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The Evolution of U.S. Retail Concentration

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Abstract

Increases in concentration are a salient feature of industry dynamics during the past 30 years. This trend is particularly notable in the U.S. retail sector, where large national firms have replaced small local firms. Existing work focuses on national trends. Yet, less is known about the dynamics of concentration in *local* markets, and the relationship between local and national trends. We address this issue by providing a novel decomposition of the national Herfindahl-Hirschman Index into a local and a cross-market component. We measure concentration using new data on product-level revenue for all U.S. retail stores. Despite concentration increasing in 83 percent of markets between 1997 and 2007, the cross-market component explains 98 percent of the rise in national concentration, reflecting the expansion of multi-market firms. We estimate an oligopoly model of retail competition and find that the increase in markups implied by rising local concentration had a modest effect on retail prices.

JEL: L8

Keywords: Retail, Concentration, Herfindahl-Hirschman Index

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1 Introduction

In the past 30 years, U.S. retailing has become substantially more concentrated. Between 1997 and 2007, the share of sales going to the 20 largest firms increased from 18.5 percent to 25.4 (Hortaçsu and Syverson, 2015). During this period, the national Herfindahl-Hirschman Index (HHI) in retail doubled. These patterns appear to be part of an economy-wide trend toward greater ownership concentration (Autor, Dorn, Katz, Patterson and Van Reenen, 2020) and an increase in the dominance of large, established firms (Decker, Haltiwanger, Jarmin and Miranda, 2014). There is also evidence that increases in concentration are accompanied by steeply rising variable markups (De Loecker, Eeckhout and Unger, 2020; Hall, 2018), which raises concerns about rising market power. However, these findings rely on national industry-based evidence.

Yet, consumers in the retail sector primarily choose between local stores selling a given product, unlike other sectors such as manufacturing where establishments compete across locations. This makes local product-based concentration more informative than national industry-based concentration about the degree of competition and the evolution of markups in retail.¹ This paper assembles data on sales by product category for all U.S. retail establishments to construct a new product-based measure of local concentration, and assess its relationship to the observed trends in national concentration.

The relationship between trends in national and local concentration is not *ex-ante* clear. Growth in national concentration may not imply increasing local concentration. To see this, suppose that each U.S. city starts with a different largest store. If a national retailer replaces the largest store in each market, without displacing any business from the smaller stores, then national concentration would rise, while local concentration would not. Alternatively, growth in national retailers might displace not just the largest stores but also smaller local ones, in which case growth in national concentration would be accompanied by growth in

¹The role of non-store/online retailers presents challenges for this analysis, but these retailers account for a small share of retail sales through 2007 (Hortaçsu and Syverson, 2015).

local concentration. Whether the national expansion of large retailers, such as Walmart and Target, increases local retail concentration depends on whether they displace large, medium-sized, or small local retailers.²

To determine the relationship between the trends of national and local concentration, we develop a novel decomposition of the national HHI into a component driven by local market concentration and a new component that we call “cross-market” concentration, which is driven by consumers in different markets shopping at the same firms. The decomposition exploits a new interpretation of the HHI as the probability that two dollars spent at random in a market are spent in the same firm. We use this decomposition to separate the contribution of changes in local markets to national concentration from the contribution of the expansion of retail chains that took place since the 1980s.

We implement our decomposition and provide new measures of product-level local concentration using new data on store-level revenue for all U.S. retailers in 8 major categories of goods between 1982 and 2007. We combine two sources of confidential U.S. Census Bureau microdata, namely the Census of Retail Trade and the Longitudinal Business Data. The coverage of the data makes it possible to document the evolution of U.S. retail concentration at the local level.

Additionally, these new data allow us to improve over previous measures of retail concentration that rely on industry-based classifications of retail markets.³ Industry-based measures do not account for the increasing importance of multi-product retailers (such as general merchandisers and non-store retailers like e-commerce merchants) that compete across various industries. For example, Walmart is in the general merchandising sub-sector (3-digit NAICS 452) but competes with grocery, clothing, and toy stores.⁴ In fact, general merchandisers account for more than 20 percent

²References to specific firms are based on public data and do not imply the company is present in the confidential microdata.

³In Appendix E we document differences between industry-based and product-based measures of concentration. These measures are conceptually different, as they have different definitions of a market.

⁴Walmart reports SIC code 5331 to the Security and Exchange Commission which corresponds to NAICS 452319 (Securities and Exchange Commission, 2020).

of sales in furniture, electronics and appliances, groceries, and clothing, demonstrating that competition across industries is a relevant feature of retail markets.

Using these data, we document three new facts on concentration in the retail sector. First, we show that both the national and local HHI increase, but at different rates, with the national HHI increasing faster than the local HHI, particularly after 1997. Second, the decomposition of national HHI shows that 98 percent of the change in national concentration is driven by consumers in different markets shopping at the same firms (cross-market concentration), not changes in local concentration. Cross-market concentration measures the probability that two dollars spent in the same product category are spent at the same firm in two different markets. It more than doubled, from around 2 percent to 5.5 percent between 1997 and 2007. Local concentration measures the probability that two dollars spent in the same market are spent at the same firm. It increased 50 percent, from 7.8 percent to 11.7 percent. Third, we show that most markets and product categories feature increasing concentration. The local HHI increased in 83 percent of commuting zones accounting for 80 percent of retail sales between 1997 and 2007. The local HHI also increased in all of the 8 major product categories in retail between 1987 and 2007.

The broad increase in local concentration implies that market power could help explain rising markups in the retail sector, which can potentially harm consumers. Studying the historic relationship between concentration and markups is challenging because long series on prices and costs for U.S. retailers are not available. Thus, we estimate a model of local retail competition based on the work of Atkeson and Burstein (2008). The model features strong parametric assumptions that make it tractable enough to derive 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. We find that increasing local concentration raised markups by 5.8 percentage points in the retail sector between 1987 and 2007, a similar increase to the change found in the Annual Retail Trade Survey.

We find that the increases in concentration and markups imply a slight decrease in welfare at worst. This is because increases in local concentration are unlikely to have substantially affected the relative price of retail goods, which fell 35 percent between 1987 and 2007, reflecting large cost-savings in the sector. These cost-savings may be due to low-costs firms increasing their market share, which increases concentration but has an ambiguous effect on welfare, making it difficult to conclude what the effect is on consumers (Bresnahan, 1989). But, even if lower costs could have been achieved without increased local concentration, an unlikely scenario, prices would have fallen by 37 percent, only 2 percentage points more over 20 years, implying a limited effect of concentration on consumers.

Our main contribution comes from distinguishing between local and national concentration by providing new direct measures of local retail concentration. Higher national concentration has been related to the decline in the labor share (Autor et al., 2020), the decline of churn and reallocation of aggregate activity to large established firms (Decker et al., 2014), lower long term growth due to lower innovation as competition decreases (Aghion, Bergeaud, Boppart, Klenow and Li, 2019), as well as concerns about market power and rising markups (De Loecker et al., 2020; Hall, 2018; Edmond et al., 2019; Traina, 2018). However, many of these concerns would operate through local markets. We explicitly show that changes in national concentration are due to the expansion of multi-market firms, and are not informative about changes in local retail concentration. Our results show that local concentration is increasing across most markets and products, but that these changes imply only modest increases in markups.

The closest paper to ours is Rossi-Hansberg, Sarte and Trachter (2020), which evaluates changes in concentration at both the national and local levels in multiple sectors (e.g. manufacturing, retail, etc.) using the U.S. National Establishment Time Series (NETS) establishment-level data set. They find that, between 1992 and 2012, concentration at the

national level increased in six major sectors, while local concentration decreased.⁵ Our findings at the national level are similar to those in Rossi-Hansberg et al. (2020). However, our results at the local level differ sharply, as we find significant increases local concentration for most product categories.⁶ There are multiple reasons for our results to differ, but a major difference is the data source. Data in the present study are based on confidential information collected by the Census Bureau and the Internal Revenue Service. They are considered the gold standard for measuring economic activity at the store level. These records make it clear that local concentration in retail has been increasing, though not as much as national concentration. We discuss this further in Appendix A.

We also contribute to substantial work documenting changes in the structure of the retail sector. Our work makes it clear that national concentration does not reflect trends in local concentration. Instead, increasing national concentration reflects consumers in different markets shopping at the same firms. Thus, we help highlight the role of the expansion of large firms in explaining changes in the U.S. firm size distribution (Cao, Hyatt, Mukoyama and Sager, 2019; Hsieh and Rossi-Hansberg, 2020). These large retail firms, particularly Walmart and Target, have been shown to lead to the closing of small stores (Jia, 2008; Haltiwanger, Jarmin and Krizan, 2010), grocery chains (Arcidiacono, Bayer, Blevins and Ellickson, 2016), and lower retail employment in local labor markets (Basker, 2005). Additionally, we measure national and local concentration using product-level revenue, which handles the multi-product nature of large retailers. This complements previous work that has found increasing national retail concentration at the industry level (Foster, Haltiwanger, Klimek, Krizan and Ohlmacher, 2015; Hortaçsu and Syverson, 2015; Grullon, Larkin and Michaely, 2019; Autor et al., 2020).

The rest of the paper proceeds as follows. Section 2 develops a decomposition of national

⁵For the retail sector national concentration increased by five percentage points, while local level concentration decreased by 14 percentage points. Numbers are taken from the retail sector line in Figure 2 in Rossi-Hansberg et al. (2020).

⁶These results are in line with other studies documenting that local trends in retail may differ from local trends in other sectors. Rinz (2018) and Lipsius (2018) find increasing labor market concentration in retail, but decreasing labor market concentration overall using census microdata.

concentration into local and cross-market concentration. Section 3 describes the data, including how we construct store-level sales by product. Section 4 measures national and local concentration and establishes the main facts about their evolution since 1982. Section 5 discusses the effects of concentration on markups. Section 6 concludes.

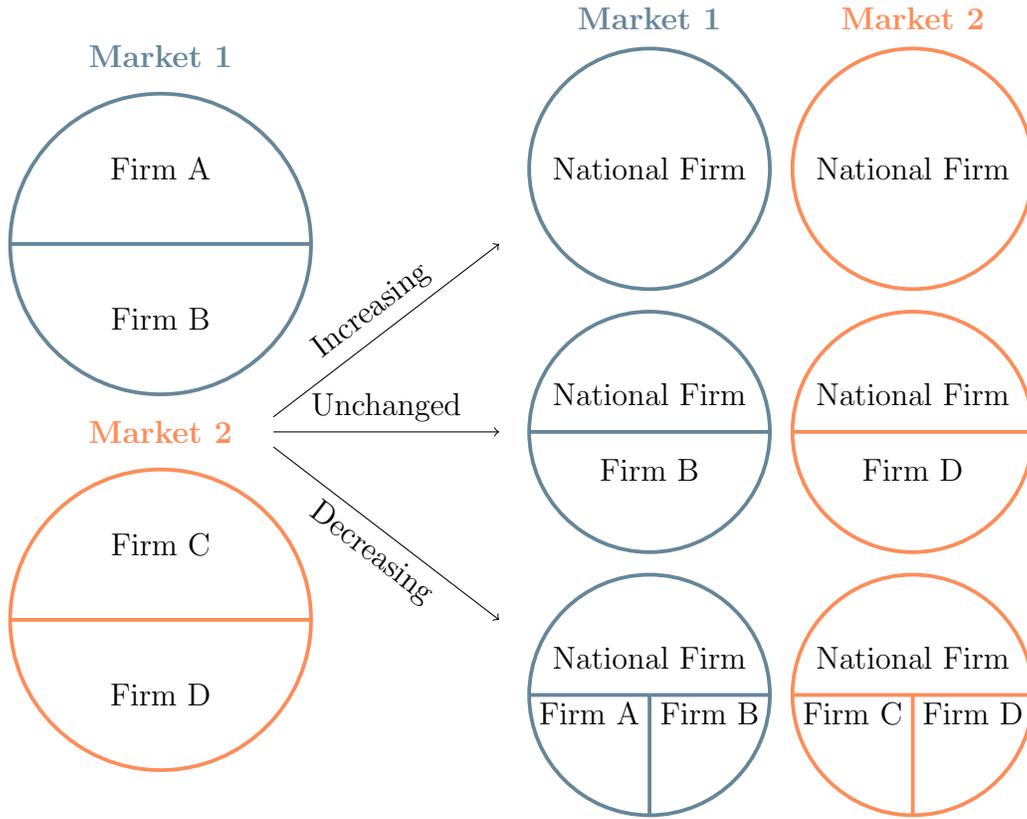
2 National and Local Concentration

The increasing trend of national concentration in various sectors of the economy has been widely documented (Autor et al., 2020; Decker et al., 2017; Akcigit and Ates, 2020; Aghion et al., 2019; Hsieh and Rossi-Hansberg, 2020). However, local concentration is the relevant measure of concentration for competition in the retail sector, as consumers typically shop at nearby stores (Rossi-Hansberg et al., 2020). One major outstanding question in this literature concerns what we can learn about local concentration from the change in national concentration.

