

Concentration in Product Markets

Internet Appendix

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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 `relink2` 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 `relink2`, 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:

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

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:

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

Hence,

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

Rearranging, we have:

$$\text{HHI}_j = \mathbb{E} \left(\sum_o \hat{s}_{oj}^2 \right) - \sum_o \text{Var} [\hat{s}_{oj}] \quad (5)$$

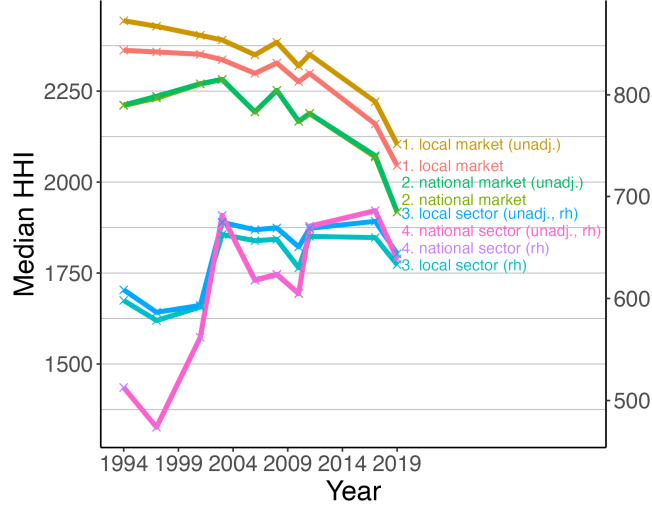
Hence, we can construct an unbiased estimator for HHI_j by subtracting $\sum_o \text{Var} [\hat{s}_{oj}]$, the sum of sample variances of the market shares $\hat{s}_{oj}$, from the sample HHI, $\sum_o \hat{s}_{oj}^2$. We calculate these sample variances using a nonparametric bootstrap. In each year of 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.

B Decomposition Calculation

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

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.

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

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

- $\mathcal{O}_{m,t}^{\text{entry}}$: 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 .
- $\mathcal{O}_{m,t}^{\text{exit}}$: Owners who exit: they have positive market share in period $t - 1$, and zero market share in period t .
- $\mathcal{O}_{m,t}^{\text{merger}}$: 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 $s_{o_2,m,t}, s_{o_3,m,t} = 0$.
- $\mathcal{O}_{m,t}^{\text{divestiture}}$: 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 .
- $\mathcal{O}_{m,t}^{\text{residual}}$: Owners with positive market shares not in any of the sets $\mathcal{O}_{m,t}^{\text{entry}}, \mathcal{O}_{m,t}^{\text{exit}}, \mathcal{O}_{m,t}^{\text{merger}}, \mathcal{O}_{m,t}^{\text{divestiture}}$.

By construction, the five sets $\mathcal{O}_{m,t}^{\text{entry}}, \mathcal{O}_{m,t}^{\text{exit}}, \mathcal{O}_{m,t}^{\text{merger}}, \mathcal{O}_{m,t}^{\text{divestiture}}, \mathcal{O}_{m,t}^{\text{residual}}$ 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:

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

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

$$\left(\underbrace{\sum_{o \notin \mathcal{O}_{m,t}^{\text{exit}}} \left(\hat{s}_{o,m,t-1}^2 - s_{o,m,t-1}^2 \right)}_A - \underbrace{\sum_{o \in \mathcal{O}_{m,t}^{\text{exit}}} s_{o,m,t-1}^2}_B \right) \quad (7)$$

in the decomposition (6) thus can be thought of as representing how HHIs would change, if all firms in $\mathcal{O}_{m,t}^{\text{exit}}$ 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:

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

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

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

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 $\mathcal{O}_{m,t}^{\text{entry}}$ 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:

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

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):

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

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):

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

which reflects the fact that the actual market share of the merged firms, $\hat{s}_{o,m,t}$, 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 occurred in period $t-1$. The divestiture term in (6):

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

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:

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

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:

