Concentration in Product Markets*

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September 2023

Abstract

This paper measures concentration in narrowly defined product markets for a broad range of consumer goods and services in the U.S. from 1994 to 2019. We document two main empirical facts. First, concentration levels are high. 44.4% of the markets in our sample are "highly concentrated" as defined by U.S. regulators. Second, market concentration has been decreasing since 1994. The median HHI falls from 2362 to 2045. These findings stand in stark contrast to the prior literature, which uses market definitions that are aggregated to a level that is typically too broad to accurately reflect competition in consumer markets.

Keywords: Concentration, antitrust

JEL classifications: L11, L40, D43

*We appreciate helpful comments from Pauline Affeldt, Sudipto Dasgupta, Rebecca Diamond, Chris Liao, Kate Reinmuth, Esteban Rossi-Hansberg, Chad Syverson, Michael Whinston, Tom Wollmann, Xinkai Wu, and Luigi Zingales. Julien Weber, Peyman Shahidi, Ishaan Singh, Jan Michael Krause, Anastasiia Malenko, Korinayo Thompson, Cathy Ruochen Wang, and Jia Wan provided outstanding research assistance. We are grateful for financial support from the Fama-Miller Center for Research in Finance at the University of Chicago Booth School of Business. Portions of this paper use data derived from a confidential, proprietary syndicated product owned by GfK US MRI, LLC which is © MRI-Simmons 2021.

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1 Introduction

Industry concentration measures are a key input used in antitrust enforcement and a barometer that many economists employ for assessing the level of competition in a market. As such, there is widespread interest in aggregate summary measures of concentration across many markets and over time. A key challenge in measuring concentration is market definition. Due to data availability, the vast majority of the prior literature has relied on production-based market definitions from the Census. The central innovation in this paper is to construct concentration measures that instead reflect narrowly defined economic product markets as would be defined in an antitrust setting or in an industry study in Industrial Organization (IO), over a broad range of consumer goods and services and over a long time frame. Importantly, our concentration measures also account for cross-brand ownership, and include imports.

Using these market definitions, the paper has two main empirical findings that are new. First, concentration levels are high. The median market HHI in our data is 2279. We find that in 10.6% of markets the HHI exceeds 5000. These levels are much higher than those reported in the prior literature using data from the Census and Compustat. However, in addition, in stark contrast to the prior literature, we find that median concentration has been *decreasing* since 1994. The magnitude of the decrease is 317 HHI points. The prior literature using Census data reports extremely low and increasing concentration levels.

The most widely cited evidence in the prior literature comes from establishment level data from the U.S. Economic Census using six digit North American Industrial Classification System (NAICS) codes.[1] Similar trends have been demonstrated using IRS data (Kwon, Ma and Zimmermann, 2023) firm level data for public firms from Compustat (Grullon, Larkin and Michaely, 2019; Gutiérrez and Philippon, 2017). The perception that there have been broad-based increases in concentration is also commonplace among politicians and in the popular press.[2] Such measurements have also provided intellectual support for calls for regulatory reform and more aggressive antitrust enforcement.[3] In

[1]Peltzman (2014), CEA (2016), Economist (2016), Barkai (2016), Autor et al. (2020), Ganapati (2020), Covarrubias, Gutiérrez and Philippon (2020)

[2]See Shapiro (2018) for an excellent discussion. Early examples include CEA (2016) and Economist (2016).

[3]`https://www.ftc.gov/system/files/ftc_gov/pdf/Remarks%20of%20Chair%20Lina%20M.%20Khan%`

the academic literature, increasing concentration has been linked to declining labor and capital shares,[4] declining investment and productivity growth,[5] and rising markups.[6]

However, as outlined in detail in Shapiro (2018), there are many problems with drawing antitrust conclusions from Census data. For antitrust purposes, economists are concerned with the ability of firms to raise prices. Antitrust markets are thus defined based on product substitutability for consumers, using own and cross price elasticities. In contrast, the Census lumps products together that are physically similar and that are produced using similar processes, anywhere in the U.S. A good example of the difference in the two definitions is metal cans, glass bottles, and plastic bottles. Since Census industries are defined based on production and not consumption, all metal cans are in the same Census industry, including soda cans, aerosol cans, paint cans, and many others. Meanwhile, all glass bottles are a separate industry, and plastic bottles a third. These groupings do not make sense for antitrust purposes because paint cans are not a substitute for soda cans, but plastic and glass soda bottles are. Census industry definitions are also often too broad. Even at the six-digit level, for example, NAICS 325620 contains at least 42 different industries, including after-shave, deodorant, mouthwash, cosmetics, sunscreen, and hair dye. NAICS 336120 includes all of heavy trucks, buses, garbage trucks, tractors, fire engines, and motor homes.[7] Section 3.3.3 shows more thoroughly how this issue heavily compromises concentration measures for many economic markets.

Census data also do not account for imports (including offshore production by domestic firms), whose share of the U.S. economy has been rising. Finally, as noted in Rossi-Hansberg, Sarte and Trachter (2020), Census industries are defined nationally, but many products are delivered locally and are not transportable. Cable TV is a good example in which national concentration has increased over the past few decades, but this is misleading because local concentration, the relevant statistic for consumers, has decreased. All of these issues are even more present in the Compustat data, which only

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[4]Autor et al. (2020), Barkai (2016)

[5]Gutiérrez and Philippon (2017)

[6]CEA (2016), Barkai (2016), Grullon, Larkin and Michaely (2019), De Loecker, Eeckhout and Unger (2020)

[7]NAICS 325620 and 336120 are two of many NAICS markets for which the 5-digit and 6-digit codes are the same. These are the most disaggregated codes available for these markets.

covers public firms and does not segment firm level sales into different product markets.

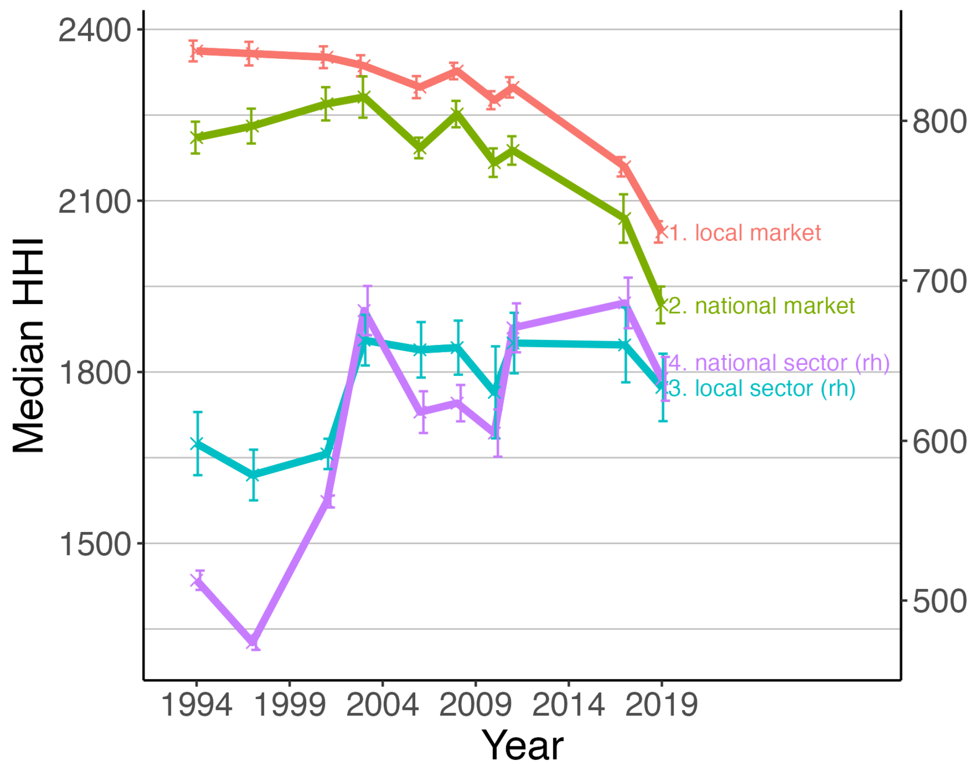
An early paper on this topic by Peltzman (2014) says, “One clear question for further research is whether concentration in economic markets has increased... along with the increased concentration in Census Bureau industries.” This paper examines exactly this issue. We utilize respondent level data for 1994-2019 from an annual consumer survey available from MRI-Simmons (MRI). The MRI data report consumers’ brand choices across 475 product markets, representing both goods and services.

The U.S. Horizontal Merger Guidelines suggest identifying the smallest market within which a hypothetical monopolist could impose a "small but significant non-transitory increase of price" (SSNIP). Such an exercise requires a detailed analysis of product level data on quantities and prices over time, and would be extremely costly to implement across such a large number of markets. Instead this paper employs markets defined by a prominent market research data firm (MRI) whose data are widely used in industry. The market definitions seem close to what might result in an antitrust setting (more details in section 2 below). In contrast to the Census, the survey data naturally include imported products. Because the survey data contain location data for each consumer, we are also able to measure concentration in geographic sub-markets, an important distinction for products that are delivered and consumed locally.

Another difficulty in measuring concentration across many markets and such a long time period is accounting for joint corporate parent ownership of brands. Many firms own multiple brands in a given product market, and brand ownership changes over time with corporate divestiture and M&A activity, so measuring corporate brand ownership is important to accurately estimate the levels and time trends of product market concentration. We solve this problem by merging the MRI survey data with newly assembled data on brand ownership over time.

Figure 1 presents the median HHI concentration measure over time for four market definitions that differ in their level of geographic and product aggregation. At the local market level, which accounts for the geographic location of consumers in 29 state-groups, the median HHI over all periods is 2279. 44.4% of industries have an HHI above 2500, the level that is considered “highly concentrated” in the U.S. Horizontal Merger Guidelines. The level of concentration is only slightly lower when markets are aggregated to the

Figure 1: Median HHI over time, by market definition



Notes. Local markets are defined as product markets in each of 29 state groups. Sectors are defined by aggregating related national product markets. Product market measures are on the left hand side axis. Sector level measures are on the right hand side axis. Error bars are 95% CIs, based on standard errors from a nonparametric bootstrap.

national level. While it is well known that high concentration does not necessarily imply weak competition, using the MRI data, this simple antitrust screen would flag many markets for further scrutiny.[8]

Applying the same simple antitrust screen to the Census data would lead to the opposite conclusion: that the vast majority of U.S. product markets are highly unconcentrated and therefore likely to be fairly competitive. Autor et al. (2020) report average HHIs from the Census ranging from a low of about 85 in the Services sector in 1987 to a high of 950 in manufacturing in 2007. Even the stricter pre-2010 merger guidelines would have labeled all of these markets as "unconcentrated".[9] If we were to take seriously the concentration measures computed from the Census, then one conclusion would be that the scope for antitrust policy in the U.S. is likely very narrow, regardless of its upward trend.

We find that the decreases in concentration over time are broad-based. Importantly, concentration in the most concentrated industries has fallen as fast or faster than in the median industry. In our data the number of industries in the "highly concentrated" range fell from 47.1% in 1994 to 39% in 2019. This finding is particularly interesting because it contradicts the prevailing popular opinion (Shapiro, 2018). We speculate that popular perception may be driven by the rapid growth and rise in prominence of firms such as Alphabet, Apple, Amazon, and Meta, as well as a few high profile mergers in industries such as hospitals (Gaynor, 2018) and airlines.[10]

We also find that local concentration decreases at a similar rate to national concentration. The latter result conforms with the main finding in Rossi-Hansberg, Sarte and Trachter (2020), who show that local market concentration has decreased in the establishment data from NETS. However, Rossi-Hansberg, Sarte and Trachter (2020) find increased national concentration in the NETS data even for the most narrow industry classifications,

[8]Our findings on concentration levels parallel Affeldt et al. (2021), who show that concentration levels are much higher than in production data using a sample of market-years in Europe that experienced a merger investigation by the European Commission.

[9]In 2010 the "unconcentrated" range was raised from <1000 to <1500 to reflect practice as detailed in Shapiro (2010).

[10]The U.S. domestic air travel industry saw mergers between US Airways and America West in 2005, Delta and Northwest in 2008, United and Continental in 2010, Southwest and Airtran in 2011, American and US Airways in 2014, and Alaska Airlines and Virgin America in 2018.

in contrast to our findings.[11]

When product markets are aggregated into broader sectors, our findings reverse: we find increases in concentration over time. After accounting for geographic location at the state level, the rise in concentration at the sector level is small. We find little evidence of firms entering adjacent geographies, as can be seen by the fact that the trends in local and national HHIs at the market level are nearly identical. Our sector level measurements are more consistent with the results in existing work using establishment level data such as Census,[12] likely because the sector level of market aggregation matches the establishment data more closely.

Given the novelty of our data and the contrast between our results and the Census data, we have attempted to verify the external and internal validity of our findings. A weakness of the MRI data is that they are focused on consumer facing product markets, including some services. Purely intermediate goods are largely missing. To evaluate the extent to which our findings are driven by market coverage, we compare our results to those from a sub-sample of the Census data that is industry matched to the MRI data. Concentration in this sub-sample in the Census data has the same overall trend as that in the complete Census data, suggesting that our different findings are due to market definitions, and not market coverage. We further compare MRI and Census concentration measures for a subset of the matched markets. We show that there is a very large difference in concentration measures between the two data sets at the market level, and that this difference mostly results from Census markets being too broadly defined to well reflect consumer product markets. We argue that the MRI data appear to provide more credible measures of concentration at the market level. Another weakness of the MRI data is that they are based on surveys rather than actual transactions. To validate the survey data we compared the MRI data with detailed data from industry sources for two industries: airlines and automobiles. For both industries, concentration in the MRI data closely matches the industry sources in both levels and trends, which gives us confidence that our results are not driven by idiosyncrasies in the survey.

[11] Smith and Ocampo (2021) also document increasing concentration at both the local and national levels in retail markets through 2012.

[12] Grullon, Larkin and Michaely (2019), Barkai (2016), Autor et al. (2020), Covarrubias, Gutiérrez and Philippon (2020)

Another potential issue is the product market definitions. Product markets in the MRI data are defined to suit the needs of the client firms who purchase data on their competitors' sales. Close inspection of the data yields the conclusion that the market definitions appear to be reasonable facsimiles of what might result from an antitrust proceeding. The only feature that stands out is that a handful of the market definitions are quite narrow. For example, domestic and imported beer are different product markets in the MRI data, as are diet and regular sodas. If the MRI market definitions are too narrow then that could bias us toward finding higher concentration levels overall, but it is not obvious that it would systematically affect the estimates of trends. Moreover, it seems plausible that formal antitrust proceedings might result in these narrow market definitions.

2 Data

2.1 Extracting product information from MRI-Simmons survey

We use respondent level data from the annual "Survey of the American Consumer" available from MRI-Simmons, a market research firm.[13] MRI surveys approximately 25000 consumers per year in a rolling fashion. We use data from 1994 to 2019. From the survey, we extract all questions that ask consumers to report brands that they purchase. For example, under "Motor oil" in the 2006 survey, the MRI data allows consumers to report purchases of 21 different brands of motor oil, such as Valvoline, Castrol, Amoco, Havoline, and Chevron, as well as an "Other" option. In total, we extract brand purchase information for 475 products; we will call these "product markets".

The main results of the paper are compiled for a balanced panel of 336 product markets that covers a broad range of consumer products markets, including services. A weakness of the MRI data is that they do not cover intermediate goods. The data cover most traditional packaged goods markets such as foods (e.g. chewing gum, butter, pickles), beverages (e.g. brandy, gin, soft drinks, instant coffee), health products (e.g.

[13]The firm administering the survey has been previously known as Mediamark Research Inc (MRI) and GfK MRI.

cold and sinus remedies, contact lenses, toothpaste), and non-food home products (e.g. diapers, luggage, light bulbs, writing instruments, glues). However, the data also cover airlines (domestic and international), auto products, car rental (business and leisure), electronics markets, credit cards, investment brokerage firms, real estate agents, hotels, auto insurance, life insurance, medical insurance, and restaurants (family and fast food), as well as several categories of retail markets. See A.2 for a full list of markets in the balanced panel. The unbalanced panel also covers many important new consumer markets, such as wireless handsets and search engines, that appeared after the beginning of our sample.[14] In appendix C we report results separately for the unbalanced panel and show that all of the main results of the paper are robust to this change.

We divide product markets into 19 broader groups, such as "Home products – Food" or "Airlines"; we will call these broader groups "sectors". Table 1, which we describe below, lists all the sectors in our data, the number of product markets in each sector, and examples of product markets within each sector. We categorize sectors into manufacturing and non-manufacturing. The non-manufacturing sectors are airlines, car rental, financial, hotels, insurance, retail, and restaurants. The data tend to cover many product markets within manufacturing sectors, and fewer within non-manufacturing sectors. Our main results include both the manufacturing and non-manufacturing sectors. For robustness, we also report results separately for the manufacturing and non-manufacturing sectors.

