in the previous decade, with 70 percent of commuting zones increasing their concentration between 1992 and 2002. Markets with increasing concentration accounting for 59 percent of retail sales 2002-2012 and 73 percent of retail sales 1992-2002. Concentration also increased for seven of the eight major product categories in retail between 1992 and 2012, with Clothing being the exception.[2]

We examine how online and other non-store retailers affect local concentration and find they have a small effect because they account for less than 10 percent of CRT sales throughout our sample. Establishing the exact effect of non-store retailers on local concentration is challenging because the CRT does not contain the location of sales for non-store retailers. Nevertheless, we obtain bounds for the effect of introducing non-store retailers by assigning their national sales to local markets using a range of assumptions on how concentrated their local sales are. Local concentration would slightly decrease relative to our main results under most assumptions.

We then measure local and national retail concentration in industries and compare these results to our product-based results. As in Autor et al. (2020), we use the industry classification of each store in the CRT to compute national concentration for retail industries, and we extend these measures to local markets defined at different levels of

[2] The eight major product categories are Clothing, Furniture, Sporting Goods, Electronics & Appliances, Health Goods, Toys, Home Goods, and Groceries. These categories account for 82 percent of retail sales throughout the sample.

geographical aggregation. We find that industry-based measures exhibit a stronger increase in concentration than product-based measures, with local industry-level concentration increasing 12.6 percentage points between 1992 and 2012, an increase 6 times larger than the increase in local product concentration.

The main difference between product- and industry-based measures of concentration is the type of competition they emphasize. Product-based measures emphasize competition in the sale of goods, while industry-based measures emphasize competition in retail services. This difference is made clear in the treatment of general merchandisers and other multi-product retailers, which, by definition, sell the same products as retailers in other industries, but offer a different service precisely by offering a wider range of products.[3] In fact, general merchandisers account for more than 20 percent of sales in Electronics & Appliances, Groceries, and Clothing, and their expansion has been linked to the closure of grocery stores (Arcidiacono, Bayer, Blevins, and Ellickson, 2016), showing that competition across industries is a relevant feature of retail markets.

Having established the increase in both national and local retail concentration, we investigate the relationship between these two trends. We do this by implementing a new decomposition of national concentration as measured by the HHI. The decomposition uses the law of total probability to separate the national HHI into a weighted average of the probability that two dollars *spent in the same market* are spent at the same firm (local concentration) and the probability that two dollars *spent in different markets* are spent at the same firm (cross-market concentration).[4] Local concentration is weighted in the decomposition by the probability that two dollars are spent in the same market *regardless of the firms* at which they are spent, a measure of how concentrated spending is across

[3]For example, Walmart is in the general merchandising subsector (three-digit NAICS 452) but competes with grocery, clothing, and toy stores. However, a retailer in a clothing industry is likely to carry a large number of clothing items, while a general merchandiser like Walmart will carry other products in addition to a smaller number of clothing items. Walmart reports SIC code 5331 to the Security and Exchange Commission, which corresponds to NAICS 452990 (Securities and Exchange Commission, 2020). References to specific firms are based on public data and do not imply the company is present in the confidential data.

[4]The tools we develop apply to decompose concentration into any set of mutually exclusive components, for instance, dividing markets by demographics, geography, or sectoral composition.

markets. We call this measure collocation.

Implementing the decomposition makes it clear that national concentration trends capture changes in cross-market concentration rather than changes in local concentration, and thus contain different information about changes in the retail sector. The distribution of retail sales across locations in the U.S. implies a low weight on local concentration—the collocation term is less than 2 percent throughout our sample—capturing the fact that even the largest retail markets in the U.S. are too small to affect national concentration. Because of this, a firm can only be large at the national level if it is present in many markets. In this sense, the trends in national concentration contain no information about the competitive environment in local markets.[5] Increases in local concentration capture consumers within a market shopping at the same firm, and these increases explain less than 1 percent of the change in national concentration. The remaining 99 percent of the change comes from consumers in different markets increasingly buying from the same firms, highlighting the role of the expansion of large firms in explaining changes in the U.S. firm size distribution (Cao et al., 2019; Hsieh and Rossi-Hansberg, 2019).[6]

Given our finding that local concentration is increasing, we study the extent to which these increases translate into higher retail markups.[7] We find that increasing local concentration raised retail markups by 2.1 percentage points between 1992 and 2012, one-third of the increase in markups found in the Annual Retail Trade Survey (ARTS). To arrive at this finding, we use a standard model of local retail competition based on Atkeson and Burstein (2008) and Grassi (2017) to ask how much markups would be

[5]A low collocation term is not a necessary feature of retail markets. In Section 4 we show that collocation can be much higher in other countries, approximately 11 percent in Canada, Chile, and Norway, implying a tighter link between local and national concentration.

[6]The expansion of large retail firms has affected local markets, leading to the closing of small stores (Jia, 2008; Haltiwanger, Jarmin, and Krizan, 2010) and grocery chains (Arcidiacono et al., 2016), as well as higher retail employment in local labor markets (Basker, 2005).

[7]Many of the concerns about concentration leading to higher markups (Hall, 2018; Traina, 2018; Edmond, Midrigan, and Xu, 2019; De Loecker et al., 2020) would operate through local markets, particularly in labor and retail markets. For instance, higher local employment concentration has been shown to negatively impact wages (Berger, Herkenhoff, and Mongey, 2019; Jarosch, Nimczik, and Sorkin, 2020; Azar, Berry, and Marinescu, 2019; Rinz, 2020).

expected to increase due to the observed increases in local concentration. The model implies an explicit link between the local HHI and average markups at the product level. We exploit this link to estimate the model with available data from the CRT and the ARTS, allowing us to calculate measures of product-level markups and to study the historic relationship between concentration and markups despite the lack of long series on prices and costs for U.S. retailers.

**Comparison of Concentration Results to Previous Concentration Results** Our finding of parallel increases in local and national concentration complements previous work that has found increasing concentration in retail and other sectors of the economy.[8] In particular, our product-based measures of national concentration complement work finding increasing national concentration at the industry level using the Census of Retail Trade (Autor et al., 2020). The local concentration trends we document are in line with Rinz (2020) and Lipsius (2018), who find increasing local labor market concentration in the retail sector using the Longitudinal Business Database (LBD), another U.S. Census dataset.[9]

However, our results differ from the retail sector results in Rossi-Hansberg, Sarte, and Trachter (2020) and the consumer brand results in Benkard, Yurukoglu, and Zhang (2021), which both find decreasing local concentration. Rossi-Hansberg et al. base their results on data from the National Establishment Time Series (NETS), which has issues tracking establishments over time, making it problematic for measuring trends (Crane and Decker, 2020). There are also methodological differences between our studies. We consider a range of methods to calculate the local HHI to make our studies more comparable, and we find increases in local concentration with all but one of them. In particular, we vary the geographical aggregation level, the definition of markets by products or industry, and the aggregation methodology. Across specifications, we find changes in local concentration

[8]See Basker, Klimek, and Van (2012); Foster, Haltiwanger, Klimek, Krizan, and Ohlmacher (2016); Hortaçsu and Syverson (2015); Grullon, Larkin, and Michaely (2019); Ganapati (2020).

[9]Multiple papers have shown decreasing local concentration outside of retail (Rinz, 2020; Lipsius, 2018; Rossi-Hansberg, Sarte, and Trachter, 2020). Our results provide more evidence that retail is the only sector with consistently increasing local concentration.

between -1.5 and 12.6 percentage points. The baseline estimate in Rossi-Hansberg et al. for the change in local retail concentration is –17 percentage points, which falls significantly outside this range. The 16 percentage point difference between our lowest estimate and the baseline estimate of Rossi-Hansberg et al. is equally due to differences in data source and the industry definition of markets.[10]

On the other hand, Benkard et al. (2021) study the brands of products that consumers purchase, finding that both national and local brand concentration decrease over time. Our results are complementary as they speak to different aspects of the retail sector. Taken together, our results imply that consumers are simultaneously purchasing a wider variety of brands as they buy those products from a smaller set of retail firms. In this way, increasing retail concentration could cause retail firms to have both more market power with consumers and better negotiating power with producers of brands.

The rest of the paper proceeds as follows. Section 2 describes the data, including how we construct store-level sales by product. Section 3 measures national and local concentration and establishes the main facts about their evolution. We also report changes in concentration across products, locations, and industries. Section 4 decompose national concentration into local and cross-market concentration. Section 5 discusses the effects of local concentration on markups. Section 6 concludes.

# 2 Data: Retailer Revenue for All U.S. Stores

This section describes the creation of new data on store-level revenue for 18 product categories for all stores with at least one employee in the U.S. retail sector. These data allow us to construct detailed measures of concentration that take into account competition between stores selling similar products in specific geographical areas.

[10] Rossi-Hansberg et al. use the NETS to calculate concentration using eight- and and four-digit SIC codes, while we use the CRT with six-digit NAICS codes. Four-digit SIC codes and six-digit NAICS codes are comparable, although SIC includes restaurants in retail, while NAICS does not. See Appendix D for further discussion.

## 2.1 Data Description

We use confidential U.S. Census Bureau microdata that cover 1992 to 2012 (U.S. Census Bureau, 1992-2012). The data source is the Census of Retail Trade (CRT), which provides revenue by product type for retail stores (establishments) in years ending in 2 and 7. We compile CRT data on product-level revenue and information on each store's location to define which stores compete with each other. Importantly, a store's local competition will include stores in many different industries inside the retail sector because stores of different industries can sell similar products. This is particularly relevant for stores in the general merchandising subsector. The data we create here are uniquely equipped to deal with cross-industry competition. We combine the CRT data with the Longitudinal Business Database (LBD) (Jarmin and Miranda, 2002), which contains data on each store's employment and allows us to track stores over time. We calculate all concentration measures at the firm level by combining store sales of a firm in each market.

## 2.2 Sample Construction

The retail sector is defined based on the North American Industrial Classification System (NAICS) as stores with a two-digit code of 44 or 45. As such, it includes stores that sell final goods to consumers without performing any transformation of materials. We use the NAICS codes available from the CRT as the industry of each store. The sample includes all stores with positive sales and valid geographic information that appear in official CRT and County Business Patterns (CBP) statistics that sell one of the product categories used in this study.[11]

Table 1 shows summary statistics for our sample. Even though the number of establishments and firms fluctuates over time, there is an overall decrease in both counts

[11] We exclude sales of gasoline and other fuels, autos and automotive parts, and non-retail products because franchising makes it difficult to identify firms. In our main results we exclude non-store retailers because sales from these stores are typically shipped to different markets than their physical location. We explore the implications of this assumption in Section 3.3.

between 1992 and 2012. Notably, the decrease in firms is double the decrease of establishments. This trend is consistent with the growing importance of multi-market firms in rising cross-market concentration that we show in Section 3. Despite these trends, employment increases over time, representing about 9 percent of U.S. employment over the whole sample period.[12]

Table 1: Sample Summary Statistics

| | 1992 | 1997 | 2002 | 2007 | 2012 |
|---|---|---|---|---|---|
| Establishments | 908 | 942 | 913 | 912 | 877 |
| Firms | 593 | 605 | 589 | 566 | 523 |
| Sales | 1,004 | 1,368 | 1,657 | 2,062 | 2,195 |
| Employment | 9.91 | 11.60 | 11.89 | 12.78 | 12.31 |

*Notes:* Establishment and firm numbers are expressed in thousands. Sales and employment numbers are expressed in millions. The numbers are based on calculations from the Census of Retail Trade and the Longitudinal Business Database.

## 2.3 Creation of Product-Level Revenue

We construct product-level revenue data for all U.S. stores, allowing us to assign a store in a given location to markets based on the types of products it carries. To do this, we exploit the CRT's establishment-level data on revenue by product line (e.g., men's footwear, women's pants, diamond jewelry). We then aggregate product line codes into 18 categories such that stores in industries outside of general merchandise and non-store retailers sell primarily one type of product.[13] For instance, stores in industries beginning with 448 (clothing and clothing accessory stores) primarily report sales in products such as women's dress pants, men's suits, and footwear, which are grouped into a Clothing category.

[12] U.S. employment numbers come from Total Nonfarm Employees in the Current Employment Statistics (Bureau of Labor Statistics, 2019).

[13] Table B.2 lists all the product categories. Unless otherwise stated, we use data from all products for our aggregate results. In Section 3.2 we focus on the eight "main" product categories that account for about 82 percent of store sales in our sample for results for individual product categories. The remaining categories are individually small and have not been released due to disclosure limitations.

Aggregating product lines into categories allows us to accurately impute revenue by category for stores that do not report product-level data. The CRT asks for sales by product lines from all stores of large firms and a sample of stores of small firms. For the remainder, store-level revenue estimates are constructed from administrative data using store characteristics (e.g., industry and multi-unit status). These revenue estimates are constructed for stores that account for about 20 percent of sales in each year. Appendix B provides the details of this procedure.

Our product-level revenue data accounts for the presence of multi-product stores. When a store sells products in more than one category, we assign the store's sales in each category to its respective product market. Consequently, a given store faces competition from stores in other industries. For example, an identical box of cereal can be purchased from Walmart (NAICS 452), the local grocery store (NAICS 448), or online (NAICS 454).[14]

Table 2 shows that cross-industry competition is pervasive in retail. On average, the main subsector for each product accounts for just over half of the product's sales. The remaining sales are accounted for by multi-product stores, particularly from the general merchandise and non-store retailer industries, which are included in the appropriate product markets based on their reported sales. The high sales shares of these multi-product stores makes industry classifications problematic when studying competition. Table C.1 reports the composition of sales for each product category, further distinguishing between general merchandisers and other multi-product retailers. Section 3.4 reports results by industry and shows that industrial concentration changes are larger than product changes.

## 2.4 Definition of Local Markets

We use the 722 commuting zones that partition the contiguous U.S. as our definition of local markets. Commuting zones are defined by the U.S. Department of Agriculture such

[14]The authors found a 10.8 oz box of Honey Nut Cheerios at Walmart, Giant Eagle, and Amazon.com on June 22, 2020.

Table 2: Share of Product Category Sales by Main Subsector

| | 1992 | 2002 | 2012 |
|---|---|---|---|
| Avg. Main Subsector Share | 55.8 | 53.2 | 50.0 |
| Max Main Subsector Share | 79.8 | 73.1 | 72.4 |
| Min Main Subsector Share | 30.3 | 27.6 | 22.0 |

*Notes:* The numbers are based on calculations from the Census of Retail Trade. The average is the arithmetic mean across the eight main product categories of the share of sales accounted by establishments in the product's associated subsector. Shares are multiplied by 100.

that the majority of individuals work and live inside the same zone, and they provide a good approximation for the retail markets in which stores compete. If individuals live and work in a commuting zone, they likely do most of their shopping in that region.

Our results regarding the increasing trends in local concentration and the role of local trends for national concentration are robust to changes in the definition of retail markets. Choosing a larger geographical unit when defining retail markets, such as commuting zones, typically increases the contribution of local concentration to national concentration relative to smaller geographical units such as counties or zip codes. Larger geographical units also tend to have lower levels of concentration than smaller units. However, despite differences in levels of concentration, measures at the zip code, county, commuting zone, and Metropolitan Statistical Area (MSA) levels lead to the same conclusions about the trend in local concentration, even in an extended sample dating back to 1982 (see Appendix C.2).

# 3 Changes in Retail Concentration

In this section, we use the detailed microdata described in Section 2 to measure national and local concentration in the U.S. retail sector. We find that local concentration has increased almost in parallel with national concentration. The increases in concentration are broad based, affecting most markets, product categories, and retail industries.

Our primary measure of concentration is the firm Herfindahl-Hirschman Index (HHI) for a given product category. We denote by $i$ an individual firm and by $j$ a product so that $s_i^{jt}$ represents the sales share of firm $i$ in product $j$ at time $t$. More generally, we define subscripts and superscripts such that $s_a^b$ is the share OF $a$ IN $b$. The national HHI in a year is defined as the sum of the product-level HHIs weighted by the share of product $j$'s sales in total retail sales, $s_j^t$:

$$HHI^t = \sum_{j=1}^{J} s_j^t HHI_j^t, \quad \text{with} \quad HHI_j^t = \sum_{i=1}^{N} \left(s_i^{jt}\right)^2, \tag{1}$$

while the HHI of location $\ell$ and product $j$ in year $t$ is calculated as

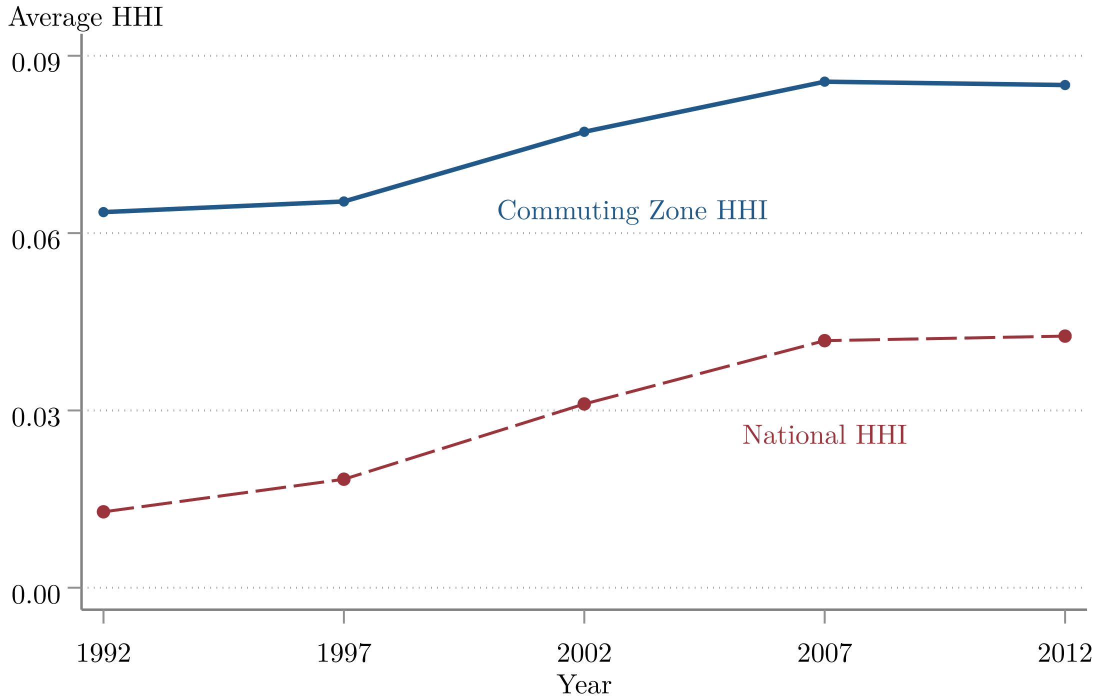
$$HHI_{\ell j}^t = \sum_{i=1}^{N} \left(s_i^{j\ell t}\right)^2. \tag{2}$$

Figure 1 plots national and local concentration in the U.S. retail sector as measured by the HHI. Between 1992 and 2012, both national and local concentration increased at a similar pace. National concentration more than tripled from 1.3 to 4.3 percent. Local concentration, measured by the commuting zone HHI, increased by 34 percent from 6.4 percent to 8.5 percent, a similar increase to that of the national HHI.