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

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

$$HHI_{jt} = \mu_t + \gamma_j + \epsilon_{jt} \quad (11)$$

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

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

Standard errors in parentheses

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

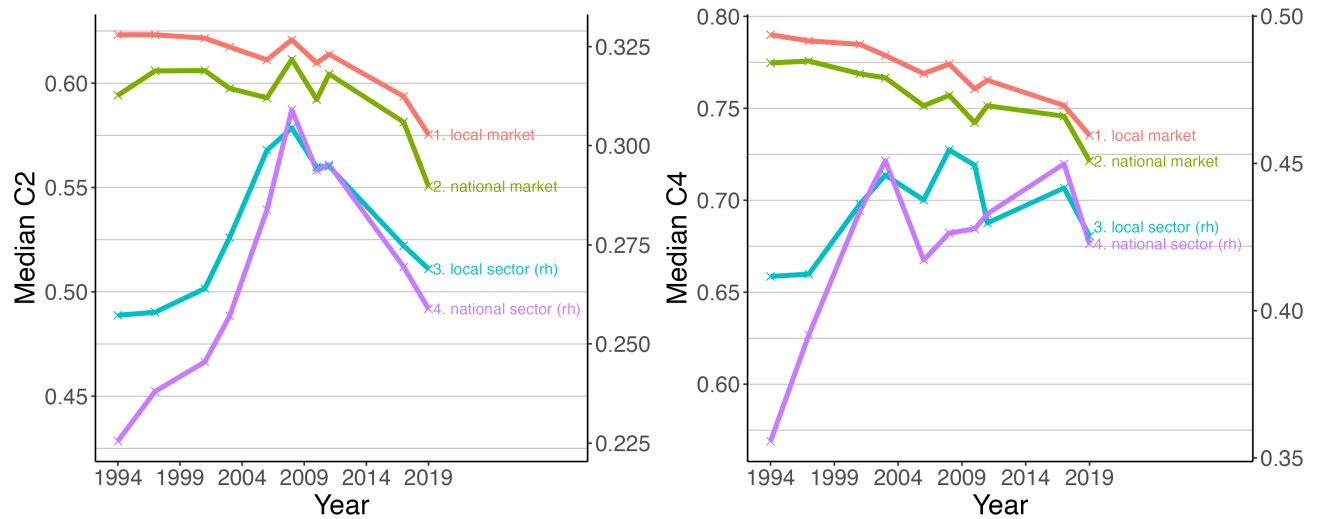
Notes. Columns 1 and 2 show the regression results for the entire census sample. Columns 3 and 4 show the results for census codes that we matched to MRI-Simmons product markets. For columns 2 and 4, we also drop any NAICS industry codes that change in the time series.

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.

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.