Increasing national concentration can be accompanied by increasing local concentration, but it may also be accompanied by decreases in local concentration. In fact, not much can be learned from the dynamics of local concentration having information only about national trends. The simple example shown in Figure 1 makes this clear. National concentration can increase by having firms expand across markets, without affecting the layout of individual markets (row 2). Alternatively, the expansion of large firms can drive out competitors in local markets, increasing national and local concentration (row 1), or can bring up more—and likely smaller—competitors, decreasing local concentration (row 3). The total effect on national and local concentration depends on how firms in individual markets respond.

The example in Figure 1 highlights the two mechanisms affecting national concentration that we study in this paper: changes in local concentration and changes in cross-market concentration. The first mechanism links changes in the composition of local markets and concentration at the national level. As local markets become more/less concentrated so

Figure 1: Effect of Increasing National Concentration on Local Concentration



Notes: The figure shows hypothetical market structures after the entry of a national firm.

does the aggregate economy (in a given sector). The second mechanism links national concentration to the presence of the same firms across various markets. As firms expand across markets they capture a larger share of national sales, in turn increasing national concentration. Note that, as shown in Figure 1, changes in cross-market concentration need not be accompanied by changes in local concentration. In what follows we make these ideas precise by developing a new decomposition of national concentration into local and cross-market concentration.

Our primary measure of concentration is the firm Herfindahl-Hirschman Index (HHI). The HHI is one of the most common measures of concentration and its formulation will prove useful in decomposing the mechanisms behind the changes in national concentration. We measure concentration at the product category level throughout the paper, using each

firm's, i , share of sales in product j at time t , s_i^{jt} —superscripts and subscripts are defined 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 :

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

while the HHI of location ℓ and product j in year t is calculated as:

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

From (1) it is clear that the national HHI for a product j measures the probability that two dollars, x and y , chosen at random, are spent at the same firm.⁷ We use the law of total probability to derive a decomposition of the HHI into two terms, based on whether the two dollars are spent in the same or different markets. The decomposition is given by:

$$\underbrace{P(i_x = i_y)}_{\text{National HHI}} = \underbrace{P(\ell_x = \ell_y)}_{\text{Collocation}} \underbrace{P(i_x = i_y | \ell_x = \ell_y)}_{\text{Local HHI}} + \underbrace{P(\ell_x \neq \ell_y)}_{\text{1 - Collocation}} \underbrace{P(i_x = i_y | \ell_x \neq \ell_y)}_{\text{Cross-Market HHI}}, \quad (3)$$

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

Equation (3) 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.⁸ The second component, $P(i_x = i_y | \ell_x = \ell_y)$, is an aggregate index of local concentration, with

⁷In what follows, the j and t superscripts are dropped on all variables for convenience. In this context a market is characterized by its location, ℓ , as the product is fixed.

⁸Collocation is calculated as: $P(\ell_x = \ell_y) = \sum_{\ell=1}^L (s_\ell)^2$, where s_ℓ is the share of location ℓ in national sales.

local concentration measured as in equation (2).⁹ 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:

$$P(i_x = i_y | \ell_x \neq \ell_y) = \underbrace{\sum_{\ell} \sum_{n \neq \ell} \frac{s_{\ell} s_n}{1 - \sum_p s_p^2}}_{\text{Weights}} \underbrace{\sum_{i=1}^N s_i^{\ell} s_i^n}_{\text{Cross-Market}} \quad (4)$$

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

Of the three terms, the collocation term plays a crucial role in determining the impact of local concentration in national measures. A low collocation term implies that local concentration can only have a limited effect on national trends, leaving the cross-market term as the driver of the national index. We will show later that this is in fact the case, which should come as no surprise, because the U.S. has many markets and even the largest markets represent only a small fraction of total U.S. sales.

To implement the decomposition presented in equation (3) we need to measure concentration in each local market for a given product, as well as to link the activities of firms across markets. Doing this requires detailed data on establishment-level revenue by product for all firms in the U.S., which we describe in the next section.

⁹In the decomposition each local market is weighted by the conditional probability that the two dollars are spent in location ℓ , given that they are spent in the same location: $s_{\ell}^2 / (1 - \sum_p s_p^2)$. This tends to weight larger markets more than the more usual weight s_{ℓ} —the share of sales (of product j) accounted for by location ℓ (at time t). To facilitate comparison of the results with other work, we present aggregated series for local concentration in Section 4 that use the latter weights. Appendix B derives these results in detail.

3 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 for the construction of detailed measures of concentration that take into account competition between stores selling similar products in specific geographical areas.¹⁰

3.1 Data Description

We use confidential U.S. Census Bureau microdata that cover 1982 to 2007.¹¹ The source of data is the Census of Retail Trade (CRT), which provides revenue by product type for retail stores in years ending in 2 and 7. The CRT data on product-level revenue and information on the location of each store are used 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 which sell multiple product types. The data we create here are uniquely equipped to deal with cross-industry competition. We combine the CRT data with the Longitudinal Business Data (LBD) (Jarmin and Miranda, 2002), which contains data on employment of each store and allows us to track stores over time.

3.2 Sample Construction

The retail sector is defined based on the North American Industrial Classification System (NAICS) as stores with a 2-digit code of 44 or 45. As such, it includes stores that sell final goods to consumers without performing any transformation of materials. From 1992 to 2007 we use the NAICS codes available from the CRT as the industry of each store. Prior to 1992 we use the store-level NAICS codes imputed by Fort and Klimek (2016). The

¹⁰We use store and establishment as synonyms.

¹¹Results including 2012 are undergoing disclosure review.

sample includes all stores with positive sales and valid geographic information that appear in official Census of Retail Trade and County Business Patterns statistics.¹²

3.3 Creation of Product-Level Revenue

We construct product-level revenue data for all U.S. stores, which allows 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 (for example, men’s footwear, women’s pants, diamond jewelry). We 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.

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, such as industry and multi-unit status. This affects stores that account for 20 percent of sales. Details of this procedure are provided in Appendix C.

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 sales of the store 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

¹²Additionally, we drop stores in motor vehicles and parts (441), gasoline stations (447), miscellaneous store retailers (453), and non-store retailers (454). We drop the first two because franchising makes it difficult to identify firms. The third is dropped because of difficulties in identifying which products stores sell. The final is dropped because sales from these stores are typically shipped to different markets than their physical location.

¹³Table C.2 lists all the product categories. We will mostly focus on the 8 “main” product categories which account for about 82 percent of sales of the stores in our sample throughout the entire time period. The remaining categories are individually small and have not been released due to disclosure limitations.

from Walmart (NAICS 452), the local grocery store (NAICS 448), or online (NAICS 454).¹⁴ Table 1 shows that this is common across retail products. The main subsector for each product accounts for between 30 and 62 percent of sales in products other than automotive goods. 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.

Table 1: Share of Product Category Sales by Establishment Subsector (2012)

	Main Subsector	GM	Other
Automotive (441)	96.6	1.0	2.4
Furniture (442)	39.0	21.4	39.6
Electronics & Appliances (443)	30.8	23.8	45.4
Home and Garden (444)	58.7	5.6	35.7
Groceries (445)	62.0	20.1	17.9
Health Goods (446)	40.0	19.3	40.7
Clothing (448)	53.4	23.7	22.9

Notes: Author’s calculation from the public Census of Retail Trade data which provide sales by product line for stores in each industry. GM includes stores in subsector 452. Other includes sales outside of the main subsector (indicated in parenthesis) and GM.

4 Changes in Retail Concentration

In this section, we exploit the detailed microdata described in Section 3 to decompose national concentration in the U.S. retail sector into local and cross-market concentration, using the identity developed in equation (3). The measure of local concentration we compute accounts for the local nature of competition in retail and has a distinct advantage in that it measures concentration at the product category level, rather than the industry level, addressing the rise of general merchandisers that compete with stores

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

across multiple industries.¹⁵ We show that local concentration has increased, although not as much as national concentration. Moreover, the decomposition reveals that national concentration is largely independent of local trends, with 98 percent of the growth in national concentration accounted by increasing cross-market concentration (consumers shopping at the same firms across markets).

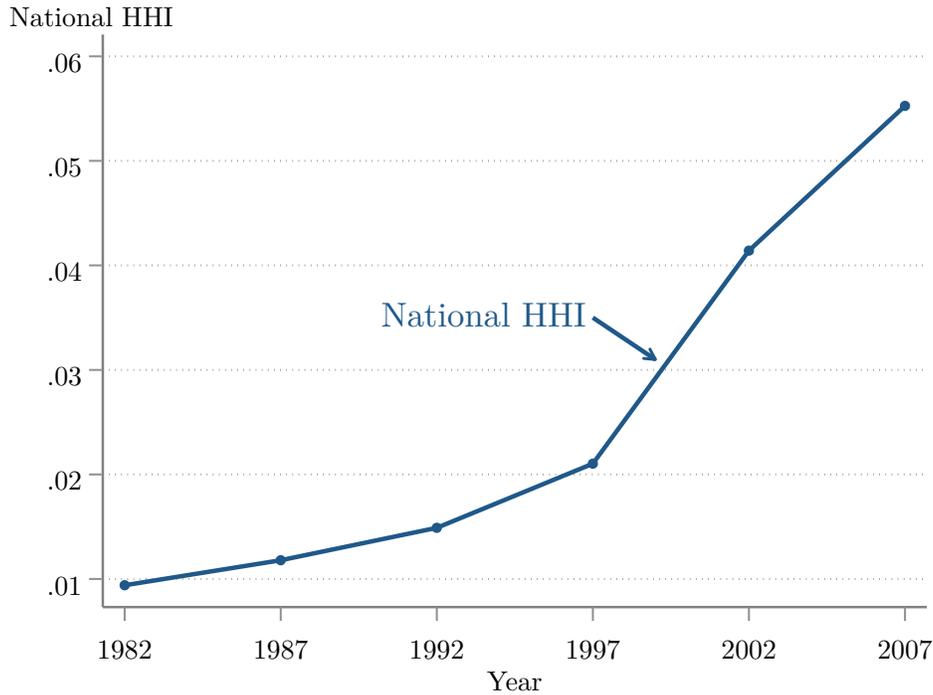
Figure 2 plots national concentration in the U.S. retail sector as measured by the HHI defined in equation (1). Between 1982 and 1997 national concentration was low, although it gradually increased over the period. In contrast, between 1997 and 2007, concentration grew at a faster pace, more than doubling from 0.02 to 0.055. However, and despite the striking increase in national concentration, Figure 2 provides almost no information on the underlying changes in local retail markets.

Figure 3 plots the level of national and local concentration between 1982 and 2007. Local concentration increases whether markets are defined by zip codes, counties, or commuting zones, and the changes are sustained throughout the sample period, with the exception of the mid 1990s. Between 1997 and 2007, all four measures increased by 3 to 5 percentage points, with the commuting zone HHI increasing by 50 percent from 0.078 to 0.117. But, contrary to the national concentration index, local concentration did not accelerate its increase in the period after 1997.