Finally, the MRI data list the zip code of each consumer in the sample, allowing us to compute market shares for local markets as well as national markets.

In addition to brand purchase information, the survey asks respondents for demographic information, in particular, the state-group that respondents live in. There are 29 state-groups; large states are reported separately, but some less populated states that are close together are grouped together, such as Minnesota/Iowa, Nebraska/Kansas, Arkansas/Louisiana/Oklahoma. We use state-group information so that we can calculate product purchases at the level of state-group-markets. Further details of data cleaning are described in appendix A.

MRI data are well known in industry and commonly employed in media planning.

[14] Note that several newer tech markets, such as search engines, are free to consumers and therefore not covered by the Census.

Table 1: Descriptive Statistics

Sector	# Markets	# Brands	# Owners	Matched brands %	Matched marketshare %	Example markets
Airlines	2	29.2	20.7	95.4	99.2	DomesticTravelAirlinesused, ForeignTravelAirlinesUsed
Apparel	2	39	29.5	90.6	96.6	AthleticShoesBrandsBought, WomensLingerieUndergarments
AutoProducts	15	191.8	96.1	87.6	96.6	AirFilters, WindshieldWipers
Automobile	2	53.8	31.1	92.5	99.3	AutomobilesAndOtherVehiclesManufacturer, MotorcyclesMake
Beverages	35	485.6	183	83.2	94.3	BottledWaterSeltzer, Vodka
CarRental	2	16.4	5	95	98.3	CarRentalBusinessUse, CarRentalPersonalUse
Electronics	7	90.3	54.8	90.8	97.4	Batteries, TelevisionSetsBrands
Entertainment	1	9	5.6	92.2	97.9	CruiseShipsCruiseLinesUsed, CruiseShipsCruiseLinesUsed
Financial	3	43.4	26.4	94.2	99.3	CreditCards, RealEstateWhichAgentUsed
Health	63	1,170.1	251.4	87.7	95.0	AdhesiveBandages, WartRemovers
HoProdChild	17	107.2	32.6	93.1	98.5	BabyBathWashAndSoap, VitaminsForChildren
HoProdFood	126	1,703.4	440.8	84.9	94.4	AmericanPasteurizedProcessedCheese, Yogurt
HoProdNonfood	43	499.2	160.7	84.5	94.4	AirFreshenersCarpetRoomDeodorizers, WritingInstrumentsBrands
HoProdPets	7	119.3	40.2	78.3	88.1	CannedWetCatFood, PackagedDryDogFood
Hotels	1	37.1	19	93.7	94.6	HotelsMotelsWhereStayed, HotelsMotelsWhereStayed
Insurance	4	99.4	56.8	92.5	98.5	AutoInsurance, MedicalInsuranceCompanies
Restaurants	2	115.5	94.5	90.7	95.8	FamilyRestaurantsSteakHouses, FastFoodDriveInRestaurants
Retail	3	72.2	62.2	90.1	96.7	ConvenienceStoresTimesShopped, DepartmentClothingSpecialtyStoresTimesShopped
Shipping	1	5.2	5.2	81.8	92.8	OvernightPackagesLetterDeliveryServicesServicesUsed

Notes. Summary statistics by sector. All numbers are averaged by year. "# markets" is the number of product markets in the sector. "# brands" and "# owners" are respectively the total number of brands and owners within a sector. "Matched brands %" and "Matched marketshare %" are, respectively, the number of brands and fraction of market share matched to owners. "Example markets" shows examples of markets within the sector

Gentzkow and Shapiro (2011) use the MRI data to measure ideological segregation in news consumption. Crawford and Yurukoglu (2012) use the MRI data to estimate demand for cable television services. Bertrand and Kamenica (2018) use MRI to document similarity in consumption between different demographic groups over time.

2.2 Brand ownership information from Kantar Adspender

We derive brand ownership information by merging MRI brand names to Kantar Adspender. Kantar Adspender is a database that tracks brands' advertising expenditures across different advertising media. We digitized hard copies of Kantar Adspender for the years 1992, 1997, 2001, 2003, 2006, and downloaded data from Kantar Adspender in 2017 and 2020.[15] Kantar Adspender contains data on advertising expenditures; the brand name advertised, and the ultimate parent company of the brand. For the pre-2016 data, only a single parent company name is available. For the 2017 and 2020 data, there are a number of different ownership fields: "ultimate parent", "parent", "subsidiary", and "advertiser". We use the "ultimate parent" field.

For each of the years in which we see Kantar Adspender, we merge the corresponding year of the MRI data to Kantar Adspender. The only exceptions are that we merge the 1992 Adspender to the 1994 MRI and the 2020 Adspender to 2019 MRI. We merge the Adspender by brand name using a two-stage fuzzy string-matching algorithm that we describe in detail in appendix A.2. We are able to match over 80% of brands in most sectors to an ultimate parent, and over 90% of market share for all sectors other than pet products (see table 1). The brand matching allows us to tell when different brands are owned by the same ultimate owner. For example, while the 2006 data reports 22 different brands of motor oil, most of these brands are owned by three companies: Chevron-Texaco, Exxon Mobil, and Royal Dutch Shell.

There is a nontrivial amount of brand co-ownership in our data. The average brand owner in our data set owns 2.89 brands. The brand ownership distribution is highly

[15]Kantar Adspender has historical information about advertising expenditures, but brand ownership information is backfilled: brands advertised in earlier years are assigned to their most recent ultimate owner. Using historical hard copies of Adspender allows us to circumvent this problem. However, the hard copies are unavailable after 2006. We found electronic reports for 2008, 2010, and 2011.

skewed, with 76.43% of owners owning only one brand, whereas the largest brand owner owns 262 brands. Ownership across product markets is also nontrivially large: the average owner owns brands across 2.06 product markets. 25.24% of brand owners own brands across at least 2 markets.

Tables 2 and 3 show the largest brand owners for different years, for manufacturing and non-manufacturing separately. For manufactures, some of the largest owners are Procter & Gamble, Kraft Heinz, Unilever, Johnson & Johnson, and Clorox. For non-manufactures, largest owners include Visa, State Farm, and Blue Shield.

Of the Fortune 100 companies in 2019, 58 appear as parent companies in the balanced panel of markets, and a total of 71 appear in the unbalanced panel of markets. Some large technology companies such as Microsoft and Apple are present in the balanced panel. Alphabet, Amazon, and Meta, which were all founded after the beginning of the sample, are present in the unbalanced panel. Other Fortune 100 companies in the sample include airlines such as United and Delta, insurers such as Geico, State Farm, and Humana, retailers such as Target and Costco, media and telecom firms such as Comcast, Disney, and Verizon, financial firms such as JP Morgan Chase and Bank of America, and other manufacturers such Coca Cola, General Motors, Nike, and Pfizer. Consistent with our data focusing on consumer markets, examples of Fortune 100 companies that do not appear in our sample are Boeing, Caterpillar, Lockheed Martin, and Oracle.

2.3 Computing market shares

The MRI data contain indicators for whether consumers have purchased a given brand, but typically do not provide quantity or expenditure information. As a workaround, we compute market shares assuming that if a customer purchases multiple products in one market, she purchases the same quantity of each product.

Let B_{mo} represent the set of brands owned by owner o in market m, let I_s represent the set of customers living in state-group s, and let I represent the set of all consumers. The market share of owner o in state-group s, market m, time t, is:

$$s_{omst} = \frac{\sum_{b \in B_{mo}} \sum_{i \in I_s} e_{ibmt}}{\sum_{o} \sum_{b \in B_{mo}} \sum_{i \in I_s} e_{ibmt}} \tag{1}$$

Table 2: Top 10 brand owners by year, manufacturing sectors

rank	1994	2003	2017
1	procter & gamble co	altria group inc	procter & gamble co
2	philip morris cos inc	procter & gamble co	kraft heinz co
3	unilever nv	unilever	unilever
4	conagra inc	conagra foods inc	johnson & johnson
5	johnson & johnson	pepsico inc	conagra brands inc
6	nestle sa	general mills inc	general mills inc
7	campbell soup co	clorox co	clorox co
8	johnson sc & sons inc	johnson & johnson	pepsico inc
9	clorox co	reckitt benckiser plc	nestle sa
10	heinz hj co	nestle sa	sc johnson & son inc

Notes. Ranking is determined by the total number of consumer purchases in the MRI data in the relevant year.

Table 3: Top 10 brand owners by year, non-manufacturing sectors

rank	1994	2003	2017
1	sears roebuck & co	state farm mutual auto	visa usa inc
2	state farm mutual auto	wal-mart stores inc	state farm mutual auto
3	k mart corp	visa usa inc	blue cross & blue shie
4	visa international	home depot inc	home depot inc
5	wal-mart stores inc	blue cross & blue shie	mastercard intl inc
6	pepsico inc	yum brands inc	lowes cos inc
7	blue cross & blue shie	allstate corp	wal-mart stores inc
8	southland corp	mcdonalds corp	allstate corp
9	mcdonalds corp	mastercard intl inc	berkshire hathaway inc
10	mastercard internation	cendant corp	seven & i holdings co

Notes. Ranking is determined by the total number of consumer purchases in the MRI data in the relevant year.

where e_{ibmt} is an indicator variable, for whether customer i reports purchasing brand b in market m at time t. The national market share of owner o in market m, time t, is:

$$s_{omt} = \frac{\sum_{b \in B_{mo}} \sum_{i \in I} e_{ibmt}}{\sum_{o} \sum_{b \in B_{mo}} \sum_{i \in I} e_{ibmt}} \tag{2}$$

We can also aggregate to the higher level of sectors, which we will index by k. Let M_k represent the set of markets in sector k. The national market share of owner o in sector k, time t is:

$$s_{okt} = \frac{\sum_{m \in M_k} \sum_{b \in B_{mo}} \sum_{i \in I} e_{ibmt}}{\sum_{o} \sum_{m \in M_k} \sum_{b \in B_{mo}} \sum_{i \in I} e_{ibmt}} \tag{3}$$

Using each of these market shares, we can then compute concentration metrics at the level of state-group-markets, national markets, state-group-sectors, and national sectors.

The MRI data includes a number of choices such as "Other" or "Store brand," that may correspond to multiple brands. For our baseline results, we include "Other" and "Store brand" in the denominator when calculating the shares (1), (2) and (3), but do not include them as owners, which is puts downward pressure on estimated concentration levels. Essentially, this is akin to assuming that "Other" and related options constitute a continuum of infinitely small brands. In a robustness check, we treat "Other" or "Store brand" as single brands. This increases measured concentration levels slightly but does not have a large affect on measured trends.

2.4 Linking Brand Owners Over Time

There is no time persistent ultimate owner key in the Kantar dataset. Thus, we link brand owners over time through a combination of brand string fuzzy-merging and manual checking. We first fuzzy-merge brand names for each product market over consecutive years. We then construct a candidate mapping of owner names in consecutive years by applying a threshold rule for large brands in common: if owner o_1 in 2019 owns a certain percentage of common brands to owner o_2 in 2017, we infer that owner o_1 and o_2 are likely the same owner. This methodology also allows us to detect brand owners' involvement in four kinds of market structure shifts: entries, exits, mergers and acquisitions, and divestitures; for example, if owner o_3 in 2019 owns all brands owned by owners o_1 and o_2 in 2017, we infer that o_1 and o_2 merged between 2017 and 2019. We then manually checked and edited the candidate assignment of owners over time, and the designation of owners to different market structure shifts.

2.5 Computing HHIs

The HHI is a convex function of market shares, which introduces an upward bias to HHIs calculated using unbiased finite-sample estimates of market shares. To account for this, all HHIs we report in the paper are adjusted using a nonparametric bootstrap procedure to correct for finite-sample bias, which we describe in appendix A.3. The bias adjustment reduces the estimates of state-group-product market HHIs by around 153 points (out of 10,000), but has negligible effects on HHI estimates at other levels of aggregation.

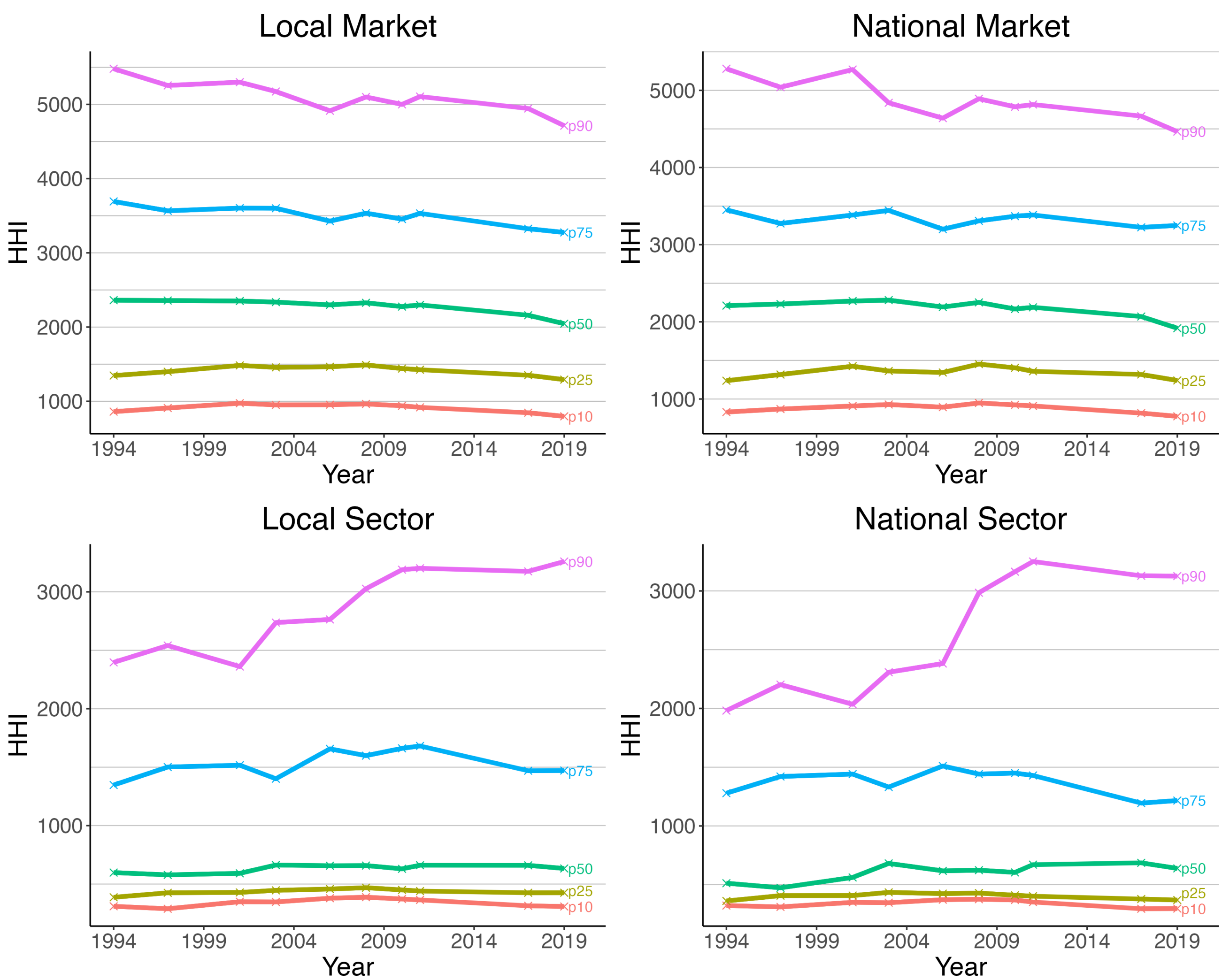
3 Results

Figure 2 shows the distribution of HHI's in our data at the state-group-market ("local market"), national market, state-group-sector ("local sector"), and national sector level over time. The DOJ-FTC 2010 Horizontal Merger Guidelines define industries with HHIs between 1500 and 2500 as "moderately concentrated," and above 2500 as "highly concentrated." According to the guidelines, proposed mergers that would raise the HHI in moderately or highly concentrated industries often warrant scrutiny.[16]

We find much higher concentration levels than those measured using production data. The median HHI in local product markets during the whole period is 2279, which is at the high end of the Guidelines' "moderately concentrated" range. An average of 44.4% of industries fall in the "highly concentrated" range. For comparison, Keil (2017) reports a median HHI of 450 between 1990 and 2012 using data from the Economic Census. Autor et al. (2020) report average HHIs from the Census ranging from a low of about 85 in the Services sector in 1987 to a high of about 950 in manufacturing in 2007. All of these numbers are deemed "unconcentrated" in the Merger Guidelines. Accounting for brand

[16]Nocke and Whinston (2020) demonstrate that changes, rather than levels, in HHI are more informative for unilateral merger effects in commonly used demand and conduct models.