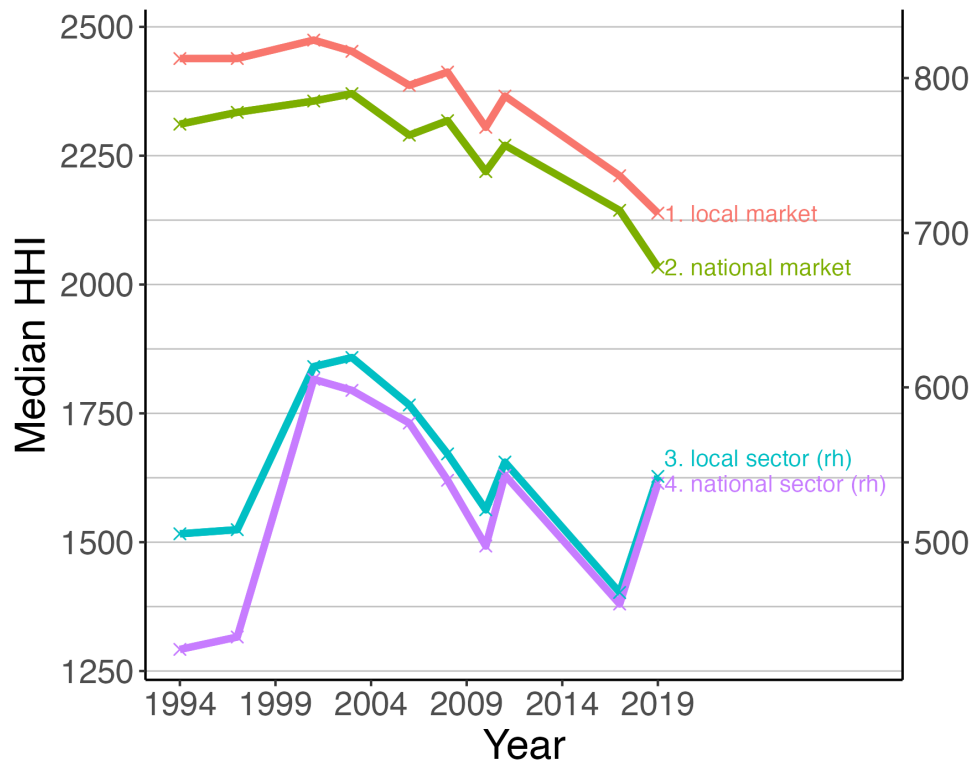
C.3 Unbalanced panel

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

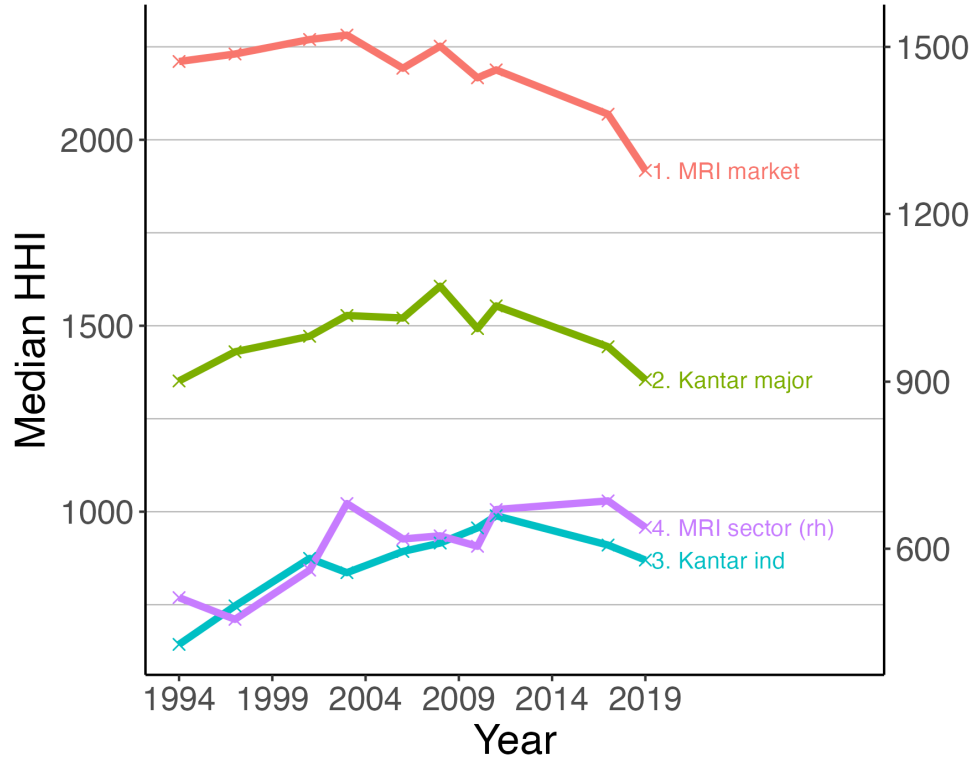


Notes. Median HHI over time, at the state-market, market, state-sector, and sector levels, for the unbalanced panel dataset. “rh” indicates right-hand axis.