We extend these results back to 1982 and consider additional measures of local concentration measures at the zip code, county, and MSA level (Appendix C.2). We find no change in the increasing trends for national and local concentration. Most of this increase occurred between 1997 and 2007, after which all concentration measures plateau. In fact, the national HHI was low and grew at a low rate before 1997. National concentration increased by 1 percentage point in the 15 years between 1982 and 1997; by contrast, it increased 2.3 percentage points in the 10 years between 1997 and 2007.

The national concentration results are consistent with previous industry-level work using sales and employment for various sectors, including retail (Basker et al., 2012; Foster et al.,

Figure 1: National and Local Concentration




*Notes:* The numbers are based on calculations from the Census of Retail Trade. The figure plots the Herfindahl-Hirschman Index (HHI) for local markets defined at the commuting zone level and national concentration. The local HHI is aggregated using each location's share of national sales within a product category. The numbers are sales-weighted averages of the corresponding HHI across product categories.

2016; Lipsius, 2018; Autor et al., 2020; Rinz, 2020; Rossi-Hansberg et al., 2020). The local concentration results are also consistent with studies on local labor market concentration that find increasing industrial concentration in retail but decreasing local concentration in other sectors (Rinz, 2020; Lipsius, 2018). We confirm that industry-based measures of output concentration also rise at both the national and local level in Section 3.4. We also confirm that increases in local concentration are found with other definitions of local markets and that these changes are broad based across productions and geographic areas.

The picture that emerges from our data differs from Rossi-Hansberg et al. (2020), who find a decrease in industrial retail concentration at the zip code level of 17 percentage points between 1992 and 2012. Our studies differ in both data and methodology. Rossi-Hansberg et al. use U.S. National Establishment Time Series (NETS) data, which defines the retail sector using Standard Industrial Classification (SIC) codes, while the CRT uses NAICS. We also differ in the aggregation methodology for local concentration. The methodology in Rossi-Hansberg et al. places more weight on markets with declining concentration because it uses each market's final share of employment and markets become less concentrated as they grow. Weighting markets using their average share of employment over time or their initial share always implies increasing local concentration.

We replicate the methodology of Rossi-Hansberg et al. in our data and find a 1.5 percentage point decrease in local industrial concentration at the zip code level. The 15.5 percentage points between our results are equally due to differences in market definition and data sources. For their baseline result, Rossi-Hansberg et al. define markets based on eight-digit SIC codes, while we use six-digit NAICS codes in our industry measures.[15] Rossi-Hansberg et al. show that moving from eight- to four-digit SIC codes in NETS implies a decline in concentration of 8 percent, explaining about half of the difference between our results. Four-digit SIC codes are comparable to the six-digit NAICS available in the CRT except NAICS does not include restaurants in retail. The change from four-digit SIC using NETS data to six-digit NAICS using CRT data explains the other half of the difference. We provide full details of these exercises in Appendix D.

All other concentration measures we calculate for the retail sector—varying the level of geographical aggregation, aggregation methodology, and definition of markets by product or industry—imply an increase in local concentration between 1992 and 2012. Taken together, we find robust evidence for increases in local retail concentration.

## 3.1 Changes in Concentration across Markets

We now turn to the distribution of changes in concentration across markets. We find that the increases in concentration have been broad based. Almost 60 percent of dollars spent in

[15] Eight-digit SIC codes may be overly detailed for retail markets because many retailers will sell multiple types of goods. For example, concentration in eggs and poultry (54999902) would miss the fact that many eggs and poultry are sold by chain grocery stores (54119904) and discount department stores (53119901).

2012 are spent in markets that have increased concentration since 2002 (Figure 2d). In just 10 years, 23 percent of markets have increases in concentration of over 5 percentage points (Figure 2b). These changes are significant. For comparison, the Department of Justice considers a 2 percentage point increase in the local HHI potential grounds for challenging a proposed merger (Department of Justice and Federal Trade Commission, 2010).

Figures 2a and 2c show that the changes in concentration were even more widespread between 1992 to 2002. Over 69 percent of markets, accounting for 72 percent of retail sales, increased their concentration. In both the 1992–2002 and 2002–2012 decades, the majority of retail sales occurred in markets with relatively small increases in concentration (between 0 and 5 percentage point increases in the market's HHI). These markets account for 66 percent of retail sales in 2002 and 55 percent in 2012.

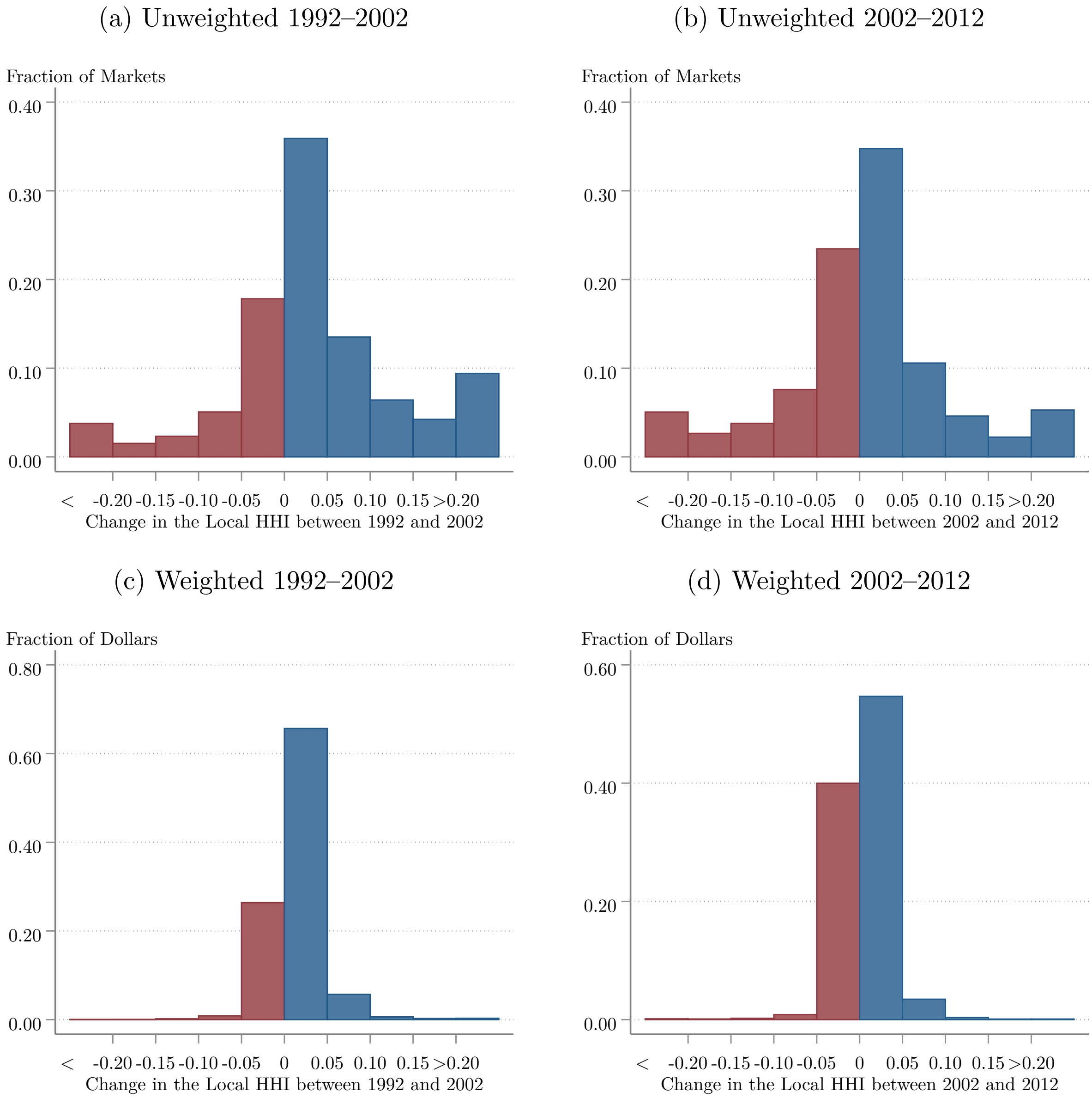
### 3.2 Changes in Concentration across Products

Between 1992 and 2012, both local and national concentration increase for seven of the eight major product categories, Clothing being the exception. Figure 3a shows that these increases were large for many products. Six of the eight categories had an increase in HHI between 3 and 4 percentage points. Despite this common trend, the changes in concentration vary substantially across product categories. Local concentration in Groceries increased by only 1.1 percentage points and decreased in Clothing by 2012, while it almost doubled in Home Goods and Electronics & Appliances.

Figure 3b shows the levels of national concentration for each product category between 1992 and 2012. The increases in national concentration are widespread and significant. Six of the categories have larger absolute changes in national concentration relative to local concentration even though the levels of national concentration are markedly lower than those of local concentration.

Finally, comparing Figures 3a and 3b shows that not all product markets evolved in the same way between 1992 and 2012. The markets for Furniture and Clothing changed

Figure 2: Changes in Concentration across Markets

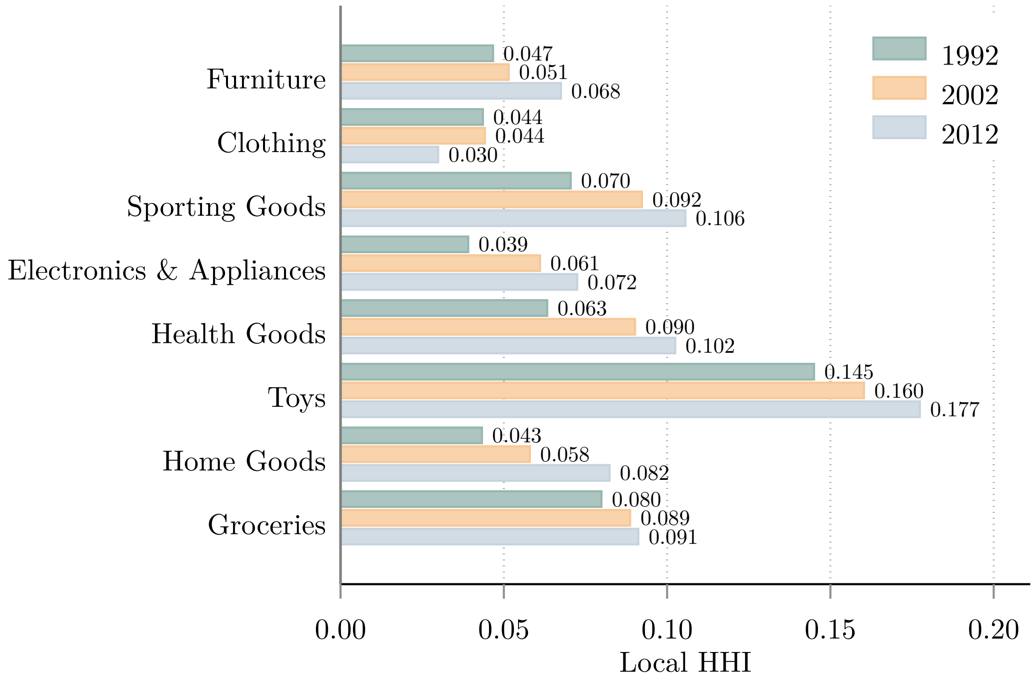



*Notes:* The numbers are based on calculations from the Census of Retail Trade. The top panels show the fraction of markets, commuting zone/product category pairs, with changes in concentration of a given size. The bottom panels weight markets by the value of sales in the product category. The columns report changes for the decades 1992 to 2002 and 2002 to 2012.

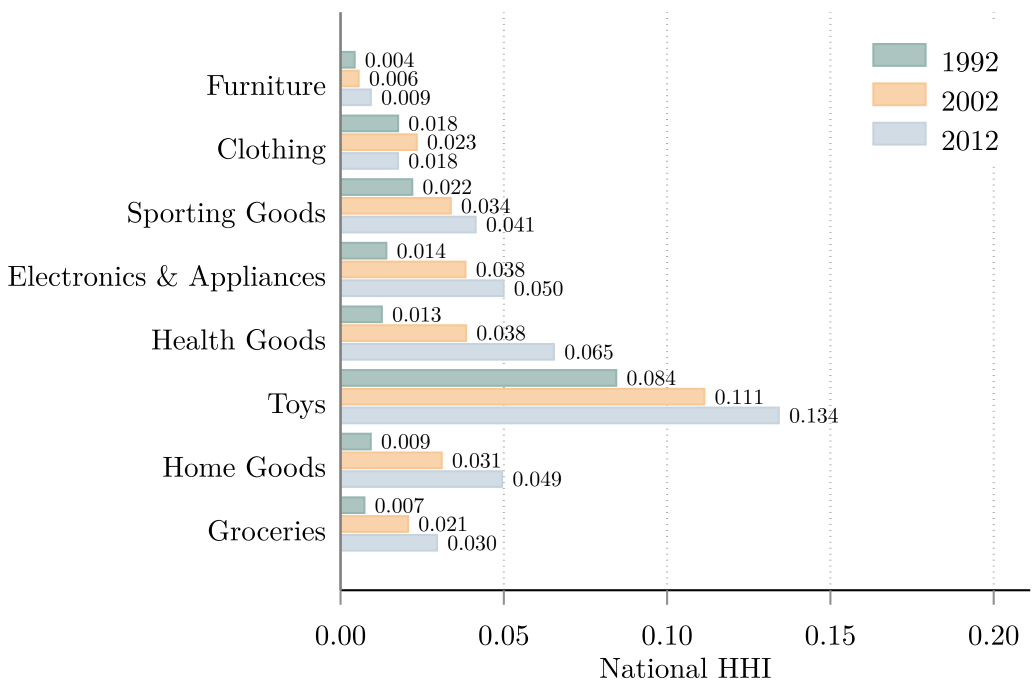
very little, and both have relatively low levels of both local and national concentration. On the other hand, local markets for Groceries and Health Goods became slightly more concentrated, while at the national level, concentration has increased more than fourfold.

Figure 3: Local and National Concentration across Product Categories

(a) Local Concentration




(b) National Concentration




*Notes:* The numbers are national and local Herfindahl-Hirschman Indexes (HHI) by product weighted by market size from the Census of Retail Trade microdata.

### 3.3 Impact of Online and Other Non-Store Retailers

The previous results calculated local concentration using only brick-and-mortar retailers. In what follows, we consider the potential impact of online and other non-store retailers on local concentration. The market share of non-store retailers has more than tripled between 1992 and 2012. However, the overall importance of non-store retailers remained limited through 2012. The initial sales share of non-store retailers is low, just 2.7 percent in 1992. This low share reflects both the absence of online retailers and the limited role of other retailers that rely on mail order and telephone sales. The sales share of non-store retailers had risen to 9.5 percent by 2012, driven by an increase in online sales. The increase was uneven across product categories. Non-store retailers had significant market share in product categories, such as Furniture, Clothing, and Sporting Goods, but have almost no market share in Groceries and Home Goods (see Appendix C.3).

The effect of online and other non-store retailers on local concentration depends on how their sales are distributed across and within markets. Unfortunately, the CRT does not record the location in which non-store retailers sell their products, making it impossible to determine the exact effect of these retailers on local concentration. Nevertheless, we can generate bounds for the effect of non-store retailers while being consistent with their behavior at the national level. To do this, we assume that the share of retail spending that goes to non-store retailers is constant across markets within a product category and is equal to the national sales share of non-store retailers in that category.

Having distributed the sales of non-store retailers across markets, we can construct a lower and upper bound for the local HHI. The total effect on concentration depends on the total market share of non-store retailers and how concentrated they are. The lower bound assumes that non-store retailers are atomistic, with the sales share of each non-store retailer equal to zero. The lower bound is

$$\underline{HHI} = (1 - s_{NS})^2 \, HHI_{BM}, \tag{3}$$

where $s_{NS}$ corresponds to the sales share of non-store retailers and $HHI_{BM}$ to the HHI of brick-and-mortar stores. In this case, non-store retailers decrease concentration by reducing the sales share of brick-and-mortar stores. The size of this decrease depends on the sales shares of non-store retailers in the product category. The upper bound assumes that all the sales of non-store retailers belong to a single stand-in firm. The upper bound is

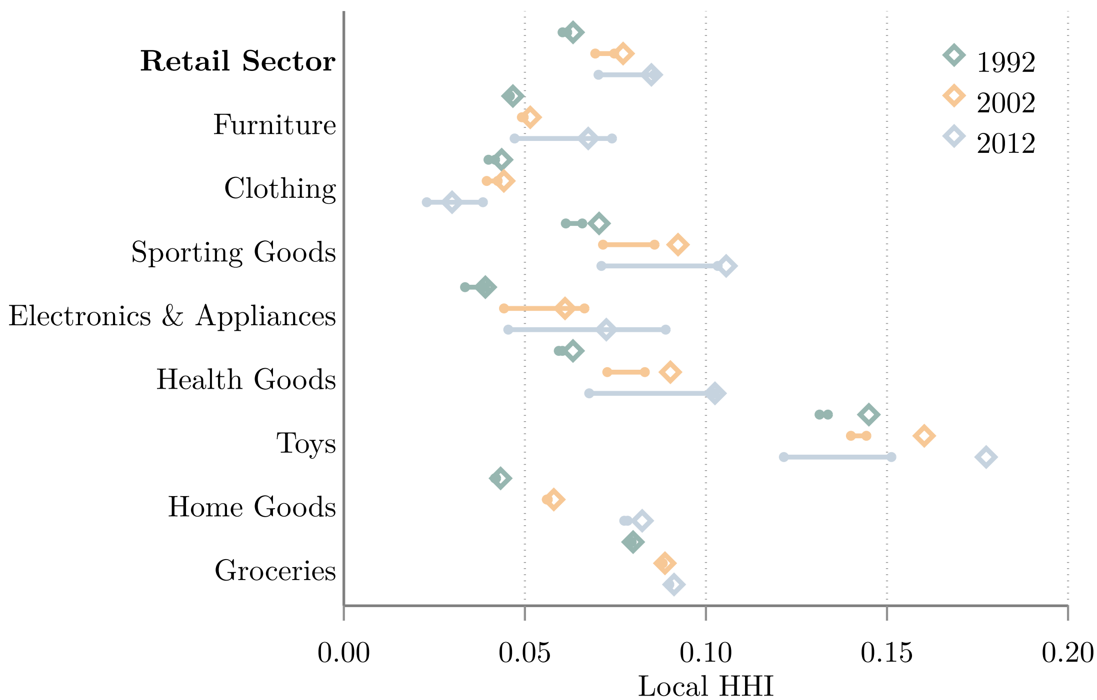
$$\overline{HHI} = (1 - s_{HS})^2 \, HHI_{BM} + s_{NS}^2. \tag{4}$$

This is an upper bound on concentration under the assumption that firms do not have both brick-and-mortar and non-store establishments, which is consistent with the data.