Figure 2: HHI percentiles for different market levels over time



Notes. Percentiles of HHI over time, at the state-group-product market (top left), product market (top right), state group-sector (bottom left), and sector (bottom right) levels.

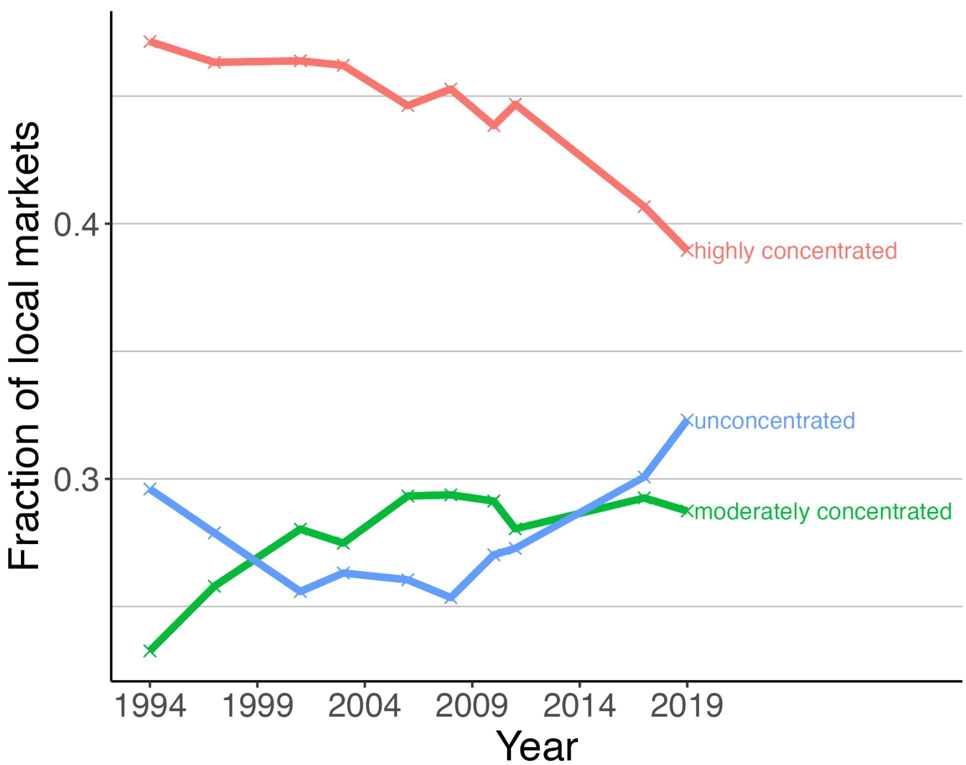
co-ownership also makes a large difference. While not the main focus of their paper, Neiman and Vavra (2018) report average HHIs of about 30 for categories in the Nielsen scanner data, not accounting for multi-product firms.

Still focusing on local product markets, the most noticeable change in the distribution of HHIs is that concentration has fallen over time – the median HHI fell from 2362 in 1994 to 2045 in 2019. Importantly, concentration fell even more in the most concentrated industries than in the median industry. The 90th percentile HHI fell from 5481 in 1994 to 4713 in 2019, while the 75th percentile fell from 3693 to 3275. Figure 3 shows that the fraction of firms in the "highly concentrated" range fell from 47.1% in 1994 to 39% in 2019. Thus, while we find very high concentration levels in a wide variety of industries, particularly in 1994, according to our data there has been substantial improvement over time. These results stand in stark contrast to the prevailing popular opinion that increases in concentration in the U.S. have been large and widespread (Shapiro, 2018).

While our findings above well represent the overall trends for much of the consumer economy, every individual product market and sector is different. Figure 4 shows local market HHI trends by sector. We weight markets according to the number of survey respondents in the market; results are not substantially different under equal weighting, and in later sections we show that results are similar when we weight markets according to approximate expenditure weights derived from the Consumer Expenditure Survey. The HHI in new automobiles, which account for roughly 3% of consumer expenditure, fell from 2506 to 1325. The largest increase in HHI is in the car rental market, where the HHI grew from 1451 to 3788. More generally, we see many manufacturing sectors experiencing a decrease in local market HHI, whereas most non-manufacturing sectors experience no substantive change (Financial and Car Rental being exceptions).

Figure 5 plots the local product markets that experienced the largest changes. The markets with the largest HHI decreases generally experienced growth in new brands or a shift of market share to store brands, rather than spreading of share among existing brands. For example, in glue, Gorilla Glue entered the market in 1999 and increased its market share to above 30% in 2019, accounting for a large fraction of the decrease in share by the dominant brands Elmer's and Krazy, both owned by the same parent. We also observe the parent of the Gorilla Glue company entering into other product markets such

Figure 3: Fraction of local markets by concentration



Notes. The fraction of local markets by their level of concentration: highly concentrated (HHI higher than 2500), moderately concentrated (HHI between 1500 and 2500), and unconcentrated (HHI lower than 1500).

as skin care by 2019. The decrease in concentration in rubber gloves is due to entry by Proctor and Gamble with the introduction of Mr. Clean brand gloves.[17] By 2019, this brand took significant market share from market leader Playtex brand.

The markets with the largest increase in HHI feature increases due to merger activity as well as a concentration of share into the highest selling brands. For example, among the largest increasing markets are car rental, dry cake mixes, and condoms. Doane et al. (2018) documents a series of mergers in the car rental industry. The increase in concentration for dry cake mixes is driven by the 2000 acquisition of Pillsbury by General Mills group.[18] The driver in condoms was through growth of the share of the top brand Trojan during this time period.

3.1 Decomposition of HHI changes

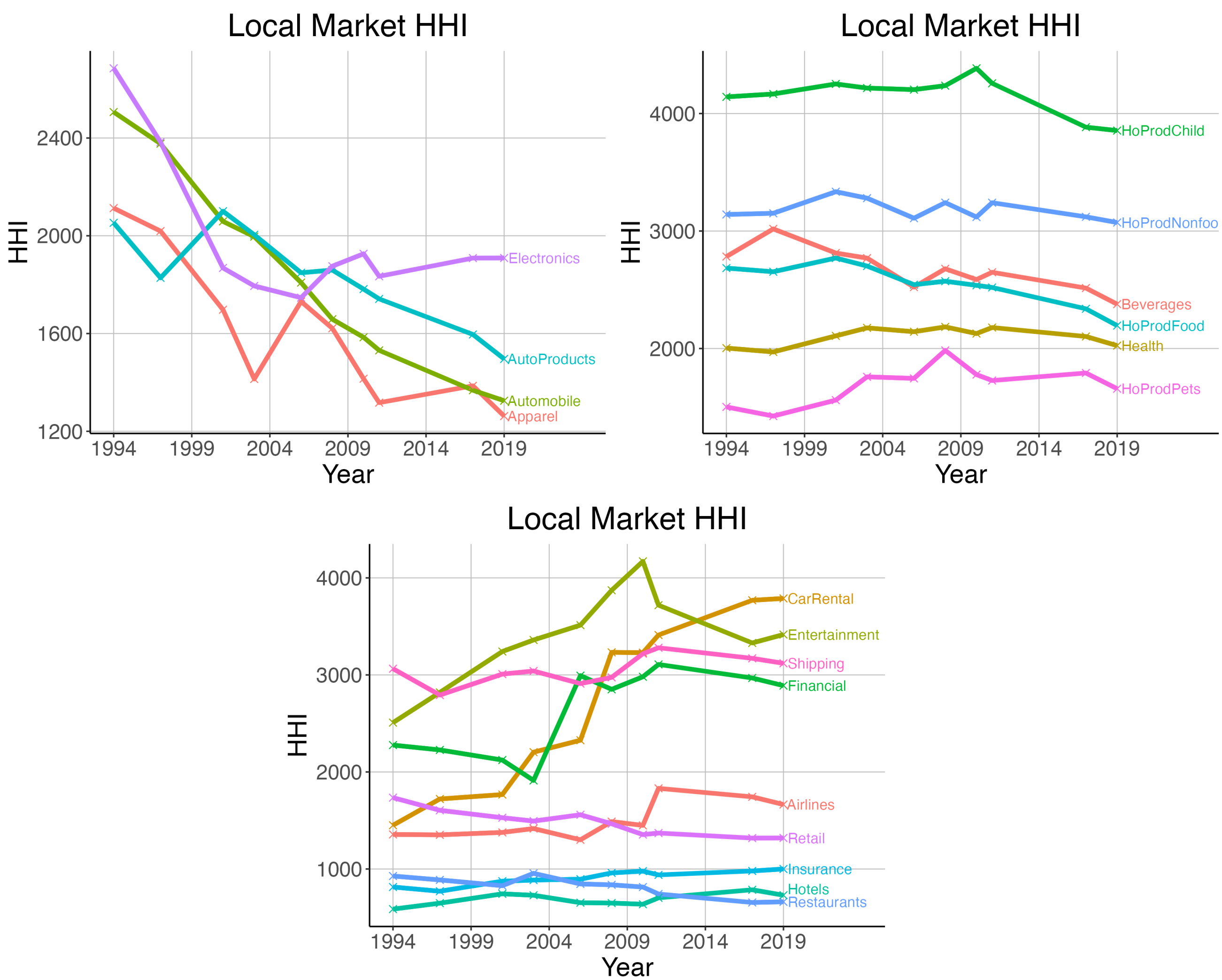
To quantify how much changes are driven by share reallocation, firm entry and exit, and mergers and divestitures, we construct a simple decomposition that attributes changes in HHIs to different driving factors. The decomposition is in spirit related to the productivity decompositions of Olley and Pakes (1996) and Melitz and Polanec (2015); the differences are that the target variable to decompose is HHIs rather than productivity, and the decomposition accounts for mergers and divestitures as well as entries and exits. In each period t and national market m, we categorize owners in periods t and $t-1$ into five groups: new period-t entrants, $\mathcal{O}_{m,t}^{entry}$; exiting owners who were present in period $t-1$ but not period t, $\mathcal{O}_{m,t}^{exit}$; groups of owners in period $t-1$ that merged into larger groups in period t, $\mathcal{O}_{m,t}^{merger}$; owners in period $t-1$ which split or divested into smaller owners in period t, $\mathcal{O}_{m,t}^{divestiture}$; and a residual group of owners in none of the other four groups, which simply persisted from period $t-1$ into period t, $\mathcal{O}_{m,t}^{residual}$.

We then define counterfactual market shares of firms, assuming entrants and exiters'

[17] https://www.core77.com/posts/22044/international-home-housewares-show-2012-mr-cleans-new-line-of-cleaning-gloves-22044

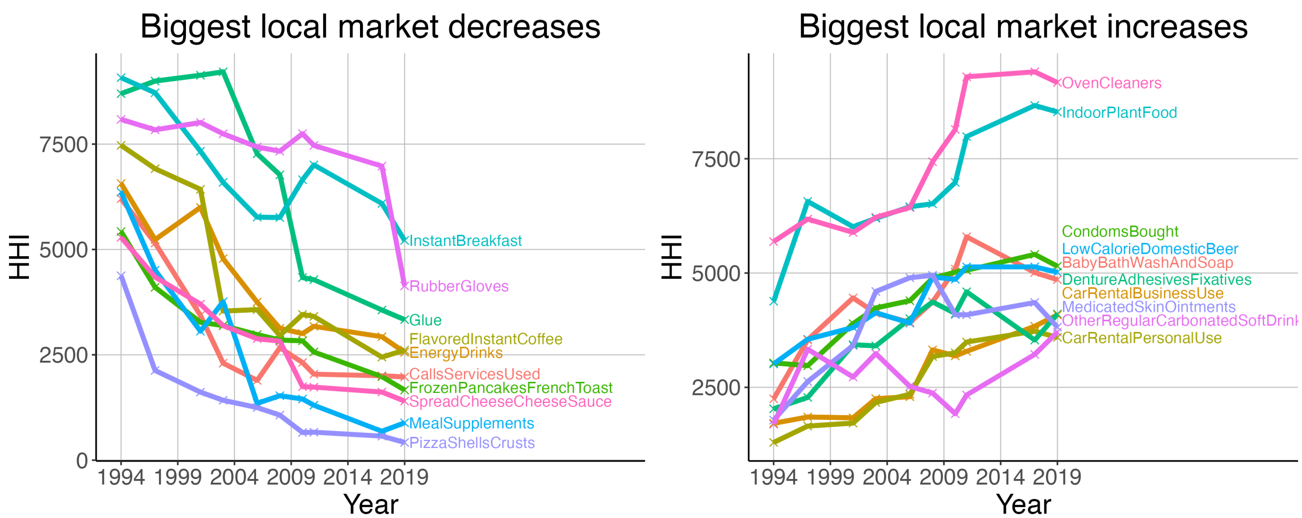
[18] https://www.wsj.com/articles/SB963782500794995149

Figure 4: Local market HHI over time, by sector



Notes. HHI over time, at the state-group-product market level. Each line shows the respondent-count-weighted average HHIs, for all state-group-markets in a given sector. The left panel shows results for manufacturing, the right panel for food, beverage, and health products, and the bottom panel shows results for non-manufacturing. appendix figure A.5 replicates this figure for different levels of aggregation.

Figure 5: Largest Changes in local HHI



Notes. HHI over time, at state group level, for the 10 product markets with the largest decreases and increases in HHI. Each line shows the respondent-count-weighted average of HHIs, for all local markets in a given market.

market shares are proportionally distributed among other firms:

$$\hat{s}_{o,m,t-1} \equiv \frac{s_{o,m,t-1}}{\left(1-\sum_{o\in\mathcal{O}^{exit}_{m,t}} s_{o,m,t-1}\right)}, \hat{s}_{o,m,t} = \frac{s_{o,m,t}}{\left(1-\sum_{o\in\mathcal{O}^{entry}_{m,t}} s_{o,m,t}\right)}$$

We also define counterfactual market shares $\tilde{s}_{o,m,t-1}, \tilde{s}_{o,m,t}$ of owners involved in mergers and divestitures, in the groups $\mathcal{O}^{merger}_{m,t}$ and $\mathcal{O}^{divestiture}_{m,t}$, assuming that these events exactly preserve merging firms' markets shares. For example, suppose owner o acquires owner o'. We then define:

$$\tilde{s}_{o,m,t-1} = \left(\hat{s}_{o,m,t-1} + \hat{s}_{o',m,t-1}\right),\ \tilde{s}_{o',m,t-1} = 0$$

For any market m and date t, we can decompose the change in HHIs as:

$$\begin{aligned}
\Delta HHI_{m,t} &= \sum_o s^2_{o,m,t} - \sum_o s^2_{o,m,t-1} \qquad (4)\\
&= \underbrace{\left(\sum_{o\notin\mathcal{O}^{exit}_{m,t}} \hat{s}^2_{o,m,t-1} - s^2_{o,m,t-1} - \sum_{o\in\mathcal{O}^{exit}_{m,t}} s^2_{o,m,t-1}\right)}_{\text{Exit}}\\
&+ \underbrace{\left(\sum_{o\notin\mathcal{O}^{entry}_{m,t}} s^2_{o,m,t} - \hat{s}^2_{o,m,t} + \sum_{o\in\mathcal{O}^{entry}_{m,t}} s^2_{o,m,t}\right)}_{\text{Entry}}\\
&+ \underbrace{\left(\sum_{o\in\mathcal{O}^{merger}_{m,t}} \tilde{s}^2_{o,m,t-1} - \hat{s}^2_{o,m,t-1}\right)}_{\text{Mergers}} + \underbrace{\left(\sum_{o\in\mathcal{O}^{divestiture}_{m,t}} \tilde{s}^2_{o,m,t-1} - \hat{s}^2_{o,m,t-1}\right)}_{\text{Divestitures}}\\
&+ \underbrace{\left(\sum_{o\in\mathcal{O}^{merger}_{m,t}} \left(\hat{s}^2_{o,m,t} - \tilde{s}^2_{o,m,t-1}\right) + \sum_{o\in\mathcal{O}^{divestiture}_{m,t}} \left(\hat{s}^2_{o,m,t} - \tilde{s}^2_{o,m,t-1}\right) + \sum_{o\in\mathcal{O}^{residual}_{m,t}} \left(\hat{s}^2_{o,m,t} - \hat{s}^2_{o,m,t-1}\right)\right)}_{\text{Share Reallocation}}
\end{aligned}$$

We describe the decomposition in (4) in detail in appendix B. In short, (4) decomposes the change in HHI in a market from period $t-1$ to t, into terms attributable to exit, entry, mergers, divestitures, and then a residual term reflecting reallocation of market shares among incumbents.

