Concentration in Product Markets*

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Abstract

This paper uses new data to reexamine trends in concentration in U.S. markets from 1994 to 2019. The paper’s main contribution is to construct concentration measures that reflect narrowly defined consumption-based product markets, as would be defined in an antitrust setting, while accounting for cross-brand ownership, and to do so over a broad range of consumer goods and services. Our findings differ substantially from well established results using production data. We find that 45% of the industries in our sample are “highly concentrated” as defined by the U.S. Horizontal Merger Guidelines, which is much higher than previous results. Also in contrast with the previous literature, we find that product market concentration has been decreasing since 1994. This finding holds at the national level and also when product markets are defined locally in 29 state groups. We find increasing concentration once markets are aggregated to a broader sector level. We argue that these two diverging trends are best explained by a simple theoretical model based on Melitz and Ottaviano (2008), in which the costs of a firm supplying adjacent geographic or product markets falls over time, and efficient firms enter each others’ home product markets.

Keywords: Concentration, Product markets

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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. A prominent and growing literature has documented economy-wide increases in industry concentration in the U.S. in the last three decades. Increasing concentration has been linked to declining labor and capital shares, declining investment and productivity growth, and rising markups. This paper uses new data to reexamine these trends. The central innovation in the paper is to construct concentration measures that reflect narrowly defined product markets as would be defined in an antitrust setting, while accounting for cross-brand ownership, and to do so over a broad range of consumer goods and services and a long time frame.

The evidence for broad-based increases in concentration is well established. The most widely cited evidence comes from establishment-level data from the U.S. Economic Census. Similar trends have been demonstrated using firm-level data for public firms from Compustat. The perception of broad-based increases in concentration is also commonplace among politicians and in the popular press.

However, as outlined in detail in Shapiro (2018), there are many problems with drawing antitrust conclusions from the 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

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2 Autor et al. (2020), Barkai (2016)
3 Gutiérrez and Philippon (2017)
6 Autor et al. (2020), Gutiérrez and Philippon (2017)
7 See Shapiro (2018) for an excellent discussion. Early examples include CEA (2016) and Economist (2016).
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 industries also tend to be 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. 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 dramatically over the past few decades, but this is misleading because local concentration, the relevant statistic for assessing market power to consumers, has decreased just as dramatically. All of these issues are even more present in the Compustat data, which only covers public firms.

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 reports consumers’ brand choices across 457 product markets, representing both goods and services.

We have already described some of the difficulties with measuring market concentration across many product markets and a long time horizon in a consistent and meaningful way. 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 whose data are widely used in industry. The market definitions seem close to what might result in an antitrust setting (more details below). Because the survey data contains 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.

These data lead to several interesting findings. Figure 1 presents the median HHI concentration measure over time for four market definitions that differ in their level of geographic and product aggregation. Our central finding is that we document a decrease in median product market concentration across a broad range of goods and services since 1994. This result lies in distinct contrast to the findings from production data in the Census. The level of concentration is higher when accounting for the geographic location of consumers in 29 state-groups, but decreases at a similar rate to national concentration. The latter result confirms the main finding in Rossi-Hansberg, Sarte and Trachter (2020) that local market concentration has decreased. However, Rossi-Hansberg, Sarte and Trachter (2020) find increased national concentration even for the most narrow industry classifications, in contrast to our findings.

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 are nearly identical. Instead, the joint finding of rising sector concentration and decreasing product market concentration implies that firms are expanding into adjacent product markets within the same sector. While this could be achieved through a combination of mergers and de novo entry, in concert with horizontal mergers and exit, our data do not allow us to distinguish the precise mechanisms behind the increase.

Our sector level measurements are more consistent with the results in existing work on the

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8The data contain numerous name changes for both firms and brands that make it difficult to link them over time.
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.
establishment data,\textsuperscript{9} likely because the sector level of market aggregation matches the establishment data more closely.

While we find broad-based decreases in concentration over time, using our market definitions, concentration levels are much higher than in the establishment-level data. In our data the median HHI over all periods is 2309, with 45\% of industries having an HHI above 2500, the level that is considered “highly concentrated” in the U.S. Horizontal Merger Guidelines. Thus, using this (admittedly too simple) antitrust screen, our data suggests that market power is potentially much higher than previously thought in a large fraction of U.S. product markets. Applying the same simple antitrust screen to the Census data would lead to the opposite conclusion that market power is generally low in U.S. markets.\textsuperscript{10} \textsuperscript{10}Author 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 pre-2010 stricter merger guidelines labeled all of these as “unconcentrated”\textsuperscript{10} Our findings on 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 which experienced a merger investigation by the European Commission.