Figure 4 shows the bounds we construct for local concentration across product categories in the retail sector. As expected, including non-store retailers for categories like Home Goods or Groceries hardly affects the level of concentration because the market share of non-store retailers remains low throughout. The effects are larger for the other categories, especially for 2012. Accounting for non-store retailers reduces concentration in most categories because of the decrease in market share among brick-and-mortar stores. For most product categories, the bounds for local concentration lie below the estimated HHI for brick-and-mortar stores (marked by the diamonds in the figure). It is only in Electronics & Appliances, and to a lesser extent in Clothing, that the market share of non-store retailers is large enough for their inclusion to potentially increase concentration.

When non-store retailers are included, there is still a clear increase in local concentration between 1992 and 2002, although the levels are slightly lower. Moving from 2002 to 2012, the story becomes ambiguous, especially for product categories with a significant share of their sales going to non-store retailers. In many cases, the bounds for 2012 contain the bounds for 2002, indicating local concentration could either be increasing or decreasing depending on the concentration among non-store sales. At a national level, non-store retailers were not highly concentrated during this time period (Hortaçsu and Syverson,

Figure 4: Local Concentration and Non-Store Retailers




*Notes:* The numbers are based on calculations from the Census of Retail Trade. Diamonds mark local concentration for brick-and-mortar stores as measured by the Herfindahl-Hirschman Index (HHI) at the commuting zone level. The continuous lines cover the bounds on concentration including non-store retailers. We assume that sales of non-store retailers are distributed across local markets proportionately to the sales of brick-and-mortar retailers. The upper bound assigns all the sales of non-store retailers to a single stand-in firm. The lower bound assumes that non-store retailers are atomistic, with the sales share of each individual non-store retailer equal to zero.

2015), and thus the increasing importance of non-store retailers is potentially decreasing local market concentration between 2002 and 2012.

## 3.4 Comparing Industry- and Product-Based Results

We now document the evolution of industry-based concentration measures. These measures capture the variation in retail services offered by different industries. For instance, general merchandisers offer a variety of products, and consumers value the ability to buy multiple products in one location (Seo, 2019). In this sense, industry based measures focus on a different dimension of competition between retail stores than the product-based measures

Table 3: Comparison of Product- and Industry-Based Concentration

| | 1992 | 1997 | 2002 | 2007 | 2012 |
|---|---|---|---|---|---|
| **National Concentration** | | | | | |
| Product Based | 0.013 | 0.019 | 0.031 | 0.042 | 0.043 |
| Industry Based | 0.029 | 0.046 | 0.085 | 0.105 | 0.116 |
| **Commuting Zone Concentration** | | | | | |
| Product Based | 0.064 | 0.066 | 0.078 | 0.086 | 0.086 |
| Industry Based | 0.177 | 0.199 | 0.263 | 0.287 | 0.303 |
| **Zip Code Concentration** | | | | | |
| Product Based | 0.264 | 0.277 | 0.288 | 0.286 | 0.277 |
| Industry Based | 0.530 | 0.552 | 0.603 | 0.611 | 0.615 |

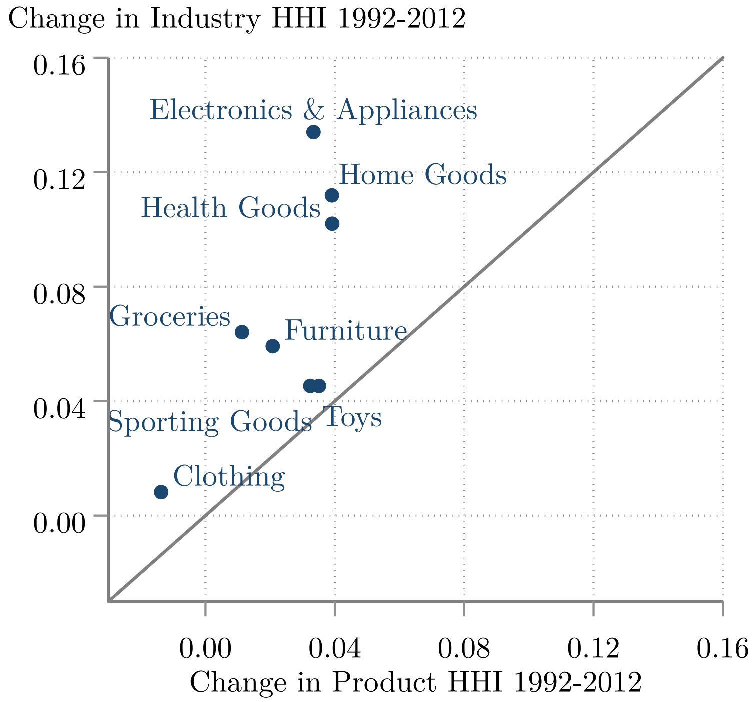
*Notes:* The numbers come from the Census of Retail Trade and are the level of concentration in a given year with markets defined according to the noted geography. All measures of concentration use the establishments included in the sample for the product-based results. Industry concentration uses six-digit NAICS codes.

we have presented.

We find larger increases in both national and local concentration at the industry level than at the product level. Table 3 shows that national concentration increases by 8.7 percentage points, 5.7 percentage points more than with product-based measures. Commuting zone concentration goes up by 12.6 percentage points between 1992 and 2012 when measured at the industry level, 10.4 percentage points more than the product-based measure. The same patterns arise when defining markets at the zip code level and show that the large increase in industry-based local concentration is not a feature of the geographical aggregation of markets. A significant portion of the increase in industry concentration comes from the general merchandise subsector (NAICS 452), where local concentration increased by 28.2 percentage points (see Figure C.4 in Appendix C.4). This change is at least partially due to general merchandisers selling an increasing number of products and may not reflect increasing market power.

We then match each product to the subsector that primarily sells that product (e.g.,

Figure 5: Product vs Industry Concentration




*Notes:* The data are from the Census of Retail Trade. Each point marks the change in local Herfindahl-Hirschman Index (HHI) of a product category and its main subsector between 1992 and 2012. Markets are defined at the commuting zone level and are aggregated using each market's share of national sales in the relevant industry or product.

Clothing and NAICS 448: Clothing and Clothing Accessory Stores) and plot the changes in concentration in Figure 5. The figure shows a positive correlation between industry and product concentration despite the differences in market definition. However, the increases in concentration are larger when measured at the industry level, which explains the larger increases in overall retail concentration shown in Table 3. Appendix C.4 complements these results by reporting the levels of local and national concentration for the industries corresponding to our main product categories and general merchandisers.

# 4 The Relationship Between National and Local HHIs

We now turn to the relationship between national and local concentration. Despite national and local concentration increasing in parallel between 1992 and 2012, the rise in national concentration does not reflect the behavior of local markets. The information in Figure 1 alone is not enough to determine the relationship between national and local concentration because they can, in principle, move independently. National concentration can increase as local markets become more concentrated, but it can also increase by having firms expand across markets, capturing a larger share of national sales. This expansion makes it so that consumers in different markets increasingly buy from the same firms. We refer to this as an increase in cross-market concentration.[16]

To address this issue, we develop a new decomposition of national concentration into local and cross-market concentration. The decomposition is based on a probabilistic interpretation of the HHI. The HHI for product $j$ measures the probability that two dollars, $x$ and $y$, chosen at random, are spent at the same firm. Our probabilistic interpretation of the HHI provides a new way to understand the level of and changes in the HHI.[17] It also lets us use the law of total probability to derive a decomposition of the HHI into any set of mutually exclusive components. In particular, we decompose the national HHI based on whether the two dollars are spent in the same or different markets:

$$\underbrace{P(i_x = i_y)}_{\text{National HHI}} = \overbrace{P(\ell_x = \ell_y)}^{\text{Collocation}} \underbrace{P(i_x = i_y | \ell_x = \ell_y)}_{\text{Local HHI}} + \overbrace{P(\ell_x \neq \ell_y)}^{1 - \text{Collocation}} \underbrace{P(i_x = i_y | \ell_x \neq \ell_y)}_{\text{Cross-Market HHI}}, \qquad (5)$$

where $i_x$ is the firm at which dollar $x$ is spent and $\ell_x$ is the location of the market in which dollar $x$ is spent, and likewise for $y$.

[16]Cross-market concentration is not necessarily accompanied by higher local concentration. It is possible that the expansion of multi-market firms brings up more—potentially smaller—competitors, decreasing local concentration. The total effect on national and local concentration depends on how firms in individual markets respond.

[17]The probability that two dollars are spent in the same firm in the U.S. goes from 1.3 percent in 1992 to 4.3 percent in 2012.

Equation (5) has three components. The first component, $P(\ell_x = \ell_y)$, which we term collocation, captures the probability that two dollars are spent in the same location.[18] The second component, $P(i_x = i_y | \ell_x = \ell_y)$, is an aggregate index of local concentration, with local concentration measured as in equation (2).[19] This captures the extent to which consumers in a local market shop at the same firm. The third component, $P(i_x = i_y | \ell_x \neq \ell_y)$, which we call cross-market concentration, captures the probability that a dollar spent in different markets is spent at the same firm:

$$P(i_x = i_y | \ell_x \neq \ell_y) = \underbrace{\sum_{\ell} \sum_{n \neq \ell} \frac{s_\ell s_n}{1 - \sum_p s_p^2}}_{\text{Weights}} \underbrace{\sum_{i=1}^{N} s_i^\ell s_i^n}_{\text{Cross-Market}} . \tag{6}$$

The cross-market concentration index between two markets (say $\ell$ and $n$) is given by the product of the shares of the firms in each location (the probability that two dollars spent in different locations are spent in the same firm). The pairs of markets are then weighted by their share of sales and are summed.

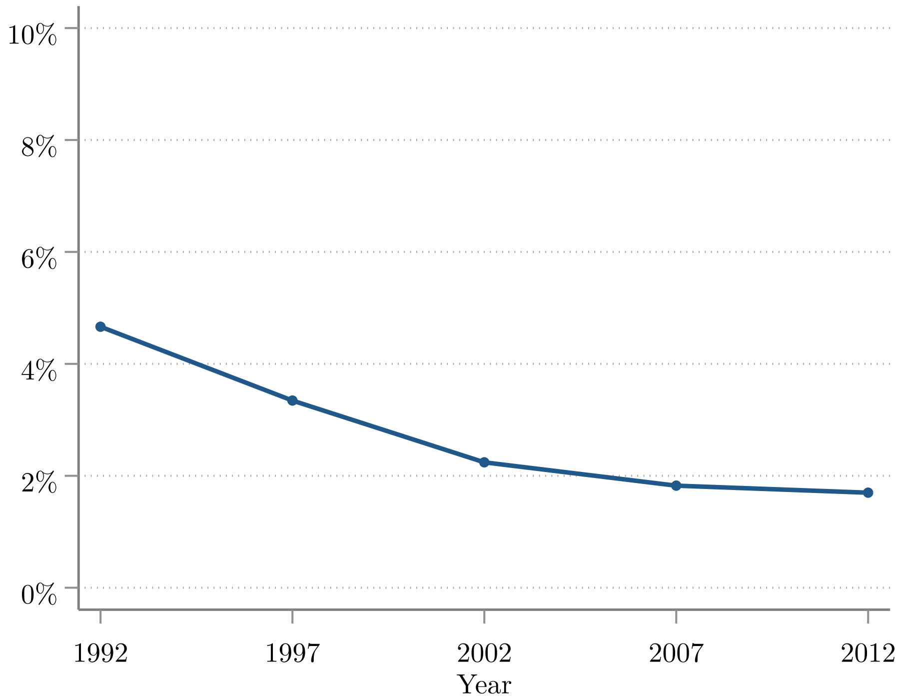
The collocation term determines how much can be learned about local competitive environments using national information. If it is large enough, national concentration numbers can be informative about local markets, as the decomposition presented in (5) shows. Conversely, a low collocation term implies that local concentration can only have a limited effect on national trends, making changes in national concentration mostly informative about cross-market concentration. Our estimates of the collocation term for the retail sector using confidential data are about 0.012.[20] In the U.S., even the largest

[18]The collocation term is $P(\ell_x = \ell_y) = \sum_{\ell=1}^{L} (s_\ell)^2$, where $s_\ell$ is the share of location $\ell$ in national sales.

[19]In the decomposition, each local market is weighted by the conditional probability that the two dollars are spent in location $\ell$ given that they are spent in the same location: $s_\ell^2 / (1 - \sum_p s_p^2)$. These weights give more importance to larger markets than the more usual weights $s_\ell$—the share of sales (of product $j$) accounted for by location $\ell$ (at time $t$). We present aggregated series for local concentration in Section 3 that use the latter weights. Appendix A derives these results in detail.

[20]The collocation term can often be approximated using publicly available data on market sizes. This provides valuable information on the relative role of local and cross-market concentration without requiring data on firm market shares at the local level. Using publicly available information from the CBP, we calculate a retail collocation term of 0.010 for retail employment in commuting zones in 2012.

Figure 6: Share of Local Concentration Term in National Concentration




*Notes:* The numbers are based on calculations from the Census of Retail Trade. The share of local concentration is measured as the ratio of the local concentration term in equation (5) to the national Herfindahl-Hirschman Index (HHI). The local concentration term is the product of the collocation term and local HHI.

markets represent only a small fraction of total U.S. retail sales, which is captured by a low collocation term.

Implementing the decomposition makes it clear that national concentration reflects the rise in cross cross-market concentration. Figure 6 shows the contribution of local concentration to the level national concentration by year.[21] Two things are clear from the figure. First, the contribution of local concentration to national concentration is small—never above 5 percent. This is because local concentration is weighted by the collocation term, which is small given the large number of markets in the country. Second, the contribution of local concentration to national concentration has been falling

[21]We formally define the relative contribution of local concentration as the product of the collocation and local HHI components divided by the national HHI. In the notation of equation (5), $P(\ell_x{=}\ell_y)P(i_x{=}i_y|\ell_x{=}\ell_y)/P(i_x{=}i_y)$.

over time as national concentration has been increasing. By 2012, local concentration accounted for just 1.7 percent of the national concentration level. The flip side of these results is the major role of cross-market concentration in shaping the national concentration index. National concentration has increased because consumers in different locations are shopping at the same (large) firms; in fact, 99 percent of the change in national concentration is accounted for by changes in cross-market concentration.

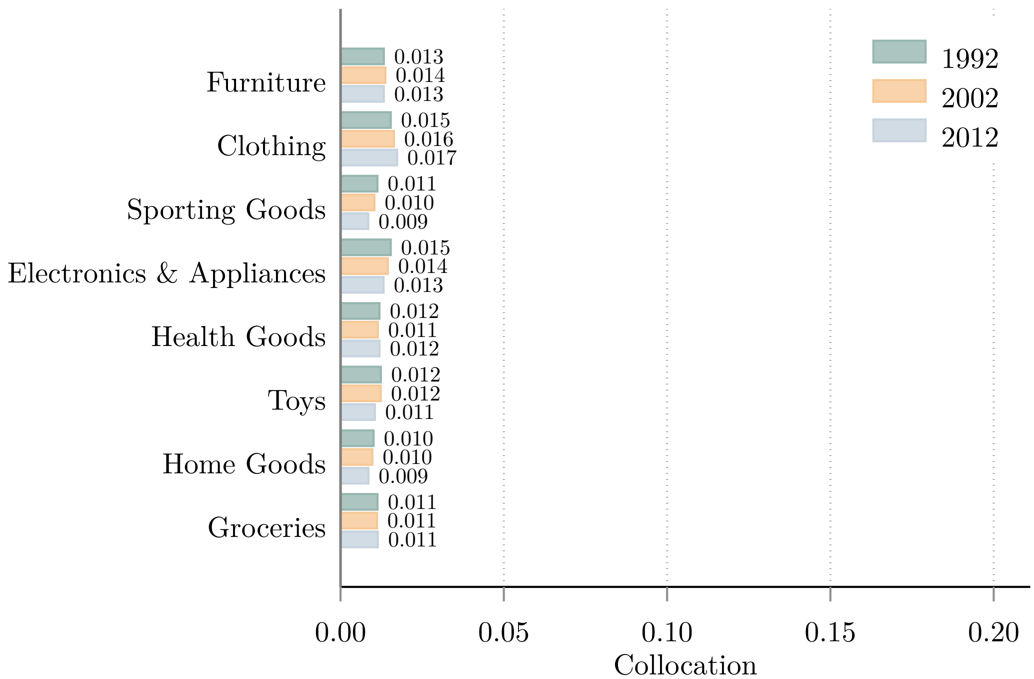
The pattern of low collocation terms and a prominent role of cross-market concentration applies across all product categories. Figure 7a shows that the collocation term is always low, less than 2 percent, and stable over time. The small magnitude of the collocation terms implies a limited role for local concentration in explaining national changes. The contribution of local concentration varies across products but it is always low. By the early 1990s, only furniture and groceries have contributions of over 10 percent, with the local contribution in all other products being no higher than 5.5 percent, and as low as 2 percent. Figure 7b shows the levels of the cross-market concentration index across products. As expected, these levels are close to those of national concentration (Figure 3b).

A low collocation term is not a necessary feature of retail markets. The importance of local concentration for aggregate trends is different in other industries and countries where the collocation term is larger. The CBP data show that the collocation term varies significantly across industries, with 1 in 10 industries having a collocation term over 10 percent. The industries with large collocations terms are mainly focused around mining, video production, ocean access, and finance. The geographic concentration of these industries makes national concentration informative about local competition. The collocation term also varies across countries, with more geographically concentrated countries exhibiting higher collocation terms. For instance, the collocation terms for Canadian metropolitan areas, Chilean provinces, and Norwegian counties are about 11 percent.[22]

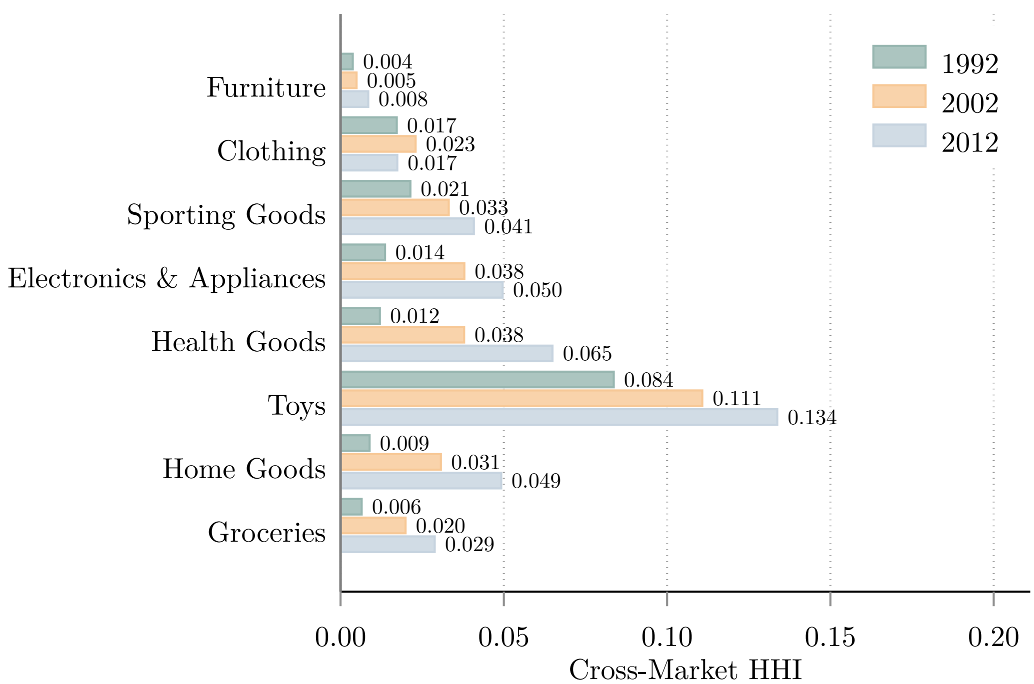
[22] We approximate the retail collocation term in each country with its population collocation, computed using publicly available data from each country's statistical authority.