The result of the HHI decomposition is shown in figure 6. We find that mergers and divestment contribute very little to the overall change in HHI in the sample. The largest contributors are firm entry and exit. However, because entry and exit are positively correlated and largely cancel each other out, the net overall change in HHI primarily reflects share reallocation, which has a positive effect on HHI early in the sample, and a negative one toward the end.

3.2 Convergence

In this section we explore the extent of convergence in product market structure over time both geographically, across local areas, and economically, across closely related product markets. Figure 7 presents HHI over time where markets are defined at varying levels of geographic aggregation from county at the most disaggregated, up to core-based statistical area (CBSA) reflecting commuting zones to state-group to national at the most aggregate. The figure shows both local and national median concentration decreasing at the market level, and increasing at the sector level.

3.2.1 Geographic Convergence

The levels and trends in national product market HHIs are close to local product market HHIs at all percentiles. We infer that there is little evidence in our data of firms entering more local geographic markets over time. Our finding of decreasing local market concentration is consistent with the main finding in Rossi-Hansberg, Sarte and Trachter (2020). However, Rossi-Hansberg, Sarte and Trachter (2020) find increasing national concentration, even for the most narrow industry definitions, whereas in our data national concentration is also falling. The differences could be explained by the fact that the NETS data in Rossi-Hansberg, Sarte and Trachter (2020) is measured at the establishment or plant level (point of production),[19] whereas the MRI data is observed at the point of consumption. Establishment data provides a good measure of market structure for goods that are produced and consumed locally such as retail stores. For goods that are

[19] See Crane and Decker (2019) for details on the reliability of the NETS sales data.

Figure 6: Decomposition of HHI Changes

Notes. The top panel shows changes in average national market HHI over time. The bottom panel decomposes changes in average national market HHI into entry, exit, share reallocation, mergers, and divestment terms, using expression (4).

produced in a small number of plants and sold nationally, such as beer, establishment data shows a very skewed local market share relative to national market share, even for goods where local and national consumption are similar. For example, in the establishment data, Budweiser has a near monopoly in local markets where there is a Budweiser plant, and close to zero market share in local markets where there is not a Budweiser plant. These market shares do not accurately reflect consumption in those areas. In addition, one might expect more geographic convergence in retail markets than in markets for manufactured products, for example through the expansion of big box retailers. Our data contain many more manufacturing product markets than retail services markets, so any convergence in retail services markets would not show up strongly in our data after aggregating over all product markets.

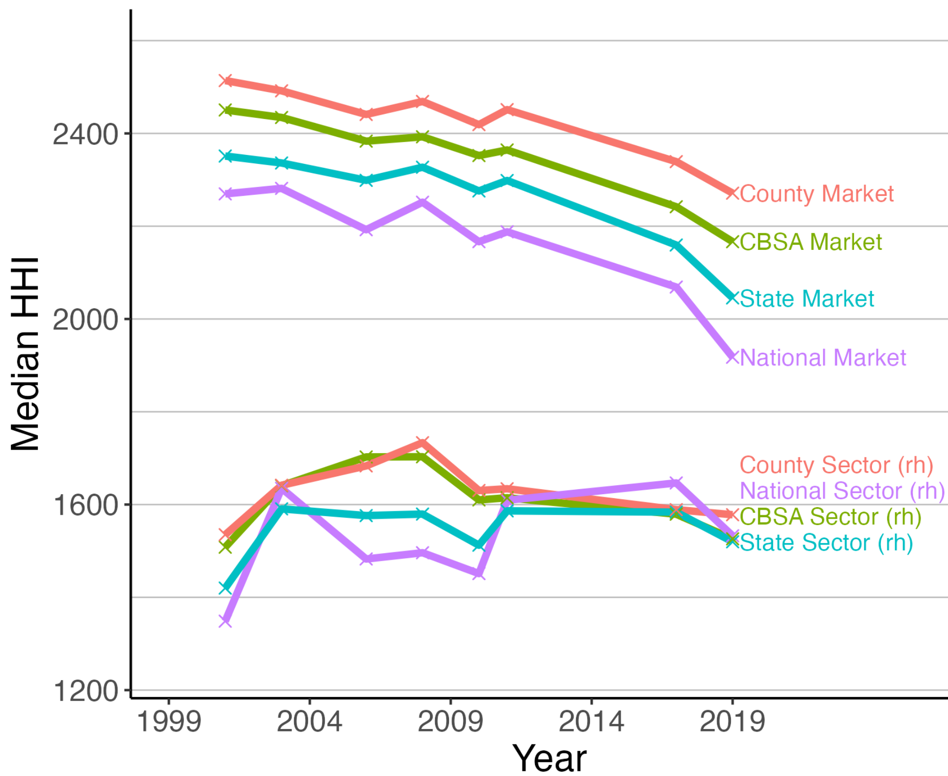
3.2.2 Market to Sector Convergence

On the other hand, aggregating product markets into broader sectors presents a qualitatively different story. At this higher level of aggregation, the 50th, 75th, and 90th percentiles all experience clear increases in concentration over time. The difference between product level and sector level HHI is evident at both the local and national levels. Our sector level measurements are more consistent with the results in existing work on the establishment data, likely because the sector level of market aggregation matches the establishment data more closely.

To evaluate the extent of convergence, for each sector we examined the joint evolution of the sector level HHI over time and the within-sector median product market HHI over time. From this angle, we found that there is no single story that explains all sectors. For some sectors, the two series move in opposite directions, while for others they move together. When they move in the same direction, sometimes the median market changes by more than the sector and sometimes not. Since the story varies across different sectors, it is difficult to draw any aggregate conclusions.

With equal weighting as in our main figures, median sector national HHI increases by 126. However, some sectors have many more markets or command a larger share of spending than others. In particular, the home products food sector contains 126 markets. This sector thus receives more weight in the market level series than in the sector level

Figure 7: Local HHI



Notes. HHIs over time, at different levels of geographic aggregation. Each line shows the median HHI, at county, CBSA, state, and national levels. The scale for the market-level lines is on the left axis, and the scale for the sector-level lines is on the right axis.

series (where it is just one of the 19 sectors). Weighting by number of markets in the sector, the median national sector HHI increases by 33.

The data in some sectors is consistent with firms expanding into "adjacent" product markets within the same sector. For example, in health and personal care products, we see the median market HHI decrease by 7 while the national sector HHI increases by 134. In home products food, we see the median national market HHI decrease by 616, while the national sector HHI only decreases by 66. However, while we do see some sectors experience relatively larger decreases in market concentration compared to sector concentration, demonstrating convergence, this pattern is not strong enough to explain the aggregate results in full.

3.3 Validity checks

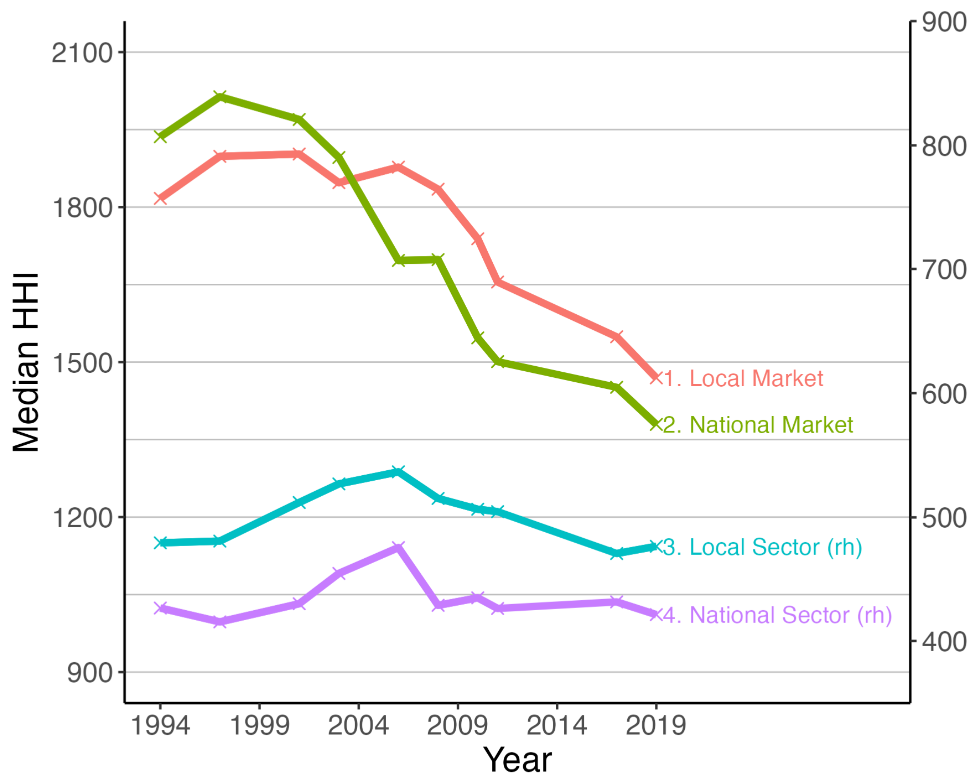
Given the novelty of our data and the contrast between our results and those from the production data, we have made several attempts to check the validity of our findings. The biggest threats to internal validity come from market entry and exit, particularly in technology markets, and from alternative ways of weighting product markets. Threats to external validity include market coverage, market definitions, and the survey nature of the data.

3.3.1 Internal validity checks

While the balanced panel includes some services and technology markets, several important markets only start being measured later in the sample. For example, wireless handsets and search engines appear as markets in our data starting in 2006 and 2008, respectively. The survey also adds and drops categories over time reflecting changing consumer behavior. For example, CD players are dropped while tablets are added. To address this issue, in table 4 we regress the logarithm of HHI at the category-year level on category fixed effects and time, including all markets in the unbalanced panel data set. We report specifications with year fixed effects and with a single time trend. The table shows that the decrease in market level HHI over the sample period is robust to the changing composition of markets in the unbalanced panel, with the largest decreases occurring in the final years, as in the balanced panel.

As some product markets constitute a larger share of spending, figure 8 re-weights markets using spending weights obtained from the Consumer Expenditure (CEX) survey. The CEX is measured at a higher level of aggregation. We match each market in our MRI data manually to the more aggregated CEX category, then assign equal weight to all markets which match to the same CEX category. The sum of the weights for the markets which match to the same CEX is equal to spending share in CEX in the given year. Using this weighting, the figure shows that median HHI levels are modestly lower, though still much higher than in Census data. Using CEX weights, we find even larger decreases in national and local concentration than in the main figures.

Figure 8: CEX Weighted HHI



Notes. Median HHI over time, as in figure 1, but with CEX weights. Each line shows the CEX-expenditure-weighted median of HHIs. "rh" indicates right-hand axis.

Table 4: Regression Analysis of HHI

	National Market log(HHI) Balanced		National Market log(HHI) Unbalanced		National Sector log(HHI) Balanced		National Sector log(HHI) Unbalanced	
Year	-0.00308**		-0.00275*		0.00392		-0.0000632	
	(-2.61)		(-2.47)		(0.92)		(-0.01)	
1997		0.00812		0.00590		0.0216		0.0247
		(0.68)		(0.52)		(0.61)		(0.60)
2001		0.0403*		0.0555**		0.0816		0.182
		(2.45)		(2.89)		(1.42)		(1.76)
2003		0.0325		0.0313		0.106		0.113
		(1.65)		(1.65)		(1.38)		(1.43)
2006		0.000354		-0.00452		0.138		0.113
		(0.02)		(-0.21)		(1.87)		(1.37)
2008		0.0283		0.0159		0.176		0.0799
		(1.23)		(0.72)		(1.99)		(0.62)
2010		0.00629		-0.0103		0.160		0.0470
		(0.25)		(-0.44)		(1.72)		(0.33)
2011		0.0101		0.0262		0.158		0.0873
		(0.39)		(0.99)		(1.67)		(0.64)
2017		-0.0379		-0.0403		0.101		0.0282
		(-1.37)		(-1.58)		(0.99)		(0.20)
2019		-0.0892**		-0.0653*		0.0728		0.0603
		(-3.08)		(-2.23)		(0.70)		(0.43)
Market FE	X	X	X	X				
Sector FE					X	X	X	X
Observations	3360	3360	4234	4234	190	190	200	200

t statistics in parentheses
Standard errors clustered at Market- and Sector-level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. The reference year is 1994. Standard errors clustered by market or sector.

3.3.2 Census Data and Market Coverage

A number of papers have shown that in the Census data concentration in production has increased over time even at the six-digit NAICS level, and this finding has been widely cited in the academic literature, public policy discourse, and the popular press, to the extent that it has become a widely believed "fact". The MRI data cover fewer markets than the Census and the selection is not random because MRI systematically omits purely intermediate goods. In this section we explore whether the differences in findings between the two data sources could be driven by sample selection.

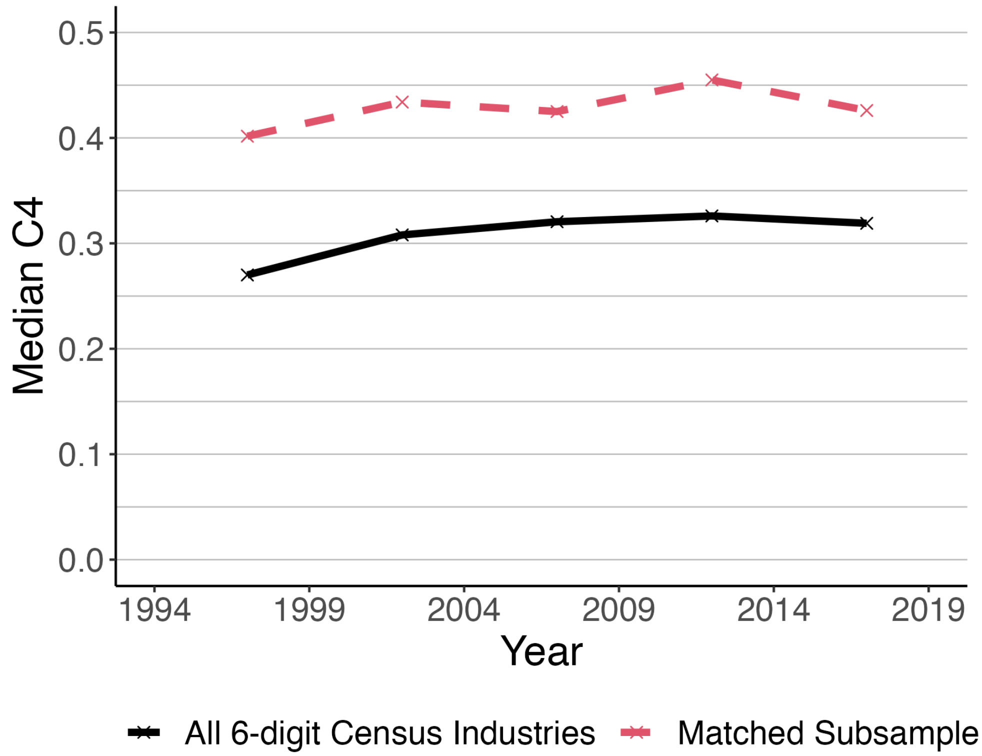
To do this, we recalculate concentration in the Census data using a subsample of the Census data that matches the MRI sample. We first cleaned the raw Census data following Barkai (2016) to get an industry-year panel for 1997 to 2012 corresponding to 2012 six-digit NAICS codes. We then hand-matched product markets from MRI to the six-digit NAICS codes. In general, this is a many-to-many mapping. We then used the Census weights to recompute concentration measures at the national level. The results are shown in figure 9. The figure plots changes in C4, which has better availability than HHI in the Census data.

First we verify the findings of the other papers: using the Census six-digit NAICS codes as definitions of product markets, concentration is increasing over time. The matched subsample of markets from MRI has higher C4 than the unmatched markets, but the trend in concentration is the same: it is increasing by a similar amount. In appendix C.1 we also use a regression technique that allows us to include in the comparison industries whose NAICS industry definition changed over time, with similar results. We conclude that the finding of decreasing concentration over time in the MRI data is due to the economic product market definitions, and not due to different market coverage.

3.3.3 Comparing MRI and Census for Individual Product Markets

Next we compare C4s between the MRI and Census for a subset of the individual markets matched above. Because it is based on location of production and not location of consumption, the Census data do not provide reasonable measures of local market concentration, so here again we look only at national markets, despite the fact that many

Figure 9: Census concentration



Notes. Median national C4s using 2012 Census six-digit NAICS codes. All Census industries (black solid), and subsample of Census industries matched to MRI (red dashed).

of the markets we consider are consumed only locally (e.g. car rental, hotels, real estate agents, restaurants, health insurance, etc). Table 10 lists the starting, ending, and mean C4 from MRI versus Census for the two most concentrated matched markets from each sector.