However, while we find high concentration levels, we reiterate that we find no evidence that market power has been getting worse over time in any broad-based way. On the contrary, concentration in the most concentrated industries has fallen as fast as the median industry. In our data the number of industries in the “highly concentrated” range fell from 48\% 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 a few prominent large firms, such as Facebook, Apple, Amazon, and Google, which have grown enormously in recent years, as well as high profile mergers in industries such as hospitals (Gaynor, 2018) and airlines\textsuperscript{11}.

We employ a simple theoretical model based on Melitz and Ottaviano (2008) to explain

\textsuperscript{9}Grullon, Larkin and Michaely (2019), Barkai (2016), Autor et al. (2020), Covarrubias, Gutiérrez and Philippon (2020)

\textsuperscript{10}In 2010 the “unconcentrated” range was raised from <1000 to <1500 to reflect practice as detailed in Shapiro (2010).

our main findings. We show that the only force in the model capable of explaining both
the product market and sector trends is a reduction in “trade costs”, the costs of a firm
supplying adjacent geographic or product markets. The reduction in trade costs could
be driven by increasing similarity of production processes, or an increasing importance
of logistics and distribution in the production process. As trade costs decrease, efficient
firms enter and compete in each others’ “home” product markets. For example, in our
data Unilever, Proctor and Gamble, and Johnson and Johnson now compete in a vast
array of consumer health and cleaning products. Another interpretation of the model
would be the nationalization of brands where, for example, west coast brands enter east
cost markets and vice-versa (Bronnenberg, Dhar and Dubé, 2009).

An important implication of our model is that these effects are welfare improving.
While sector level concentration increases, the increase is driven by efficiency considera-
tions and consumers benefit. Autor et al. (2020) describe an alternative model in which
technological change directly favors more efficient firms. Changes in industry concen-
tration are similarly driven by increasing efficiency and also yield improving welfare.
However, their model implies increasing concentration at both the product market and
sector levels, whereas our model predicts decreasing concentration at the product market
level.

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 it is 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 subsample of the Census data that is industry matched to the MRI data.
Concentration in the subsample 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. 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
idiosyncracies in the survey.
Another potential issue is the product market definitions in the MRI data. 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 few 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 we do not think that it would systematically affect our estimates of trends. Moreover, it seems plausible that formal antitrust proceedings might result in these narrow market definitions.

Finally, our model rules out changes in market power due to changes in vertical relationships. It is theoretically possible that large firms like Johnson and Johnson can extract more rents from stores like CVS/Walgreens/Safeway in bargaining if they supply a broader range of products, even if those products are in unrelated product markets, as in Dafny, Ho and Lee (2019). If this effect is helping drive the observed trends in market and sector concentration, then there would be an additional force causing market power to increase that is unaccounted for in our model. In that case the welfare effects of the increase in sector concentration would depend on which force is quantitatively more important.

2 Data

2.1 Extracting product information from the GFK MRI

We use respondent level data from the annual “Survey of the American Consumer” available from MRI Simmons, a market research firm.\textsuperscript{12} We use data from 1994 to 2019. MRI surveys approximately 25000 consumers per year in a rolling fashion.

From the survey, we extract all questions which ask consumers to report brands that

\textsuperscript{12}The firm administering the survey has undergone several changes in ownership and has been previously known as Mediamark Research Inc (MRI) and GfK MRI.
they purchase. For example, under “Motor oil” in the 2006 survey, the MRI data allows consumers to report purchases of 24 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 457 products; we will call these “product markets”. We divide these product markets into 17 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 also distinguish between “manufacturing” and “non-manufacturing” sectors. The manufacturing sectors tend to have a larger number of product 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 stategroup-markets. Further details of data cleaning are described in appendix A.

MRI data are well known in industry and commonly employed in media planning. [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 the 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[13] Kantar Adspender contains data on advertising expenditures; the brand

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13 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
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 datasets by brand name using a two-stage fuzzy string-matching algorithm that we describe in detail in appendix A.2.

The brand matching allows us to tell when different brands are owned by the same ultimate owner. For example, while the 2006 data reports 24 different brands of motor oil, most of these brands are owned by three companies: Chevron-Texaco, Exxon Mobil, and Royal Dutch Shell.