Figure 7: Collocation and Cross-Market Concentration across Product Categories

(a) Collocation




(b) Cross-Market Concentration




*Notes:* The numbers are collocation and cross-market Herfindahl-Hirschman Indexes (HHI) by product weighted by market size from the Census of Retail Trade microdata.

# 5 Effects of Local Concentration on Markups

As discussed previously, local retail concentration increased by 2.1 percentage points between 1992 and 2012. These changes can imply higher markups and ultimately affect consumer prices. In this section, we study the relationship between local concentration and markups. However, studying this relationship is challenging because long series on prices and costs for U.S. retailers are unavailable. Nevertheless, linking changes in concentration to changes in prices is critical for assessing the potential impact of concentration on consumers.

To deal with data limitations, we use a standard model of Cournot competition based on the work of Atkeson and Burstein (2008) and Grassi (2017). This model provides us with an explicit link between the local HHI and average product markups. We find that increases in local concentration imply a 2.1 percentage point increase in markups between 1992 and 2012, roughly a third of the observed increase in markups during that period.

The model features three key assumptions to maintain tractability. We assume that 1) firms face isoelastic demand curves, with elasticities of demand varying by product but not by location; 2) firms operate a constant returns to scale technology within a market; and 3) pricing decisions are taken at the market level, ignoring links between stores of the same firm across locations. Under these assumptions, the competitive environment faced by a firm is completely described by the firm's local market share. This allows us to then link local concentration, as measured by the local HHI, to prices and markups. In this way, our model is limited by the extent to which the distribution of market shares captures the competitive environment in retail markets (Appendix E describes the model in detail and discusses extensions).

The model economy contains $I$ firms operating in $L$ different locations (representing commuting zones) where $J$ different products are traded. Firms compete in quantities in a non-cooperative fashion and have market power in the local product markets in which they operate. A market is characterized by a pair $(j, \ell)$ of a product $j$ and a location $\ell$, with an isoelastic demand curve for each product. Firms produce using a constant returns to scale technology and differ in their in their productivity, $z_i^{j\ell}$. The firm's marginal cost is $\lambda_i^{j\ell}$.

The solution to each firm's problem is to charge a market-specific markup, $\mu_i^{j\ell}$, over the firm's marginal cost so that the price is $p_i^{j\ell} = \mu_i^{j\ell} \lambda_i^{j\ell}$.[23] The markup is characterized in terms of the firm's market share, $s_i^{j\ell}$, and the product's elasticity of demand, $\epsilon_j$:

$$\mu_i^{j\ell} = \frac{\epsilon_j}{(\epsilon_j - 1)(1 - s_i^{j\ell})}. \tag{7}$$

Markups will be larger for firms with higher market shares and for products with a less elastic demand. Importantly, equation (7) allows us to estimate markups using only data on market shares and elasticities of demand.

The model provides an explicit link between local retail concentration and markups faced by consumers (Grassi, 2017). We use the firm-specific markups in equation (7) to derive closed-form expressions for markups in each market ($\mu_j^\ell$) as well as for the average markup of each product nationally ($\mu_j$). Both markups directly depend on the local HHI:

$$\mu_j^\ell = \frac{\epsilon_j}{\epsilon_j - 1} \left[1 - \mathrm{HHI}_j^\ell\right]^{-1}, \tag{8}$$

$$\mu_j = \frac{\epsilon_j}{\epsilon_j - 1} \left[1 - \sum_{\ell=1}^{L} s_\ell^j \mathrm{HHI}_j^\ell\right]^{-1}, \tag{9}$$

where $\mathrm{HHI}_j^\ell$ is the HHI of product $j$ in location $\ell$ and $s_\ell^j$ is the share of location $\ell$ in the national sales of product $j$. As markets become more concentrated, average markups increase. The sensitivity of markups to increases in concentration is larger for products with a lower elasticity of demand.

[23]There is evidence that firms charge similar and even the same prices across locations in building material (Adams and Williams, 2019) and groceries (Dellavigna and Gentzkow, 2019). Appendix E.4 shows that uniform pricing depends on a weighted average of local market power. Thus, our assumption of pricing-to-market should have a small effect on aggregate conclusions but may have distributional impacts.

## 5.1 Estimation and Data

The two key ingredients for analyzing markups are firms' market shares by product in each location, $s_i^{j\ell}$, and the elasticity of substitution for each product, $\epsilon_j$. We obtain the shares directly from the CRT and estimate the elasticities using equation (9). Specifically, we use the product HHIs calculated in Section 3.2 and gross margins from the Annual Retail Trade Survey (ARTS).

The ARTS provides the best source to compare our results to because it computes markups using cost of goods sold, which are the most direct data analogue to markups in the model (see Appendix E.2). The ARTS samples firms with activity in retail, collecting data on sales and costs for each firm. The firm-level markups collected by ARTS represent an average markup across the products that the firm sells. The information available is similar to information in Compustat, but the ARTS includes activity of non-public firms that account for a significant share of retail sales.

The ARTS also provides us with markups for detailed industries, which we convert to product markups using the CRT.[24] We do this in three steps. First, we compute markups for the industries most closely related to each of the eight major product categories as well as for general merchandisers (NAICS 452).[25] As before, the sales of each specialized industry are all assigned to its own product category, while the sales of general merchandisers are divided across products using the share of each product category's sales that come from general merchandisers in the CRT. Second, we estimate a scaling factor $\lambda = 0.82$ that measures how large general merchandise markups are relative to what would be implied by other industries' markups:

$$\mu_{GM}^{ARTS} = \lambda \sum_j \omega_j^{GM} \mu_j^{ARTS}, \tag{10}$$

[24]Appendix C.5 presents additional results based on industry-level markups as well as robustness exercises with alternative measures of product markups.

[25]For instance, we relate clothing to NAICS 448 and groceries to NAICS 445; see Appendix C.4 for a complete list.

where $\mu_j^{ARTS}$ is the measured markups of industry $j$ in the ARTS and $\omega_j^{GM}$ is the share of sales of product $j$ in general merchandising from the CRT. We use the scaling factor $\lambda$ to construct product-specific markups for general merchandisers while being consistent with the measured markups from the ARTS. The markup of general merchandisers in product $j$ is then $\mu_{GM}^j = \lambda\mu_j^{ARTS}$. Finally, we compute product-level markups in a model-consistent way as

$$\mu_j = \left(\frac{1-\omega_{GM}^j}{\mu_j^{ARTS}} + \frac{\omega_{GM}^j}{\mu_{GM}^j}\right)^{-1}, \tag{11}$$

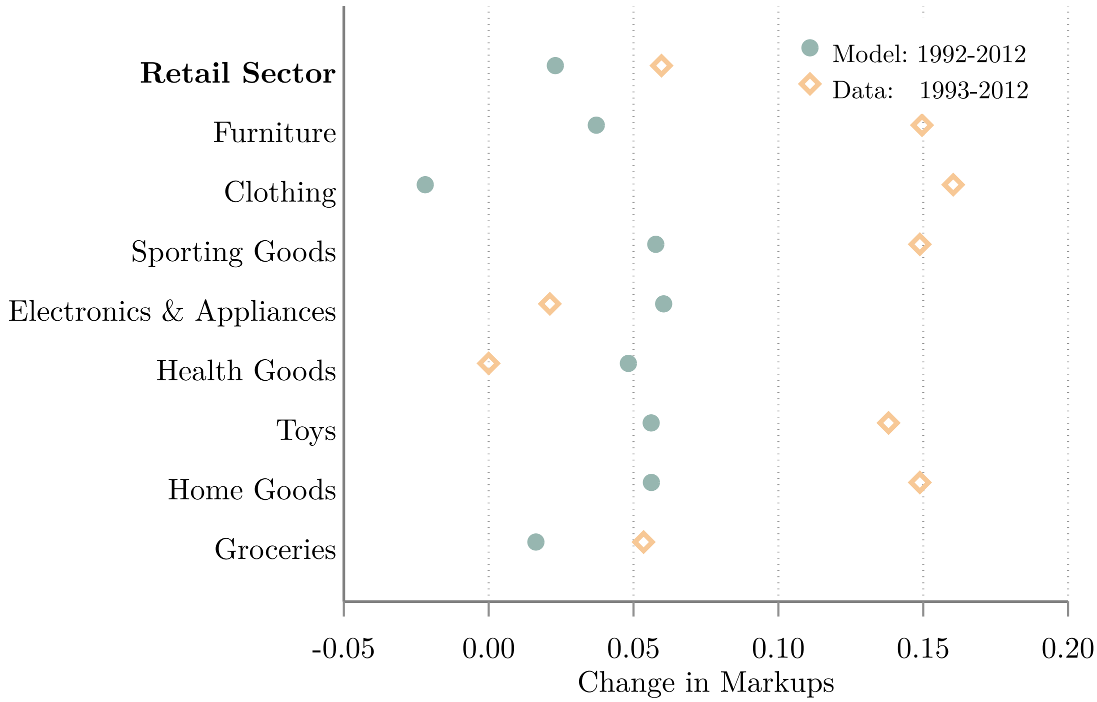
where $\omega_{GM}^j$ is the share of general merchandisers in product $j$'s sales. In this way, product-level markups incorporate the effect of competition from general merchandisers.

## 5.2 Changes in Concentration and Markups

We conduct two exercises with the model. First, we fit the model to match product markups in 1992 given the observed levels of local concentration, which provides us with estimates of the elasticities of substitution for each product category. Holding these estimates fixed, we can extend the model through 2012 and obtain the change in markups implied by the observed increase in local concentration. This exercise explains one-third of the increase in markups observed in the ARTS. Second, we can fit the model to match observed markups for each economic census year by allowing the elasticities of substitution to be time varying. To match the increase in markups, the model implies a decrease in the elasticity of substitution for most products.

The increase in local concentration implies an increase in retail markups of 2.1 percentage points between 1992 and 2012, about one-third of the 6 percentage point increase in product-level markups. Figure 8 shows that in all but two product categories, the observed increase in markups is higher than what is implied by the rise in product-level HHI. These results are robust to alternative measures of product markups

Figure 8: Local Concentration and Markups




*Notes:* Diamonds mark the change in product markups between 1992 and 2012 from the Annual Retail Trade Survey and Census of Retail Trade data and a weighted average across products for the retail sector. Circles mark the change in markups implied by the change in local concentration given the model estimates for 1992.

(see Appendix C.5). The changes in model markups in Figure 8 assume that the elasticity of demand faced by firms are constant over time and vary only because of changes in local HHI. However, many changes in the competitive environment of retail can be reflected in changes in these elasticities rather than changes in market concentration.

Table 4 shows the value of the elasticity of substitution needed to match the level of markups in each year. We find the lowest elasticities of substitution in Clothing and Furniture. These are categories that feature many different brands only available from a small set of retail firms, leaving more room for differentiation than in products such as Toys and Groceries, where different firms carry similar or even identical physical products.

To match the observed increase in markups, most product categories require a decrease in their elasticity of substitution. The magnitude of the decrease depends on the initial level

Table 4: Estimated Elasticities of Substitution

| Product Category | $\epsilon_j$ 1992 | 2002 | 2012 |
|---|---|---|---|
| Furniture | 2.70 | 2.43 | 2.43 |
| Clothing | 3.07 | 2.83 | 2.48 |
| Sporting Goods | 3.73 | 3.77 | 3.20 |
| Electronics & Appliances | 4.48 | 5.74 | 4.95 |
| Health Goods | 4.38 | 5.30 | 5.09 |
| Toys | 5.55 | 5.91 | 4.91 |
| Home Goods | 4.85 | 4.13 | 3.92 |
| Groceries | 5.82 | 5.39 | 6.40 |

*Notes:* The data are authors' estimates of product elasticities of substitution using industry markups from the Annual Retail Trade Survey and product-level local Herfindahl-Hirschman Indexes calculated from the Census of Retail Trade. The elasticities are the solution to equation (9).

of the elasticities as markups respond more to changes for lower elasticities. The decreasing trend for the elasticities of substitution is consistent with the findings of Bornstein (2018), Brand (2020), and Neiman and Vavra (2020), who link the decrease to the rise of store and brand loyalty/inertia. The exception to the trend of decreasing elasticities of substitution are Electronics & Appliances and Health Goods, which instead require an increase in their elasticities. Health Goods had almost no change in markups in the data, but based on the change in concentration, markups should have increased by about 5 percentage points.

Altogether, our results suggest that changes in local concentration explain about one-third of the increase in markups, increasing from 1.38 in 1992 to 1.40 in 2012. These increases are small relative to the 34 percent decrease in the relative price of retail goods during this period. The increases in markups and concentration may be the result of low-cost firms gaining market share, in which case the decrease in prices cannot be separated from the increase in concentration. Even if the implicit reduction in costs is realized without an increase in concentration, the decrease in prices would have been 35 percent.

# 6 Conclusion

Consumers have traditionally chosen between nearby stores selling a given product when purchasing goods. This fact makes local market conditions relevant for assessing the competitive environment in the retail sector. Accordingly, we measure concentration on local product markets using novel Census data on all U.S. retailers. We find increases in concentration covering the majority of markets which hold for product- and industry-based measures of concentration, even after taking into account the role of online and other non-store retailers. However, we show that local and national concentration reflect different changes. The increases in national concentration reflect the expansion of multi-market firms through what we call the cross-market HHI.

The increases in local concentration may reflect increasing local market power leading to larger markups. If increases in concentration are caused by low-cost multi-market firms increasing their market share, prices may fall despite increases in markups (Bresnahan, 1989). In fact, the 2.1 percentage point increase in markups due to local concentration is small relative to the 34 percent decrease in relative retail prices observed in the same period. These cost advantages may be due to direct foreign sourcing (Smith, 2019), negotiating power with suppliers (Benkard et al., 2021), or investments in information and communication technologies (Hsieh and Rossi-Hansberg, 2019). Moreover, increases in e-commerce penetration since 2012 may have tempered the increasing trends in local concentration.

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# Appendices for Online Publication

## Table of Contents

# A Concentration Decomposition

We calculate the HHI for the retail sector at a time $t$, as the sales-weighted average of the product-HHIs:

$$HHI^t \equiv \sum_{j=1}^{J} s_j^t HHI_j^t. \tag{A.1}$$

The HHI for a given product $j$, $HHI_j^t$, can be decomposed into the contribution of local and cross-market concentration. The decomposition starts from the probability that two dollars $(x, y)$ spent on a product during some time period are spent at the same firm $(i)$, which gives the HHI at the national level:

$$HHI_j^t \equiv P(i_x = i_y; j, t) = \sum_i \left(s_i^{jt}\right)^2, \tag{A.2}$$

where $s_i^{jt}$ is the share of firm $i$ in product $j$ during period $t$. This probability can be divided into two terms by conditioning on the dollars being spent in the same location, $\ell_x = \ell_y$:

$$\begin{aligned} P(i_x = i_y; j, t) = {} & \underbrace{\overbrace{P(i_x = i_y | \ell_x = \ell_y; j, t)}^{\text{Local Concentration}} \overbrace{P(\ell_x = \ell_y; j, t)}^{\text{Collocation}}}_{\textbf{Local Term}} \\ & + \underbrace{\overbrace{P(i_x = i_y | \ell_x \neq \ell_y; j, t)}^{\text{Cross-Market Concentration}} \overbrace{P(\ell_x \neq \ell_y; j, t)}^{\text{1 - Collocation}}}_{\textbf{Cross-Market Term}} \end{aligned} \tag{A.3}$$

When we report contribution of local and cross-market concentration for the retail sector, we report the sales-weighted average of these two terms across products.

The collocation probability is calculated as:

$$P(\ell_x = \ell_y; j, t) = \sum_{\ell=1}^{L} \left(s_\ell^{jt}\right)^2. \tag{A.4}$$

When we report the collocation for the retail sector, we report the sales-weighted average of collocation across products: $\text{Collocation}_t = \sum_j s_j^t P(\ell_x = \ell_y; j, t)$.

Local concentration is calculated as:

$$\begin{aligned} P\left(i_x = i_y | \ell_x = \ell_y; j, t\right) &= \sum_{\ell=1}^{L} \underbrace{P\left(\ell_x = \ell | \ell_x = \ell_y; j, t\right)}_{\text{Location Weights}} \overbrace{P\left(i_x = i_y | \ell_x = \ell, \ell_x = \ell_y; j, t\right)}^{\text{Local HHI}} \\ &= \sum_{\ell=1}^{L} \frac{(s_\ell^{jt})^2}{\sum_n (s_n^{jt})^2} \sum_{k=1}^{K} \left(s_k^{j\ell t}\right)^2 \end{aligned} \tag{A.5}$$

When we report the local HHI for individual product categories we also report the retail sector's average local HHI using sales weights instead of the weights implied by the decomposition to facilitate comparison to other research:

$$\mathrm{HHI}_t^{\mathrm{Local}} = \sum_j^J s_j^t \sum_\ell^L s_\ell^{jt} \sum_i \left(s_i^{j\ell t}\right)^2 \tag{A.6}$$

The cross-market term is calculated as:

$$\begin{aligned} P\left(\ell_x = \ell_y; j, t\right) P\left(i_x = i_y | \ell_x \neq \ell_y; j, t\right) &= (1 - \sum_{\ell=1}^L \left(s_\ell^{jt}\right)^2) \sum_{k=1}^L \sum_{\ell \neq k} \frac{s_k^{jt} s_\ell^{jt}}{1 - \sum_m^L \left(s_m^{jt}\right)^2} \sum_{i=1}^I s_i^{kjt} s_i^{\ell jt} \\ &= \sum_{k=1}^L \sum_{\ell \neq k} s_k^{jt} s_\ell^{jt} \sum_{i=1}^I s_i^{kjt} s_i^{j\ell t}. \end{aligned}$$

This calculation is the same in the results for product category because $1 - \sum_m^L \left(s_m^{jt}\right)^2$ cancels in the calculation of the collocation term.

# B Cleaning and Aggregating Product Lines Data

The Economic Census collects data on establishment-level sales in a number of product categories (Figure B.1 provides an example form). Many establishments have missing product line sales either due to them not responding to questions or because they do not receive a form.[26] In total, reported product lines data account for about 80 percent of sales. We develop an algorithm to impute data for missing establishments, which involves aggregating product line codes into categories such that we can accurately infer each establishment's sales by category with available information. For example, we aggregate lines for women's clothes, men's clothes, children's clothes, and footwear into a product category called clothing.