The mean MRI C4 is higher than the Census C4 for every single market listed, and typically much higher. The two measures match closely for only a small handful of the listed markets (e.g., autos and computers). A common issue is that the matched Census market is too broad to provide a meaningful measure of consumer product market concentration. Many Census market definitions are catch all categories such as "All other ..." that do not closely reflect any particular product market. Of the eight markets listed in the home products sectors, for example, all have C4s that are higher than 0.90 in the MRI data, while of the corresponding matched markets in the Census, five of eight markets have C4s below 0.36. This is a stark difference. A closer inspection shows that the MRI market definitions more closely match what economists think of as consumer product markets, containing only a set of products that are close substitutes. For example, the market for Children's pain relievers in MRI matches to "Pharmaceutical preparation mfg" in the Census, a broad category that includes many other markets including the MRI category "wart removers" in the same table. This Census market does not well reflect the market structure of any particular consumer market. In only one of the eight home products markets does the Census market appear to closely match a well defined consumer product market: "Breakfast cereal mfg".[20] In general, the Census C4s appear more credible for the more narrowly defined Census markets such as airlines, autos, car rental, hotels, and real estate agents.

Our main takeaways from this comparison are twofold: (1) MRI and Census do not match closely for most markets, and (2) when they do not match, the MRI concentration data appears to provide a more credible measure of actual consumer choice.

3.3.4 Comparison to industry specific measures

One downside of the survey data is that they do not reflect actual transactions. Respondents may not remember what they purchased or may not face strong incentives to accurately report what they purchased. To check the accuracy of market shares from our dataset, we compare our results to two industry-specific datasets that have been heavily used in the literature and that are thought to be of high quality.

For automobiles, we use sales information to construct product market HHI using Ward's Automotive Research data as used in Berry, Levinsohn and Pakes (1995). Refer to Grieco, Murry and Yurukoglu (2020) for a detailed description of the cleaning process. The results are shown in the left panel of figure 11. Both the levels and trends are very similar between the two datasets: HHI declines from around 2200-2500 in 1994 to around 1200 in 2018.

For airlines, we use the Airline Origin and Destination Survey from the Bureau of

[20] "Dog & cat food mfg" is also close to representing a well defined consumer market, except that dog and cat foods are not generally considered substitutes.

Figure 10: MRI-Census Comparison

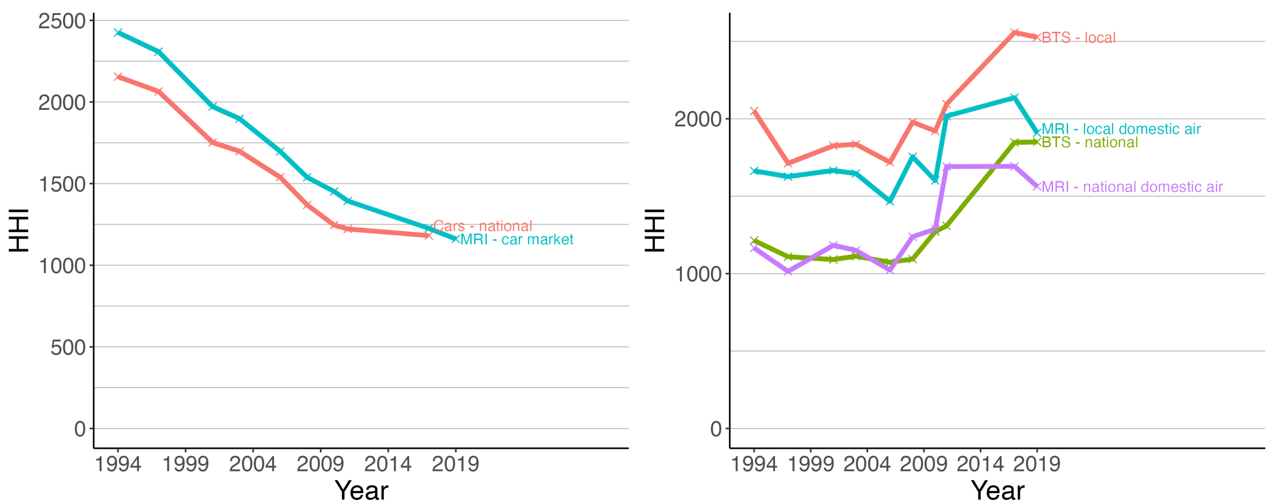
MRI Sector	Category Description	NAICS Code	Category Description	MRI C4 begin	MRI C4 end	MRI C4 mean	Census C4 begin	Census C4 end	Census C4 mean
Airlines	DomesticTravelAirlinesused	481111	Scheduled passenger air transportation	0.53	0.77	0.64	0.29	0.65	0.43
Airlines	ForeignTravelAirlinesUsed	481111	Scheduled passenger air transportation	0.47	0.59	0.53	0.29	0.65	0.43
Apparel	WomensLingerieUndergarments	315231	Women's & girls' cut/sew lingerie & nightwear mfg	0.70	0.64	0.67	0.43	0.22	0.49
Apparel	AthleticShoesBrandsBought	339920	Sporting & athletic goods mfg	0.59	0.60	0.60	0.21	0.32	0.26
AutoProducts	LeatherAndVinylProtectants	316999	All other leather good mfg	0.94	0.93	0.94	0.25	0.19	0.24
AutoProducts	AntiFreezeCoolant	325998	All other miscellaneous chemical product & preparation mfg	0.80	0.80	0.80	0.20	0.19	0.20
Automobile	MotorcyclesMake	336111	Automobile mfg	0.84	0.75	0.81	0.80	0.60	0.71
Automobile	AutomobilesAndOtherVehicles	336111	Automobile mfg	0.82	0.62	0.73	0.80	0.60	0.71
Beverages	LowCalorieDomesticBeer	312120	Breweries	0.96	0.98	0.97	0.90	0.88	0.89
Beverages	Cognac	312140	Distilleries	0.95	0.95	0.95	0.60	0.65	0.66
CarRental	CarRentalBusinessUse	532111	Passenger car rental	0.76	0.97	0.87	0.66	0.90	0.79
CarRental	CarRentalPersonalUse	532111	Passenger car rental	0.73	0.96	0.85	0.66	0.90	0.79
Electronics	Batteries	335911	Storage battery mfg	0.94	0.85	0.88	0.90	0.87	0.75
Electronics	PersonalComputers	334111	Electronic computer mfg	0.48	0.69	0.66	0.45	0.51	0.65
Entertainment	CruiseShipsCruiseLinesUsed	487210	Scenic and Sightseeing Transp, Water	0.78	0.92	0.88	0.20	0.16	0.16
Financial	CreditCards	522210	Credit card issuing	0.87	0.95	0.91	0.54	0.78	0.72
Financial	RealEstateWhichAgentUsed	531210	Offices of Real Estate Agents & Brokers	0.44	0.41	0.43	0.07	0.13	0.10
Health	RazorBlades	332211	Cutlery & flatware (exc. precious)	0.96	0.93	0.95	0.65	0.69	0.68
Health	WartRemovers	325412	Pharmaceutical preparation mfg	0.94	0.92	0.93	0.36	0.37	0.36
HoProdChild	InfantCereal	311230	Breakfast cereal mfg	0.98	0.93	0.96	0.83	0.79	0.80
HoProdChild	PainRelieversFeverReducersForChildren	325412	Pharmaceutical preparation mfg	0.90	0.95	0.94	0.36	0.37	0.36
HoProdFood	Yeast	311999	All other miscellaneous food mfg	0.97	0.95	0.96	0.23	0.28	0.24
HoProdFood	LunchCombinationsKits	311991	Perishable prepared food mfg	0.97	0.95	0.95	0.24	0.30	0.26
HoProdNonfood	OvenCleaners	325612	Polish & other sanitation good mfg	0.98	0.97	0.96	0.55	0.58	0.58
HoProdNonfood	Glue	325520	Adhesive mfg	0.95	0.97	0.96	0.22	0.18	0.22
HoProdPets	CannedWetCatFood	311111	Dog & cat food mfg	0.79	0.82	0.77	0.58	0.68	0.65
HoProdPets	CatLitter	325998	All other miscellaneous chemical product & preparation mfg	0.59	0.75	0.71	0.20	0.19	0.20
Hotels	HotelsMotelsWhereStayed	721110	Hotels (except casino hotels) & motels	0.44	0.46	0.44	0.16	0.20	0.20
Insurance	MedicalInsuranceCompanies	524114	Direct health & medical insurance	0.41	0.60	0.53	0.20	0.34	0.29
Insurance	HomeownersOrPersonalPropertyIns	524126	Direct property & casualty insurance	0.45	0.44	0.46	0.28	0.31	0.30
Restaurants	FastFoodDriveInRestaurants	722211	Limited-service restaurants	0.58	0.39	0.51	0.12	0.06	0.09
Restaurants	FamilyRestaurantsSteakHouses	722110	Full-service restaurants	0.32	0.35	0.35	0.07	0.08	0.08
Retail	ApplianceHardwareElectronicsStores	335228	Other major household appliance mfg	0.69	0.77	0.74	0.57	0.71	0.61
Retail	DepartmentClothingSpecialtyStores	448190	Other clothing stores	0.65	0.43	0.54	0.61	0.61	0.46
Shipping	OvernightPackagesLetterDeliveryServ	492110	Couriers and Express Delivery Services	0.95	0.98	0.97	0.84	0.93	0.90

Notes. Starting, ending, and mean national C4 from MRI and Census for matched markets, top two markets for each sector. For a few sectors, only one matched market is available.

Transportation Statistics (BTS). This survey is a 10% sample of airline tickets from all US domestic carriers and includes origin, destination and ticket details. We aggregate total revenues by carrier group which include airlines that operate under different brands but under common ownership. Using the BTS data, we can construct both local and national HHI measures. To calculate local HHIs, for comparability to the MRI, we aggregate the BTS data, by total revenue, to the level of MRI state-groups, and then we calculate HHIs at the state-group level. We define stategroups by origin airport states, but we have verified that the results hold for destination airport states as well. For national HHIs, we aggregate BTS data to the national level to construct market shares by total revenue.

We show the results in the right panel of figure 11. As with the automobile data, the two datasets are very similar in both levels and trends, at both the local and national level.

Figure 11: Automobile and Airlines Robustness Check



Notes. The left panel shows the estimated automobile market HHI from the MRI (blue), against the estimated national HHI for the car market from Ward's (red). The right panel shows the estimated HHI from the MRI, for domestic airlines, at the local market (blue) and national market (purple) levels, against BTS airline data local (red) and national (green) HHIs. For local concentration we take median HHIs.

3.4 Additional Robustness Checks

We have also computed concentration using several alternative concentration measures and market definitions. The details of these analyses can be found in appendix C. Our results hold if we measure concentration using C2 and C4 instead of HHIs. The results reported above are for a balanced panel of industries, but they also hold for the full unbalanced panel and under alternative assumptions about industries that change definition over time.

Second, we examine concentration at two intermediate levels of market aggregation between product markets and sectors, and we find that the general trend continues to hold: concentration is increasing over time at higher levels of aggregation, and decreasing at lower levels of aggregation.

Finally, we show that the results of decreasing median HHI are robust to treating the "store brand" in each market as a single firm, rather than our baseline assumption of treating each "store brand" response as corresponding to a separate firm.

4 Conclusion

This paper measures long term trends in product market concentration across a wide swath of the U.S. economy, using market definitions that more closely reflect consumption-based economic markets, and accounting for multi-brand ownership and imports. We find both the levels and trends in market concentration in economic markets to be quite different from those reported in the past literature using production markets such as those defined in Census.

We find that concentration levels are high in nearly half of the markets covered in our sample. In the Census data there are almost no highly concentrated markets. We also find that product market concentration has been decreasing over time, particularly in the most concentrated industries. This finding is also the opposite of well known results from production data.

Concentration measures from the Census data have been relied on heavily to guide the academic literature interpreting recent macroeconomic trends, as well as public policy debates on antitrust enforcement. Given the prominence of these issues, we think that the new results are potentially important.

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Internet Appendix

A Data Appendix

A.1 Cleaning Kantar Adspender

From the Kantar Adspender data, we observe brand names, ultimate parents, and product categories. Product category verbal descriptions and codes are available for the years 1994, 2003, and 2017. For the other years, only Kantar's category "codes" are available. The codes appear to be consistent for nearby years, so we impute verbal descriptions for the 1997 data using the 1994 data, and for the 2001 and 2006 data using the 2003 data.

A.2 Merging MRI-Simmons and Kantar Adspender

We use a fuzzy merging algorithm to match brands from the MRI-Simmons data to the Kantar Adspender data. The MRI-Simmons data contain approximately 450 product markets per year, which are relatively stable over time. Kantar Adspender is also divided into around 550 categories, which change somewhat over time. We do the match entirely separately for each year of the dataset.

Data cleaning. We begin by cleaning both datasets, standardizing brand names. We replace accented characters with their closest alphabetic equivalents, remove all non-alphanumeric characters, remove excess whitespace, and lowercase all brands. Additionally, we remove common words such as "and", "any", and "or". Second, from Adspender brands, we remove categorizing words such as "auto" and "corp", which allows longer Adspender brands ("audi auto corp") to match with shorter MRI-Simmons brands ("audi"). Many brands in the Adspender data are very long, including "brand" words followed by "product descriptors", such as "OSCAR DE LA RENTA DRESSES WOMEN". We thus trim brands with many words, by removing either 1 or two words from the end of the brand string; we never trim brands down to less than 3 words.

We manually edit the match, removing around 350 words that are specific enough that they are used for matching by the fuzzy merge algorithm, but are not brand words, and thus induce bad matches. We also manually delete a few owners and brands which seem to match poorly.

Fuzzy merging. We then merge brand names from the two datasets using a two-step process. We first match MRI-Simmons product markets to Kantar product categories, then run the Stata reclink2 package, created by Wasi and Flaaen (2015), to match MRI brands to Kantar brands. Reclink2 is a fuzzy text merging algorithm, which calculates the distance between strings using a modified bigram algorithm: roughly speaking, this calculates the ratio of the number of common two consecutive letters of the two strings and their average length minus one.

In the first stage, we construct a one-to-many match of MRI-Simmons product markets to Kantar product categories. We first naively fuzzy-merge the full list of MRI-Simmons brands to the full list of Kantar brands. We then check, for each MRI-Simmons product market, the Kantar categories which are matched to the product market most often. We hand-check this merge, adding and subtracting some associations which are not well-captured by the algorithm.

Next, once we have constructed the MRI-Simmons to Kantar category crosswalk, we re-run reclink2, matching brands from MRI-Simmons to Kantar brands within the matched categories. Since the lists of brands to be matched are smaller, false positives are less likely, so we can use a lower match score cutoff.

We use a few more post-processing steps for the merge. In some cases, an MRI-Simmons brand is matched to the same Kantar owner for, for example, 1997 and 2003, but not 2001; this is likely to be a false negative for 2001, so we assign the brand in 2001 to its 1997 and 2003 owner. To improve on the missed matches for brands that have a high market-share, in some cases we manually check brand information using web searches and company websites to assign an owner.

For brands where we are unable to impute an owner using Kantar, we group together brands within the same product category that start with the same first word together; this largely allows us to capture minor products which have the same owner, for example, "Lipton Decaffeinated Iced Tea", "Lipton Iced Tea Mix" and "Lipton Tea & Honey". We then restrict attention to MRI-Simmons product markets for which we are able to impute owners for at least 60% of market share, for all 6 years in our dataset. This reduces the sample from 475 product markets to 336 product markets. In subsection C.3, we also report results for the unbalanced panel, including all 475 product markets.

A.3 Adjusting HHI estimates for finite-sample bias

The HHI is a convex function of market shares. Thus, if we calculate HHIs by plugging in unbiased estimators of market shares, the HHI estimates will tend to be biased upwards. However, this bias can be estimated, allowing us to construct approximately unbiased estimates of the HHI.