### 2.3 Computing market shares

The MRI data contains indicators for whether consumers have purchased a given brand, but typically does 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 $o$, let $I_s$ represent the set of customers living in state $s$, and let $I$ represent the set of all consumers. The market share of owner $o$ in state $s$, market $m$, time $t$, is:

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

where $e_{ibmt}$ is an indicator variable, for whether customer $i$ reports purchasing brand $b$ in market $m$ at time $t$, multiplied by the sampling weight on customer $i$. The national owner. Using historical hard copies of Adspender allows us to circumvent this problem.
market share of owner o in market m, time t, is:

\[ \sum_{b \in B_{mo}} \sum_{i \in I} e_{ibmt} \]

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:

\[ \sum_{m \in M_k} \sum_{b \in B_{mo}} \sum_{i \in I} e_{ibmt} \]

Using each of these market shares, we can then compute concentration metrics – HHI, C4, and C2 – at the level of stategroup-markets, markets, stategroup-sectors, and sectors.

The MRI data includes a number of choices such as “Other” or “Store brand,” that may correspond to multiple brands; treating these as single brands may lead to overestimating market concentration. We take the opposite approach, which is conservative for estimating concentration: we include “Other” and “Store brand” in the denominator when calculating the shares (1), (2) and (3), but do not include them as owners. Essentially, this is like assuming that “Other” and related options constitute a continuum of infinitely small brands.

2.4 Summary of Sectors

Table 1 describes the sectors we analyze. Our main results focus on a balanced panel of the set of product markets that appear in each year from 1994 to 2019. A non-trivial number of product markets appear in only a subset of years. For example, wireless handsets were not measured prior to 2004. We also report results separately for the unbalanced panel consisting of all product markets that appear in the data.

We categorize sectors into manufacturing and non-manufacturing. The data tend to cover many product markets within manufacturing sectors, and relatively fewer for non-manufacturing sectors. Our main results include both manufacturing and non-manufacturing sectors. For robustness, we also report results separately for manufacturing and non-manufacturing sectors.
We are able to match over 80% of brands in most sectors, and over 90% of market share for all sectors other than pet products. There is a nontrivial amount of brand co-ownership in our data. The average brand owner in our data set owns 2.88 brands. The brand ownership distribution is highly skewed, with 76.3% of owners owning only one brand, whereas the largest brand owner owns 253 brands. Ownership across product markets is also nontrivially large: the average owner owns brands across 2.11 product markets. 26.4% 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, Blue Shield.

3 Results

Figure 2 shows the distribution of HHI’s in our data at the stategroup-market (“local market”), market, stategroup-sector (“local sector”), and sector level over time. The DoJ-FTC 2010 Horizontal Merger Guidelines define industries with HHI’s between 1500 and 2500 as “moderately concentrated,” and above 2500 as “highly concentrated.” According to the guidelines, mergers that raise the HHI in moderately or highly concentrated industries often warrant scrutiny.\footnote{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.}