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

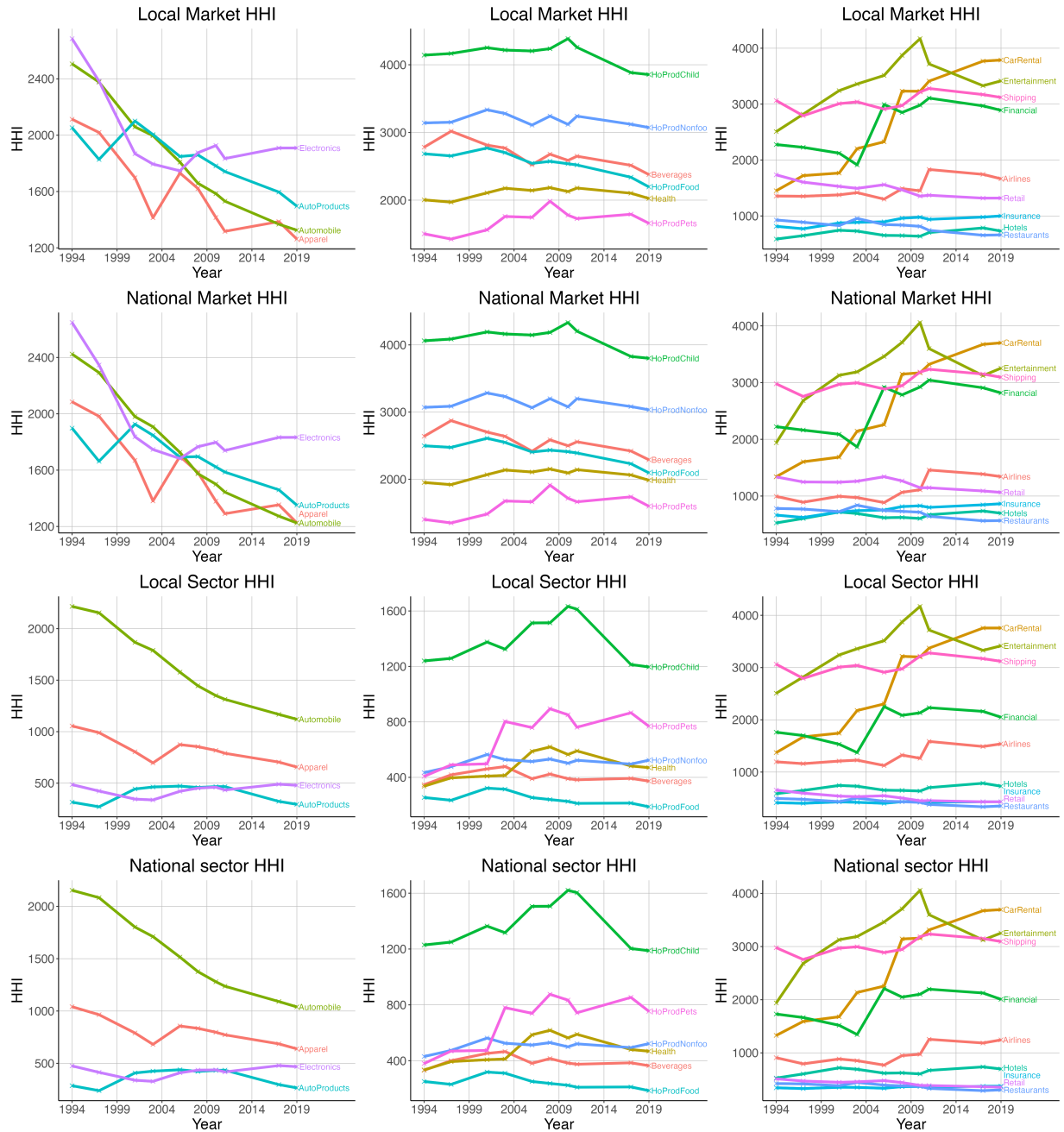
Notes. MRI-Simmons product market names and sector names in our data.