We then establish 18 product categories detailed in Table B.1. Of these 18 product categories, 8 categories that we label "Main" account for over 80 percent of store sales in the sample. The other 10 product categories are specialty categories that account for a small fraction of aggregate sales and are sold primarily by establishments in one specific industry. For example, glasses are sold almost exclusively by establishments in 446130 (optical goods stores). We create these categories so that establishments that sell these products are not included in concentration measures for the 8 main product categories.

## B.1 Aggregating Product Lines

The first step of cleaning the data is to aggregate reported broad and detailed product line codes into categories. Some codes reported by retailers do not correspond to valid product line codes, and we allocate those sales to a miscellaneous category. The Census analyzes reported product line codes to check for issues and flags observations as usable if they pass this check. We include only observations that are usable and then map these codes to categories. We use the reported percentage of total sales accounted for by each product line instead of the dollar value because the dollar value is often missing. Typically an establishment either reports product line data for 100 percent of its sales or does not report any data. For the small number of establishments that report product lines data summing to a number other than 100 percent, we rescale the percentages so that they sum to one.[27] After this procedure, we have sales by product category for all establishments that reported lines data. The resulting categories are listed in Table B.1.

[26] Establishments of large firms are always mailed a form, but small firms are sampled.

[27] This procedure has a minimal effect on aggregate retail sales in each category.

Figure B.1: Sample Product Lines Form

**Item 10.** MERCHANDISE LINES

**Report sales for each merchandise line sold by this establishment, either as a dollar figure or as a whole percent of total sales.** *(See HOW TO REPORT DOLLAR FIGURES on page 1 and HOW TO REPORT PERCENTS below)*

| *HOW TO REPORT PERCENTS* | If figure is **38.76%** of total sales: | Mil. | Thou. | Dol. | Per- cent |
|---|---|---|---|---|---|
| | • ***Report whole percents*** | | | | **39** |
| | *Not acceptable* | | | | 38.76 |

| Merchandise lines | Cen- sus use | ESTIMATES are acceptable. Report dollars OR percents. Mil. | Thou. | Dol. | Per- cent |
|---|---|---|---|---|---|
| | 230 | 231 | | | 232 |
| **1.** Women's, juniors', and misses' wear (Report girls' and infants' and toddlers' wear on line 3 and footwear on line 4) | **0220** | | | | |
| **2.** Men's wear (Report boys' wear on line 3 and footwear on line 4) | **0200** | | | | |
| **3.** Children's wear (Include boys' (sizes 2 to 7 and 8 to 20), girls' (sizes 4 to 6x and 7 to 14), and infants' and toddlers' clothing and accessories. Report footwear on line 4.) | **0240** | | | | |
| **4.** Footwear (include accessories) | **0260** | | | | |

FORM RT-5302

## B.2 Imputing Missing Data

For the remaining establishments, we impute data using the NAICS code of the establishment, reported sales of other establishments of the same firm in the same industry, and reported activity of the same establishment in other census years.[28] Most establishments are part of single-unit firms, and many do not appear in multiple census years; thus their sales are imputed using only industry information.

Using this aggregation method, almost all establishments have significant sales in only two product categories, which increases confidence in the imputation. Additionally, we have compared the aggregate sales in our data to the Consumer Expenditure Survey (an independent Bureau of Labor Statistics program), and they are in line with the numbers

[28]Reported product line sales are very similar across establishments of the same firm and the same establishment over time.

Table B.1: List of Product Categories

| Product Category | Main | Corresponding Industry | Example Firm |
|---|---|---|---|
| Automotive Goods | N | 441 | Ford Dealer |
| Clothing | Y | 448 | Old Navy |
| Electronics and Appliances | Y | 443 | Best Buy |
| Furniture | Y | 442 | Ikea |
| Services | N | N/A | |
| Other Retail Goods | N | N/A | |
| Groceries | Y | 445 | Trader Joe's |
| Health Products | Y | 446 | CVS |
| Fuel | N | 447 | Shell Gasoline |
| Sporting Goods | Y | 451 | Dick's Sporting Goods |
| Toys | Y | 451 | Toys "R" Us |
| Home & Garden | Y | 444 | Home Depot |
| Paper Products | N | 453210 | |
| Jewelry | N | 423940 | Jared |
| Luggage | N | 448320 | Samsonite |
| Optical Goods | N | 446130 | Lenscrafters |
| Non-Retail Goods | N | N/A | |
| Books | N | 451211 | Borders |

*Notes:* Authors' created list of product categories. The Main column indicates that a product category is included in concentration calculations. Firm names were created for illustrative purposes based on industries reported to the Securities and Exchange Commission and do not imply that the firm is in the analytical sample.

from that source.[29]

Where relevant, all sales are deflated using consumer price indexes. We use the food deflator for Groceries, clothing and apparel deflator for Clothing, and the deflator for all goods excluding food and fuel for all other categories.

We find that this procedure predicts sales accurately for most establishments, but a small number of stores in each industry report selling very different products than all other stores in that industry. In these cases, the prediction can produce substantial error.

[29] Retail sales include some sales to companies, so it is expected that retail sales in a product category exceed consumer spending on that category.

# C Additional Tables and Figures

## C.1 The Role of Multi-Product Retailers

Table C.1 shows how sales for each main product category are distributed across sets of industries. This informs us of which type of establishment accounts for the sales of each product. The main subsector column refers to the NAICS subsector that most closely corresponds to the product category. The NAICS code of the subsector is indicated next to each product category. The main subsector accounts for just over half of sales on average, but this figure varies depending on the product. A larger fraction of sales of Furniture, Home Goods, and Groceries comes from establishments in their respective NAICS subsectors, while Electronics and Toys are more commonly sold by establishments in other subsectors. Over time, the share of sales accounted by the product's own subsector has decreased for most products, with the difference captured by establishments outside of the general merchandise subsector.

Table C.1: Share of Product Category Sales by Establishment Subsector

| | Main Subsector | | | GM | | | Other | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1992 | 2002 | 2012 | 1992 | 2002 | 2012 | 1992 | 2002 | 2012 |
| Furniture (442) | 76.3 | 73.1 | 64.4 | 16.9 | 13.3 | 11.2 | 6.8 | 13.6 | 24.4 |
| Clothing (448) | 50.9 | 51.8 | 51.1 | 41.4 | 37.7 | 27.4 | 7.7 | 10.5 | 21.5 |
| Sporting Goods (451) | 55.4 | 52.3 | 54.2 | 30.7 | 29.1 | 21.2 | 14.0 | 18.7 | 24.6 |
| Electronic & Appliances (443) | 30.3 | 31.0 | 29.5 | 34.1 | 27.1 | 24.9 | 35.6 | 41.9 | 45.6 |
| Health Goods (446) | 49.0 | 50.0 | 46.8 | 19.0 | 21.3 | 20.5 | 32.0 | 28.7 | 32.6 |
| Toys (451) | 40.7 | 27.6 | 22.0 | 45.2 | 47.7 | 46.9 | 14.1 | 24.7 | 31.1 |
| Home Goods (444) | 63.9 | 72.8 | 72.4 | 17.2 | 11.6 | 10.9 | 18.9 | 15.6 | 16.6 |
| Groceries (445) | 79.8 | 67.2 | 59.7 | 6.6 | 16.2 | 22.8 | 13.6 | 16.6 | 17.5 |
| Average | 55.8 | 53.2 | 50.0 | 26.4 | 25.5 | 23.2 | 17.8 | 21.3 | 26.8 |

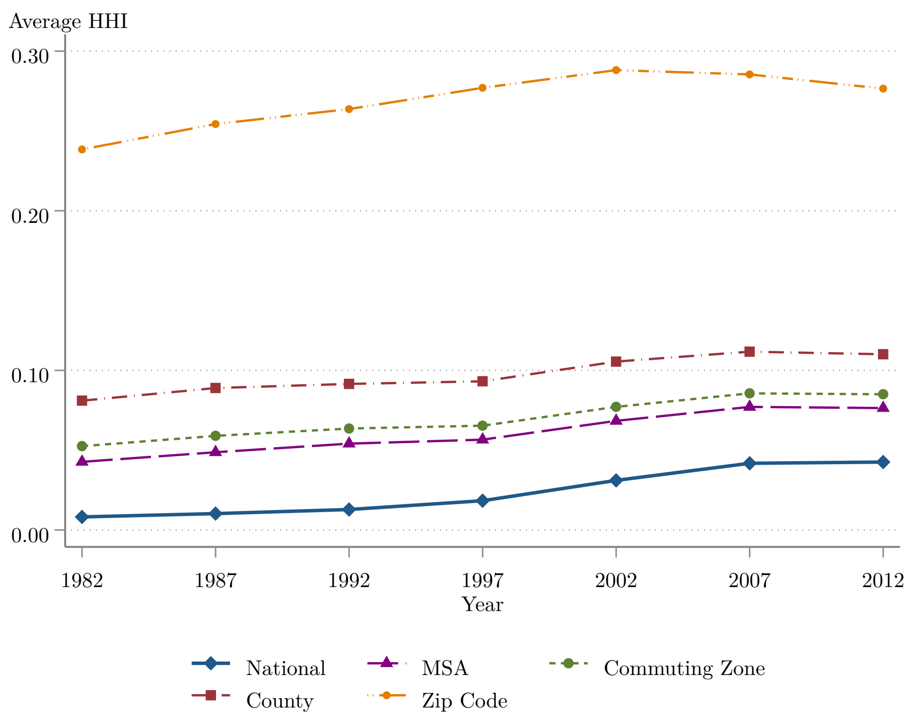
*Notes:* The numbers come from the Census of Retail Trade data. GM includes stores in subsector 452. Other includes sales outside of the main subsector (indicated in parenthesis) and GM. Average is the arithmetic mean of the numbers in the column.

## C.2 Extended Sample

We now present results with an extended sample that covers the period 1982 to 2012. The 1982 and 1987 Censuses of Retail Trade do not include product-level sales for all the categories we consider in our main sample (1992-2012). The affected product categories, Toys and Sporting Goods, account for a relatively small share of total retail sales. Therefore, we focus on results for the retail sector as a whole which we believe are reliable for this time period.

Figure C.1 presents measured concentration indexes for different definitions of local markets and the retail sector as a whole going back to 1982. We use the store-level NAICS codes imputed by Fort and Klimek (2018) to identify retail establishments prior to 1992. Relative to Figure 1 we also include a measure of local concentration where markets are defined by Metropolitan Statistical Areas (MSA). There are more MSAs than commuting zones (about 900 vs 722) and MSAs do not partition the U.S., omitting rural areas. In

Figure C.1: National and Local Concentration



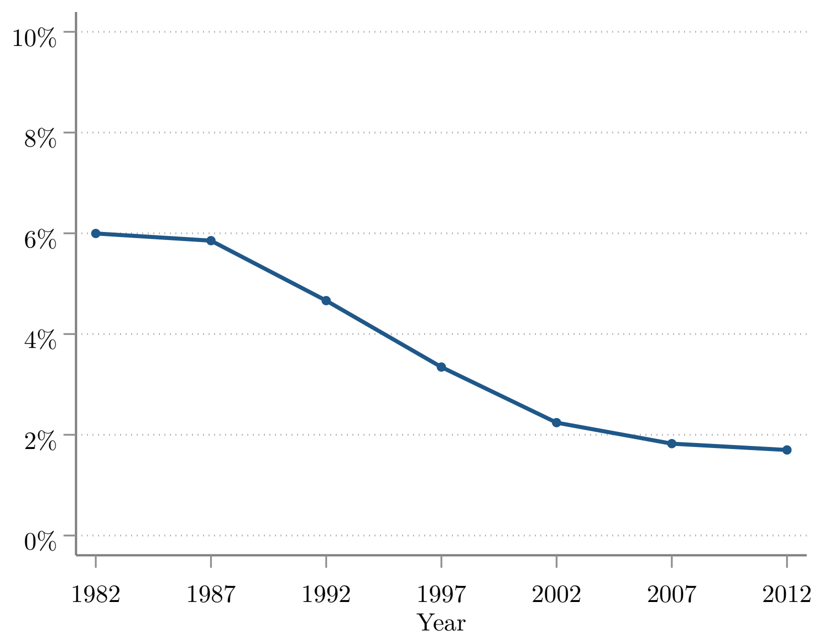

*Notes:* The data are from the Census of Retail Trade. The Herfindahl-Hirschman Index (HHI) for four different geographic definitions of local markets and national concentration are plotted. The local HHI is aggregated using each location's share of national sales within a product category. The numbers are sales weighted averages of the corresponding HHI in the product categories.

practice, the measured concentration level for MSAs is similar to that of commuting zones.

Extending our sample to 1982 does not change the main result of increasing national and local concentration. All measures show sustained increases between 1982 and 2002. Looking at the full sample highlights the change in the rate of increase of national concentration after 1997 which contrasts with the slow increase during the 1980s.

Finally, we extend the decomposition exercise of Figure 6 to 1982. The results, shown in Figure C.2, show a stark decrease in the contribution of local concentration to national concentration. Even though the role of local concentration was never large (always below 6 percent), the share of national concentration attributed to local concentration fell sharply during the 1990s, ending at roughly 2 percent in 2002.

Figure C.2: Share of Local Concentration Term in National Concentration

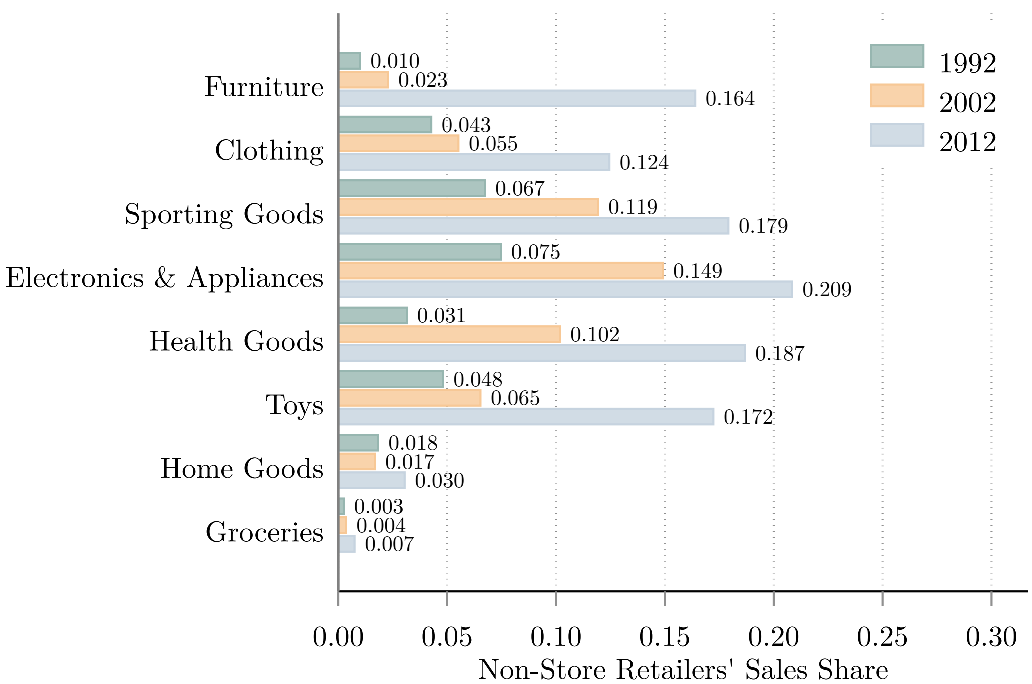



*Notes:* The numbers are from the Census of Retail Trade. The share of local concentration is measured as the ratio of the local concentration term in equation (5) to the national Herfindahl-Hirschman Index (HHI). We aggregate the local concentration terms across the product categories using their sales shares.

## C.3 Non-Store Retailer Market Shares

The penetration of non-store retailers varies widely across products. As Figure C.3 shows, the sales share of non-store retailers is highest in Electronics and Appliances, with an initial share of 7.5 percent in 1992 and a share of 20.9 percent in 2012. The initial differences were large, with only two categories (Electronics and Sporting Goods) having a share of more than 5 percent. By 2012, non-store retailers accounted for more than 15 percent of sales in five of the eight major categories. Despite this widespread increase, not all products are sold online. By 2012, only 0.7 percent of Groceries sales and 3 percent of Home Goods sales were accounted for by non-store retailers. These two categories account for almost half of all retail sales, which explains the overall low sales share of non-store retailers.

Figure C.3: Non-Store Retailers Share across Product Categories



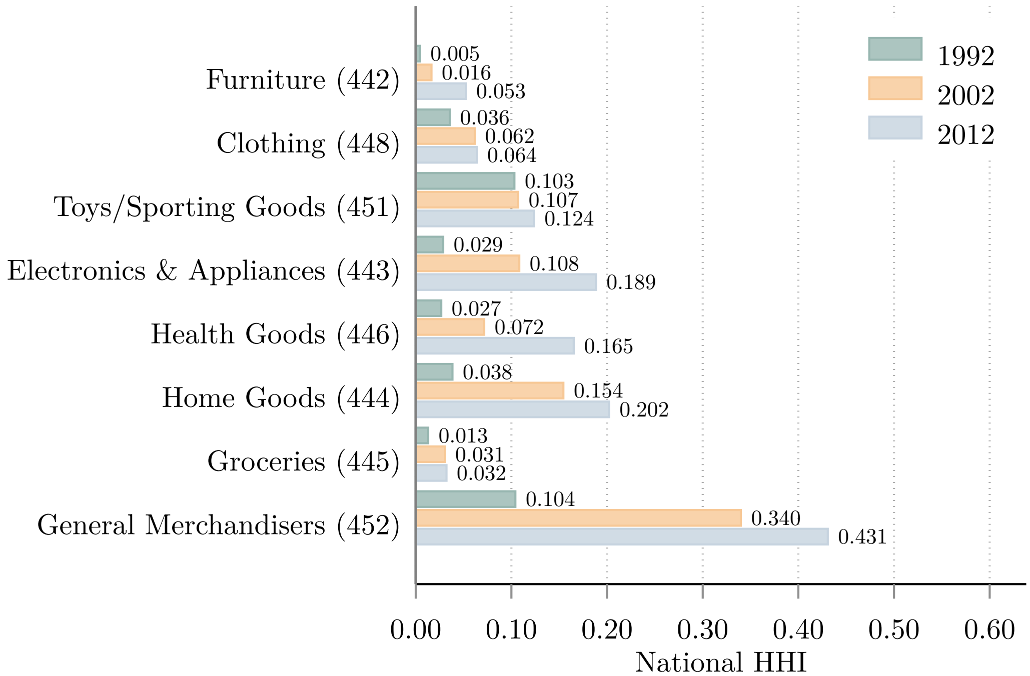

*Notes:* The numbers are the national sales shares of non-store retailers by product category from the Census of Retail Trade microdata.