We find much higher concentration levels than those measured using production data. The median HHI in local product markets during the whole period is 2309, with an average of 45% of industries falling 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. Accounting for multi-product ownership also makes a large difference. While not the main focus of their paper, Neiman and Vavra (2018) reports average HHIs of about 30 for categories in the Nielsen scanner data, not accounting for multi-product firms.
Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Sector</th>
<th># Markets</th>
<th># Brands</th>
<th># Owners</th>
<th>Matched brands %</th>
<th>Matched marketshare %</th>
<th>Example markets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airlines</td>
<td>2</td>
<td>28.3</td>
<td>20.1</td>
<td>95.7</td>
<td>99.3</td>
<td>DomesticTravelAi, ForeignTravelAir</td>
</tr>
<tr>
<td>Apparel</td>
<td>2</td>
<td>40.9</td>
<td>31.1</td>
<td>89.1</td>
<td>96.3</td>
<td>AthleticShoesBra, WomensLingerieUn</td>
</tr>
<tr>
<td>AutoProducts</td>
<td>15</td>
<td>196.9</td>
<td>97.6</td>
<td>86.7</td>
<td>96.7</td>
<td>AirFilters, WindshieldWipers</td>
</tr>
<tr>
<td>Automobile</td>
<td>2</td>
<td>52</td>
<td>29.1</td>
<td>89.5</td>
<td>98.8</td>
<td>AutomobilesAndOt, MotorcyclesMake</td>
</tr>
<tr>
<td>Beverages</td>
<td>39</td>
<td>531.3</td>
<td>176.9</td>
<td>83.6</td>
<td>96.4</td>
<td>BottledWaterSelt, Vodka</td>
</tr>
<tr>
<td>CarRental</td>
<td>3</td>
<td>20.6</td>
<td>7</td>
<td>100</td>
<td>100</td>
<td>CarRentalBusines, TruckTrailerRent</td>
</tr>
<tr>
<td>Electronics</td>
<td>5</td>
<td>78.1</td>
<td>46.3</td>
<td>89.0</td>
<td>94.1</td>
<td>Batteries, TelevisionSetsBr</td>
</tr>
<tr>
<td>Financial</td>
<td>3</td>
<td>42.6</td>
<td>26.9</td>
<td>92.7</td>
<td>94.1</td>
<td>CreditCards, RealEstateWhichA</td>
</tr>
<tr>
<td>Health</td>
<td>62</td>
<td>1,127.9</td>
<td>239.7</td>
<td>86.8</td>
<td>94.1</td>
<td>AdhesiveBandages, WartRemovers</td>
</tr>
<tr>
<td>HoProdChild</td>
<td>17</td>
<td>103.3</td>
<td>31.4</td>
<td>93.6</td>
<td>98.5</td>
<td>BabyBathWashAndS, VitaminsForChild</td>
</tr>
<tr>
<td>HoProdFood</td>
<td>126</td>
<td>1,700.7</td>
<td>445</td>
<td>83.0</td>
<td>93.8</td>
<td>AmericanPasteuri, Yogurt</td>
</tr>
<tr>
<td>HoProdNonfood</td>
<td>43</td>
<td>511.1</td>
<td>170.6</td>
<td>81.3</td>
<td>93.0</td>
<td>AirFreshenersCar, WritingInstrumen</td>
</tr>
<tr>
<td>HoProdPets</td>
<td>7</td>
<td>118.3</td>
<td>41.4</td>
<td>76.5</td>
<td>86.6</td>
<td>CannedWetCatFood, PackagedDryDogFood</td>
</tr>
<tr>
<td>Hotels</td>
<td>1</td>
<td>34.4</td>
<td>17.1</td>
<td>96.3</td>
<td>98.0</td>
<td>HotelsMotelW, HotelsWheer</td>
</tr>
<tr>
<td>Insurance</td>
<td>4</td>
<td>102.3</td>
<td>56.7</td>
<td>91.4</td>
<td>98.4</td>
<td>AutoInsurance, MedicalInsurance</td>
</tr>
<tr>
<td>Restaurants</td>
<td>2</td>
<td>114.4</td>
<td>92.7</td>
<td>88.5</td>
<td>94.8</td>
<td>FamilyRestaurant, FastFoodDriveInR</td>
</tr>
<tr>
<td>Retail</td>
<td>4</td>
<td>74.4</td>
<td>64.7</td>
<td>89.7</td>
<td>97.0</td>
<td>ApplianceHardwar, FurnitureStoresT</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>rank</th>
<th>1994</th>
<th>2003</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>procter &amp; gamble co</td>
<td>altria group inc</td>
<td>procter &amp; gamble co</td>
</tr>
<tr>
<td>2</td>
<td>philip morris cos inc</td>
<td>procter &amp; gamble co</td>
<td>kraft heinz co</td>
</tr>
<tr>
<td>3</td>
<td>unilever nv</td>
<td>unilever</td>
<td>unilever</td>
</tr>
<tr>
<td>4</td>
<td>conagra inc</td>
<td>general mills inc</td>
<td>general mills inc</td>
</tr>
<tr>
<td>5</td>
<td>johnson &amp; johnson</td>
<td>conagra foods inc</td>
<td>johnson &amp; johnson</td>
</tr>
<tr>
<td>6</td>
<td>nestle sa</td>
<td>clorox co</td>
<td>conagra brands inc</td>
</tr>
<tr>
<td>7</td>
<td>campbell soup co</td>
<td>pepsico inc</td>
<td>clorox co</td>
</tr>
<tr>
<td>8</td>
<td>johnson sc &amp; sons inc</td>
<td>johnson &amp; johnson</td>
<td>nestle sa</td>
</tr>
<tr>
<td>9</td>
<td>general mills inc</td>
<td>reckitt benckiser plc</td>
<td>sc johnson &amp; son inc</td>
</tr>
<tr>
<td>10</td>
<td>clorox co</td>
<td>nestle sa</td>
<td>jm smucker co</td>
</tr>
</tbody>
</table>

Notes. Top 10 largest brand owners by year for manufacturing sectors.