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

Product market	Sector	Product market	Sector
FrozenYogurt	HoProdFood	TableSyrupMolasses	HoProdFood
GelatinAndGelatinDesserts	HoProdFood	ToasterProducts	HoProdFood
GratedCheese	HoProdFood	Vinegar	HoProdFood
GravySauceMixesAndCookingSauces	HoProdFood	WaffleOrPancakeMix	HoProdFood
GroundCoffee	HoProdFood	WhippedTopping	HoProdFood
HardRollCandy	HoProdFood	WholeCoffeeBeans	HoProdFood
Honey	HoProdFood	Yeast	HoProdFood
IceCreamBarsSandwichesBonBons	HoProdFood	Yogurt	HoProdFood
IceCreamIceMilkSherbet	HoProdFood	AirFreshenersCarpetRoomDeodorizers	HoProdNonfood
InstantBreakfast	HoProdFood	AluminumFoil	HoProdNonfood
InstantIcedTeaMix	HoProdFood	AutomaticDishwasherDetergent	HoProdNonfood
InstantOrFreezeDriedCoffee	HoProdFood	Bleach	HoProdNonfood
JamsJellies	HoProdFood	CarpetAndRugCleaners	HoProdNonfood
KetchupCatsup	HoProdFood	Charcoal	HoProdNonfood
LunchCombinationsKits	HoProdFood	CharcoalLighterFluid	HoProdNonfood
Margarine	HoProdFood	ChewingAndSmokelessTobacco	HoProdNonfood
MayonnaiseAndMayonnaiseTypeSaladDressing	HoProdFood	DishwashingLiquid	HoProdNonfood
MeatSnacks	HoProdFood	DisposableCups	HoProdNonfood
MexicanFoods	HoProdFood	DisposablePlates	HoProdNonfood
Mints	HoProdFood	DrainCleaners	HoProdNonfood
Mustard	HoProdFood	FabricSofteners	HoProdNonfood
NaturalOrImportedCheese	HoProdFood	FacialTissues	HoProdNonfood
Nectars	HoProdFood	Firelogs	HoProdNonfood
NonDairyCreamSubstitutes	HoProdFood	FloorWaxPolish	HoProdNonfood
Nuts	HoProdFood	FurniturePolish	HoProdNonfood
OrangeJuiceNotFrozen	HoProdFood	GlassAndSurfaceCleaners	HoProdNonfood
PackagedDinnersSideDishesMixesOrPrepared	HoProdFood	Glue	HoProdNonfood
PackagedFrozenRefrigeratedPasta	HoProdFood	HouseholdCleaners	HoProdNonfood
PackagedInstantPotatoes	HoProdFood	InBowlToiletBowlCleaners	HoProdNonfood
PackagesOfMiniatureCandy	HoProdFood	InHomeShoppingCompanies	HoProdNonfood
PeanutButter	HoProdFood	InTankToiletBowlCleaners	HoProdNonfood
PickleRelish	HoProdFood	IndoorInsecticides	HoProdNonfood
Pickles	HoProdFood	IndoorPlantFood	HoProdNonfood
PizzaMixesAndSauces	HoProdFood	InsectRepellents	HoProdNonfood
PizzaShellsCrusts	HoProdFood	LaundryPreTreatmentsPreCleaners	HoProdNonfood
PoppingCornPopcornSnacks	HoProdFood	LightBulbs	HoProdNonfood
Pretzels	HoProdFood	Luggage	HoProdNonfood
PuddingsPieFillings	HoProdFood	OutdoorInsecticides	HoProdNonfood
ReadyToEatDoughnuts	HoProdFood	OvenCleaners	HoProdNonfood
ReadyToEatMuffins	HoProdFood	PaintStain	HoProdNonfood
ReadyToEatSweetRollsPastries	HoProdFood	PaperNapkins	HoProdNonfood
RefrigeratedFrozenBreadAndDoughProducts	HoProdFood	PaperTowels	HoProdNonfood
Rice	HoProdFood	PlasticGarbageBagsTrashCanLiners	HoProdNonfood
RiceCakes	HoProdFood	PlasticSandwichFoodStorageFreezerBags	HoProdNonfood
SaladOrCookingOil	HoProdFood	RubberGloves	HoProdNonfood
SaladToppings	HoProdFood	ScouringCleasers	HoProdNonfood
Salt	HoProdFood	SoapDetergentsForFineFabrics	HoProdNonfood
SaltAlternatives	HoProdFood	SoapDetergentsForRegularLaundry	HoProdNonfood
Sausage	HoProdFood	ToiletPaper	HoProdNonfood
SeasoningsSpices	HoProdFood	TransparentTape	HoProdNonfood
Shortening	HoProdFood	WritingInstrumentsBrands	HoProdNonfood
SnackCakes	HoProdFood	CannedWetCatFood	HoProdPets
SourCream	HoProdFood	CannedWetDogFood	HoProdPets
SoySauce	HoProdFood	CatLitter	HoProdPets
SpaghettiPastaSauce	HoProdFood	DogBiscuitsOrTreats	HoProdPets
SprayNonStickCookingProducts	HoProdFood	FleaTickCareProductsForDogsCats	HoProdPets
SpreadCheeseCheeseSauce	HoProdFood	PackagedDryCatFood	HoProdPets
StuffingMixesAndStuffingProducts	HoProdFood	PackagedDryDogFood	HoProdPets
Sugar	HoProdFood	HotelsMotelsWhereStayed	Hotels
		AutoInsurance	Insurance
		HomeownersOrPersonalPropertyInsuranceCompany	Insurance
		LifeInsuranceCompanies	Insurance
		MedicalInsuranceCompanies	Insurance
		FamilyRestaurantsSteakHouses	Restaurants
		FastFoodDriveInRestaurants	Restaurants
		ApplianceHardwareElectronicsStoresTimesShopped	Retail
		ConvenienceStoresTimesShopped	Retail
		DepartmentClothingSpecialtyStoresTimesShopped	Retail
		OvernightPackagesLetterDeliveryServicesServicesUsed	Shipping