Suppose we wish to estimate the market share s_{oj} of owner o in market j. j could represent any level of aggregation, from state-group-product market, to national sector. Suppose we have some unbiased estimator $\hat{s}_{oj}$ of s_{oj}, that is:

$$E\left[\hat{s}_{oj}\right] = s_{oj}$$

We wish to estimate the HHI in market j, which is:

$$HHI_j = \sum_o s_{oj}^2$$

If we simply estimate the HHI using the sum of squares of estimated market shares, $\hat{s}_{oj}^2$, this will tend to be upwards biased. To see this, note that:

$$E\left[\hat{s}_{oj}^2\right] = \left(E\left[\hat{s}_{oj}\right]\right)^2 + Var\left[\hat{s}_{oj}\right] = s_{oj}^2 + Var\left[\hat{s}_{oj}\right]$$

Hence,

$$E\left(\sum_o \hat{s}_{oj}^2\right) = \sum_o s_{oj}^2 + \sum_o Var\left[\hat{s}_{oj}\right] = HHI_j + \sum_o Var\left[\hat{s}_{oj}\right]$$

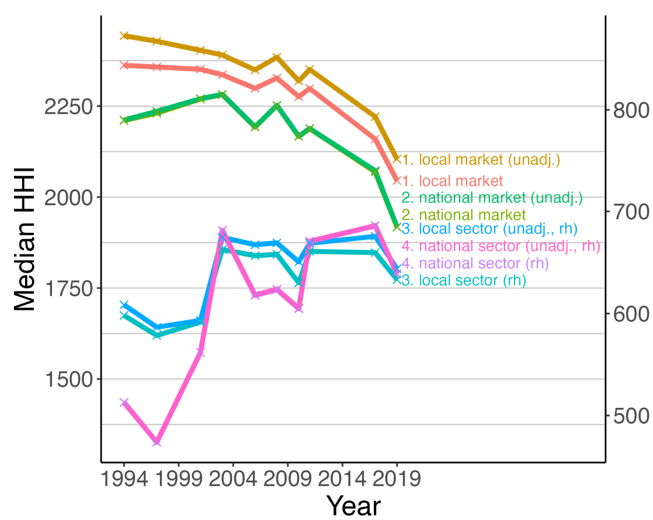
Rearranging, we have:

$$HHI_j = E\left(\sum_o \hat{s}_{oj}^2\right) - \sum_o Var\left[\hat{s}_{oj}\right] \tag{5}$$

Hence, we can construct an unbiased estimator for HHI_j by subtracting $\sum_o Var\left[\hat{s}_{oj}\right]$, the sum of sample variances of the market shares $\hat{s}_{oj}$, from the sample HHI, $\sum_o \hat{s}_{oj}^2$. We calculate these sample variances using a nonparametric bootstrap. In each year of the original survey, we draw 100 samples of users with replacement from the original sample. We calculate market shares at each level of aggregation using these resampled datasets, and take the variance in all market shares over the bootstrap samples. We then use these variances to adjust sample HHIs, using expression (5). All HHI estimates from MRI-Simmons data in the paper include the adjustment in (5).

To illustrate how much the bias correction affects our estimates, figure A.1 compares our HHI estimates from figure 1 to raw HHIs without the adjustment in (5). At the local product market level, the adjustment is fairly large, shifting the estimated median HHI by approximately 130 (out of 10,000). This is because the number of respondents in each local product market is not large – around a few hundred on average – so local product market shares have fairly high sample variances, making the adjustment term in (5) fairly large. In contrast, the adjustment term is essentially negligible at the national product market, local sector, and national sector levels.

Figure A.1: Effect of finite-sample HHI adjustment



Notes. Effect of the finite-sample HHI bias adjustment, (5), on our HHI estimates. Lines labelled "unadj." are the raw sample HHIs, $\sum_o \hat{s}_{oj}^2$. The other lines are identical to those from Figure 1. The left hand axis corresponds to the market level lines. The right hand axis corresponds to the sector level lines.

B Decomposition Calculation

In this appendix, we describe in detail how we calculate (4). Repeating the decomposition in (4), we have:

$$\begin{aligned}
\Delta \mathrm{HHI}_{m,t} &= \sum_{o} s_{o,m,t}^2 - \sum_{o} s_{o,m,t-1}^2 \qquad (6)\\
&= \underbrace{\left(\sum_{o \notin \mathcal{O}_{m,t}^{exit}} \hat{s}_{o,m,t-1}^2 - s_{o,m,t-1}^2 - \sum_{o \in \mathcal{O}_{m,t}^{exit}} s_{o,m,t-1}^2 \right)}_{\text{Exit}} \\
&+ \underbrace{\left(\sum_{o \notin \mathcal{O}_{m,t}^{entry}} s_{o,m,t}^2 - \hat{s}_{o,m,t}^2 + \sum_{o \in \mathcal{O}_{m,t}^{entry}} s_{o,m,t}^2 \right)}_{\text{Entry}} \\
&+ \underbrace{\left(\sum_{o \in \mathcal{O}_{m,t}^{merger}} \tilde{s}_{o,m,t-1}^2 - \hat{s}_{o,m,t-1}^2 \right)}_{\text{Mergers}} + \underbrace{\left(\sum_{o \in \mathcal{O}_{m,t}^{divestiture}} \tilde{s}_{o,m,t-1}^2 - \hat{s}_{o,m,t-1}^2 \right)}_{\text{Divestitures}} \\
&+ \underbrace{\left(\sum_{o \in \mathcal{O}_{m,t}^{merger}} \left(\hat{s}_{o,m,t}^2 - \tilde{s}_{o,m,t-1}^2 \right) + \sum_{o \in \mathcal{O}_{m,t}^{divestiture}} \left(\hat{s}_{o,m,t}^2 - \tilde{s}_{o,m,t-1}^2 \right) + \sum_{o \in \mathcal{O}_{m,t}^{residual}} \left(\hat{s}_{o,m,t}^2 - \hat{s}_{o,m,t-1}^2 \right) \right)}_{\text{Share Reallocation}}
\end{aligned}$$

Where, the definitions of each set of owners is as follows:

- $\mathcal{O}_{m,t}^{entry}$: Owners who enter between period $t-1$ and period t: they have 0 market share in period $t-1$, and positive market share in period t.
- $\mathcal{O}_{m,t}^{exit}$: Owners who exit: they have positive market share in period $t-1$, and zero market share in period t.
- $\mathcal{O}_{m,t}^{merger}$: Owners involved in mergers or acquisitions. For notational convenience, when two or more firms o_1, o_2, o_3 merge, we will think of this as o_1 acquiring the other firms, so that $s_{o_1,m,t} > 0$ and $s_{o_2,m,t}, s_{o_3,m,t} = 0$.
- $\mathcal{O}_{m,t}^{divestiture}$: Owners involved in divestitures. Again, when a firm divests, for

notational convenience we think of o_2 and o_3 having zero market shares in period $t-1$, and positive shares in period t.

- $\mathcal{O}^{residual}_{m,t}$: Owners with positive market shares not in any of the sets $\mathcal{O}^{entry}_{mt}$,$\mathcal{O}^{exit}_{mt}$, $\mathcal{O}^{merger}_{m,t}$,$\mathcal{O}^{divestiture}_{mt}$.

By construction, the five sets $\mathcal{O}^{entry}_{m,t}$, $\mathcal{O}^{exit}_{m,t}$, $\mathcal{O}^{merger}_{m,t}$, $\mathcal{O}^{divestiture}_{m,t}$, $\mathcal{O}^{residual}_{m,t}$ are disjoint, and their union is all owners with positive market shares in periods t or $t-1$ in market m. Next, we describe each of the components of the decomposition (6).

Exit. Define:

$$\hat{s}_{o,m,t-1} \equiv \frac{s_{o,m,t-1}}{\left(1 - \sum_{o \in \mathcal{O}^{exit}_{m,t}} s_{o,m,t-1}\right)}$$

as the market share of owner o in period $t-1$, as a fraction of the market share of all owners besides those in $\mathcal{O}^{exit}_{m,t}$ that exit in period t. The term:

$$\left(\underbrace{\sum_{o \notin \mathcal{O}^{exit}_{m,t}} \left(\hat{s}^2_{o,m,t-1} - s^2_{o,m,t-1}\right)}_{A} - \underbrace{\sum_{o \in \mathcal{O}^{exit}_{m,t}} s^2_{o,m,t-1}}_{B} \right) \tag{7}$$

in the decomposition (6) thus can be thought of as representing how HHIs would change, if all firms in $\mathcal{O}^{exit}_{m,t}$ exited, represented by term B in (7); and then exiting firms' market shares were proportionally redistributed to non-exiting firms according to their existing market shares, represented by term A.

Entry. Analogously, define:

$$\hat{s}_{o,m,t} = \frac{s_{o,m,t}}{\left(1 - \sum_{o \in \mathcal{O}^{entry}_{m,t}} s_{o,m,t}\right)}$$

as the market share of owner o in period t, as a fraction of the market share of all owners besides those in $\mathcal{O}_{m,t}^{entry}$, which enter the market in period t. The term

$$\left(\underbrace{\sum_{o \notin \mathcal{O}_{m,t}^{entry}} \left(s_{o,m,t}^2 - \hat{s}_{o,m,t}^2 \right)}_{A} + \underbrace{\sum_{o \in \mathcal{O}_{m,t}^{entry}} s_{o,m,t}^2}_{B} \right) \tag{8}$$

in (6) thus reflects the change in HHIs that would result, if market shares of incumbents were originally $\hat{s}_{o,m,t}$, and then entrants in $\mathcal{O}_{m,t}^{entry}$ enter, represented by term B in (8); and then entrants steal market share proportionally from incumbents to decrease their market shares to $s_{o,m,t}$, represented by term A. Equations (7) and (8) do not have unambiguous signs. If exiting firms tend to be small, (7) tends to be positive, so exits tend to increase HHI; if exiting firms tend to be large, (7) may actually be negative. Analogously, (8) may be positive or negative.

Mergers. Suppose two firms A and B merged to form firm C. Essentially, we decompose the effect of the merger into a "pure merger" effect, which purely combines the market shares of A and B without any reallocation; and a "reallocation" effect, which reflects the fact that firm C's market share may be different from the market shares of A and B. Suppose owners o and o' from period $t-1$ merge to become one firm in period t; we will think of this as firm m' being acquired by firm m, so that $\tilde{s}_{o',m,t} = 0$. We then define:

$$\tilde{s}_{o,m,t-1} \equiv \left(\hat{s}_{o,m,t-1} + \hat{s}_{o',m,t-1} \right), \; \tilde{s}_{o',m,t-1} \equiv 0$$

That is, $\tilde{s}_{o,m,t-1}$ is the sum of the market shares $\hat{s}_{o,m,t-1}$ and $\hat{s}_{o',m,t-1}$; it is the market share which would result if firms o and o' merged, and the market share of the combined firm was exactly equal to the sum of the original firms' market shares. The definition with more than two firms is analogous, simply setting all shares $\tilde{s}_{o',m,t-1}$ other than the first to 0. The merger term in (6):

$$\left(\sum_{o \in \mathcal{O}_{m,t}^{merger}} \tilde{s}_{o,m,t-1}^2 - \hat{s}_{o,m,t-1}^2 \right) \tag{9}$$

can thus be thought of as the HHI change from two firms merging, if there were no changes in shares other than adding the firms' market shares. This term is unambiguously positive; mergers always contribute to increasing HHI. There is also a residual term in (6):

$$\sum_{o \in \mathcal{O}_{m,t}^{merger}} \left(\hat{s}_{o,m,t}^2 - \tilde{s}_{o,m,t-1}^2\right)$$

which reflects the fact that the actual market share of the merged firms, $\hat{s}_{o,m,t}^2$, may not exactly be the sum of the merging firms' shares; we think of this as a "reallocation" effect, and group it with reallocation among incumbents.

Divestitures. Analogous to the merger term (9), suppose owner o from period $t-1$ splits into two owners o, o' in period t. We will define:

$$\hat{s}_{o,m,t-1} \equiv \tilde{s}_{o,m,t-1} + \tilde{s}_{o',m,t-1}, \hat{s}_{o',m,t-1} \equiv 0$$

In contrast to the merger case, this time $\tilde{s}_{o,m,t-1}, \tilde{s}_{o',m,t-1}$ represent the split, after-exit market shares of o, o' had the divestiture occured in period $t-1$. The divestiture term in (6):

$$\left(\sum_{o \in \mathcal{O}_{m,t}^{divestiture}} \tilde{s}_{o,m,t-1}^2 - \hat{s}_{o,m,t-1}^2\right) \tag{10}$$

can thus be thought of as the HHI change from a firm splitting into two or more sub-firms, if there were no changes in shares besides dividing the firm's market share between its constituents. This term is unambiguously negative: divestitures always contribute to decreasing HHI. As in the merger case, there is a residual term:

$$\sum_{o \in \mathcal{O}_{m,t}^{divestiture}} \left(\hat{s}_{o,m,t}^2 - \tilde{s}_{o,m,t-1}^2\right)$$

which reflects the fact that the market share of the original large firm may not exactly be the sum of the divested constituents' shares; we group this together with reallocation among incumbents.

Reallocation. Finally, for firms which are not involved in entry, exit, mergers, and acquisitions, there is a “reallocation” term which captures how changes in these firms' market shares, adjusted for entry and exit, affect HHIs:

$$\sum_{o\in\mathcal{O}_{m,t}^{residual}}\left(\hat{s}_{o,m,t}^2-\hat{s}_{o,m,t-1}^2\right)$$

This term can be positive or negative, depending on whether large firms or small firms tend to gain market shares.

Another way to summarize our decomposition is that it can be thought of in terms of 5 stepwise changes in market structure, each of which have mechanical effects on market shares.

1. Firms in $\mathcal{O}_{m,t}^{exit}$ exit, changing non-exiters' market shares from $s_{o,m,t-1}$ to $\hat{s}_{o,m,t-1}$.
2. Firms in $\mathcal{O}_{m,t}^{merger}$ merge, changing merged firms' market shares from $\hat{s}_{o,m,t-1}$ to $\tilde{s}_{o,m,t-1}$.
3. Firms in $\mathcal{O}_{m,t}^{divestiture}$ divest, shifting their market shares from $\hat{s}_{o,m,t-1}$ to $\tilde{s}_{o,m,t-1}$.
4. Market shares reallocate, changing merged ($\mathcal{O}_{m,t}^{merger}$) and divesting ($\mathcal{O}_{m,t}^{divestiture}$) firms' market shares from $\tilde{s}_{o,m,t-1}^2$ to $\hat{s}_{o,m,t}^2$, and residual firms' ($\mathcal{O}_{m,t}^{residual}$) market shares from $\hat{s}_{o,m,t-1}^2$ to $\hat{s}_{o,m,t}^2$.
5. Firms in $\mathcal{O}_{m,t}^{entry}$ enter, shifting incumbents' market shares from $\hat{s}_{o,m,t}^2$ to $s_{o,m,t}^2$.

C Robustness checks

Subsection C.1 does a more detailed comparison of our results to the Census data, accounting for changing definitions of NAICS codes over time. Subsection C.2 uses top-2 and top-4 market shares, instead of HHIs, as our measure of concentration. Subsection C.3 uses the entire unbalanced panel of product markets, instead of dropping markets to balance the panel. Figure 8 weights sector HHIs by expenditure shares from the Consumer Expenditure Survey. In all three cases, our baseline results are qualitatively and quantitatively unchanged. Finally, subsection C.4 analyzes concentration at two intermediate levels of aggregation between product markets and sectors, and finds that the general trend continues to hold: concentration is increasing over time at higher levels of aggregation, and decreasing at lower levels of aggregation.

C.1 Market coverage – accounting for changing NAICS definitions

In the main text of the paper we show that C4 rises over time at the 6-digit NAICS level for a subsample of Census industries matched to the MRI-Simmons data. One issue with this simple comparison is that NAICS code definitions are changing over time. This issue is also present in previous work measuring concentration in the Census data. The typical solution in that literature is to drop markets whose definitions changed during the sample period. To show that NAICS code redefinitions are not driving our results, we conduct the following exercise. We run a simple regression:

$$\mathrm{HHI}_{jt} = \mu_t + \gamma_j + \epsilon_{jt} \tag{11}$$

where j indexes NAICS codes, t indexes periods of 5 years, and ϵ_{jt} is an error term that is independent of μ_t and γ_j. If a NAICS code is ever affected by a split or merger, we treat it as a separate NAICS code pre- and post-merger. We are interested in the μ_t coefficients from specification (11). Effectively, (11) is a fixed-effects specification: the time fixed effects μ_t estimate changes in concentration, using only variation within given NAICS codes, over time periods where that code is not affected by code merger events. Specification (11) is a simple way to use all the variation in concentration over time in the Census that is not affected by NAICS code redefinitions. The results of specification (11), for various subsets of the data, are shown in table A.1. For all census subsamples, we find that the fixed effects μ_t are increasing uniformly from 1997 to 2012.

C.2 C2 and C4 concentration measures

Figure A.2 replicates figure 1 using two alternative measures of concentration: the sum of the top two owner market shares (C2), and the sum of the top four owner market shares (C4). The trends are similar to using HHI.