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

<table>
<thead>
<tr>
<th>rank</th>
<th>1994</th>
<th>2003</th>
<th>2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>sears roebuck &amp; co</td>
<td>state farm mutual auto</td>
<td>visa usa inc</td>
</tr>
<tr>
<td>2</td>
<td>state farm mutual auto</td>
<td>wal-mart stores inc</td>
<td>state farm mutual auto</td>
</tr>
<tr>
<td>3</td>
<td>k mart corp</td>
<td>visa usa inc</td>
<td>blue cross &amp; blue shie</td>
</tr>
<tr>
<td>4</td>
<td>visa international</td>
<td>home depot inc</td>
<td>home depot inc</td>
</tr>
<tr>
<td>5</td>
<td>wal-mart stores inc</td>
<td>blue cross &amp; blue shie</td>
<td>mastercard Intl inc</td>
</tr>
<tr>
<td>6</td>
<td>pepsico inc</td>
<td>allstate corp</td>
<td>lowes cos inc</td>
</tr>
<tr>
<td>7</td>
<td>blue cross &amp; blue shie</td>
<td>mcdonalds corp</td>
<td>wal-mart stores inc</td>
</tr>
<tr>
<td>8</td>
<td>southland corp</td>
<td>cendant corp</td>
<td>berkshire hathaway inc</td>
</tr>
<tr>
<td>9</td>
<td>mcdonalds corp</td>
<td>mastercardIntl inc</td>
<td>allstate corp</td>
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<tr>
<td>10</td>
<td>mastercard internation</td>
<td>ito-yokado co ltd</td>
<td>seven &amp; i holdings co</td>
</tr>
</tbody>
</table>

Notes. Top 10 largest brand owners by year for non-manufacturing sectors.
Figure 2: HHI Percentile at 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.
Again 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 2425 in 1994 to 2070 in 2019. Importantly, concentration fell as much in the most concentrated industries as in the median industry. The 90th percentile HHI fell from 5482 in 1994 to 4741 in 2019, while the 75th percentile fell from 3729 to 3297. Figure 3 shows that the fraction of firms in the “highly concentrated” range fell from 48% in 1994 to 39% in 2019. Thus, while we find high concentration levels, particularly in 1994, according to our data there has been substantial improvement over time. These findings are in conflict with the prevailing popular opinion that increases in market power in the U.S. have been large and widespread.\footnote{Shapiro (2018).}

Aggregating product markets into sectors presents a qualitatively different story. At this higher level of aggregation, the 50th, 75th, and 90th percentiles all experience clear increases. The difference between product level and sector level HHI trends could in principle result from firms entering adjacent product markets in the same sector as well as firms entering the same product market in adjacent geographies. Looking back to figure 1, we can see that local product market concentration is higher than national product market concentration, but their trends are nearly identical. The trends in local and national sector concentration are also very similar. We infer that there is little evidence in our data (at the median) of firms entering adjacent geographic markets. The stark difference in trends shows up between product markets and sectors, both local and national, suggesting that the primary cause for the difference is firms entering adjacent product markets in the same sector.

While our findings above well represent the overall trends for the whole economy, every individual product market and sector is different. Figure 4 shows local market HHI trends by sector. HHI in new automobiles, which account for roughly 3% of consumer expenditure, fell from 2550 to 1349. The largest increase in HHI is in the car rental market, where HHI grew from 2201 to 3754. More generally, we see many manufacturing sectors experiencing a decrease in local market HHI (median fell from 2496 to 2120), and most non-manufacturing sectors experiencing no substantive change (median approximately constant, exceptions being Financial and Car Rental).

\footnote{Shapiro (2018).}
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).
Figure 5 plots the local product markets that experienced the largest changes. The largest decrease markets 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 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. By 2019, this brand took a significant market share from market leader Playtex brand.

The largest increase markets include 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. The driver in condoms was through growth of the share of the top brand, Trojan, during this time period.

3.1 Robustness checks

Given the novelty of our data and the contrast between our results and those from the production data sources, we have made several attempts to check the external and internal validity of our findings. The biggest threats to external validity are market coverage, market definitions, and the survey nature of the data. We address these issues first. The detailed results are in appendix B.

To evaluate the extent to which our findings are driven by market coverage, we computed concentration for a subsample of the Census data that is industry matched to the MRI data. Concentration in the subsample has the same overall trend as that in the complete Census data, suggesting that our different findings are due to market definitions.

[17]https://www.wsj.com/articles/SB963782500794995149
Figure 4: Local market HHI over time, by sector

Notes. HHI over time, at the stategroup-product market level. Each line shows the expenditure-weighted average of HHIs, for all stategroup-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.7 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 expenditure-weighted average of HHI, for all local markets in a given market.
and not market coverage.