The national concentration results are consistent with previous industry-level work using sales and employment for various sectors, including retail (Rossi-Hansberg et al., 2020; Autor et al., 2020; Foster et al., 2015; Basker et al., 2012; Lipsius, 2018; Rinz, 2018). The local concentration results are also consistent with studies on local labor market concentration that find increasing concentration in retail, but decreasing local concentration overall (Rinz, 2018; Lipsius, 2018). Our results suggest that increasing local retail concentration may help explain the increases in markups documented in De Loecker et al. (2020). We show in section 5 that this is in fact the case, with local concentration

¹⁵We calculate all concentration measures at the firm level by combining sales of the stores of a firm in each market.

Figure 2: National Concentration



Notes: The data are from the CRT microdata. The numbers are sales weighted averages of national HHI in eight main product categories.

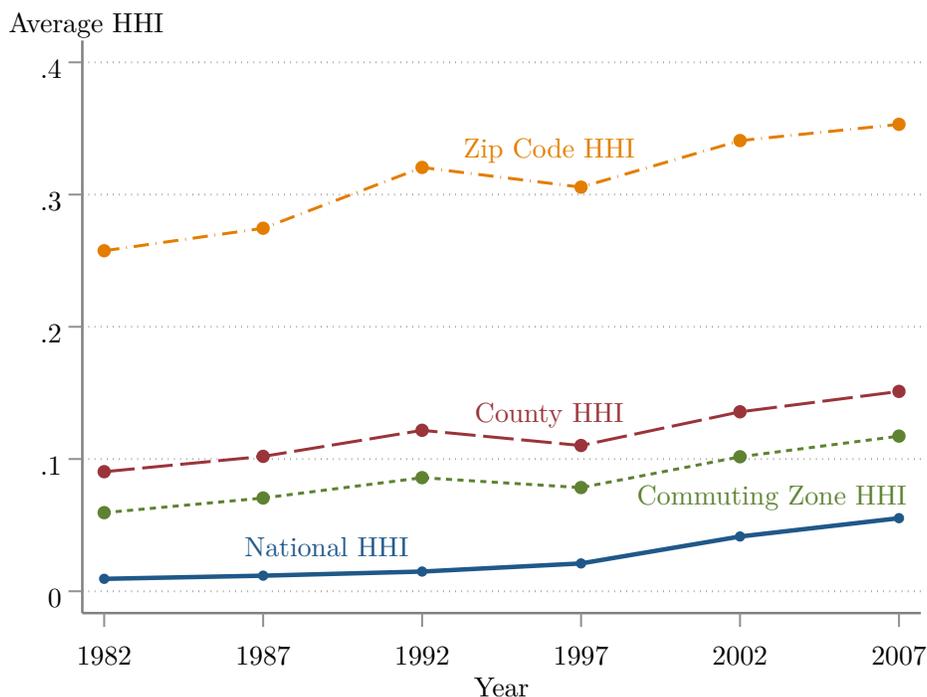
implying modest increases in markups for all product categories.

However, the picture that emerges from our data differs from the findings at the local level of Rossi-Hansberg, Sarte and Trachter (2020), who find that local retail concentration has been steadily falling since 1992. Our results differ for multiple reasons. First, a different data set is used.¹⁶ Second, different definitions of which stores are retailers are employed. Rossi-Hansberg, Sarte and Trachter use Standard Industrial Classification (SIC) codes while this paper uses NAICS.¹⁷ Finally, the aggregate index of local HHI is calculated differently. Rossi-Hansberg, Sarte and Trachter report the average change in the local HHI, weighting by the end-of-period sales/employment of each market, while we report the change in the average local HHI, weighting markets in each year according to that year's

¹⁶Rossi-Hansberg, Sarte and Trachter use U.S. National Establishment Time Series (NETS) data.

¹⁷The primary difference between SIC and NAICS is that SIC includes restaurants in retail.

Figure 3: National and Local Concentration



Notes: The data are from the CRT microdata. The HHI for three 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 eight main product categories.

sales. This distinction matters because as markets become bigger, they also tend to become less concentrated. This mechanically gives more weight to markets where concentration is decreasing. In fact, when we repeat our exercise using end-of-period weights we find slight decreases in local concentration when measured at the industry or product level. We choose current period weights in order to be able to decompose national concentration as described in section 2. More details on differences between our studies are in appendix A.

These results document the average evolution of both national and local concentration. In the following three subsections we expand on these results in three ways. First, we use the decomposition from equation (3) to show the relationship between local and national concentration. Second, we describe the distribution of changes in concentration across

locations. Finally, we provide more detail on the changes for individual product categories.

4.1 Decomposing National Concentration

We now assess the contribution of local and cross-market concentration to national concentration, using the decomposition in equation (3). We focus on the 722 commuting zones which partition the contiguous U.S. as our definition of local markets in what follows. Commuting zones are defined by the United States Department of Agriculture such that the majority of individuals work and live inside the same one and provide a good approximation for the retail markets in which stores compete.¹⁸ Choosing a larger geographical unit when defining retail markets decreases the level of local concentration and increases the contribution of local concentration to national concentration, relative to smaller geographical units like counties or zip codes.

Table 2: Local Concentration Contribution to National Concentration

	1987	1997	2007
Furniture	11.0	8.3	7.0
Electronics & Appliances	6.2	2.2	1.2
Home Goods	23.3	2.2	1.5
Groceries	10.2	9.9	2.9
Health Goods	6.6	2.8	1.6
Clothing	3.4	2.8	1.8
Toys	2.9	1.5	1.0
Sporting Goods	2.3	1.9	2.0
Retail Sector	7.1	4.6	2.1

Notes: The data are from the CRT microdata. Numbers are percent of national concentration that is due to local (commuting zone) concentration calculated as the first term in (3) divided by national concentration multiplied by 100. Retail sector is an expenditure-share-weighted average of the contributions of each product category.

¹⁸It seems likely that if individuals live and work in a commuting zone they do the majority of their shopping in that region. Calculating results in this way causes us to potentially overstate the role of local concentration in national trends relative to using smaller geographic units.

Table 2 shows the contribution of local concentration to national concentration by product category and year. Two things are clear. First, the contribution of local concentration to national concentration is small, with the contribution for most product categories no higher than 2 percent. This is because local concentration is weighted by the collocation term—the probability that two dollars spent in the U.S. are spent in the same market—which is small given the large number of markets in the United States.¹⁹ Second, the contribution of local concentration to national concentration has been falling over time as national concentration has been increasing. By 2007 local concentration accounted for less than 3 percent of the level of national concentration in all of the main product categories except furniture. In 1987 the national HHI was just 0.01, as a consequence the contribution of local concentration was higher, even though the local HHI was lower than it is today and had roughly the same weight in the decomposition.

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, 98 percent of the change in national concentration is accounted for by changes in cross-market concentration.

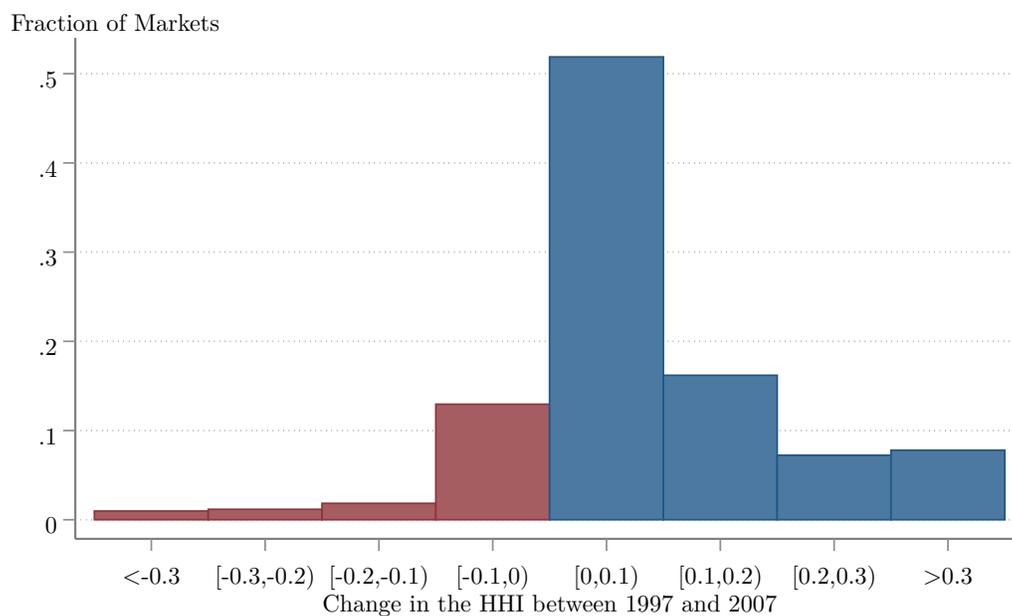
4.2 Changes in Concentration Across Locations

The increases in concentration have been broad-based. Over 72 percent of dollars spent in 2007 are spent in markets which have increased concentration since 1997. Figure 4 shows the distribution of changes in concentration between 1997 and 2007. In just 10 years, 52 percent of markets had increases in concentration of over 5 percentage points. These markets account for 32 percent of sales in 2007. These changes are significant. One criterion used by the Department of Justice to determine when to challenge mergers is whether the local HHI will increase by 2 percentage points (Department of Justice and Federal Trade Commission, 2010).

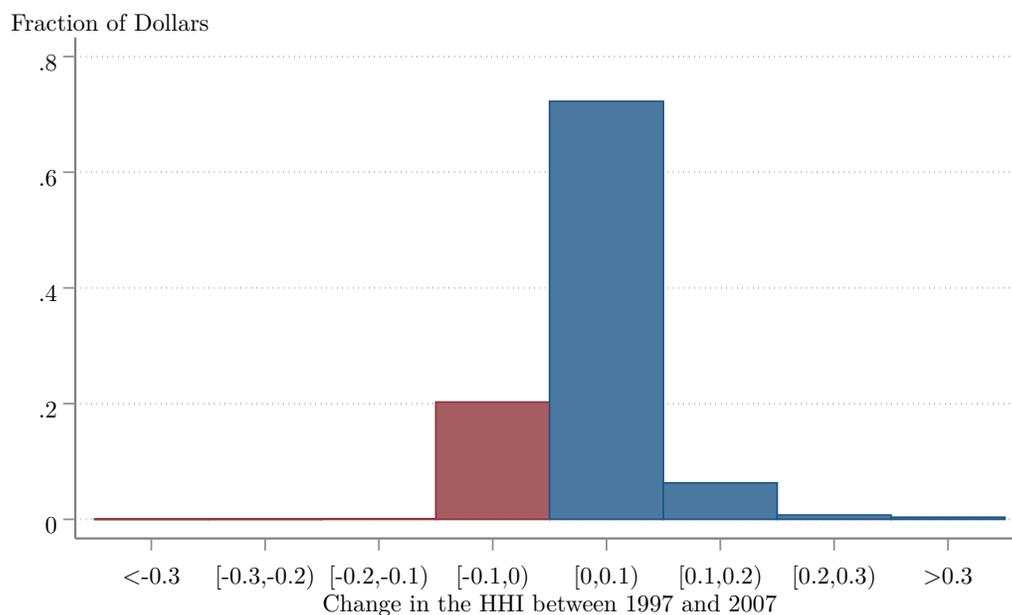
¹⁹The collocation term is stable at around 2 percent in each year. See Appendix D.