Table A.1: Census HHI over time, fixed effects specification

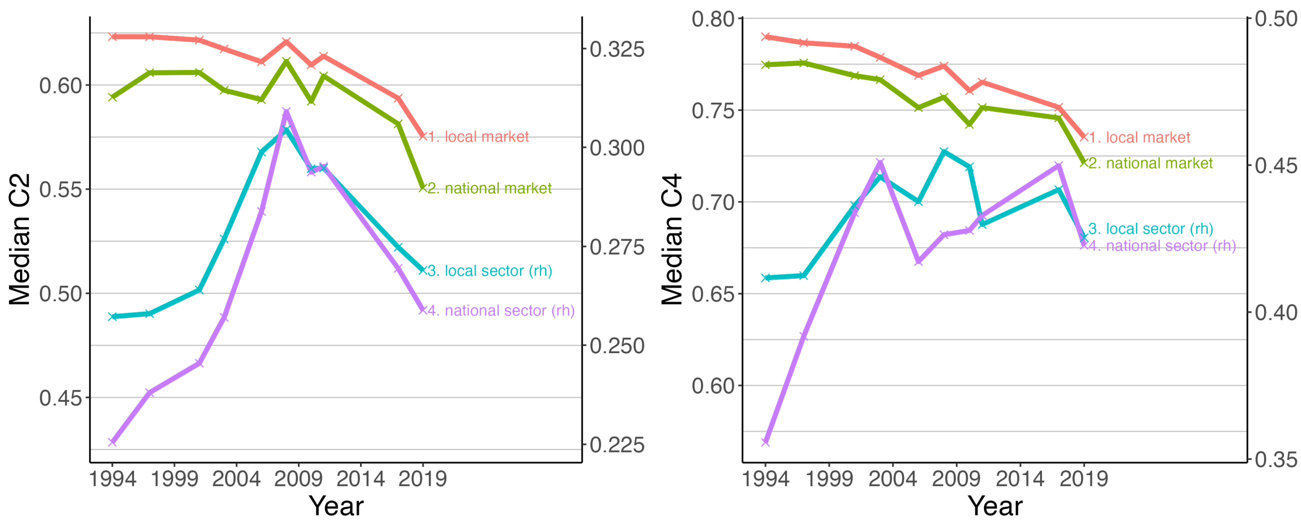
	(1) All	(2) All unchanged codes	(3) Matched codes	(4) Matched unchanged codes
μ_{2002}	2.550***	2.715***	3.652***	3.671***
	(0.361)	(0.369)	(0.987)	(0.903)
μ_{2007}	3.797***	3.854***	3.928***	4.253***
	(0.374)	(0.379)	(0.978)	(0.942)
μ_{2012}	4.479***	4.789***	3.238**	4.016***
	(0.420)	(0.416)	(1.232)	(1.020)
Constant	32.12***	32.11***	42.52***	42.77***
	(0.301)	(0.310)	(0.809)	(0.760)
N	3429	2737	392	376
R^2	0.930	0.934	0.911	0.932

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes. Columns 1 and 2 show the regression results for the entire census sample. Columns 3 and 4 show the results for census codes that we matched to MRI-Simmons product markets. For columns 2 and 4, we also drop any NAICS industry codes that change in the time series.

Figure A.2: Median C2 and C4 over time, by market definition



Notes. Local markets are defined as product markets intersected with 29 stategroups. Sectors are defined by aggregating related national product markets. rh indicates right-hand axis.

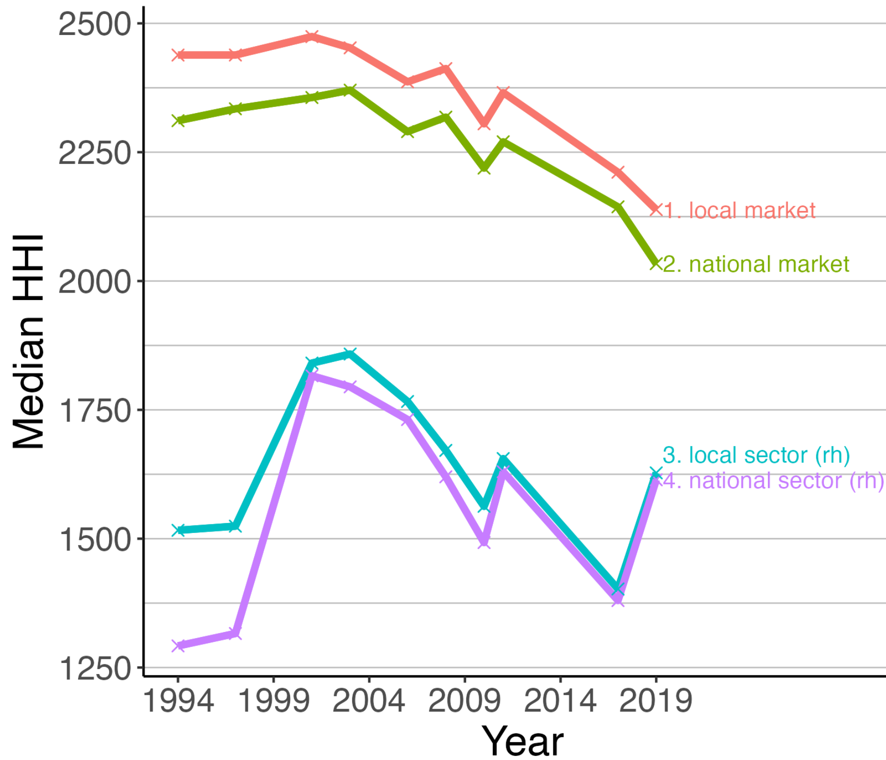
C.3 Unbalanced panel

Figure A.3 shows the result of figure 1 using all 475 markets we observe in the sample; thus, brand merge rates are lower, and the composition of product markets shifts over time. Nonetheless, the basic pattern that concentration is decreasing at the market level, and somewhat increasing at the sector level, is still present.

C.4 Alternative levels of market aggregation

One weakness of our main data is that we only have two market definitions: markets, and sectors. However, the Kantar dataset, for 2017, has multiple levels of market aggregation: "majors" and "industries", which are somewhat lower-level than MRI-Simmons sectors. While we only have these aggregation variables for a single year of the Kantar data, if we hold fixed the mapping from markets to majors and industries over time, we can use this to analyze concentration at different levels of market aggregation. That is, we first match MRI-Simmons markets to fine Kantar product categories; we then impute

Figure A.3: Median HHI for different market definitions over time, unbalanced panel

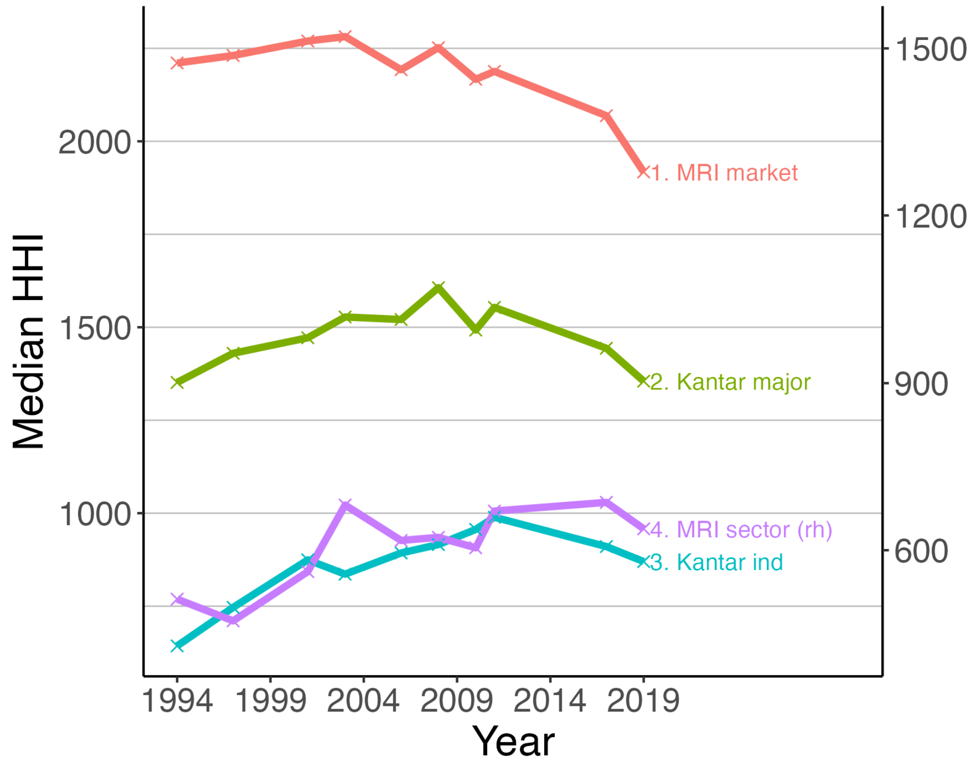


Notes. Median HHI over time, at the state-market, market, state-sector, and sector levels, for the unbalanced panel dataset. "rh" indicates right-hand axis.

Kantar "majors" and "industries" using the 2017 Kantar definitions. This gives us two more levels of aggregation for analyzing concentration: in the balanced panel, we have 336 MRI-Simmons product markets, 120 Kantar majors, 46 Kantar industries, and 19 MRI-Simmons sectors.

In figure A.4, we show how concentration varies at each of these levels of aggregation. MRI-Simmons markets are the finest level of aggregation, followed by Kantar majors, Kantar industries, and MRI-Simmons sectors. The "divergence" trend is relatively uniform. Concentration is decreasing over time at the MRI-Simmons market level, roughly flat at the Kantar major and industry levels, and increasing over time at the MRI-Simmons sector level.

Figure A.4: Median HHI including Kantar major and industry levels



Notes. Equivalent of figure 1, including Kantar major (green) and industry (blue) levels. MRI-Simmons product markets (red) and MRI-Simmons sectors (purple) are identical to figure 1. rh indicates right-hand axis.

C.5 HHI by sector and aggregation level

To complement figure 4, local product market HHI over time by sector, figure A.5 shows national product market, local sector HHI, and national sector HHI over time by sector, in addition to local product market HHI.

C.6 Store Brands

In our main specification, we treated each response of store brand as a single unit of market share for a separate firm. In Figure A.6, we take the other extreme and treat the store brand as a single firm in each market. In reality, it is likely that there are a handful of different store brands in each market which would be an intermediate case to the two extremes we consider. Treating store brands as a single firm reduces the magnitude of the fall in median HHI somewhat, but the result that median HHI is decreasing is robust to the two extremes of how to treat store brands.

D Data coverage

Table A.2 shows the names of each MRI-Simmons product market in the balanced panel. Product market and sector names are defined by MRI-Simmons.

Table A.2: Balanced panel product market coverage

Product market	Sector
DomesticTravelAirlinesused	Airlines
ForeignTravelAirlinesUsed	Airlines
AthleticShoesBrandsBought	Apparel
WomensLingerieUndergarments	Apparel
AirFilters	AutoProducts
AntiFreezeCoolant	AutoProducts
CarBatteriesBrands	AutoProducts
CarWaxPolish	AutoProducts
Gasoline	AutoProducts
GasolineAdditives	AutoProducts
LeatherAndVinylProtectants	AutoProducts
MotorOil	AutoProducts
MotorOilAdditives	AutoProducts
MufflersBrands	AutoProducts
OilFilters	AutoProducts
ShockAbsorbersStruts	AutoProducts
SparkPlugs	AutoProducts
Tires	AutoProducts
WindshieldWipers	AutoProducts
AutomobilesAndOtherVehiclesManufacturer	Automobile
MotorcyclesMake	Automobile
BottledWaterSeltzer	Beverages
Bourbon	Beverages
Brandy	Beverages
CanadianWhisky	Beverages
ChampagneSparklingWines	Beverages
Cognac	Beverages
DietColaDrinks	Beverages
DomesticDinnerTableWines	Beverages
EnergyDrinks	Beverages
EvaporatedCondensedMilk	Beverages
FlavoredAlcoholicBeveragesCoolers	Beverages
FlavoredInstantCoffee	Beverages
Gin	Beverages
GrapefruitJuice	Beverages
ImportedBeer	Beverages
ImportedDinnerTableWines	Beverages
LowCalorieDomesticBeer	Beverages
MaltLiquor	Beverages
OtherDietSoftDrinksNotColas	Beverages
OtherFruitJuicesDrinks	Beverages
OtherRegularCarbonatedSoftDrinks	Beverages
PortSherryDessertWines	Beverages
PowderedFruitSoftDrinks	Beverages
PreparedMixedDrinksWithoutLiquor	Beverages
ReadyToDrinkIcedTea	Beverages
RegularColaDrinksNotDiet	Beverages
RegularDomesticBeer	Beverages
RegularTea	Beverages
Rum	Beverages
RyeOrBlendedWhiskey	Beverages
ScotchWhisky	Beverages
Tequila	Beverages
TomatoAndVegetableJuices	Beverages
Vermouth	Beverages
Vodka	Beverages
CarRentalBusinessUse	CarRental
CarRentalPersonalUse	CarRental
Batteries	Electronics
CallsServicesUsed	Electronics
CamerasCamcordersBrands	Electronics
DVDBluRayPlayersBrands	Electronics
PersonalComputers	Electronics
TelephoneCallingCards	Electronics
TelevisionSetsBrands	Electronics
CruiseShipsCruiseLinesUsed	Entertainment
CreditCards	Financial
InvestmentActivityBrokerageFirms	Financial
RealEstateWhichAgentUsed	Financial
AdhesiveBandages	Health
AftershaveLotionCologneForMen	Health
AthletesFootFootCareProducts	Health
BathShowerAdditivesWomen	Health
BleachAndDepilatories	Health
BlusherWomen	Health
BodyPowder	Health
ColdSinusAndAllergyRemediesNonprescr	Health
ComplexionCareProducts	Health
CondomsBought	Health
ContactLensCleaningWettingSolutions	Health
CoughDropsNonprescription	Health
CoughSyrupNonprescription	Health
DentalFloss	Health
DentureAdhesivesFixatives	Health
DentureCleaners	Health
DeodorantsAndAntiperspirants	Health
DiarrheaRemedies	Health
DisposableRazors	Health
ElectricShavers	Health
EyeLinerWomen	Health
EyeShadowWomen	Health
EyeWashAndDrops	Health
FacialMoisturizersWomen	Health
FeminineHygieneDeodorantCleansingProducts	Health
FeminineMedicatedProductsWomen	Health
FoundationMakeUpWomen	Health
HairColoringProductsForUseAtHome	Health
HairConditionersForUseAtHome	Health
HairConditioningTreatmentForUseAtHome	Health
HairSpraysForUseAtHome	Health
HairStylingGelsLotions	Health
HairTonicOrDressingMen	Health
HandBodyCreamLotionOrOil	Health
HeadacheRemediesAndPainRelieversNonprescr	Health
HemorrhoidRemedies	Health
HomePermanentsWomen	Health
Laxatives	Health
LipCare	Health
LipstickLipGlossWomen	Health
LiquidSoapsHandSanitizers	Health
LooseFacePowderWomen	Health
MascaraWomen	Health
MealSupplements	Health
MedicatedSkinOintments	Health
Mouthwash	Health
NailCareProductsPolishWomen	Health
NailPolishRemoverWomen	Health
PainRelievingRubsLiquidsNonprescription	Health
PersonalCareSoapsBar	Health
RazorBlades	Health
SanitaryNapkinsAndPantilinersWomen	Health
ShampooForUseAtHome	Health
ShavingCreamsOrGels	Health
SleepingTabletsNonprescription	Health
SuntanSunscreenProducts	Health
TamponsWomen	Health
ToothacheGumCankerSoreRemedies	Health
Toothbrushes	Health
Toothpaste	Health
Toothpolish	Health
VitaminAndMineralSupplements	Health
WartRemovers	Health
BabyBathWashAndSoap	HoProdChild
BabyFoods	HoProdChild
BabyLotion	HoProdChild
BabyNursers	HoProdChild
BabyOil	HoProdChild
BabyOintments	HoProdChild
BabyPowder	HoProdChild
BabyShampoo	HoProdChild
ChildrensColdTabletsLiquids	HoProdChild
ChildrensCoughSyrup	HoProdChild
CottonSwabs	HoProdChild
DisposableDiapers	HoProdChild
InfantCereal	HoProdChild
PainRelieversFeverReducersForChildren	HoProdChild
PreMoistenedBabyWipes	HoProdChild
TeethingRemedies	HoProdChild
VitaminsForChildren	HoProdChild
AmericanPasteurizedProcessedCheese	HoProdFood
ArtificialSweeteners	HoProdFood
BaconAndBreakfastStrips	HoProdFood
BakingChips	HoProdFood
BakingCoconut	HoProdFood
BakingMixesExcludingCakeMixes	HoProdFood
BakingPowderAndSoda	HoProdFood
BarBakingChocolate	HoProdFood
BottledBarbecueSeasoningSauces	HoProdFood
BoxedChocolates	HoProdFood
Bread	HoProdFood
BreadCrumbsCoatingMixes	HoProdFood
BreakfastCerealGranolaBars	HoProdFood
BreakfastCerealsCold	HoProdFood
BreakfastCerealsHot	HoProdFood
BrownieCookieMixes	HoProdFood
Butter	HoProdFood
CandyRegularOrKingSize	HoProdFood
CannedBeansWithSauce	HoProdFood
CannedChicken	HoProdFood
CannedOrJarredFruit	HoProdFood
CannedOrJarredSoup	HoProdFood
CannedOrJarredSpaghettiMacaroni	HoProdFood
CannedOrJarredVegetables	HoProdFood
CannedStews	HoProdFood
CannedTomatoes	HoProdFood
ChewingGum	HoProdFood
ChickenTurkeyFreshOrFrozen	HoProdFood
Chili	HoProdFood
CocoaPowder	HoProdFood
ColdCuts	HoProdFood
CookedHams	HoProdFood
CookiesReadyToEat	HoProdFood
CornTortillaOtherChipsCheeseSnacks	HoProdFood
CottageCheese	HoProdFood
Crackers	HoProdFood
CreamCheese	HoProdFood
DrinkAdditivesHotCocoaAddMilkOrWater	HoProdFood
DryCakeMixes	HoProdFood
DrySoupBouillon	HoProdFood
EggAlternatives	HoProdFood
EnglishMuffins	HoProdFood
Extracts	HoProdFood
FishSeafoodFreshOrFrozen	HoProdFood
FlavoredSeasonedRice	HoProdFood
FrankfurtersWieners	HoProdFood
Frostings	HoProdFood
FrozenBreadedChicken	HoProdFood
FrozenBreakfasts	HoProdFood
FrozenCompleteDinners	HoProdFood
FrozenDesserts	HoProdFood
FrozenHotSnacks	HoProdFood
FrozenMainCourses	HoProdFood
FrozenOrangeJuice	HoProdFood
FrozenPancakesFrenchToast	HoProdFood
FrozenPizza	HoProdFood
FrozenRefrigeratedPotatoProducts	HoProdFood
FrozenVegetables	HoProdFood
FrozenWaffles	HoProdFood