To validate the survey data we compared the results from the MRI data with concentration measures computed using detailed data from industry sources for two industries: airlines and automobiles. For both industries there was a close match in both levels and trends, which gives us confidence that our results are not driven by idiosyncracies in the survey.

We have also computed concentration using several alternative concentration measures and market definitions. 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. Our results also hold when we re-weight sectors according to expenditure shares from the Consumer Expenditure Survey. Finally, 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.

4 Model

To rationalize our empirical results, we use a simple version of the Melitz and Ottaviano (2008) model to study the determinants of concentration at different levels of market definition. We derive analytical expressions for HHIs in the model, and show which changes in model primitives are consistent with the trends we observe in the data.

Assume that there are two identical markets, 1 and 2, indexed by j. These markets can be interpreted in two ways. First, they can be thought of as two geographic regions, such as US states, in which the same product is sold. A firm which is headquartered in one state can export to another state, but has a higher marginal cost of production. Second, the markets can be interpreted as two products within a sector; for example, market 1 could represent orange juice, while market 2 represents soda. Each firms specializes in producing either orange juice or soda; orange juice producers can also produce soda, but face higher marginal costs of doing so.
Each market contains a unit mass of consumers. Consumers’ preferences are defined over a continuum of differentiated varieties; each firm, indexed by \( i \in \Omega \), produces a single variety. There is a numeraire good, \( q_0 \). Consumers’ utility is:

\[
U = q_0 + \alpha \int_{i \in \Omega} q_i \, di - \frac{1}{2} \gamma \int_{i \in \Omega} (q_i)^2 \, di - \frac{1}{2} \eta \left( \int_{i \in \Omega} q_i \, di \right)^2
\]

with a larger \( \gamma \) implying a stronger taste for variety. We assume that there is an infinite measure of potential firm entrants in each market. Each entrant must pay some irreversible fixed cost \( f_E \) to enter. Once a firm \( i \) has entered, the firm draws a marginal cost \( c \), distributed as:

\[
G(c) = \left( \frac{c}{c_M} \right)^k
\]

That is, \( \frac{1}{c} \) is Pareto distributed, with lower bound \( \frac{1}{c_M} \), and shape parameter \( k \geq 1 \). Firms can produce in their local market at constant marginal cost \( c \). Firms can also “export” to the other market. The marginal cost a firm faces for producing in the export market is \( \tau c \), where \( \tau > 1 \). Thus, when \( \tau \) is low, firms have similar production costs in both markets; when \( \tau \) is very high, a firm based in one market faces a very high marginal cost of producing in the other market.

The interpretation of \( \tau \) differs, depending on whether markets represent geographic regions or product markets. If the two markets are interpreted as geographies, \( \tau \) can be thought of as representing product trade costs. These could include, for example, physical transportation costs if the product is produced in the headquarters state, or increased operational costs of advertising and selling across state borders.

If the two markets are interpreted as product markets within a sector, such as orange juice and soda, \( \tau \) represents the additional costs that an orange juice-specialized firm faces when it produces soda. When \( \tau \) is low, productive firms have low marginal costs for producing both products. Firms specializing in orange juice likely have a higher marginal production cost for soda than soda-specialized firms, due to accumulated experience from learning-by-doing, or because their production equipment is better suited to orange juice production. The benefits to specialization may vary across sectors and over time, depending on technological factors and the composition of marginal costs. For example,
certain kinds of costs, such as transportation, logistics, and marketing costs, are more likely to be common within a given firm across different product markets. In sectors and time periods where these factors make up a larger share of marginal costs, $\tau$ will tend to be lower: when logistics and advertising are important, firms who have low costs in one product market likely also have low costs in many other markets.

In equilibrium, firms enter until the expected profits from entry equal $f_E$, for entrants in both markets. In equilibrium, there will be some cost cutoff $c_D$, such that firms who draw costs $c$ higher than $c_D$ will choose to produce nothing. The following proposition characterizes the measure of firms that enter, the cutoff cost for production, and the domestic and export quantities produced by firms in the unique equilibrium of the model.