## C.4 Industry-Based Results

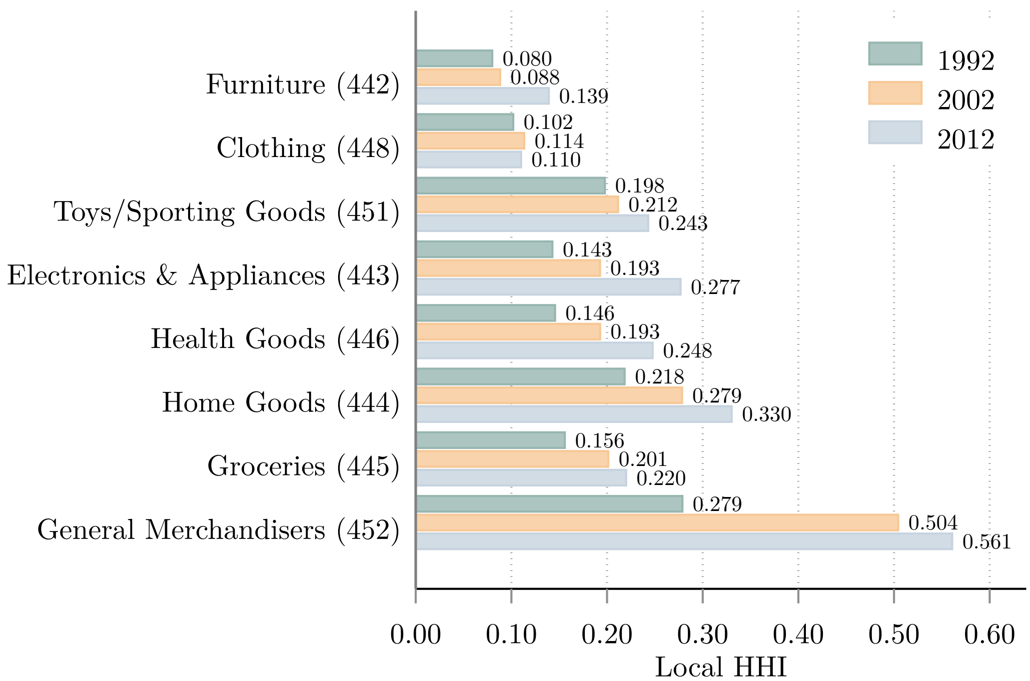
This subsection provides more details on our industry based results. Figure C.4 shows national and local concentration for eight retail subsectors (3-digit NAICS). Local concentration is defined at the commuting zone level. The increasing trends we documented for national concentration in the retail sector are present in all subsectors, but the increase is particularly strong for general merchandisers (NAICS 452) at both the national and at the local level. The general merchandise subsector includes department stores, discount general merchandisers, and supercenters. Over time a small number of firms have come to dominate this format. Similar patterns arise in local concentration. Figure C.4b shows local concentration for the major subsectors, calculated as a weighted average of the industries comprising each subsector. Local industry concentration levels are higher than national and they also increase.

Figure C.4: National and Local Concentration Across Industries

(a) National Concentration




(b) Local Concentration




*Notes:* The data are from the Census of Retail Trade. Numbers are the national and local (commuting zone) Herfindahl-Hirschman Index (HHI) for various industries weighted by market size. Concentration is calculated using 6-digit NAICS codes and aggregated to the 3-digit NAICS using each industry's share of sales.

## C.5 Additional Markup Results

We perform the same exercises as in Section 5 using various assumptions regarding the behavior of markups. Our first set of results changes only the measure of markups we use, keeping the change in local concentration constant as measured by product-level local (commuting-zone) HHI. We find that the changes implied by the change in local product-level concentration on markups are robust to changes in the level of markups. The second set of results uses changes in industry-level concentration instead of product-level concentration. We find that these changes imply implausible increases in markups for the retail sector as a whole. This overstatement follows from the fact that industry-level measures of concentration ignore the competition between general merchandisers and other retailers.

**Product-based results** We consider four alternative measures of markups. Our baseline measure constructs product-level markups combining information from the ARTS and the CRT as explained in Section 5. Our second measure assigns to each product category the markup of its main NAICS industry without adjusting for the role of general merchandisers. Our last two measures consider the possibility that markups are much lower or higher than we estimate, respectively decreasing markups by fifty percent or doubling the product-level markups we constructed in our baseline. Table C.2 reports the level of markups in 1992 under each of our alternative measures.

We estimate the implied elasticity of substitution for each product category using equation (9) from the model. The implied elasticities are reported in Table C.2. The level of the elasticities varies to match the level of markups under each alternative specification but the general rank stays largely unchanged between the product- and industry-based exercises.

Finally, we use the changes in product-based local HHI computed in Section 3 along with equation (9) to compute the change in markups implied by the model and the changes in local concentration. Table C.3 presents the implied change in markups under our four alternative measures. It is clear that the choice of of the level of markups does not affect our main result regarding the effect of local concentration on markups.

**Industry-based results** We also consider how our results would change if used industry- rather than product-level measures of concentration. In Section 3.4 we show that this leads to larger measured changes in local concentration at the industry level. Consequently, using industry-level measures of concentration would have led to a higher implied change in markups.

Table C.2: Markups Robustness: Estimated Elasticities of Substitution

| | Product $\mu$ | | Industry $\mu$ | | Low $\mu$ | | High $\mu$ | |
|---|---|---|---|---|---|---|---|---|
| | $\mu_j^{92}$ | $\epsilon_j$ | $\mu_j^{92}$ | $\epsilon_j$ | $\mu_j^{92}$ | $\epsilon_j$ | $\mu_j^{92}$ | $\epsilon_j$ |
| Furniture | 1.67 | 2.7 | 1.73 | 2.5 | 1.33 | 4.7 | 2.33 | 1.8 |
| Clothing | 1.55 | 3.1 | 1.69 | 2.6 | 1.28 | 5.6 | 2.10 | 2.0 |
| Sporting Goods | 1.47 | 3.7 | 1.57 | 3.2 | 1.24 | 7.8 | 1.94 | 2.2 |
| Electronics & Appliances | 1.34 | 4.5 | 1.44 | 3.6 | 1.17 | 9.1 | 1.68 | 2.6 |
| Health Goods | 1.38 | 4.4 | 1.44 | 3.8 | 1.19 | 9.6 | 1.77 | 2.5 |
| Toys | 1.43 | 5.6 | 1.57 | 3.9 | 1.21 | 27.8 | 1.85 | 2.7 |
| Home Goods | 1.32 | 4.9 | 1.37 | 4.2 | 1.16 | 10.2 | 1.63 | 2.8 |
| Groceries | 1.31 | 5.8 | 1.33 | 5.4 | 1.16 | 16.7 | 1.62 | 3.0 |

*Notes:* The data are authors' estimates of product elasticities of substitution using different measures of markups for each product category in 1992. Our baseline measures correspond to product-level markups. In industry $\mu$ we assign to each product category the markup of its main NAICS industry. In low $\mu$ we half the product-level markup. In low $\mu$ we double the product-level markup. Markup information comes from the Annual Retail Trade Survey. The elasticities are the solution to equation (9) using the measured product-level local Herfindahl-Hirschman Indexes from the Census of Retail Trade.

Table C.3: Markups Robustness: Implied changes in markups

| | Product $\mu$ | Industry $\mu$ | Low $\mu$ | High $\mu$ |
|---|---|---|---|---|
| Furniture | 0.04 | 0.04 | 0.03 | 0.05 |
| Clothing | −0.02 | −0.02 | −0.02 | −0.03 |
| Sporting Goods | 0.06 | 0.06 | 0.05 | 0.08 |
| Electronics & Appliances | 0.05 | 0.05 | 0.04 | 0.06 |
| Health Goods | 0.06 | 0.06 | 0.05 | 0.08 |
| Toys | 0.06 | 0.06 | 0.05 | 0.07 |
| Home Goods | 0.06 | 0.06 | 0.05 | 0.07 |
| Groceries | 0.02 | 0.02 | 0.01 | 0.02 |
| **Retail Sector** | 0.02 | 0.02 | 0.02 | 0.03 |

*Notes:* The data are authors' estimates of the changes in markups implied by the change in product-level local concentration. Our baseline measures uses product-level markups. In "Industry $\mu$" we assign to each product category the markup of its main NAICS subsector. In "Low $\mu$" we half the product-level markup. In "High $\mu$" we double the product-level markup. Markup information comes from the Annual Retail Trade Survey and product-level local Herfindahl-Hirschman Indexes from the Census of Retail Trade.

Table C.4: Markups Robustness: Industry Estimates

| | $\text{HHI}_i^{92}$ | $\text{HHI}_i^{12}$ | $\epsilon_i$ | $\mu_i^{92}$ | $\Delta\mu_i^{\text{ARTS}}$ | $\Delta\mu_i^{\text{Model}}$ |
|---|---|---|---|---|---|---|
| Furniture (442) | 0.08 | 0.14 | 2.7 | 1.73 | 0.15 | 0.12 |
| Clothing (448) | 0.10 | 0.11 | 2.9 | 1.69 | 0.16 | 0.02 |
| Electronics & Appliances (443) | 0.14 | 0.28 | 5.2 | 1.44 | 0.00 | 0.27 |
| Health Goods (446) | 0.15 | 0.25 | 5.3 | 1.44 | 0.02 | 0.20 |
| Toys and Sporting Goods (451) | 0.20 | 0.24 | 4.8 | 1.57 | 0.15 | 0.09 |
| Home Goods (444) | 0.22 | 0.30 | 15.4 | 1.37 | 0.14 | 0.23 |
| Groceries (445) | 0.16 | 0.22 | 9.1 | 1.33 | 0.05 | 0.11 |
| General Merchandisers (452) | 0.28 | 0.56 | 3606 | 1.39 | −0.03 | 0.89 |
| Retail Sector | | | | 1.42 | 0.05 | 0.30 |

*Notes:* The data are industry-level local Herfindahl-Hirschman Indexes from the Census of Retail Trade and markups from the Annual Retail Trade Survey. The elasticities are the solution to equation (9). Decimal places are not shown on the $\epsilon_i$ for General Merchandisers due to its magnitude. High levels of $\epsilon$ imply essentially the same markups. For instance an $\epsilon_{GM} = 165.7$ implies the same level of markups up to the second decimal as the estimate we report.

Table C.4 presents the results of our exercise using industry-level markups from the ARTS and industry-level local concentration from the CRT. The change in industry-level concentration are much larger than those in product-based measures. This is particularly true in the general merchandise subsector (NAICS 452), where the change in local concentration implies a change in markups of 89 percentage points. During this period general merchandiser markups were almost unchanged in ARTS. These two facts can be reconciled by the fact that general merchandisers face significant competition from retailers outside of their industry. When aggregated, these changes imply an increase in retail markups of 30 percentage points which significantly exceeds the markups observed in the ARTS (5 percentage points).

# D Comparison to Rossi-Hansberg, Sarte, and Trachter (2020)

This section compares our results to those in Rossi-Hansberg, Sarte, and Trachter (2020) (hereafter RST) for the retail sector and explains the factors contributing to the differences between our papers. Unlike us, they find a reduction in the local HHI for the retail sector between 1990 and 2014. RST present results for many sectors of the economy. In what follows we discuss only their results in the retail sector. However, our discussion of aggregation methods is relevant for all sectors.

There are three key differences between our paper and RST's that each partially explains the opposite results regarding local concentration. First, we use different data sources: while RST use the National Establishment Time Series (NETS), this paper uses confidential data from the CRT and the LBD. Second, we have different definitions of markets: this paper defines markets by product based on NAICS-6 classification of establishments, while RST define markets by industry based on SIC-8 or SIC-4 classification of establishments. Third, we differ in the methodology used to aggregate markets. This paper aggregates market-level concentration using contemporaneous weights, and we report the change in this (aggregate) index of local concentration. In contrast, RST aggregate the change in market-level concentration using end-of-period weights and report this (aggregate) change.

We argue that the CRT is likely to provide better data for the study of concentration in local markets, and we show that changing from NETS to CRT data alone explains a third of the discrepancy in the change of local concentration (while controlling for market definition and aggregation methodology). Another third of the difference in estimates is explained by the definition of product markets (by changing detailed SIC-8 industries to more aggregated SIC-4 industries). The proper definition of a product market (SIC-8, SIC-4, NAICS-6, product category) can depend on the question being asked. We argue in Section 2.3 that product categories are the proper way to study retail markets. The final third of the difference in estimates is explained by the aggregation methodology. We argue that the method used by RST is biased toward finding decreasing local concentration, and we show that their method could find evidence of decreasing concentration in a time series, even when concentration is not changing in the cross-section. This occurs when markets become less concentrated as they grow. Below we expand upon these differences and their implications for the measurement of local concentration.

**Data sources** The baseline results in RST are based on the NETS, a data product from Walls and Associates that contains information on industry, employment, and sales by establishments. These data have been shown to match county-level employment counts relatively closely (Barnatchez, Crane, and Decker, 2017), but the data do not match the dynamics of businesses Crane and Decker (2020). The results in this paper are based on the CRT, a data set assembled and maintained by the U.S. Census Bureau covering all employer retail establishments.

Both the NETS data and the CRT use the establishment's reported industry and sales when available and both have some degree of imputation for establishments that do not report. However, the CRT can often impute using administrative records from the IRS.[30] Beyond this, the two data sets differ in other two relevant aspects. First, the CRT contains sales by product category for the majority of sales, while the NETS contains only industry, allowing us to define markets by product categories and account for cross-industry competition by general merchandisers (see Section 2.3). Second, the NETS includes non-employer establishments, while the CRT does not. According to official estimates, non-employer establishments account for about 2 percent of retail sales in 2012 (Economy-Wide Key Statistics: 2012 Economic Census of the United States).[31] On the whole, the CRT provides a more accurate picture of activity in the retail sector.

**Definition of product markets** We adopt a different definition than RST for what constitutes a product market. Each definition of product market has its own pros and cons, and researchers may choose one over the other depending on the specific context. We define markets by a combination of a geographical location and a product category that we construct using the detailed data on sales provided by the CRT, along with the (NAICS-6) industry classification of establishments (see Section 2.3). As we mentioned above, doing this treats multi-product retailers as separate firms, ignoring economies of scope, in favor of putting all sales in a product category in the same market. However, we also present results defining markets by industry and find that the same patterns of higher national and local concentration arise, but with stronger magnitudes. See Section 3.4.

In contrast, RST define markets by the establishment's industry, using both SIC-8 and SIC-4 codes. Some examples of SIC-8 codes are department stores, discount (53119901); eggs and poultry (54999902); and Thai restaurants (58120115).[32] SIC-8 codes may be overly

[30]Response to the CRT is required by law. Single-unit establishments are randomly sampled for sales in the CRT, while the non-sampled units have their sales imputed. See http://dominic-smith.com/data/CRT/crt_sample.html for more details.

[31]https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ECN_2012_US_00A1&prodType=table

[32]NETS allows for 914 retail SIC-8 codes. A full list is available at https://www.dnb.com/content/dam/english/dnb-solutions/sales-and-marketing/sic_8_digit_codes.xls. RST indicate that many SIC-8 codes are rarely used (data appendix), but without access to the NETS data, we cannot assess the relative significance of each code for economic activity.

detailed for retail product markets, to the point that many retailers will sell multiple types of goods. For example, calculating concentration in eggs and poultry (54999902) would miss the fact that many eggs and poultry are sold by chain grocery stores (54119904) and discount department stores (53119901). This suggests that aggregating to less detailed codes may provide a better definition of product markets. To that end, RST present results for SIC-4 codes. When concentration is calculated using SIC-4 codes, the decrease in local concentration is much smaller, a 8 percentage point decrease instead of a 17 percentage point decrease.[33]

Incidentally, the SIC-4 codes are quite similar to the NAICS-6 codes available in the CRT, except restaurants are included in the SIC definition of retail but not in NAICS.[34] This makes the concentration measures based on each classification more closely comparable. Yet, even in this setting (NETS SIC-4 versus CRT NAICS-6) there are still significant differences between our studies. We will go back to this comparison when we discuss Figure D.2 and Table D.1 below.

**Aggregation methodology** The final difference comes from how we aggregate the market-level changes in concentration into an aggregate index of local concentration. We compute the local HHI index by first computing the HHI for each pair of product category ($j$) and location ($\ell$). Then we aggregate across locations, weighting each market (location-product) HHI by the market's share of the product's national sales. Doing this provides a measure of the average local HHI for each product. Finally, we aggregate across products, weighting by the product's share of national retail sales, to obtain an average local HHI. Every step in the aggregation maintains the interpretation of the HHI as a probability, which also makes the levels of the HHI comparable across time. We do this for each period ($t$) and report the time series for this index. The average local HHI is then given by

$$HHI_t = \underbrace{\sum_j s_j^t}_{Products} \underbrace{\sum_\ell s_\ell^{jt}}_{Locations} \cdot HHI_{j\ell t}, \quad \text{where } HHI_{j\ell t} = \sum_i \left(s_i^{j\ell t}\right)^2. \tag{D.1}$$

RST use a different methodology. Instead of computing concentration in the cross-section, they calculate the change in concentration between $t$ and some initial period and

[33]The change from SIC-8 to SIC-4 has little effect on concentration outside of retail (RST Data Appendix). The numbers are read off graphs for the change in retail sector concentration for zip codes between 1990 and 2012.

[34]In the results in the main text, we exclude automotive dealers, gas stations, and non-store retailers because of concerns related to ownership data and defining which markets they serve (see Section 2 for further discussion). This has little impact on the estimates for local concentration.

then aggregate these changes weighting by the period $t$ share of employment of each industry ($j$) in total retail employment. Their index for the change in concentration is given by[35]

$$\Delta HHI_t^{RST} = \sum_{j\ell} s_{j\ell}^t \Delta HHI_{j\ell t}, \tag{D.2}$$

where $s_{j\ell}^t$ is the sales share of industry $j$ and location $\ell$ in the country at time $t$[36] and $\Delta HHI_{j\ell t}$ is the change in the revenue-based HHI in industry $j$ and location $\ell$ between the base period and time $t$.

The key difference between the methodologies is that RST do not account for the size of a market in the initial period. This is shown in equation D.3, which subtracts the two measures of concentration from each other. After canceling terms, the difference between the two measures is

$$\Delta HHI - \Delta HHI^{RST} = \sum_{j\ell} \underbrace{(s_{j\ell}^t - s_{j\ell}^0)}_{\Delta s_{j\ell}^t} \cdot HHI_{m\ell 0}. \tag{D.3}$$

RST will weight markets that increase in size over time by more in the initial period, while those that decrease will be weighted less relative to our measure. As markets grow, they typically become less concentrated resulting in RST weighting markets with decreasing concentration more than markets with increasing concentration.[37]

Figure D.1 shows that this methodology can find decreasing concentration in a time series, even when concentration is not changing in the cross-section. Consider three firms (A, B, and C) that operate in two markets and have the same size. In the first period ($t-1$), firms A and B operate in market 1 and firm C operates in market 2. Consequently, the HHI is 0.5 and 1 for each market, respectively, and the aggregate (cross-sectional) HHI is $^2/_3$. In period $t$, market 1 shrinks and market 2 grows, with firm B changing markets. This change does not affect the cross-sectional distribution of local (market-specific) concentration, but it does imply an increase in concentration in market 1 and a decrease in market 2. Despite there being no changes in the cross-sectional HHI, RST's methodology would report a decrease in local concentration ($\Delta HHI = {}^{-1}/_6$), driven by the decrease in market 2's HHI (which happens to be the largest market in period $t$).