Figure 4: Changes in Concentration Across Markets

(a) Unweighted



(b) Weighted

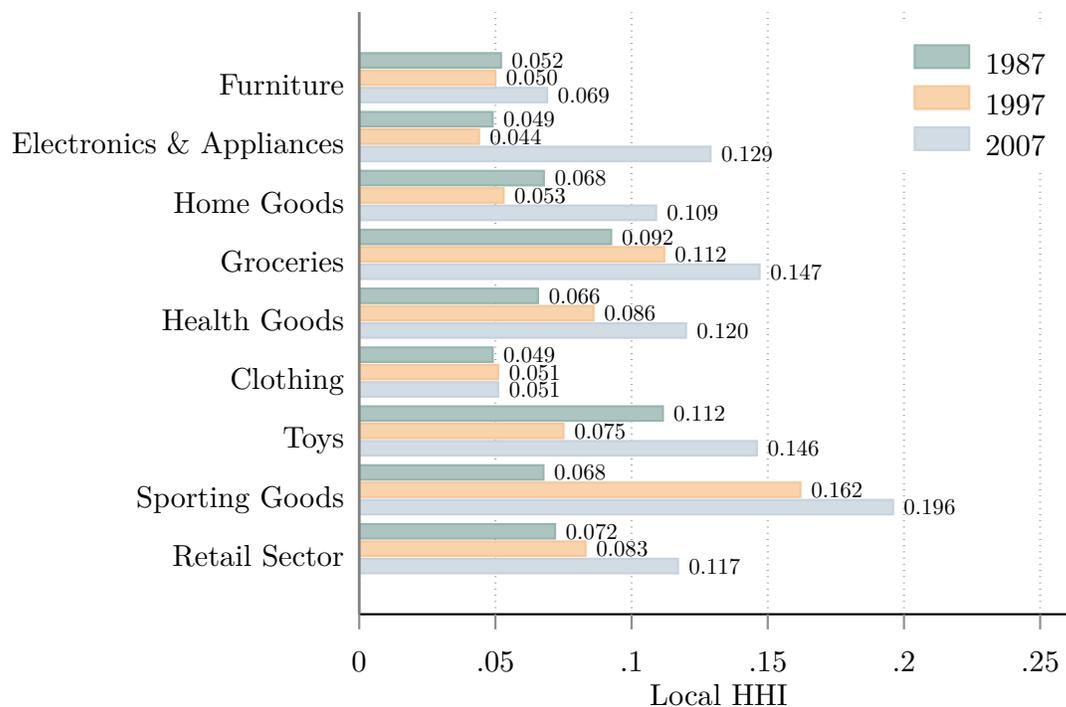


Notes: The data are from the CRT microdata. The top panel shows the fraction of markets, commuting zone/product category pairs, with changes in concentration of a given size. The bottom panel weights markets by value of sales in the product category.

4.3 Changes in Concentration Across Products

Both local and national concentration increased for all of the eight major product categories between 1987 and 2007. Figure 5 shows that these increases were significant for many products. In 1987, the average level of the local HHI was relatively low, only Toys was above 0.1. By 2007, six of the eight categories had an average local HHI above 0.1. Despite this common trend, there is substantial variation across product categories in the changes in concentration. Local concentration in furniture and clothing barely increased, while it more than doubled in sporting goods and electronics and appliances. However, almost every category experienced larger changes in national and cross-market concentration.

Figure 5: Local Concentration Across Product Categories

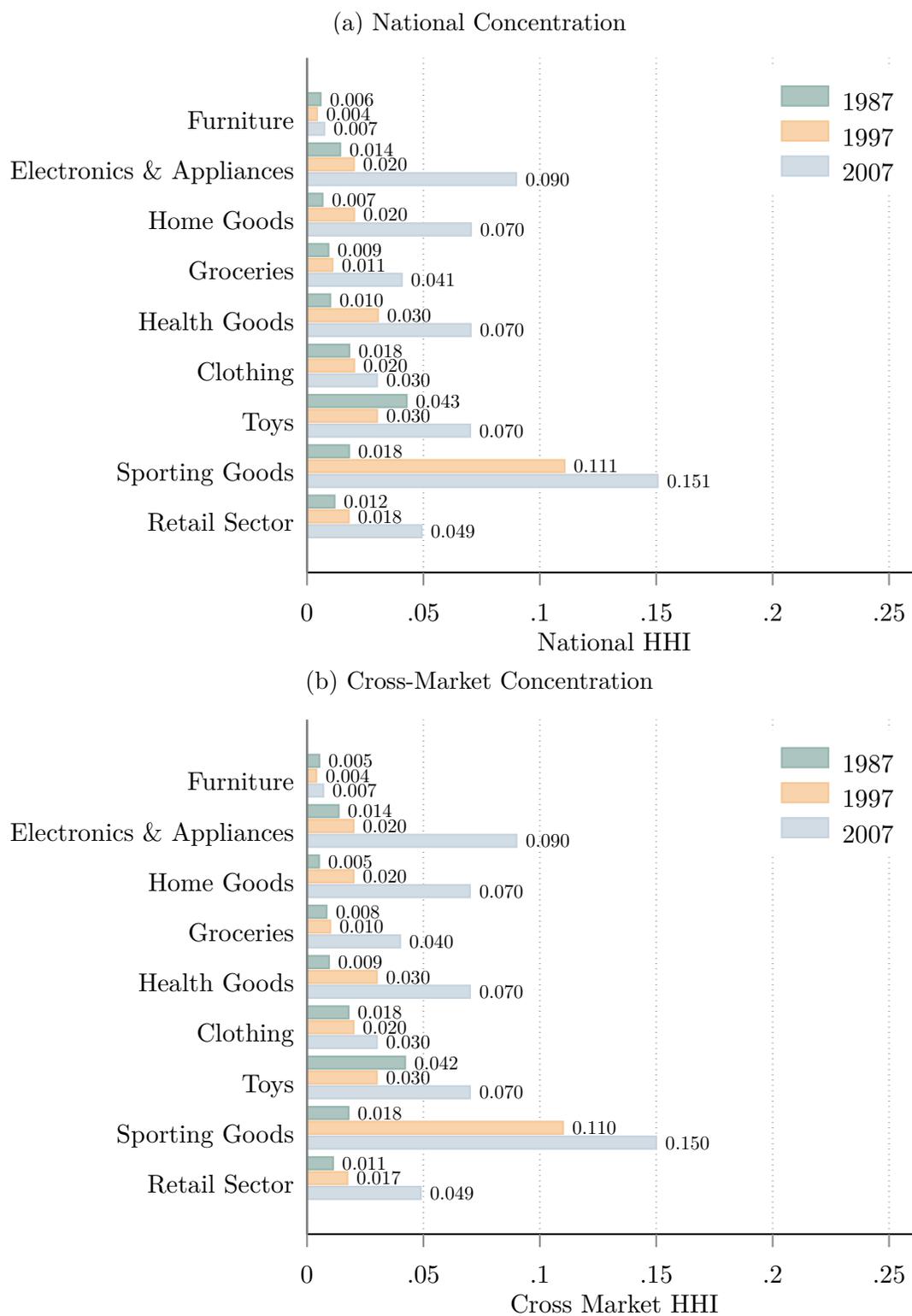


Notes: The data are local HHI by product weighted by market size from the CRT microdata.

Figure 6a shows results for national concentration. Levels of national concentration are lower than those of local concentration. In 1987, the national HHI in each of the product categories was essentially zero with the exception of “Toys.” In the next 20 years many of the national HHI’s grew more than four-fold as national retailers became the dominant source of these product categories, as evidenced by the change in cross-market concentration (Figure 6b). The increases in cross-market concentration are large enough that national concentration is almost equal to local concentration in three product categories by 2007. For example, in 2007 sporting goods had a local HHI of 0.196, while its cross-market index was 0.150. This implies that the probability that two dollars spent in different markets were spent at the same firm was almost the same as the probability that two dollars spent in the same market were spent at the same firm.

Comparing figures 6a and 6b makes clear the tight link between national and cross-market concentration indexes. Both measures show the same patterns, with only small differences due to changes in local concentration. Despite large changes in the makeup of retail as a whole, and variation across the changes experienced in different product markets, the contribution of local concentration to national trends has remained limited. Figures 5 and 6 also show that not all product-markets evolved in the same way between 1987 and 2007. The markets for furniture and clothing changed very little, both have relatively low levels of both local and national concentration. On the other hand, local markets for groceries and health goods have become slightly more concentrated, while at the national level concentration has increased from essentially zero to noticeable levels.

Figure 6: National and Cross-Market Concentration Across Product Categories



Notes: The data are from the CRT microdata. Numbers are the national and cross-market HHI for various product categories weighted by market size.

5 Markups and Local Concentration

In the previous sections we documented that local concentration increased by 4 percentage points on average between 1987 and 2007. These changes can imply higher markups and ultimately affect consumer prices. However, studying this relationship is challenging because long series on prices and costs for U.S. retailers are not available. Nevertheless, linking changes in concentration to changes in prices is critical to assess 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 5.8 percentage point increase in markups between 1987 and 2007. However, this increase is small relative to the implied decrease in costs which may have been an impetus for the increase in concentration.

The model features strong parametric assumptions on firms to maintain tractability. In particular, we assume firms face isoelastic demand curves, with elasticities of demand varying by product but not by location or over time; firms operate a constant returns to scale technology and produce using only labor; and 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 link local concentration, as measured by the local HHI, to prices and markups without firm level data on prices or costs. In this way, our model is limited by the extent to which the distribution of market shares captures the competitive environment in retail markets. In Appendices F.4 and F.6 we discuss how to relax some of the assumptions listed above and the effects on our results.

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.²⁰ A market is characterized by a pair (j, ℓ) of a product and a location, with an isoelastic demand curve for each product. Firms produce using only labor and differ only in their productivity, $z_i^{j\ell}$. We assume labor to be immobile across locations, so each location has a specific wage, w_ℓ . Thus, the firm's marginal cost is $\lambda_i^{j\ell} \equiv w_\ell/z_i^{j\ell}$. A complete description of the model is in Appendix F.

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: $p_i^{j\ell} = \mu_i^{j\ell} \lambda_i^{j\ell}$.²¹ The markup is characterized in terms of the firm's market share, $s_i^{j\ell}$, and the product's elasticity of demand, ϵ_j :

$$\mu_i^{j\ell} = \frac{\epsilon_j}{(\epsilon_j - 1)(1 - s_i^{j\ell})}. \quad (5)$$

Markups will be larger for firms with higher market shares and products with a less elastic demand. Importantly, equation (5) 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. We use the firm-specific markups in (5) to derive closed form expressions for markups in each market (μ_j^ℓ), as well as the average markup of each product nationally (μ_j). Appendix F.2 presents the derivations. Both markups directly depend on the local Herfindahl-Hirschman Index:

$$\mu_j^\ell = \frac{\epsilon_j}{\epsilon_j - 1} [1 - HHI_j^\ell]^{-1}, \quad (6)$$

$$\mu_j = \frac{\epsilon_j}{\epsilon_j - 1} \left[1 - \sum_{\ell=1}^L s_\ell^j HHI_j^\ell \right]^{-1}, \quad (7)$$

where HHI_j^ℓ is the HHI of product j in location ℓ and s_ℓ^j is the share of location ℓ in the

²⁰In Appendix F.1.2 we solve the model for competition in prices and monopolistic competition.

²¹Recent work has indicated that firms charge similar and even the same prices across locations in building material (Adams and Williams, 2019) and groceries (Dellavigna and Gentzkow, 2019). Whether the phenomenon holds more broadly is a subject for further research. Appendix F.6 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 conclusion, but may have distributional impacts.

Table 3: Estimated Elasticities of Substitution

Product Category	ϵ_j	Product Category	ϵ_j
Furniture	2.3	Home Goods	4.1
Clothing	2.3	Health Goods	4.5
Sporting Goods	2.9	Electronics & Appliances	4.6
Toys	3.8	Groceries	4.7

Notes: The data are authors' estimates of product elasticities of substitution using industry markups from the ARTS and product-level local HHIs calculated from the CRT. The elasticities are the solution to equation (7).

national sales of product j . As the local HHI approaches zero, markups approach the Dixit-Stiglitz markups under monopolistic competition. As markets become more concentrated, average markups increase. The sensitivity of markups to increases in concentration is larger for products with lower elasticity of demand.

5.1 Estimation and Model Fit

The two key ingredients for analyzing markups are firm's market shares by product in each location, $s_i^{j\ell}$, and the elasticity of substitution for each product, ϵ_j . We obtain the shares directly from the CRT and we estimate the elasticities using equation (7). Specifically, we use the product HHIs calculated in section 4.2 and gross margins by industry from the Annual Retail Trade Survey (ARTS). Our estimation based on product level data allows us to discuss how conditions in the average U.S. market has changed.²²

Table 3 presents the estimates for the elasticities of substitution. We find the largest elasticities of substitution in groceries, electronics & appliances, and health goods. These are categories where different firms carry similar or even identical physical products, leaving less room for differentiation than in products such as clothing and furniture which feature many different brands that are only available from a small set of retail firms.