**Proposition 1.** There is a unique equilibrium of the model. The production cost cutoff satisfies:

$$c_D = \left[ \frac{2 \gamma (k+1) (k+2) (c_M)^k f_E}{(1+\frac{1}{\tau})} \right]^{\frac{1}{k+2}} \tag{4}$$

The number of varieties produced in each market, by domestic producers as well as exporters, is:

$$N = \frac{2 (k+1) \gamma \alpha - c_D}{\eta} \frac{c_D}{c_D} \tag{5}$$

In equilibrium, firms produce in their local market if $c < c_D$. The quantity produced by a firm with cost $c$ in the local market $j$ is:

$$q_j(c) = \frac{1}{2\gamma} (c_D - c) \tag{6}$$

Firms export positive quantities if $\tau c < c_D$. The quantity produced by a firm with cost $c$ in the export market $j$ is:

$$q_X^j(c) = \frac{1}{2\gamma} (c_D - \tau c) \tag{7}$$

Consumer welfare is:

$$1 + \frac{1}{2\eta} (\alpha - c_D) \left( \alpha - \frac{k+1}{k+2} c_D \right) \tag{8}$$

We build on Melitz and Ottaviano by calculating market shares and Herfindahl-
Hirschman indices (HHIs) at the local and national market level, and showing how they vary with model primitives. Define the total quantity in market \( j \) as the integral over all firms’ production in market \( j \):

\[
Q_j \equiv \int_{i \in \Omega} q_j(c_i) \, di
\]

We can then define the market share of a firm \( i \) in market \( j \), \( s_j(i) \), as the ratio of her quantity produced to the total quantity in market \( j \), and the national market share \( s(i) \) as \( i \)'s total quantity across both markets, divided by national market quantity. That is:

\[
s_j(i) \equiv \frac{q_j(c_i)}{Q_j}, \quad s(i) = \frac{\sum_{j=1}^{m} q_j(c_i)}{\sum_{j=1}^{m} Q_j}
\]  

These are the natural continuous equivalent of market shares with a discrete number of firms. We can then define HHIs at the local and national level as follows.

**Definition 1.** Define the local HHI in market \( j \) as:

\[
HHI_j = \int_{i \in \Omega} (s_j(i))^2 \, di
\]

and the national HHI as:

\[
HHI = \int_{i \in \Omega} (s(i))^2 \, di
\]

“Local” and “national” correspond to the the geographic interpretation of markets. If markets are interpreted as products within a sector, \( HHI_j \) corresponds to the product market HHI, and \( HHI \) corresponds to the sector HHI. The following proposition characterizes local and national HHIs in the model.

**Proposition 2.** Local HHIs are:

\[
HHI_j = 1 + \frac{2 + 2k}{N \cdot 2 + k}
\]

National HHIs are:

\[
HHI = HHI_j - \frac{k + 1}{N \left(1 + \frac{1}{\tau^k}\right)(k + 2)} \left[1 - \frac{1}{2}k(k + 1)(k + 2) \left(\frac{1}{k\tau^k} - \frac{2}{(k + 1) \tau^{k+1}} + \frac{2\tau - \tau^2}{(k + 2) \tau^{k+2}}\right)\right]
\]
The difference between the local and national HHIs, $\text{HHI}_l - \text{HHI}$, is increasing in $\tau$.

Proposition 2 shows that the local HHI is a function of the number of firms that enter in equilibrium, and $k$, which controls the dispersion in firms’ marginal cost draws. From (13), the national HHI is always lower than the local HHI. The difference between national and local HHIs is increasing in $\tau$. Intuitively, when $\tau$ is high, many firms produce only in one market or the other, so local markets may be quite concentrated, even if the total number of entrants across both markets is fairly large. On the other hand, when $\tau$ is low, most firms produce similar amounts in both markets, so national and local concentration are very similar.

Figure 6 shows how changes in model primitives affect local and national HHIs, as well as consumer welfare. The left column shows the result of varying trade costs, $\tau$. As shown in proposition 2, decreasing $\tau$ tends to make local HHIs decrease, while national HHIs increase. Intuitively, this is because, when trade costs are lower, productive firms enter and compete more aggressively in export markets; this additional source of competition decreases local HHIs. Since markets are more connected, large firms in one market tend also to be large in the other market, national concentration may be higher.

The middle and right columns show how HHIs change as we vary other parameters. In the middle column, we vary the fixed costs of firm entry, $f_E$; higher entry costs tend to increase concentration at both the local and national levels, without a large effect on the difference. The right column shows the effect of varying $k$, which controls the dispersion in firm productivity draws; lower values of $k$ correspond to more dispersion in productivity, as the distribution of productivity draws is more long-tailed. In order to isolate the effect of changing productivity dispersion, as we vary $k$, we simultaneously vary the entry cost, $f_E$, so that the firm entry cutoff $c_D$ remains fixed. Similar to fixed costs, decreasing $k$ tends to increase both local and national HHIs.