[35]Equation D.2 is taken from RST, with notation adjusted to match the notation in this paper.

[36]RST weight markets by their employment share $\left(e_{j\ell}^t\right)$ instead of their sales share $\left(s_i^{j\ell t}\right)$. However, their data appendix shows this has no effect on the results.

[37]A similar point is made in Appendix E of Ganapati (2020) using LBD data.

**Quantifying differences** Figure D.2 quantifies the role of each of the differences highlighted above for the change in local concentration between 1992 and 2012.[38] To make the comparison clear, we define markets by industry throughout the exercise.[39] Overall, Figure D.2 shows that the difference in the estimated change of local HHI is explained in roughly equal parts by the three differences highlighted above: data source (CRT versus NETS), industry definition (NAICS-6 versus SIC-8), and aggregation methodology. We discuss each step in more detail below.

The lowest estimate for the change in local concentration (a decrease of 0.17 points in local HHI) corresponds to RST's baseline estimate using NETS data and SIC-8 for industry classification. Once industries are aggregated to the SIC-4 level (to improve comparability across establishments), the estimate increases by 9 percentage points, still implying a reduction of 8 percentage points in the local HHI. The next estimate reproduces RST's methodology using microdata from the CRT. Changing from NETS to CRT data implies a further increase in the estimate of 6.5 percentage points, with the overall change suggesting a minor decease of local HHI of 1.5 percentage points.[40] Next we change the weighting methodology to ours (as explained above). Doing so increases the estimated change of local concentration again (by 9.5 percentage points), implying an overall increase of local HHI of 8 percentage points.[41]

Table D.1 provides a more detailed account of the estimates presented in Figure D.2 and also includes estimates of changes in local concentration for intermediate census years (1997, 2002, and 2007). In the first panel, national concentration, we compare the numbers in RST (Figure 1b) to numbers calculated for NAICS-based measures (including all 6-digit industries in NAICS) and product-based measures. In all three cases, national concentration is increasing significantly. Despite differences in the initial levels of concentration (column 1), the national HHI increases by two to three times.[42]

The second panel of Table D.1 compares concentration measured at the zip code level using RST's weighting methodology as described above. We also provide results for the set

[38] RST use 1990 as the base year instead of 1992. This is unlikely to matter as RST find small changes in concentration between 1990 and 1992.

[39] To be precise, we define a market either by an SIC-8, an SIC-4, or a NAICS-6 industry in a given location. Our preferred definition of markets by product categories implies a change in the level of the HHI that makes the comparison with the results in RST less transparent.

[40] Part of this difference could be explained in theory by the inclusion of restaurants in SIC-4; however, the industry by industry results in RST's Figure 7 suggest that this is not the case because they find diverging trends in most retail industries.

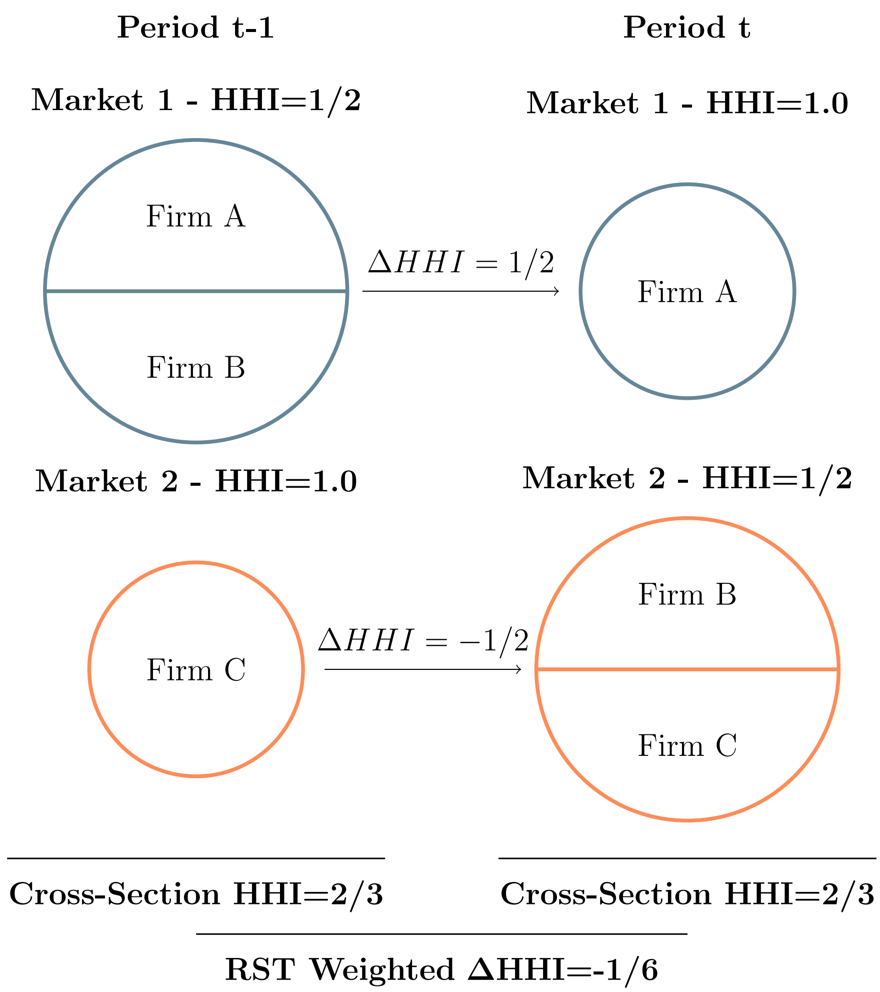
[41] These numbers use all retail firms, including those that were dropped for the main sample in the paper. Concentration numbers are calculated for zip codes and aggregated according to each zip code's share of employment.

[42] The level of concentration is not provided in RST.

of establishments that are included in the product-based results in the paper. Using their methodology, we find evidence for slight decreases in local concentration of 1 to 2 percentage points whether markets are aggregated using sales or employment weights. These decreases are much less severe than the 17 percentage point decrease in RST.

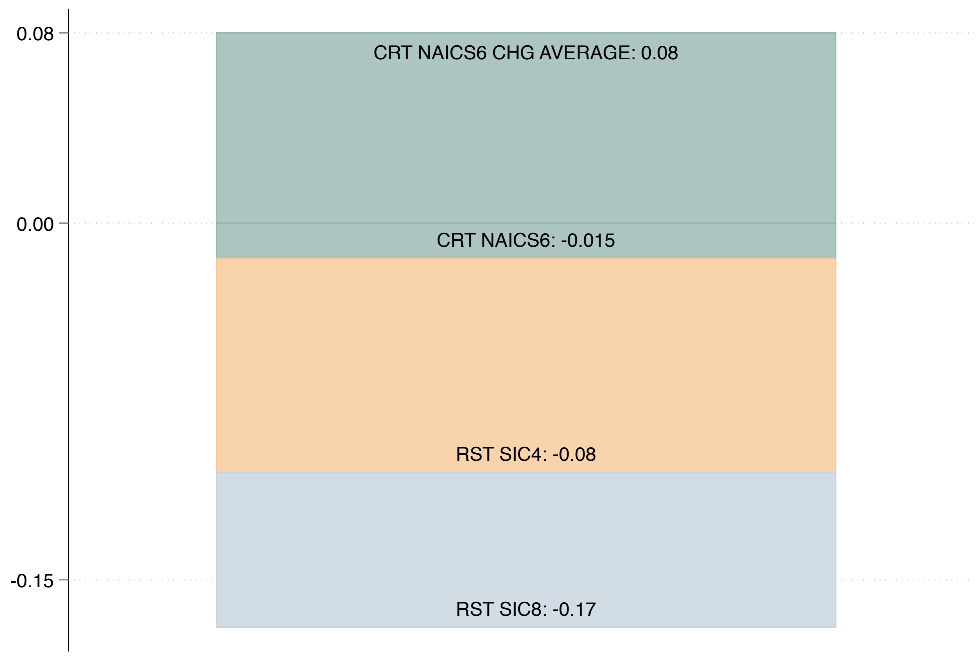
The final panel of Table D.1 compares concentration measured at the zip code level using our aggregation method. This method finds significant increases in local concentration across both NAICS samples. Local HHI increased between 7.1 and 8.5 percentage points; that is, the average dollar in 2012 is spent in a more concentrated market than the average dollar in 1992.

Figure D.1: Example of RST Methodology




*Notes:* The figure shows how market and cross-sectional concentration indices are computed under our methodology (difference in cross-section Herfindahl-Hirschman Index (HHI)) and that of Rossi-Hansberg et al. (2020). The economy has two markets and three firms. Firms are of the same size. Markets change size from period $t-1$ to period $t$, but the cross-sectional distribution of markets and concentration does not change. The weighting methodology used by Rossi-Hansberg et al. (2020) puts more weight on market 2, which increases size between $t-1$ and $t$ and has a reduction in concentration. The result is a decrease in aggregate concentration when changes are measured according to this methodology, while cross-section HHI does not change.

Figure D.2: RST Comparison




*Notes:* The figure shows various estimates for the change in local HHI between 1992 and 2012. The estimates vary according to the data source, industry definition, and aggregation methodology. The lowest estimate corresponds to Rossi-Hansberg et al. (2020)'s estimate using SIC-8 industries, and the second lowest estimate corresponds to using SIC-4 industries. The second highest estimate corresponds to using Census of Retail Trade microdata and NAICS-6 industries (which are similar to SIC-4 industries), and the highest estimate computes indices under our aggregation methodology instead of that of Rossi-Hansberg et al. (2020).

Table D.1: Comparison of Concentration to RST

| | | | | | | |
|---|---|---|---|---|---|---|
| National Concentration | | | | | | |
| | Weight | Level 1992 | Change from 1992: 1997 | 2002 | 2007 | 2012 |
| RST | Emp. | N/A | 0.020 | 0.030 | 0.050 | 0.055 |
| NAICS Based | Sales | 0.029 | 0.017 | 0.056 | 0.076 | 0.087 |
| Product Based | Sales | 0.013 | 0.006 | 0.018 | 0.029 | 0.030 |
| Zip Code Concentration: End-of-Period Weights | | | | | | |
| | Weight | Level | Change from 1992 | | | |
| RST | Emp. | N/A | -0.070 | -0.100 | -0.140 | -0.170 |
| NAICS Based | Emp. | | -0.022 | -0.016 | -0.019 | -0.015 |
| | Sales | | -0.023 | -0.015 | -0.017 | -0.011 |
| Paper Sample | Emp. | | -0.002 | -0.013 | -0.018 | -0.017 |
| | Sales | | -0.024 | -0.009 | -0.013 | -0.011 |
| Product based | N/A | | N/A | N/A | N/A | N/A |
| Zip Code Concentration: Current Period Weights | | | | | | |
| | Weight | Level | Change from 1992 | | | |
| RST | N/A | N/A | N/A | N/A | N/A | N/A |
| NAICS Based | Emp. | 0.507 | 0.025 | 0.060 | 0.068 | 0.080 |
| | Sales | 0.498 | 0.018 | 0.052 | 0.062 | 0.071 |
| Paper Sample | Emp. | 0.524 | 0.029 | 0.069 | 0.075 | 0.083 |
| | Sales | 0.530 | 0.022 | 0.073 | 0.081 | 0.085 |
| Product Based | Sales | 0.2637 | 0.013 | 0.024 | 0.022 | 0.013 |

*Notes:* The numbers come from the Census of Retail Trade and Rossi-Hansberg et al. (2020) (RST). Numbers from RST are taken from retail series in Figure 2. The level column contains the 1992 level of concentration. The formula for changes in concentration using end-of-period weights does not depend on the initial 1992 level as shown in RST, and consequently the level column does not apply to these calculations. NAICS-based measures concentration calculated including all NAICS industries. Paper sample uses only establishments included in the sample for the product-based results. Retail in RST is defined using SIC codes that include restaurants.

# E Model of Firm's Markups

We now provide more detail on the model described in section 5. We follow Grassi (2017) who builds on Atkeson and Burstein (2008). The model's objective is to provide a link between local retail concentration and markups faced by consumers. We focus on how heterogeneous firms compete in an oligopolistic setup. Firms have market power in the local product markets in which they operate. To ensure tractability, we keep the modeling of demand as simple as possible. Demand for goods comes from a representative consumer, who supplies labor inelastically in each market and demands a national consumption good—a composite of all goods in the economy. There is a perfectly competitive sector that aggregates individual goods from each market into the national consumption good.

## E.1 The Model Economy

The model economy is formed by $L$ locations, in each of them there are $J$ products being transacted in local product markets. Each product market has $N_{j\ell}$ retail firms that compete with one another in product $j$. Competition takes place at the location-product level. A perfectly competitive sector aggregates goods across firms for each product and location, aggregates products by location into location-specific retail goods, and aggregates each location's retail output into a final consumption good. A single representative consumer demands the final consumption good and supplies labor in each location.

### E.1.1 Technology

A retailer $i$ selling product $j$ in location $\ell$ produces using a constant-returns-to-scale technology that combines labor ($n$) and potentially other inputs $\{x_k\}_{k=1}^{K}$:

$$y_i^{j\ell} = z_i^{j\ell} F\left(x_1, \ldots, x_K, n_i^{j\ell}\right), \tag{E.1}$$

where $z_i^{j\ell}$ represents the productivity of the retailer and $F$ is homogeneous of degree 1.

The homogeneity of $F$ implies that the retailer has a constant marginal cost of production that we denote $\lambda_i^{j\ell}$. Retailers differ in their marginal costs because of differences in productivity and in the prices of the inputs they require for production. Retailers maximize profits for each market they operate in:

$$\pi_i^{j\ell} = p_i^{j\ell} y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell}, \tag{E.2}$$

The demand faced by the individual retailer comes from the aggregation sector that serves the consumer. Aggregation takes place in three levels. First, a local aggregator firm that combines the output of the $N_{j\ell}$ retail firms selling product $j$ in location $\ell$. The firm operates competitively using the following technology:

$$y_j^\ell = \left( \sum_{i=1}^{N_{j\ell}} \left( y_i^{j\ell} \right)^{\frac{\epsilon_j - 1}{\epsilon_j}} \right)^{\frac{\epsilon_j}{\epsilon_j - 1}} ; \qquad \epsilon_j > 1. \tag{E.3}$$

Then, the combined product bundles, $y_j^\ell$, are themselves aggregated into local retail output, $y_\ell$, through the following technology:

$$y_\ell = \prod_{j=1}^{J} \left( y_j^\ell \right)^{\gamma_j^\ell} ; \qquad \sum_{j=1}^{J} \gamma_j^\ell = 1, \tag{E.4}$$

where $\gamma_j^\ell$ is the share of product $j$ in retail sales in location $\ell$

Finally, the national retail output is created by combining local output, $y_\ell$, from the $L$ locations in the country:

$$y = \prod_{\ell=1}^{L} \left( y_\ell \right)^{\beta_\ell} ; \qquad \sum_{\ell=1}^{L} \beta_\ell = 1, \tag{E.5}$$

where $\beta_\ell$ corresponds to the share of location $\ell$ in national retail sales.

The aggregation process implies the following demand and prices:

$$y_\ell = \beta_\ell \frac{P}{p_\ell} \cdot y \qquad P = \prod_{\ell=1}^{L} \left( \frac{p_\ell}{\beta_\ell} \right)^{\beta_\ell} \tag{E.6}$$

$$y_j^\ell = \gamma_j^\ell \frac{p_\ell}{p_j^\ell} y_\ell \qquad p_\ell = \prod_{j=1}^{J} \left( \frac{p_j^\ell}{\gamma_j^\ell} \right)^{\gamma_j^\ell} \tag{E.7}$$

$$y_i^{j\ell} = \left( \frac{p_i^{j\ell}}{p_j^\ell} \right)^{-\epsilon_j} y_j^\ell \qquad p_j^\ell = \left( \sum_{i=1}^{N} \left( p_i^{j\ell} \right)^{1-\epsilon_j} \right)^{\frac{1}{1-\epsilon_j}} \tag{E.8}$$

### E.1.2 Pricing to market

Firms compete directly in the sales of each product in a given location. Firms compete à la Cournot, choosing the quantity $\left( y_i^{j\ell} \right)$ in a non-cooperative fashion, taking as given the choices of other firms. Firms are aware of the effect of their choices $\left( p_i^{j\ell}, y_i^{j\ell} \right)$ on the price and quantity of the product in the market they operate in $\left( p_j^\ell, y_j^\ell \right)$. The choice of quantity implies a pricing policy for the firms according to their residual demand.

The solution to the pricing problem is summarized in the following proposition taken from Grassi (2017):

**Proposition 1.** *The optimal price of a firm takes the form:* $p_i^{j\ell} = \mu_i^{j\ell} \lambda_i^{j\ell}$, *where* $\mu_i^{j\ell}$ *is a* *firm-product-market specific markup:*

$$\mu_i^{j\ell} = \frac{\epsilon_j}{\epsilon_j - 1}\left[1 - s_i^{j\ell}\right]^{-1} \tag{E.9}$$

*and $s_i^{j\ell}$ is the sales share of the firm in the given product market:*

$$s_i^{j\ell} = \frac{p_i^{j\ell} y_i^{j\ell}}{p_j^{\ell} y_j^{\ell}} = \left(\frac{p_i^{j\ell}}{p_j^{\ell}}\right)^{1-\epsilon_j} = \left(\frac{y_i^{j\ell}}{y_j^{\ell}}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}} \tag{E.10}$$

We show details for the derivation in what follows.