We now compare changes in markups from ARTS between 1997 and 2007 with the

²²Estimation using local level data to study the distribution of changes is in progress.

changes implied by our model using observed changes in the local HHI. The ARTS provides the best source to compare our results to because it computes markups using cost of goods sold and reports them for detailed industries. Markups using cost of goods sold are the most direct data analogue to markups in the model, as shown in Appendices F.2 and F.4. Additionally, data by industry allows us to compare markups by product and focus on the changes in retail only for the products in our study, omitting the contribution of automotive related retailers which contribute to sector-level alternatives.

However, there are still issues with comparing the industry-level results in ARTS to our product-level results. Industry markups and product markups may move in opposite directions due to changes in composition. For example, if low margin clothing stores have been replaced by lower margin general merchandise stores, markups in the clothing industry would rise, while markups on clothing would decrease. Additionally, changes in average markups in our model capture only changes in local HHI, as implied by equation (7), missing changes in elasticities of substitution due to changes in product mix and demographics. We also miss any changes to local competitive environments not captured by the HHI.

Table 4 displays the results of comparing our model to ARTS. The predictions of the model match the data fairly closely for four product categories: groceries, sporting goods, toys, and home goods. However, there are larger misses in the remaining four product categories. Some product markets such as clothing experienced significant changes in composition, while the products in certain product categories have changed significantly. For example, mobile phones were introduced to electronics & appliances during this time period. Despite these issues we match the overall change in markup.

5.2 Changes in Concentration and Markups

We now use the changes in local HHI to infer changes in markups back to 1987. We plot the change in markup by product against the change in each product's HHI in Figure 7. These results show that markups have risen across the retail sector over 20 years, with

Table 4: Model Fit

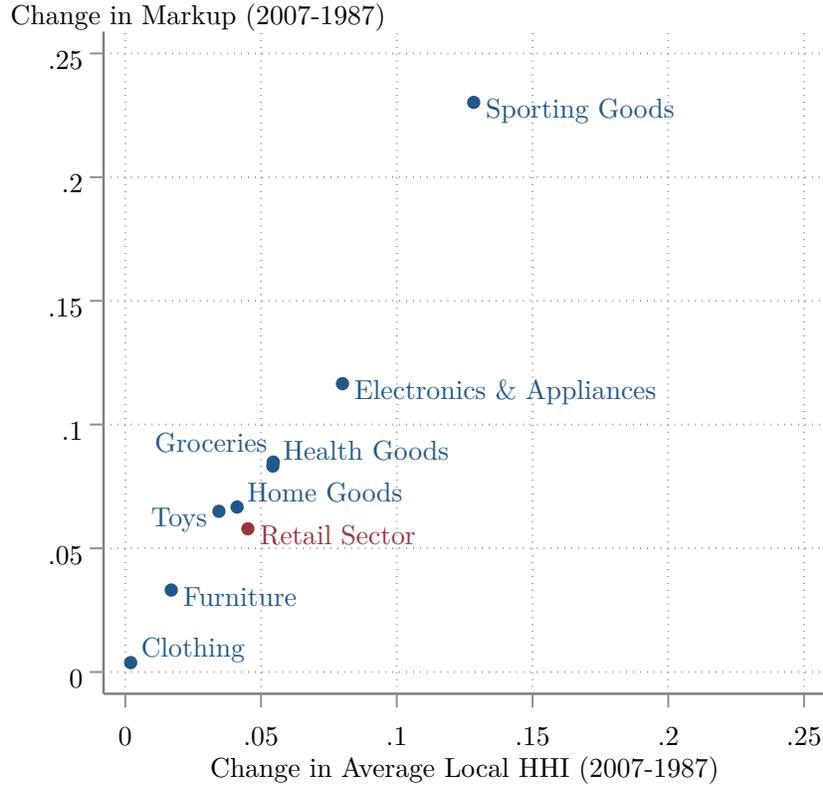
Product Category	Δ Markup (07-97)		Markups 2007
	Model	Data	
Furniture	0.04	0.11	1.85
Clothing	0.00	0.10	1.81
Sporting Goods	0.07	0.09	1.67
Toys	0.13	0.09	1.67
Home Goods	0.09	0.11	1.51
Health	0.05	-0.03	1.43
Electronics & Appliances	0.12	0.03	1.39
Groceries	0.08	0.06	1.41
Retail Sector	0.05	0.05	1.52

Notes: The model results come from elasticities of substitution estimated in 2007 and changes in local HHIs for each product category using equation (7). Data estimates come from industry data in ARTS. Markups in 2007 come from ARTS and are matched exactly by the model. The retail sector markup measure corresponds to an expenditure share weighted harmonic average of the product categories.

average markups in most products increasing no more than 10 percentage points. The average increase for the retail sector as a whole implied by the change in local HHI is 5.8 percentage points. These findings, based on changes in local retail concentration, are consistent with the trends from the beginning of the ARTS in 1993 to 2007 in which average markups increased by 5.1 percentage points. The results also consistent with the general trends in previous work documenting increases in markups over the last decades for various sectors of the economy (De Loecker et al., 2020; Hall, 2018; Traina, 2018). We find that product categories with larger changes in the local HHI have consistently larger predicted changes in markups, despite differences in elasticity of substitution across products. An increase of one percentage point in the product’s average HHI raises markups by 1.71 points on average.

The increases in markups we obtain imply a modest effect of increased concentration on the pass-through of lower costs to consumers. Although concentration and markups

Figure 7: Markups and Local Concentration Over Time



Notes: The data are authors' estimates of the change in product markups from 1987 to 2007 using changes in product-level concentration in local markets over time. The retail sector markup measure corresponds to an expenditure share weighted harmonic average of the product categories. Herfindahl-Hirschman indexes are computed for each product category from CRT data following equation (7).

increased between 1987 and 2007, the relative price of final goods in these product categories fell by 35 percent during the same period, implying a reduction in costs of 38 percent. However, the increases in markups and concentration may be the result of low-cost firms gaining market share, in which case the decrease in costs cannot be separated from the increase in concentration. Even if the full reduction in costs is realized without an increase in concentration, the decrease in prices would have been 37 percent, only 6 percent larger than what we observed in the data.²³

²³To compare our model's cross-sectional results across time we choose normalizations for aggregate prices that make them consistent with the change of retail good prices from the Price Indexes for Personal Consumption from the Bureau of Economic Analysis. Full details on this process are in appendix F.3.1.

Table 5: Model Aggregates

	1987	1997	2007
Prices	1.000	0.841	0.655
Markups	1.461	1.473	1.519
Costs	0.684	0.571	0.431

Notes: Prices are estimated using price indexes from the PCEPI. Markups and costs are aggregated from product level average markups and costs as explained in Appendix F.3.

6 Conclusion

Despite the attention given to the rise of national concentration in the U.S., less is known about the dynamics of local concentration, and the relationship between observed national trends and the behavior of local markets. This paper helps to shed light on these issues by contributing in three related fronts. First, we decompose national concentration measures into a local component (national concentration rises as local markets become more concentrated), and a cross-market component (national concentration rises as the same firms are present in more markets, increasing their national market share). Second, we measure concentration at a granular level by compiling new Census microdata covering all U.S. retailers. Third, we estimate a model of oligopolistic competition that features an explicit link between the local HHI and markups to quantify the effect of concentration on retail markups.

We show that local concentration has a limited effect on national concentration measures. Instead, it is cross-market concentration what explains most of the increase in national concentration observed since 1982. That is, national concentration is driven by consumers in different locations shopping at the same firms, highlighting the role of large multi-market retailers in explaining the dynamics of the retail sector.

Our measures of local concentration document broad increases across locations and

products since the 1980s, although at lower rates than the increases in national concentration. We link these changes to increasing markups for all major product categories in retail. Our results suggest that these higher markups have increased prices by at most 2 percentage points between 1987 and 2007, a small effect compared to the 35 percent decrease of relative retail prices during that same period. We conclude that despite the stark increases in national concentration (doubling between 1997 and 2007), and broad-based changes in retail markets, increasing concentration has had a limited effect on consumer welfare.

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Appendices

Table of Contents

A	Comparison to Rossi-Hansberg, Sarte and Trachter (2020)	36
B	Concentration Decomposition	45
C	Cleaning and Aggregating Product Lines Data	47
C.1	Aggregating Product Lines	47
C.2	Imputing Missing Data	48
D	Additional Tables and Figures	51
E	Industry-Based Results	52
F	Model of Firm’s Markups	54
F.1	The Model Economy	54
F.2	Aggregating Markups	60
F.3	Estimation Steps	63
F.4	Discussion: Marginal Costs Functional Form	66
F.5	Extension: Elastic Labor Supply	67
F.6	Extension: Uniform prices across locations	68

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

This section compares our results to those in Rossi-Hansberg, Sarte and Trachter (2020), and explains the factors contributing to the differences between our papers. In what follows we will refer to Rossi-Hansberg et al. (2020) as RST. RST calculate changes in the HHI for all sectors of the economy for 1990 to 2014. Unlike us, they find a reduction in the local HHI for the retail sector during the time period they analyse.²⁴

There are three key differences between this paper and RST that each partially explain the opposite results regarding local concentration. First, we use different data sources. This paper uses confidential data from the Census of Retail Trade (CRT) and the Longitudinal Business Database (LBD), while RST use the National Establishment Time Series (NETS). Second, our definitions of product markets differ. 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, we report the change in this (aggregate) index of local concentration, while RST aggregates the change in market level concentration using end-of-period weights, they 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

²⁴RST 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.

Section 3.3 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 towards finding decreasing local concentration. 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 National Establishment Time Series (NETS), a data-product from Walls and Associates. The data contain 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 performance of the NETS data in matching sales numbers is unknown. The results in this paper are based on the Census of Retail Trade (CRT), a data set assembled and maintained by the U.S. Census Bureau covering the universe of retail establishments.

Both the NETS data and the CRT use the establishment’s reported industry and sales when available. Both sources have some degree of imputation for establishments that do not report. However, the CRT is often able to impute using administrative records from the IRS.²⁵ 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. This makes it possible for us to define markets by product categories, accounting for cross-industry competition by general merchandisers (see Section 3.3). Second, the NETS includes non-employer establishments, while the CRT does not. Official estimates are that non-employer establishments account for about 2 percent of retail sales in 2012 (Economy-Wide Key Statistics: 2012 Economic Census of the United States).²⁶ On the

²⁵Response 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 dominic-smith.com/data/CRT/crt_sample.html for more details.

²⁶https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ECN_2012_US_00A1&prodType=table

whole, there is significant reason to believe that the CRT is 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 chose one over the other depending on the specific context. We define markets by a combination of a geographical location and a product category which we construct using the detailed data on sales provided by the CRT, along with the (NAICS-6) industry classification of establishments (see Section 3.3). 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. In contrast, RST define markets by the industry of the establishment, using both SIC-8 and SIC-4 codes. Some examples of SIC-8 codes are: Department Stores, discount (53119901); Eggs and poultry (54999902); Thai Restaurants (58120115).²⁷

SIC-8 codes may be overly 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 fall instead of a 17 percentage point decrease.²⁸

Incidentally, the SIC-4 codes are quite similar to the NAICS-6 codes available in the CRT, with the exception that restaurants are included in the SIC definition of retail, but

²⁷NETS 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 SIC8 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.

²⁸The change from SIC-8 to SIC-4 has little effect on concentration outside of retail (RST Data Appendix). Numbers read off graphs for the change in retail sector concentration for zip codes between 1990 and 2012.

not in NAICS.²⁹ This makes the concentration measures based on each classification more closely comparable. Yet, even in this setting (NETS SIC-4 vs. CRT NAICS-6) there are still significant differences between our studies. We will go back to this comparison when we discuss Figure A.2 and Table A.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 a location (ℓ) and. Then we aggregate across locations weighting each market (location-product) HHI by the market’s share of the product’s national sales, 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. This is done for each period (t), and we report the time series for this index. The average local HHI is then given by:

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

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 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:³⁰

$$\Delta HHI_t^{RST} = \sum_{j\ell} s_{j\ell}^t \Delta HHI_{j\ell t}, \quad (\text{A.2})$$

²⁹In 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 3 for further discussion). This has little impact on the estimates for local concentration.