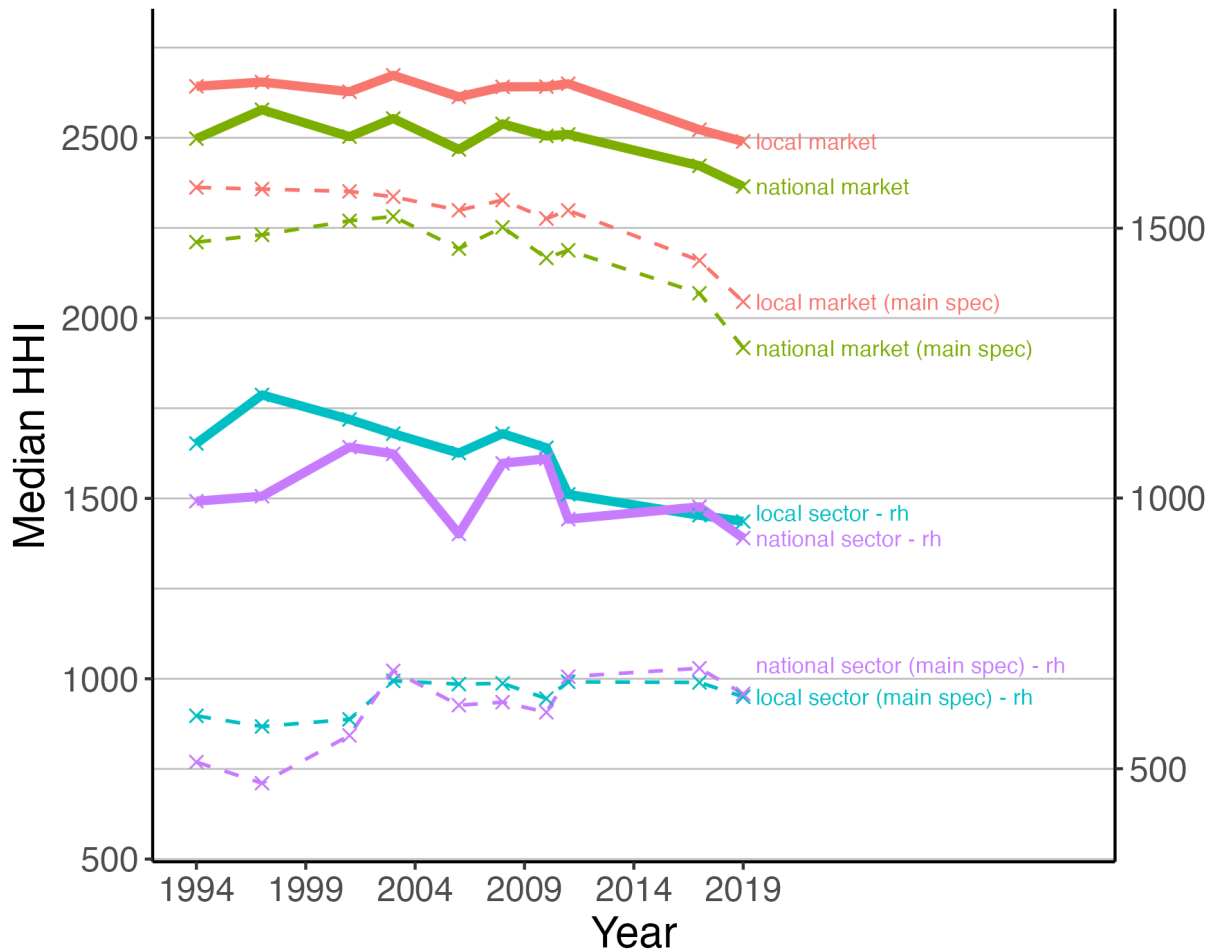
Notes. MRI-Simmons product market names and sector names in our data.

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.