The problem takes into account the effect of changes in the firm's own price on the product's price $\left(p_j^{\ell}\right)$ and aggregate demand $\left(y_j^{\ell}\right)$. The objective is to maximize profits by choosing the firm's quantity $\left(y_i^{j\ell}\right)$:

$$\max_{y_i^{j\ell}} p_i^{j\ell} y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell}$$

$$\text{s.t. } p_i^{j\ell} = \left(\frac{y_i^{j\ell}}{y_j^{\ell}}\right)^{\frac{-1}{\epsilon_j}} p_j^{\ell} \qquad p_j^{\ell} = \gamma_j^{\ell} \frac{p_\ell y_\ell}{y_j^{\ell}} \qquad y_j^{\ell} = \left(\sum_{i=1}^{N} \left(y_i^{j\ell}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}}\right)^{\frac{\epsilon_j}{\epsilon_j - 1}}$$

Replacing the constraints:

$$\max_{y_i^{j\ell}} \left(y_i^{j\ell}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}} \left(\sum_{i=1}^{N} \left(y_i^{j\ell}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}}\right)^{-1} \gamma_j^{\ell} p_\ell y_\ell - \lambda_i^{j\ell} y_i^{j\ell}$$

The first order condition is:

$$0 = \frac{\epsilon_j - 1}{\epsilon_j}\left[\left(y_i^{j\ell}\right)^{\frac{-1}{\epsilon_j}} \left(y_j^{\ell}\right)^{\frac{1-\epsilon_j}{\epsilon_j}} - \left(y_i^{j\ell}\right)^{2\frac{\epsilon_j - 1}{\epsilon_j} - 1} \left(y_j^{\ell}\right)^{2\frac{1-\epsilon_j}{\epsilon_j}}\right] \gamma_j^{\ell} p_\ell y_\ell - \lambda_i^{j\ell}$$

$$0 = (\epsilon_j - 1)\left[1 - \left(\frac{y_i^{j\ell}}{y_j^{\ell}}\right)^{\frac{\epsilon_j - 1}{\epsilon_j}}\right] \left(\frac{y_i^{j\ell}}{y_j^{\ell}}\right)^{\frac{-1}{\epsilon_j}} \frac{\gamma_j^{\ell} p_\ell y_\ell}{y_j^{\ell}} - \epsilon_j \lambda_i^{j\ell}$$

$$0 = (\epsilon_j - 1)\left[1 - s_i^{j\ell}\right] p_i^{j\ell} - \epsilon_j \lambda_i^{j\ell}$$

Rearranging gives the result:

$$p_i^{j\ell} = \mu_i^{j\ell} \lambda_i^{j\ell} \qquad \mu_i^{j\ell} = \frac{\epsilon_j}{\epsilon_j - 1}\left[1 - s_i^{j\ell}\right]^{-1}$$

### E.1.3 Consumers

There is a representative consumer who has preferences over consumption of a national retail good, $c$, and leisure/labor in each location: $u(c, n_1, \ldots, n_L)$. The consumer receives income from profits and wages. The consumer's problem is:

$$\max_{\{c\}} u\left(c, n_1, \ldots, n_L\right) \qquad \text{s.t. } P \cdot c \leq \sum_{\ell=1}^{L} n_\ell w_\ell + \Pi. \tag{E.11}$$

The first order conditions for an interior solution imply:

$$\frac{u_{n_\ell}\left(c, \{n_\ell\}\right)}{u_c\left(c, \{n_\ell\}\right)} = \frac{w_\ell}{P}.$$

The labor endowment of each location can be different. Wages adjust in each location to clear the labor market.

## E.2 Aggregating Markups

We now aggregate markups and productivity at the three levels of the economy (product-location, location, national).

### E.2.1 Product-Location Level

The objective is to define an average markup for product $j$ in location $\ell$ $\left(\mu_j^\ell\right)$, as well as the average productivity of firms producing product $j$ in location $\ell$ $\left(z_j^\ell\right)$.

**Average Markup** The average markup is given by the ratio between the price $p_j^\ell$ and product-market marginal cost $\lambda_j^\ell$. Because of constant returns to scale $\lambda_j^\ell$ is also the average cost:

$$\lambda_j^\ell = \frac{\sum_i \lambda_i^{j\ell} y_i^{j\ell}}{y_j^\ell} = \sum_{i=1}^{N} \lambda_i^{j\ell} \frac{y_i^{j\ell}}{y_j^\ell}$$

then the average markup is:

$$\mu_j^\ell = \frac{p_j^\ell}{\lambda_j^\ell} = \left[\sum_{i=1}^{N} \lambda_i^{j\ell} \frac{y_i^{j\ell}}{p_j^\ell y_j^\ell}\right]^{-1} = \left[\sum_{i=1}^{N} \left(\frac{\lambda_i^{j\ell}}{p_i^{j\ell}}\right)\left(\frac{p_i^{j\ell} y_i^{j\ell}}{p_j^\ell y_j^\ell}\right)\right]^{-1} = \left[\sum_{i=1}^{N} \left(\mu_i^{j\ell}\right)^{-1} s_i^{j\ell}\right]^{-1},$$

that is, a harmonic mean of individual markups, weighted by sales shares.

It is possible to further solve for the markup using the solution to the pricing problem above. The result is taken from Proposition 4 in Grassi (2017):

**Proposition 2.** *The average markup for product $j$ in market $m$ is:*

$$\mu_j^\ell = \frac{\epsilon_j}{\epsilon_j - 1}\left[1 - HHI_j^\ell\right]^{-1}$$

*where and $HHI_j^\ell = \sum_i \left(s_i^{j\ell}\right)^2$ is the Herfindahl-Hirschman Index.*

**Average Productivity** The average product is also obtained from the marginal (average) cost:

$$\lambda_j^\ell = \sum_{i=1}^{N} \lambda_i^{j\ell} \frac{y_i^{j\ell}}{y_j^\ell} = \left[ \sum_{i=1}^{N} \left( z_i^{j\ell} \right)^{-1} \frac{y_i^{j\ell}}{y_j^\ell} \right] w_\ell$$

which implies:

$$z_j^\ell = \left[ \sum_{i=1}^{N} \left( z_i^{j\ell} \right)^{-1} \frac{y_i^{j\ell}}{y_j^\ell} \right]^{-1},$$

an output-weighted harmonic mean of productivities.

### E.2.2 Local market and national level

Markups and productivities can be aggregated again at the market level (aggregating across products) by defining first the market's marginal (average) cost:

$$\lambda_\ell = \frac{\sum \lambda_j^\ell y_j^\ell}{y_\ell}$$

For markups this implies:

$$\mu_\ell = \frac{p_\ell}{\lambda_\ell} = \left[ \sum_{j=1}^{J} \left( \mu_j^\ell \right)^{-1} s_j^\ell \right]^{-1} = \left[ \sum_{j=1}^{J} \left( \mu_j^\ell \right)^{-1} \gamma_j^\ell \right]^{-1}$$

For productivity:

$$z_\ell = \frac{w_\ell}{\lambda_\ell} = \left[ \sum_{j=1}^{J} \left( z_j^\ell \right)^{-1} \frac{y_j^\ell}{y_\ell} \right]^{-1}$$

The same procedure gives the markup for the national level:

$$\mu = \left[ \sum_{\ell=1}^{L} \left( \mu_\ell \right)^{-1} \beta_\ell \right]^{-1}$$

We define the productivity at the national level as the harmonic mean of local productivities weighted by output shares:

$$z \equiv \left[ \sum_{\ell=1}^{L} \left( z_\ell \right)^{-1} \frac{y_\ell}{y} \right]^{-1}$$

This expression does not follow as the others because the cost of production ($w_\ell$) differs across markets.

**Multi-product/Multi-market firm** The equations above also apply to firms that sell various products and operate in various markets, modifying the sums to account for the firm's products and/or markets. In this way, we capture the role of market concentration for multi-product and multi-market firms. These firms have high market shares across products and locations, which the model translates into higher markups and lower costs (necessary to achieve larger market shares). Despite capturing the role of concentration, we miss the role of economies of scope in demand or uniform pricing across locations. Economies of scope in demand are likely to increase the demand for multi-product retailers, resulting in higher markups given some level of market concentration. Uniform pricing reflects the average market share of the firm as we show in Section E.4.

### E.2.3 Product aggregation

We also compute the average markup of a product across markets. This measure is relevant because it can be obtained directly from the data. We define the average markup

$$\mu_j \equiv \frac{\sum_{\ell=1}^{L} p_j^\ell y_j^\ell}{\sum_{\ell=1}^{L} w_\ell l_j^\ell}$$

as the ratio between product $j's$ total sales and total labor costs of the product across markets ($\ell = 1, \ldots, L$). The average markup is given in the model by:

$$\mu_j \equiv \frac{\sum_{\ell=1}^{L} p_j^\ell y_j^\ell}{\sum_{\ell=1}^{L} w_\ell l_j^\ell} = \frac{\sum_{\ell=1}^{L} p_j^\ell y_j^\ell}{\sum_{\ell=1}^{L} \frac{\lambda_j^\ell}{p_j^\ell} p_j^\ell y_j^\ell} = \left[\sum_{\ell=1}^{L} \left(\mu_j^\ell\right)^{-1} \theta_j^\ell\right]^{-1},$$

a harmonic mean of market level markups for product $j$, weighted by the share of product $j$ sales in market $\ell$ captured by $\theta_j^\ell \equiv \frac{p_j^\ell y_j^\ell}{\sum_{\ell=1}^{L} p_j^\ell y_j^\ell} = \frac{\gamma_j^\ell \beta_\ell}{\sum_{\ell=1}^{L} \gamma_j^\ell \beta_\ell}$.

Using the result in Proposition 2 it is possible to express the product markup in terms of market concentration. For the case of Cournot competition it gives:

$$\mu_j = \left[\sum_{\ell=1}^{L} \left(\frac{\epsilon_j^\ell}{\epsilon_j^\ell - 1}\right)^{-1} \left[1 - \mathrm{HHI}_j^\ell\right] \theta_j^\ell\right]^{-1}$$

If the elasticity of substitution across varieties of good $j$ is common across markets the expression simplifies to:

$$\mu_j = \frac{\epsilon_j}{\epsilon_j - 1} \left[1 - \mathrm{HHI}_j\right]^{-1},$$

where $\mathrm{HHI}_j \equiv \sum_{\ell=1}^{L} \mathrm{HHI}_j^\ell \theta_j^\ell$ is the sales weighted Herfindahl-Hirschman Index of product $j$ across market.

## E.3 Estimation Steps

We estimate the model using product level data from the Census of Retail Trade and the Annual Retail Trade Survey. This allows us to discuss how conditions in the average U.S.

market has changed. To accomplish this we use the estimates of local concentration from section 3.1 and data on markups, prices, output, and labor supply. As in the empirical analysis of sections 2 and 3, we define markets in the model as pairs of a commuting zone and one of the product categories described in Table B.1.

The Cobb-Douglas parameters, $\beta_\ell$ and $\gamma_j^\ell$, are obtained from the Census of Retail Trade as the share of spending on each product in a commuting zone. The estimation of the elasticity of substitution parameters consists on matching the product level markup from the ARTS given the product's average local concentration. From equation (9) we get:

$$\hat{\epsilon}_j = \frac{\hat{\mu}_j \left[1 - \sum_\ell s_\ell^j HHI_j^\ell\right]}{\hat{\mu}_j \left[1 - \sum_\ell s_\ell^j HHI_j^\ell\right] - 1} \tag{E.12}$$

where $\hat{\mu}_j = {}^{\text{Sales}_j}/_{\text{Cost of Goods Sold}_j}$ is the gross markup for product $j$. We use 2007 ARTS data for the estimation of the elasticity of substitution, matching all products' markups in that year by construction. Using our estimate of the elasticity of substitution parameters and the measured series for the product-level HHI we construct the series of markups implied by the model through equation (9).

We also define implicit price and quantity indexes for each product such that they are consistent with total sales of the product across markets:

$$P_j Y_j = \sum_\ell p_j^\ell y_j^\ell \tag{E.13}$$

Given the quantity index we define the average (marginal) cost of goods for a product, $\lambda_j$, as the output-weighted average of the individual market costs:

$$\lambda_j \equiv \sum_\ell \lambda_j^\ell \frac{y_j^\ell}{Y_j}. \tag{E.14}$$

Note that the average cost satisfies the following pricing equation at the product level:

$$P_j = \mu_j \lambda_j. \tag{E.15}$$

Finally, we can aggregate our product-level results to obtain a measure of the average retail cost and markup. The average cost is defined, as before, as the output-weighted average of the individual product costs:

$$\lambda \equiv \sum_j \lambda_j \frac{y_j}{Y}, \tag{E.16}$$

where $Y$ is a quantity index for the retail sector. The average markup is defined as the ratio of total sales to cost:

$$\mu \equiv \frac{\sum_j P_j Y_j}{\sum_j \lambda_j Y_j} = \frac{\sum_j P_j Y_j}{\sum_j \frac{\lambda_j}{P_j} P_j Y_j} = \left[\sum_j (\mu_j)^{-1} s_j\right]^{-1}, \tag{E.17}$$

where $s_j$ is the expenditure share of product $j$. As before this measure of markup satisfies the pricing equation at the national level:

$$P = \mu\lambda, \tag{E.18}$$

where $P$ is a retail price index satisfying:

$$PY = \sum_j P_j Y_j. \tag{E.19}$$

### E.3.1 Comparing Results Across Time

To compare our model's cross-sectional results across time we choose normalizations for prices that make aggregate numbers consistent with published statistics.[43] We use data on the change of retail good prices from the Price Indexes for Personal Consumption, from the U.S. Bureau of Economic Analysis (2020). These data provides us with series for the price index of each good category.[44] Each price index defines the inflation of prices in its respective category. We normalize the index so that $P_j^{1987} = 1$ for all product categories $j = 1, \ldots, J$. The level of the price index in year $t$ reflects the cumulative (gross) inflation of prices in the product category.

We aggregate the individual category price indexes following the same procedure as the BEA. This procedure defines the aggregate index as an expenditure share weighted geometric average of the categories' indexes, the same definition as in our model (see equation E.6). Since the level of the individual indexes is arbitrary and only allows for direct comparisons across time and not products, we construct the aggregate index indirectly by computing its change over time:

$$\frac{P_t}{P_{t-1}} = \prod_{j=1}^{J} \left( \frac{P_j^t}{P_j^{t-1}} \right)^{s_j^t}. \tag{E.20}$$

We normalize the aggregate index so that $P_{1992} = 1$, and obtain the level in subsequent periods by concatenating the changes obtained in equation (E.20). As before the index provides the cumulative (gross) inflation in retail prices since 1992.

Finally, we deflate our retail price index by overall inflation. Without this adjustment the index reflects not only changes in retail prices, but also trends in overall inflation due to monetary or technological phenomena that are outside of the scope of the model. From these data we find retail prices decreased 35 percent relative to overall inflation. We use

[43] The level of the aggregate price does not affect relative prices, output, or markups in the model.

[44] The price index for some product categories is not directly provided by the BEA data. In these cases we construct the category's index from individual product's series in the same way as we construct the aggregate retail index from the product category indexes.

aggregate price index we obtain and the average retail markup (equation E.17) to compute the value of the average marginal cost $\lambda$, implied by equation (E.18).

## E.4 Extension: Uniform prices across locations

Consider now the problem of firm $i$ that sales product $j$ across various markets $\ell \in \mathcal{L}_i$. There are three options for pricing: pricing to market, ignoring linkages of demand across markets, pricing to market incorporating linkages of demand, uniform pricing. We deal with them in turn.

The first price option (pricing to market, ignoring effects on demand across markets) gives the same solution as above, and the aggregation is also the same. The second option would require the firm to take into account the effect on the demand for groceries in New York of a price change in groceries in Minneapolis. We consider this to be implausible, and the effect to be likely very small (even if firms are taking into account). Thus we think this case is well approximated by our baseline case above. The final option is uniform pricing, which we solve for below.

The problem of the firm is:

$$\max_{p_i^j} \sum_{\ell \in \mathcal{L}_i} \left[ p_i^j y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell} \right]$$

$$\text{s.t. } y_i^{j\ell} = \left( \frac{p_i^j}{p_j^\ell} \right)^{-\epsilon_j} y_j^\ell \qquad y_j^\ell = \gamma_j^\ell \frac{p_\ell y_\ell}{p_j^\ell} \qquad p_j^\ell = \left( \sum_{i=1}^N \left( p_i^{j\ell} \right)^{1-\epsilon_j} \right)^{\frac{1}{1-\epsilon_j}}$$

Replacing the constraints:

$$\max_{p_i^j} \sum_{\ell \in \mathcal{L}_i} \left[ \left( p_i^j \right)^{1-\epsilon_j} - \lambda_i^{j\ell} \left( p_i^j \right)^{-\epsilon_j} \right] \left( \sum_{i=1}^N \left( p_i^{j\ell} \right)^{1-\epsilon_j} \right)^{-1} \gamma_j^\ell p_\ell y_\ell$$

The first order condition is:

$$0 = \sum_{\ell \in \mathcal{L}_i} \left[ \left[ (1-\epsilon_j) p_i^j + \epsilon_j \lambda_i^{j\ell} \right] \frac{y_i^{j\ell}}{p_i^j} - (1-\epsilon_j) \left[ p_i^j - \lambda_i^{j\ell} \right] s_i^{j\ell} \frac{y_i^{j\ell}}{p_i^j} \right]$$

$$0 = \sum_{\ell \in \mathcal{L}_i} \left[ -(\epsilon_j - 1) \left( 1 - s_i^{j\ell} \right) y_i^{j\ell} p_i^j + \left( \epsilon_j - (\epsilon_j - 1) s_i^{j\ell} \right) \lambda_i^{j\ell} y_i^{j\ell} \right]$$

Rearranging:

$$p_i^j = \frac{\sum_\ell \left( \epsilon_j - (\epsilon_j - 1) s_i^{j\ell} \right) \lambda_i^{j\ell} y_i^{j\ell}}{\sum_\ell (\epsilon_j - 1) \left( 1 - s_i^{j\ell} \right) y_i^{j\ell}}$$

If marginal cost is constant across markets then we define the markup :

$$p_i^j = \mu_i^j \lambda_i^j \qquad \mu_i^j = \frac{\sum_\ell \left(\epsilon_j - (\epsilon_j - 1)\, s_i^{j\ell}\right) y_i^{j\ell}}{\sum_\ell (\epsilon_j - 1) \left(1 - s_i^{j\ell}\right) y_i^{j\ell}}$$

The firm's markup reflects its market power across different markets, captured by the firm's output-weighted average share, $\hat{s}_i^j$. Define $\hat{y}_i^{j\ell} = y_i^{j\ell} / \sum_\ell y_i^{j\ell}$, then:

$$\mu_i^j = \frac{\sum_\ell \left(\epsilon_j - (\epsilon_j - 1)\, s_i^{j\ell}\right) \hat{y}_i^{j\ell}}{\sum_\ell (\epsilon_j - 1) \left(1 - s_i^{j\ell}\right) \hat{y}_i^{j\ell}} = \frac{\epsilon_j - (\epsilon_j - 1) \sum_\ell s_i^{j\ell} \hat{y}_i^{j\ell}}{(\epsilon_j - 1) \left(1 - \sum_\ell s_i^{j\ell} \hat{y}_i^{j\ell}\right)} = \frac{\epsilon_j - (\epsilon_j - 1)\, \hat{s}_i^j}{(\epsilon_j - 1) \left(1 - \hat{s}_i^j\right)}$$

The firm's uniform markup is lower than the average markup if the firm chooses prices in each market separately. To see this, define the firm's average price in product $j$ such that:

$$p_i^j y_i^j = \sum_\ell p_i^{j\ell} y_i^{j\ell},$$

where $y_i^j \equiv \sum_\ell y_i^{j\ell}$. It follows that $p_i^j = \sum_\ell p_i^{j\ell} \hat{y}_i^{j\ell}$. The average markup would then be:

$$\mu_i \equiv \frac{p_i^j}{\lambda_i^j} = \sum_\ell \frac{p_i^{j\ell}}{\lambda_i^j} \hat{y}_i^{j\ell} = \sum_\ell \mu_i^{j\ell} \hat{y}_i^{j\ell},$$

which is the output-weighted average of the individual market markups. This average is higher than the uniform markup. The result follows from Jensen's inequality as the Bertrand markup is convex in the firm's sales share.