³⁰Equation A.2 is taken from RST, with notation adjusted to match the notation in this paper.

where $s_{j\ell}^t$ is the sales share of industry j and location ℓ in the country at time t .³¹ While $\Delta HHI_{j\ell t}$ is the change in the revenue-based HHI in industry j and location ℓ 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 A.3, which subtracts the two measures of concentration from each other. After canceling terms the difference between the two measures is

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

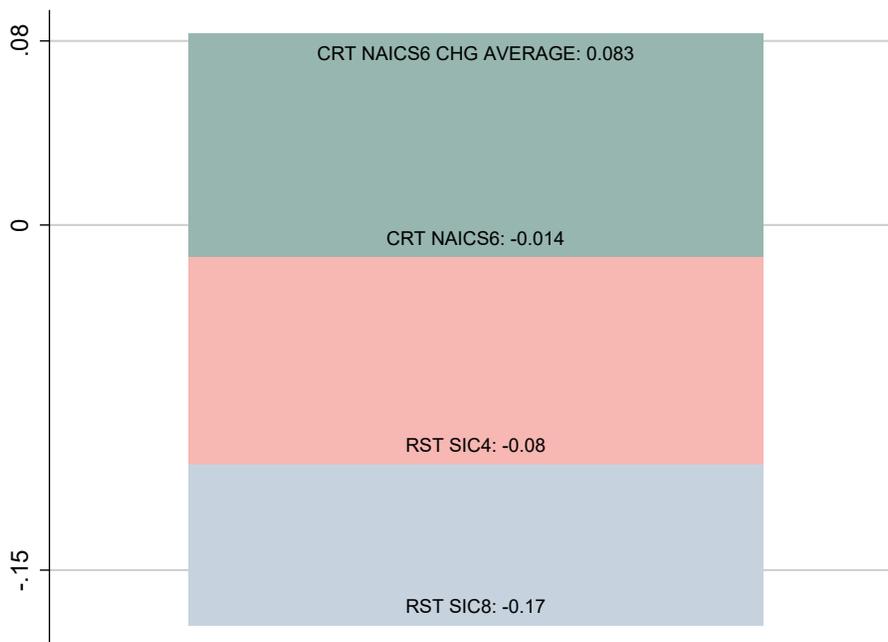
RST will weight markets that increase in size over time by more in the initial period, while those that decrease will be weighted less relative to our measure. As markets grow they become less concentrated on average, which results in RST weighting markets that were initially concentrated but grew (becoming less concentrated), more than markets that were initially unconcentrated, but shrank (becoming more concentrated).³²

Figure A.1 shows 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. All firms 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, the methodology used by RST would report a decrease in local concentration ($\Delta HHI = -1/6$), driven by the decrease in HHI of

³¹Note that RST weight markets by their employment share ($e_{j\ell}^t$), instead of their sales share ($s_i^{j\ell t}$). However, their data appendix shows that this has no effect on the results.

³²A similar point is made in Appendix E of Ganapati (2020) using LBD data.

Figure A.2: RST Comparison



Notes: Figure shows various estimates for the change in local HHI between 1992 and 2007. The estimates vary according to the data source, industry definition, and aggregation methodology. Lowest estimate corresponds to Rossi-Hansberg et al. (2020) estimate using SIC-8 industries. Next estimate corresponds to using SIC-4 industries. Next estimate corresponds to using CRT microdata and NAICS-6 industries (which are similar to SIC-4 industries). Next estimate computes indices under our aggregation methodology instead of that of Rossi-Hansberg et al. (2020).

make the comparison clear we define markets by industry throughout the exercise.³⁴ Overall, Figure A.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 vs NETS), industry definition (NAICS-6 vs 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

³⁴To 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.

implying a reduction of 8 percentage points in the local HHI. The next estimate reproduces RST’s methodology using microdata from the Census of Retail Trade. Changing from NETS to CRT data implies a further increase in the estimate of 6.6 percentage points, with the overall change suggesting a minor decrease of local HHI of 1.4 percentage points.³⁵ Next we change the weighting methodology to ours (as explained above). Doing so increases the estimated change of local concentration again (by 9 percentage points), implying an overall increase of local HHI of 8.3 percentage points.

Table A.1 provides a more detailed account of the estimates presented in Figure A.2, and also includes estimates of changes in local concentration for intermediate census years (1997, 2002, and 2007). In the first section, national concentration, we compare the numbers in RST (Figure 1b) to numbers calculated for three different samples. NAICS-based measures calculate concentration separately for all 6-digit industries in NAICS. Select NAICS calculates concentration for all 6-digit NAICS excluding auto dealers and auto-parts stores (441), gasoline stations (447), and non-store retailers (454). Finally, product-based measures calculate concentration for the eight major product categories defined in Section 4.2. In all four 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 in all cases.³⁶

The second portion of table A.1 compares concentration measured at the zip code level using RST’s weighting methodology as described above. Using their methodology we find evidence for slight decreases in local concentration. RST find local concentration falls by 17 percentage points, but we find it falls by less than two percentage points.

The final part of table A.1 compares concentration measured at the zip code level using our aggregation method. This aggregation method finds significant increases in local concentration across both samples. That is, the average dollar in 2012 is spent in a more

³⁵Part of this difference could be explained in theory by the inclusion of restaurants in SIC-4, however, the industry by industry results in RST figure 7 suggest that this is not the case because they find diverging trends in most retail industries.

³⁶The level of concentration is not provided in RST.

concentrated market than the average dollar in 1992.

Table A.1: Comparison of Concentration to RST

National Concentration					
	Level	Change from 1992			
	1992	1997	2002	2007	2012
RST	N/A	0.020	0.030	0.050	0.055
NAICS-based	0.029	0.017	0.056	0.076	0.087
Select NAICS	0.046	0.034	0.097	0.136	0.149
Product-based	0.015	0.006	0.027	0.040	N/A
Zip Code Concentration - End-of-Period Weights					
	Level	Change from 1992			
	1992	1997	2002	2007	2012
RST	N/A	-0.070	-0.100	-0.140	-0.017
NAICS-based	0.507	0.024	-0.018	-0.019	-0.014
Select NAICS	0.552	-0.021	-0.018	-0.015	-0.016
Product-based	N/A	N/A	N/A	N/A	N/A
Zip Code Concentration - Current Period Weights					
	Level	Change from 1992			
	1992	1997	2002	2007	2012
RST	N/A	N/A	N/A	N/A	N/A
NAICS-based	0.507	0.022	0.057	0.072	0.083
Select NAICS	0.552	0.026	0.067	0.083	0.083
Product-based	0.321	-0.015	0.020	0.033	N/A

Notes: Comparison of concentration numbers calculated using the Census of Retail Trade to Rossi-Hansberg et al. (2020). Numbers from RST taken from retail series in Figure 2. 1992 column contains the level of concentration, which is not available in RST. NAICS-based measures concentration calculated including all NAICS industries. Select NAICS drops subsectors 441, 447, and 454. Product-based measures calculate concentration for the eight major product categories. Retail in RST is defined using SIC codes which includes restaurants. Product-based measures with RST’s methodology have not been disclosed.

B Concentration Decomposition

The Herfindahl-Hirschman Index for the retail sector is given by the sales-weighted average of the product-HHI:

$$HHI^t \equiv \sum_{j=1}^J s_j^t HHI_j^t. \quad (\text{B.1})$$

The HHI for a given product can be decomposed into the contribution of local and cross-market concentration. This section provides additional details on the concentration decomposition. The decomposition starts from the probability that two dollars (x, y) are spent at the same firm (i), which gives the HHI at the national level:

$$HHI_j^t \equiv P(i_x = i_y; j, t) = \sum_{\ell=1}^L \sum_i (s_i^{j\ell t})^2. \quad (\text{B.2})$$

This probability can be divided into two terms:

$$\begin{aligned}
 P(i_x = i_y; j, t) &= \underbrace{P(i_x = i_y | \ell_x = \ell_y; j, t)}_{\text{Local Concentration}} \underbrace{P(\ell_x = \ell_y; j, t)}_{\text{Collocation}} \\
 &\quad \underbrace{\hspace{10em}}_{\text{Local Term}} \\
 &+ \underbrace{P(i_x = i_y | \ell_x \neq \ell_y; j, t)}_{\text{Cross-Market Concentration}} \underbrace{P(\ell_x \neq \ell_y; j, t)}_{\text{1 - Collocation}} \\
 &\quad \underbrace{\hspace{10em}}_{\text{Cross-Market Term}}
 \end{aligned} \quad (\text{B.3})$$

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:

$$P(\ell_x = \ell_y; j, t) = \sum_{\ell} (s_{\ell}^{j t})^2. \quad (\text{B.4})$$

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:

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

This probability can be further decomposed into a term due to the average number of firms in each market (location) and a term due to the inequality of shares across firms within a market:

$$\begin{aligned}
P(i_x = i_y | \ell_x = \ell_y; j, t) &= \sum_{\ell=1}^L s_\ell^{jt} \left(\frac{1}{N_\ell} + \sum_{k \in K_\ell} \left(s_k^{j\ell t} - \frac{1}{N_\ell} \right)^2 \right) \\
&= \underbrace{\sum_{\ell=1}^L s_\ell^{jt} \frac{1}{N_\ell}}_{\text{Average Number of Firms}} + \sum_{\ell=1}^L s_\ell^{jt} \underbrace{\sum_{i \in K_\ell} \left(s_k^{j\ell t} - \frac{1}{N_\ell} \right)^2}_{\text{Inequality of shares}}
\end{aligned}$$

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 such as Rinz (2018) and Lipsius (2018):

$$\text{HHI}_t^{\text{Local}} = \sum_j s_j^t \sum_{\ell} s_\ell^{jt} \sum_i (s_i^{j\ell t})^2 \tag{B.6}$$

The cross-market term is calculated as:

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

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

C Cleaning and Aggregating Product Lines Data

The Census collects data on establishment-level sales in a number of product categories. An example form is provided in Figure C.1. Many establishments have missing product line sales either due to them not responding to questions or because they do not receive a form.³⁷ In total, reported product lines data account for about 80 percent of sales. We develop an algorithm to impute data for missing establishments. This 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 establish 18 product categories detailed in table C.1. Of these 18 product categories, 8 categories that we label “Main” account for over 80 percent of sales of stores 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.

C.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. 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. We 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

³⁷Establishments of large firms are always mailed a form, but small firms are sampled.

Figure C.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	
1. Women's, juniors', and misses' wear (Report girls' and infants' and toddlers' wear on line 3 and footwear on line 4)	230 0220	231			232	
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

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.³⁸ After this procedure, we have sales by product category for all establishments that reported lines data. The resulting categories are listed in Table C.1.

C.2 Imputing Missing Data

For the remaining establishments we impute data using the NAICS 8 industry of the establishment, reported sales of other establishments of the same firm in the same

³⁸This procedure has a minimal effect on aggregate retail sales in each category.

Table C.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: Author created list of product categories. Main indicates that a product category is included in concentration calculations. Firm names for illustrative purposes based on industries reported to the SIC and do not imply that firm is in the analytical sample.

industry, and reported activity of the same establishment in other census years.³⁹ 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 from that source.⁴⁰

³⁹Reported product line sales are very similar across establishments of the same firm and the same establishment over time.

⁴⁰Retail sales include some sales to companies so it is expected that retail sales in a product category to exceed consumer spending on that category.