Notes. MRI-Simmons product market names and sector names in our data.

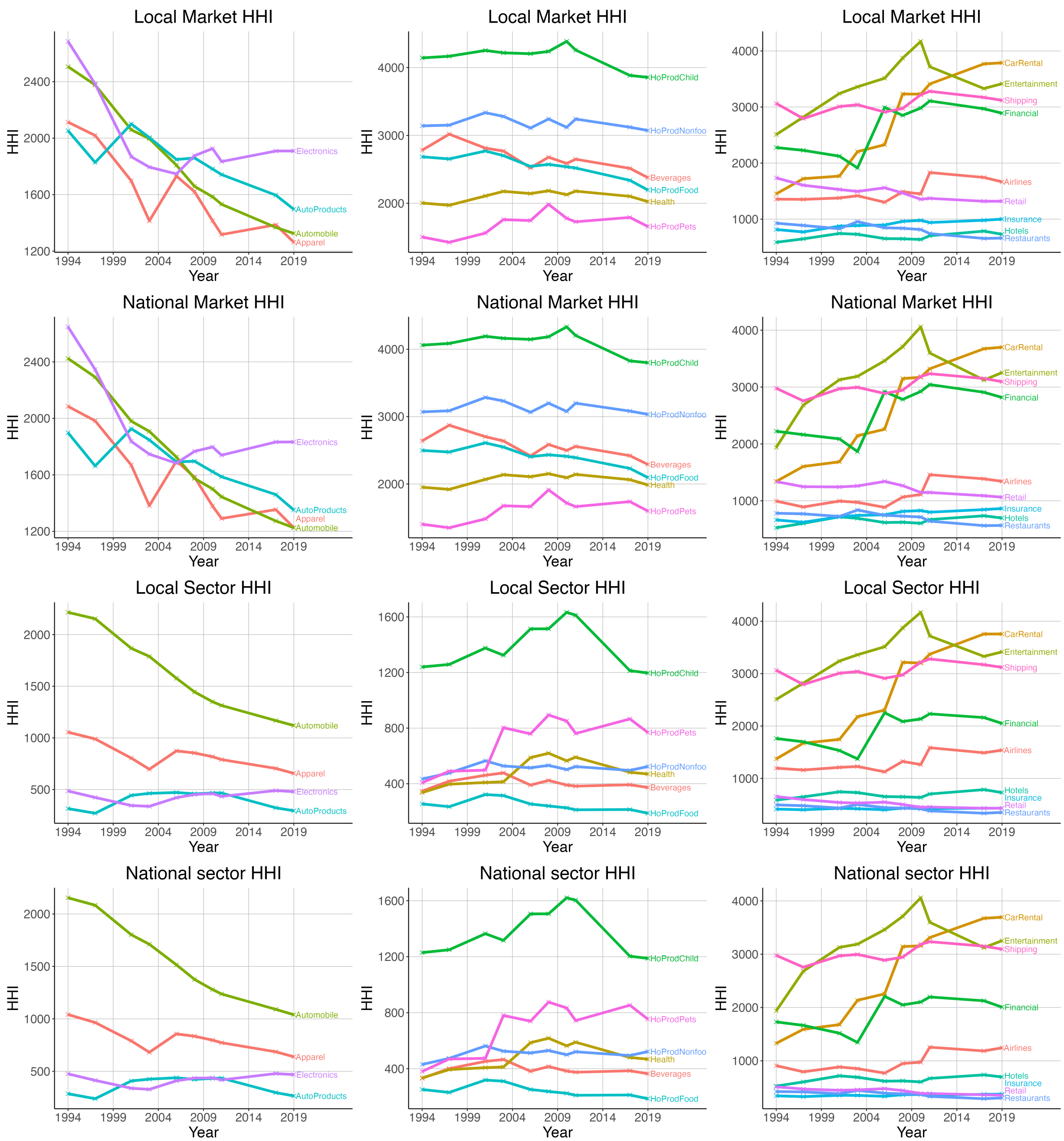
Table A.2 (continued): Balanced panel product market coverage

Product market	Sector
FrozenYogurt	HoProdFood
GelatinAndGelatinDesserts	HoProdFood
GratedCheese	HoProdFood
GravySauceMixesAndCookingSauces	HoProdFood
GroundCoffee	HoProdFood
HardRollCandy	HoProdFood
Honey	HoProdFood
IceCreamBarsSandwichesBonBons	HoProdFood
IceCreamIceMilkSherbet	HoProdFood
InstantBreakfast	HoProdFood
InstantIcedTeaMix	HoProdFood
InstantOrFreezeDriedCoffee	HoProdFood
JamsJellies	HoProdFood
KetchupCatsup	HoProdFood
LunchCombinationsKits	HoProdFood
Margarine	HoProdFood
MayonnaiseAndMayonnaiseTypeSaladDressing	HoProdFood
MeatSnacks	HoProdFood
MexicanFoods	HoProdFood
Mints	HoProdFood
Mustard	HoProdFood
NaturalOrImportedCheese	HoProdFood
Nectars	HoProdFood
NonDairyCreamSubstitutes	HoProdFood
Nuts	HoProdFood
OrangeJuiceNotFrozen	HoProdFood
PackagedDinnersSideDishesMixesOrPrepared	HoProdFood
PackagedFrozenRefrigeratedPasta	HoProdFood
PackagedInstantPotatoes	HoProdFood
PackagesOfMiniatureCandy	HoProdFood
PeanutButter	HoProdFood
PickleRelish	HoProdFood
Pickles	HoProdFood
PizzaMixesAndSauces	HoProdFood
PizzaShellsCrusts	HoProdFood
PoppingCornPopcornSnacks	HoProdFood
Pretzels	HoProdFood
PuddingsPieFillings	HoProdFood
ReadyToEatDoughnuts	HoProdFood
ReadyToEatMuffins	HoProdFood
ReadyToEatSweetRollsPastries	HoProdFood
RefrigeratedFrozenBreadAndDoughProducts	HoProdFood
Rice	HoProdFood
RiceCakes	HoProdFood
SaladOrCookingOil	HoProdFood
SaladToppings	HoProdFood
Salt	HoProdFood
SaltAlternatives	HoProdFood
Sausage	HoProdFood
SeasoningsSpices	HoProdFood
Shortening	HoProdFood
SnackCakes	HoProdFood
SourCream	HoProdFood
SoySauce	HoProdFood
SpaghettiPastaSauce	HoProdFood
SprayNonStickCookingProducts	HoProdFood
SpreadCheeseCheeseSauce	HoProdFood
StuffingMixesAndStuffingProducts	HoProdFood
Sugar	HoProdFood

Product market	Sector
TableSyrupMolasses	HoProdFood
ToasterProducts	HoProdFood
Vinegar	HoProdFood
WaffleOrPancakeMix	HoProdFood
WhippedTopping	HoProdFood
WholeCoffeeBeans	HoProdFood
Yeast	HoProdFood
Yogurt	HoProdFood
AirFreshenersCarpetRoomDeodorizers	HoProdNonfood
AluminumFoil	HoProdNonfood
AutomaticDishwasherDetergent	HoProdNonfood
Bleach	HoProdNonfood
CarpetAndRugCleaners	HoProdNonfood
Charcoal	HoProdNonfood
CharcoalLighterFluid	HoProdNonfood
ChewingAndSmokelessTobacco	HoProdNonfood
DishwashingLiquid	HoProdNonfood
DisposableCups	HoProdNonfood
DisposablePlates	HoProdNonfood
DrainCleaners	HoProdNonfood
FabricSofteners	HoProdNonfood
FacialTissues	HoProdNonfood
Firelogs	HoProdNonfood
FloorWaxPolish	HoProdNonfood
FurniturePolish	HoProdNonfood
GlassAndSurfaceCleaners	HoProdNonfood
Glue	HoProdNonfood
HouseholdCleaners	HoProdNonfood
InBowlToiletBowlCleaners	HoProdNonfood
InHomeShoppingCompanies	HoProdNonfood
InTankToiletBowlCleaners	HoProdNonfood
IndoorInsecticides	HoProdNonfood
IndoorPlantFood	HoProdNonfood
InsectRepellents	HoProdNonfood
LaundryPreTreatmentsPreCleaners	HoProdNonfood
LightBulbs	HoProdNonfood
Luggage	HoProdNonfood
OutdoorInsecticides	HoProdNonfood
OvenCleaners	HoProdNonfood
PaintStain	HoProdNonfood
PaperNapkins	HoProdNonfood
PaperTowels	HoProdNonfood
PlasticGarbageBagsTrashCanLiners	HoProdNonfood
PlasticSandwichFoodStorageFreezerBags	HoProdNonfood
RubberGloves	HoProdNonfood
ScouringCleansers	HoProdNonfood
SoapDetergentsForFineFabrics	HoProdNonfood
SoapDetergentsForRegularLaundry	HoProdNonfood
ToiletPaper	HoProdNonfood
TransparentTape	HoProdNonfood
WritingInstrumentsBrands	HoProdNonfood
CannedWetCatFood	HoProdPets
CannedWetDogFood	HoProdPets
CatLitter	HoProdPets
DogBiscuitsOrTreats	HoProdPets
FleaTickCareProductsForDogsCats	HoProdPets
PackagedDryCatFood	HoProdPets
PackagedDryDogFood	HoProdPets
HotelsMotelsWhereStayed	Hotels
AutoInsurance	Insurance
HomeownersOrPersonalPropertyInsuranceCompany	Insurance
LifeInsuranceCompanies	Insurance
MedicalInsuranceCompanies	Insurance
FamilyRestaurantsSteakHouses	Restaurants
FastFoodDriveInRestaurants	Restaurants
ApplianceHardwareElectronicsStoresTimesShopped	Retail
ConvenienceStoresTimesShopped	Retail
DepartmentClothingSpecialtyStoresTimesShopped	Retail
OvernightPackagesLetterDeliveryServicesServicesUsed	Shipping

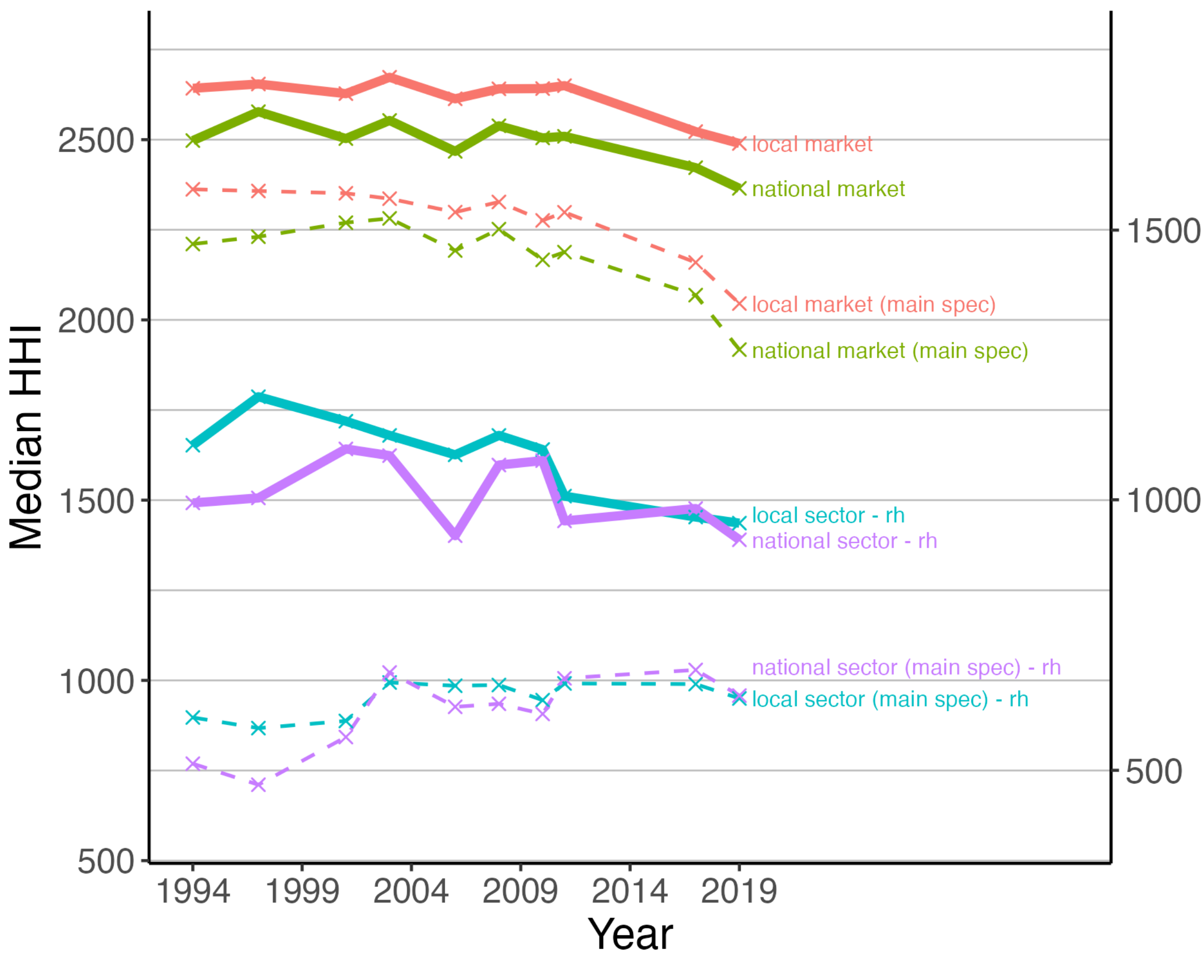
Notes. MRI-Simmons product market names and sector names in our data.

Figure A.5: HHI over time, by sector and aggregation level



Notes. HHI over time, at the state group – product market (top), product market (second row), state group – sector (third row), and sector (bottom) levels. Each line shows the expenditure-weighted average of HHIs. The left column shows results for manufacturing, the center column for food, beverage, and health products, and the right column shows results for non-manufacturing.

Figure A.6: Store Brands as Single Firm



Notes. This figure shows median HHI at the local market, national market, local sector, and national sector level in the baseline data (dashed line), and in an alternative specification where we assume all store brands constitute a single firm for the purposes of HHI calculation.