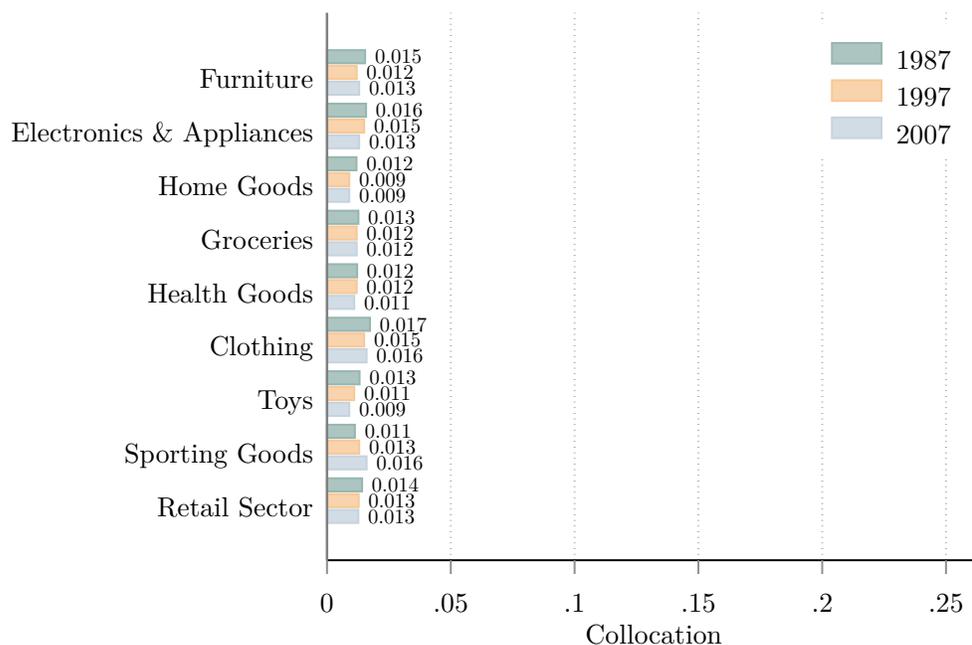
Where relevant, all sales are deflated using consumer price indexes. We use the food deflator for Groceries, Clothing and Apparel deflator for Clothing and the deflator for all goods excluding food and fuel for all other categories.

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.

D Additional Tables and Figures

Figure D.1 shows the collocation term by product category. The numbers are the probability that two random dollars are spent in the same commuting zone for each year. These numbers are small, less than 2 percent, and stable over time. There is also little variation across product categories because spending on product categories is approximately proportional to each market's size. These numbers form the weights for the local HHI in the decomposition of national concentration. Their small magnitude explains the limited role of local concentration in explaining national changes.

Figure D.1: Collocation Term Product Categories



Notes: The data are from the CRT microdata. Numbers are the collocation term for commuting zones which forms the weight for the local HHI in the decomposition of national concentration.

E Industry-Based Results

A central contribution of this paper is the creation of store-level sales by product category for all U.S. retail stores. This allows us to define competition based on products rather than industry-based measures. Industries, either NAICS or SIC codes, are regularly used to define markets. This approach is often necessitated by data availability and in many sectors is likely to be a good approximation (e.g. manufacturing).

This is not the case in the retail sector. The retail sector has one set of industries, general merchandise stores (NAICS 452), that compete with stores in many industries. By construction these industries are composed by establishment that sell many types of products. Thus, industry-based measures ignore the competition faced by stores selling a given product, coming from general merchandise stores. The measures we developed in Section 4 overcome this shortcoming.

Table E.1 presents industry-based and product-based concentration measures. There are two industry-based measures, the first one (NAICS-based) calculates concentration separately for all 6-digit industries in NAICS, while the second one (Select NAICS) calculates concentration for all 6-digit NAICS excluding auto dealers and auto-parts stores (441), gasoline stations (447), and non-store retailers (454). The product-based measure calculates concentration for the eight major product categories discussed in Section 4.2. As discussed above, each measure captures different concepts, as they define a market in a different way. These differences are more than just conceptual. The level of the different measures gives a different picture of how concentrated markets are. Product-based measures are about a third of the Select NAICS measure and half of the NAICS-based measure with all industries.⁴¹ Despite their differences all measures of concentration exhibit similar dynamics, with national concentration measures increasing five- to six-fold since 1982, and local concentration measures roughly doubling.

⁴¹The differences in level across concentration measures cross the different thresholds for concentration establish by the Justice Department.

Table E.1: Industry-Based and Product-Based Concentration Measures

National Concentration							
	1982	1987	1992	1997	2002	2007	2012
NAICS-based	0.019	0.029	0.029	0.046	0.085	0.105	0.116
Select NAICS	0.030	0.043	0.046	0.080	0.143	0.182	0.195
Product-based	0.010	0.012	0.015	0.021	0.041	0.055	
Local Concentration - Commuting zone							
	1982	1987	1992	1997	2002	2007	2012
NAICS-based	0.120	0.143	0.143	0.160	0.203	0.226	0.246
Select NAICS	0.155	0.184	0.191	0.222	0.279	0.313	0.326
Product-based	0.059	0.071	0.086	0.078	0.102	0.117	

Notes: All concentration measures correspond to average Herfindahl-Hirschman indices. NAICS-based measures are calculated including all NAICS industries. Select NAICS drops subsectors 441, 447, and 454. Product-based measures calculate concentration for eight major product categories. Product-based measures for commuting zones in 2012 have not been disclosed.

F 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. The model closes with a perfectly competitive sector that aggregates individual goods from each market into the national consumption good.

F.1 The Model Economy

The model economy contains L locations, in each of them there are J products being transacted in local markets. Each location has N_ℓ retail firms that compete with one another in each good. 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.

F.1.1 Technology

A retailer i selling product j in location ℓ produces using only labor through a linear technology. $z_i^{j\ell}$ represents the productivity of the retailer:

$$y_i^{j\ell} = z_i^{j\ell} n_i^{j\ell}. \tag{F.1}$$

Labor is immobile across locations, but not products, so each location has a specific

wage, w_ℓ . Firms maximize profits for each market they operate in:

$$\pi_i^{j\ell} = p_i^{j\ell} y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell}, \quad (\text{F.2})$$

where $\lambda_i^{j\ell} = w_\ell / z_i^{j\ell}$ is the marginal cost of production.

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_ℓ retail firms selling product j in location ℓ . The firm operates competitively using the following technology:

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

Then, the combined product bundles, y_j^ℓ , are themselves aggregated into local retail output, y_ℓ , through the following technology:

$$y_\ell = \prod_{j=1}^J \left(y_j^\ell \right)^{\gamma_j^\ell}; \quad \sum_{j=1}^J \gamma_j^\ell = 1, \quad (\text{F.4})$$

where γ_j^ℓ is the share of product j in retail sales in location ℓ

Finally, the national retail output is created by combining local output, y_ℓ , from the L locations in the country:

$$y = \prod_{\ell=1}^L \left(y_\ell \right)^{\beta_\ell}; \quad \sum_{\ell=1}^L \beta_\ell = 1, \quad (\text{F.5})$$

where β_ℓ corresponds to the share of location ℓ in national retail sales.

The aggregation process implies the following demand and prices:

$$y_\ell = \beta_\ell \frac{P}{p_\ell} \cdot y \quad P = \prod_{\ell=1}^L \left(\frac{p_\ell}{\beta_\ell} \right)^{\beta_\ell} \quad (\text{F.6})$$

$$y_j^\ell = \gamma_j^\ell \frac{p_\ell}{p_j^\ell} y_\ell \quad p_\ell = \prod_{j=1}^J \left(\frac{p_j^\ell}{\gamma_j^\ell} \right)^{\gamma_j^\ell} \quad (\text{F.7})$$

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

F.1.2 Pricing to market

Firms compete directly in the sales of each product in a given location. We assume that firms are aware of the effect of their choices $(p_i^{j\ell}, y_i^{j\ell})$ on the price and quantity of the product in the market they operate in (p_j^ℓ, y_j^ℓ) , but take as given the prices and quantities of other products in the same market, and of all products in other markets.

Firms choose either the price of their good $(p_i^{j\ell})$ or the quantity $(y_i^{j\ell})$ in a noncooperative fashion, taking as given the choices of other firms. We solve the pricing problem for Bertrand and Cournot competition (choosing prices or quantities respectively), as well as for the Dixit-Stiglitz monopolistic competition case, which serves as a useful framework.

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 that depends on the form of competition:*

$$\mu_i^{j\ell} = \begin{cases} \frac{\epsilon_j}{\epsilon_j - 1} & \text{if Dixit-Stiglitz monopolistic competition} \\ \frac{\epsilon_j - (\epsilon_j - 1)s_i^{j\ell}}{\epsilon_j - 1 - (\epsilon_j - 1)s_i^{j\ell}} & \text{if Bertrand competition} \\ \frac{\epsilon_j}{\epsilon_j - 1 - (\epsilon_j - 1)s_i^{j\ell}} & \text{if Cournot competition} \end{cases} \quad (\text{F.9})$$

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

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

We show details for the derivation in what follows.

Dixit-Stiglitz monopolistic competition The problem takes as given the product's price (p_j^ℓ) and aggregate demand (y_j^ℓ) . The objective is to maximize profits by choosing

the firm's price $(p_i^{j\ell})$:

$$\max_{p_i^{j\ell}} p_i^{j\ell} y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell} \quad \text{s.t.} \quad y_i^{j\ell} = \left(\frac{p_i^{j\ell}}{p_j^\ell} \right)^{-\epsilon_j} y_j^\ell$$

Replacing the constraint:

$$\max_{p_i^{j\ell}} \left[\left(p_i^{j\ell} \right)^{1-\epsilon_j} - \lambda_i^{j\ell} \left(p_i^{j\ell} \right)^{-\epsilon_j} \right] \left(p_j^\ell \right)^{\epsilon_j} y_j^\ell$$

The first order condition is:

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

$$0 = (1 - \epsilon_j) p_i^{j\ell} + \epsilon_j \lambda_i^{j\ell}$$

Rearranging gives the result:

$$p_i^{j\ell} = \mu_i^{j\ell} \lambda_i^{j\ell} \quad \mu_i^{j\ell} = \frac{\epsilon_j}{\epsilon_j - 1}$$

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

$$\begin{aligned} & \max_{p_i^{j\ell}} p_i^{j\ell} y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell} \\ \text{s.t.} \quad & y_i^{j\ell} = \left(\frac{p_i^{j\ell}}{p_j^\ell} \right)^{-\epsilon_j} y_j^\ell \quad y_j^\ell = \gamma_j^\ell \frac{p_m y_\ell}{p_j^\ell} \quad p_j^\ell = \left(\sum_{i=1}^N \left(p_i^{j\ell} \right)^{1-\epsilon_j} \right)^{\frac{1}{1-\epsilon_j}} \end{aligned}$$

Replacing the constraints:

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

The first order condition is:

$$\begin{aligned}
0 &= \left[(1 - \epsilon_j) \left(p_i^{j\ell} \right)^{-\epsilon_j} + \epsilon_j \lambda_i^{j\ell} \left(p_i^{j\ell} \right)^{-\epsilon_j - 1} \right] \left(\sum_{i=1}^N \left(p_i^{j\ell} \right)^{1 - \epsilon_j} \right)^{-1} \\
&\quad - (1 - \epsilon_j) \left[\left(p_i^{j\ell} \right)^{1 - \epsilon_j} - \lambda_i^{j\ell} \left(p_i^{j\ell} \right)^{-\epsilon_j} \right] \left(\sum_{i=1}^N \left(p_i^{j\ell} \right)^{1 - \epsilon_j} \right)^{-2} \left(p_i^{j\ell} \right)^{-\epsilon_j} \\
0 &= \left[(1 - \epsilon_j) p_i^{j\ell} + \epsilon_j \lambda_i^{j\ell} \right] - (1 - \epsilon_j) \left[p_i^{j\ell} - \lambda_i^{j\ell} \right] \left(p_i^{j\ell} \right)^{1 - \epsilon_j} \left(p_j^\ell \right)^{\epsilon_j - 1} \\
0 &= \left[(1 - \epsilon_j) p_i^{j\ell} + \epsilon_j \lambda_i^{j\ell} \right] - (1 - \epsilon_j) \left[p_i^{j\ell} - \lambda_i^{j\ell} \right] s_i^{j\ell}
\end{aligned}$$

Rearranging gives the result:

$$p_i^{j\ell} = \mu_i^{j\ell} \lambda_i^{j\ell} \quad \mu_i^{j\ell} = \frac{\epsilon_j - (\epsilon_j - 1) s_i^{j\ell}}{\epsilon_j - 1 - (\epsilon_j - 1) s_i^{j\ell}}$$

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

$$\begin{aligned}
&\max_{y_i^{j\ell}} p_i^{j\ell} y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell} \\
\text{s.t. } p_i^{j\ell} &= \left(\frac{y_i^{j\ell}}{y_j^\ell} \right)^{\frac{-1}{\epsilon_j}} p_j^\ell \quad p_j^\ell = \gamma_j^\ell \frac{p_\ell y_\ell}{y_j^\ell} \quad y_j^\ell = \left(\sum_{i=1}^N \left(y_i^{j\ell} \right)^{\frac{\epsilon_j - 1}{\epsilon_j}} \right)^{\frac{\epsilon_j}{\epsilon_j - 1}}
\end{aligned}$$

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:

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

Rearranging gives the result:

$$p_i^{j\ell} = \mu_i^{j\ell} \lambda_i^{j\ell} \quad \mu_i^{j\ell} = \frac{\epsilon_j}{\epsilon_j - 1 - (\epsilon_j - 1) s_i^{j\ell}}$$

F.1.3 Consumers

There is a representative consumer who has preferences over consumption of a national retail good, c . The consumer supplies labor inelastically in each location, with the local labor supply given by $\{n_\ell\}$.⁴² The consumer receives income from profits and wages. The consumer's problem is:

$$\max_{\{c\}} u(c) = \frac{c^{1-\sigma}}{1-\sigma} \quad \text{s.t.} \quad p \cdot c \leq \sum_{\ell} n_{\ell} w_{\ell} + \Pi. \quad (\text{F.11})$$

We normalize total labor supply, $n^S \equiv \sum_{\ell=1}^L n_{\ell}$, to one.

F.1.4 Equilibrium

The equilibrium of the model is standard and consists of a set of prices $\{P, \{p_{\ell}\}, \{p_j^{\ell}\}, \{p_i^{j\ell}\}\}$, wages $\{w_{\ell}\}$, outputs $\{y, \{y_{\ell}\}, \{y_j^{\ell}\}, \{y_i^{j\ell}\}\}$ and aggregate consumption demand, c , such that:

1. Aggregate prices and quantities satisfy F.6, F.7, and F.8.
2. Firm prices satisfy F.9, with the market share of each firm satisfying F.10.
3. Firm i 's labor demand is given by $n_i^{j\ell} = y_i^{j\ell} / y_i^{j\ell}$.
4. Wages are such that local labor markets clear, that is, for each ℓ :

$$n_{\ell} = \sum_{j=1}^J \sum_{i=1}^{N_{\ell}} n_i^{j\ell},$$

where $n_i^{j\ell} = y_i^{j\ell} / y_i^{j\ell}$ corresponds to firm i 's labor demand.

⁴²In appendix F.5 we extend the model to include elastic labor supply.

F.2 Aggregating Markups

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

F.2.1 Product-Location Level

The objective is to define an average markup for product j in location ℓ (μ_j^ℓ), as well as the average productivity of firms producing product j in location ℓ (z_j^ℓ).

Average Markup The average markup is given by the ratio between the price p_j^ℓ and product-market marginal cost λ_j^ℓ . Because of constant returns to scale λ_j^ℓ 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:

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

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:*

$$\mu_j^\ell = \begin{cases} \frac{\epsilon_j}{\epsilon_j - 1} & \text{if Dixit-Stiglitz monopolistic competition} \\ \frac{\epsilon_j}{\epsilon_j - 1} \left[\frac{1}{\epsilon_j - 1} \sum_{k=2}^{\infty} \left(\frac{\epsilon_j - 1}{\epsilon_j} \right)^{k-1} (HK_j^\ell(k))^k \right]^{-1} & \text{if Bertrand competition} \\ \frac{\epsilon_j}{\epsilon_j - 1} [1 - HHI_j^\ell]^{-1} & \text{if Cournot competition} \end{cases}$$

where $HK_j^\ell(k)$ is the Hanna & Kay (1977) concentration index of order k :

$$HK_j^\ell(k) = \left[\sum_{i=1}^N \left(s_i^{j\ell} \right)^k \right]^{\frac{1}{k}},$$

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

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

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

which implies:

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

an output-weighted harmonic mean of productivities.

F.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:

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

For productivity:

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

The same procedure gives the markup for the national level:

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

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

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

This expression does not follow as the others because the cost of production (w_ℓ) differs across markets.

Multi-product/Multi-market firm Note that the equations above also apply to firms that sell various products and operate in various markets, modifying the sums to account only for the firm's products and markets.

F.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 ($\ell = 1, \dots, L$). The average markup is given in the model by:

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

a harmonic mean of market level markups for product j , weighted by the share of product j sales in market ℓ 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:

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

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

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

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

F.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 4.2 and data on markups, prices, output, and labor supply. As in the empirical analysis of sections 3 and 4, we define markets in the model as pairs of a commuting zone and one of the product categories described in Table C.1.

The Cobb-Douglas parameters, β_ℓ and γ_j^ℓ , 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 (7) we get:

$$\hat{\epsilon}_j = \frac{\hat{\mu}_j [1 - \sum_\ell s_\ell^j HHI_j^\ell]}{\hat{\mu}_j [1 - \sum_\ell s_\ell^j HHI_j^\ell] - 1} \quad (\text{F.12})$$

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 (7).

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

$$P_j Y_j = \sum_\ell p_j^\ell y_j^\ell \quad (\text{F.13})$$

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

$$\lambda_j \equiv \sum_\ell \lambda_j^\ell \frac{y_j^\ell}{Y_j}. \quad (\text{F.14})$$

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

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

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:

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

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

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

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

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

where P is a retail price index satisfying:

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

Table F.1 reports the markups implied by the model given the elasticities of substitution estimated in Table 3 and the product-level HHIs computed from local concentration measures. The HHI measures are also reported.

F.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

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

Table F.1: Markups and Local Concentration Over Time

Product Category	1987		1997		2007	
	μ_j^{1987}	HHI_j^{1987}	μ_j^{1997}	HHI_j^{1997}	μ_j^{2007}	HHI_j^{2007}
Furniture	1.819	0.052	1.815	0.050	1.852	0.069
Clothing	1.808	0.049	1.812	0.051	1.812	0.051
Sporting Goods	1.442	0.067	1.604	0.162	1.672	0.196
Toys	1.607	0.112	1.544	0.075	1.672	0.146
Home Goods	1.442	0.068	1.419	0.053	1.508	0.109
Health	1.347	0.066	1.377	0.086	1.431	0.120
Electronics & Appliances	1.269	0.049	1.262	0.044	1.385	0.129
Groceries	1.328	0.093	1.357	0.112	1.412	0.147
Retail Sector	1.462	0.072	1.474	0.083	1.520	0.117

Notes: The data are authors' estimates of product markups using changes in product-level concentration over time. The retail sector markup is an expenditure share weighted harmonic average of the product categories. Herfindahl-Hirschman indexes are computed for each product category from CRT data following equation (7).

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 $j = 1, \dots, J$. 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 F.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:

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

We normalize the aggregate index so that $P_{1987} = 1$, and obtain the level in subsequent

⁴⁴The 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.

periods by concatenating the changes obtained in equation (F.20). As before the index provides the cumulative (gross) inflation in retail prices since 1987.

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

F.4 Discussion: Marginal Costs Functional Form

In the baseline model production at a retail uses only labor as an input. In this section we evaluate how our setup maps to the case where the firms uses an arbitrary constant-returns-to-scale technology that uses labor and other materials.

Consider the problem of retail firms that use multiple inputs $\{x_k\}_{k=1}^K$ in addition to labor to produce:

$$y_i^{j\ell} = \tilde{z}_i^{j\ell} F \left(x_1, \dots, x_K, n_i^{j\ell} \right), \quad (\text{F.21})$$

where the function F is strictly concave, twice continuously differentiable, and has constant returns to scale. Letting the prices of inputs be $\{\tilde{p}_k\}_{k=1}^K$ and \tilde{w}_ℓ respectively, we know from the firm's optimality condition that:

$$\tilde{z}_i^{j\ell} F_k \left(\frac{x_1}{n_i^{j\ell}}, \dots, \frac{x_K}{n_i^{j\ell}}, 1 \right) = \tilde{p}_k \quad (\text{F.22})$$

recalling that, because of Euler's theorem, F_k is homogeneous of degree zero for every k .

The equations defined by (F.22) define a square system in the ratio ratio of each input x_k to labor. The system has a solution that gives the ratios in terms of parameters:

$$\frac{x_k}{n_i^{j\ell}} = g_k \left(\tilde{z}_i^{j\ell}, \tilde{p}_1, \dots, \tilde{p}_K \right) \quad (\text{F.23})$$

The existence of a solution follows from the inverse function theorem applied to the function

$\nabla_x F : \mathbb{R}_{++}^K \rightarrow \mathbb{R}_{++}^K$, where the operator ∇_x gives the first derivatives of F with respect to the variables $\{x_k\}_{k=1}^K$. Note that the Jacobian of ∇F is given by the first K rows and columns of the Hessian of F , which is negative definite for all interior points by the strict concavity of F . The negative definiteness of the Jacobian ensures the invertibility of $\nabla_x F$.

Given the system's solution we express the production function in terms of labor alone:

$$y_i^{j\ell} = \tilde{z}_i^{j\ell} F \left(\frac{x_1}{n_i^{j\ell}}, \dots, \frac{x_K}{n_i^{j\ell}}, 1 \right) n_i^{j\ell} = z_i^{j\ell} n_i^{j\ell}$$

where we define the effective productivity of labor as $z_i^{j\ell} \equiv \tilde{z}_i^{j\ell} F(x_1/n_i^{j\ell}, \dots, x_K/n_i^{j\ell}, 1)$ with the ratios $x_k/n_i^{j\ell}$ given as in (F.23). Thus, z_i^j is a function of productivity $\tilde{z}_i^{j\ell}$ and the price of the other inputs. This is the production function we use in the main model.

Finally, the cost of labor must take into account that other inputs react to changes in labor according to (F.23). Then, the cost of the firm is given by:

$$\sum_{k=1}^K \tilde{p}_k x_k + \tilde{w}_\ell n_i^{j\ell} = \left(\sum_{k=1}^K \tilde{p}_k \frac{x_k}{n_i^{j\ell}} + \tilde{w}_\ell \right) n_i^{j\ell} = w_\ell n_i^{j\ell}$$

where $w_\ell n_i^{j\ell}$ represents the cost of goods sold, and w_ℓ is not directly the wage, but a measure of costs that takes into account the price of other inputs and the change in their demand in response to changes in the firm's labor demand.

F.5 Extension: Elastic Labor Supply

In this section we outline a version of the model where consumers have preferences over national consumption (c) and leisure/labor in each location: $u(c, n_1, \dots, n_L)$. This setup does not affect any of the results in the paper as all results using the markup equation go through unchanged.

We consider a utility function that is separable in consumption and labor:

$$u(c, \{n_\ell\}) = \frac{c^{1-\sigma}}{1-\sigma} - \chi \sum_{\ell=1}^L \frac{(n_\ell)^{1+\frac{1}{\phi}}}{1+\frac{1}{\phi}} \quad \text{and} \quad \chi c^\sigma (n_\ell)^{\frac{1}{\phi}} = \frac{w_\ell}{P}.$$

ϕ corresponds to the Frisch elasticity of labor supply. σ is the curvature of utility in

consumption.

The first order conditions of the consumer imply:

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

This governs how total labor supply reacts to changes in prices and changes in markups. These results affect how productivity and output respond to changes in prices.

F.6 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:

$$\begin{aligned} \max_{p_i^j} \quad & \sum_{\ell \in \mathcal{L}_i} \left[p_i^j y_i^{j\ell} - \lambda_i^{j\ell} y_i^{j\ell} \right] \\ \text{s.t.} \quad & y_i^{j\ell} = \left(\frac{p_i^j}{p_j^\ell} \right)^{-\epsilon_j} y_j^\ell \quad y_j^\ell = \gamma_j \frac{p_\ell y_\ell}{p_j^\ell} \quad p_j^\ell = \left(\sum_{i=1}^N (p_i^{j\ell})^{1-\epsilon_j} \right)^{\frac{1}{1-\epsilon_j}} \end{aligned}$$

Replacing the constraints:

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

The first order condition is:

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

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

Rearranging:

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

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

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

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:

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

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.