Distinguishing between different drivers of concentration changes is important, because they have different implications for consumer welfare. The bottom row of figure 6 shows the national HHI is not monotone in $\tau$: when trade costs are low, decreasing $\tau$ further tends to decrease the national HHI. However, the difference between local and national HHIs is always lower when $\tau$ is lower.

Formally, the variance of productivity, $\frac{1}{\xi}$, is decreasing in $k$ for $k > 2$. When $k \leq 2$, the variance of productivity does not exist. 

---

18 In figure 6, the national HHI is not monotone in $\tau$: when trade costs are low, decreasing $\tau$ further tends to decrease the national HHI. However, the difference between local and national HHIs is always lower when $\tau$ is lower.

19 Formally, the variance of productivity, $\frac{1}{\xi}$, is decreasing in $k$ for $k > 2$. When $k \leq 2$, the variance of productivity does not exist.
Notes. Comparative statics of local and national HHI (top row) and household welfare (bottom row), as we vary trade costs $\tau$ (left), fixed entry costs $f_E$ (middle), and firms’ productivity dispersion, $\frac{1}{k}$ (right). When $\frac{1}{k}$ is higher, firms’ productivity draws are more long-tailed. We vary $\tau$ and $f_E$ holding all other parameters fixed. When we vary $k$, we vary $f_E$ to hold $c_D$ fixed.

shows how welfare varies with respect to each model primitive. The left column shows that, as $\tau$ decreases, consumer welfare increases. Thus, if national HHIs increase because of a fall in trade costs, consumer welfare will increase. The middle column shows that, as $f_E$ increases, consumer welfare decreases; that is, if concentration increases because of an increase in firms’ entry costs, consumer welfare will tend to decrease. The right column shows that an increase in firm productivity dispersion (a decrease in $k$) tends to increase consumer welfare slightly.
5 Interpretation of Results

The primary stylized facts from Figure 1 are that concentration at the level of product markets has decreased at the national and local levels, and that concentration at the sector level has increased. If we interpret the two markets in our model as products within a sector, the model implies that \( \tau \) has declined over time. The comparative statics in Figure 6 show that only an increase in \( \tau \), not a change in \( k \) or \( f_E \), can cause market-level concentration to decrease while sector-level concentration increases.

Intuitively, a decrease in the market/sector \( \tau \) can be interpreted as follows. Firms may have become more efficient at producing multiple products within a sector: using our example, orange juice producers have become increasingly more efficient at producing soda, as well as other products within the same sector. This could be because differences in firms’ productivity are increasingly driven by general factors – for example, managing automated production processes, supply chain efficiency, or advertising effectiveness – rather than product specific factors. Atalay, Hortaçsu and Syverson (2014) provide evidence that integration into non-competing markets is used to facilitate intangible inputs.

The model then suggests that these changes may be welfare-improving for consumers. Consumers do not care directly about sector-level concentration. In our model, if firms are increasingly able to branch out to multiple product markets, but the result is more competition within each product market, sector-level concentration may increase, but consumers can still be better off.

Regarding geographic concentration in Figure 1, the difference between local and national product-level concentration is roughly constant from 1994-2019. On the other hand, the local-national difference in sector-level concentration declined somewhat from around 1994-2006. Figure 6 suggests that there are multiple possible drivers of this convergence: trade costs \( \tau \) decreasing, or the dispersion \( k \) index decreasing, can both cause national and local HHIs to converge. However, throughout our sample period, the local-national HHI difference is quite low relative to the market-sector HHI difference. This suggests that geographic trade costs were relatively low, so product markets within the US have been relatively well-integrated across states, throughout our sample period.
Eckel and Neary (2010) and Bernard, Redding and Schott (2011) study the impact of lower geographical trade costs on multiproduct firms. They establish a core competency effect whereby firms drop their least efficient products as trade costs decrease. In our sample, these effects are outgunned by the decrease in costs across product markets leading to an increase in sector level concentration.

6 Conclusion

In conclusion, this paper attempts to measure long term trends in local product market concentration across a wide swath of the U.S. economy, using market definitions that more closely reflect consumption-based economic markets. We find that concentration levels are high in nearly half of the industries covered in our sample, suggesting that market power may be more widespread than previously thought.

We also find that product market concentration has been decreasing over time, particularly in the most concentrated industries. This finding is the opposite of well known results from production data. We do find increasing concentration when product markets are aggregated into sectors, which is consistent with the production data.

An economic model featuring increasing correlation of costs across product markets explains these two trends. Efficient firms in single product markets enter each others’ “home” product markets, thereby increasing aggregate concentration while reducing product level concentration. The model suggests that this process is welfare improving for consumers.

Trends in product market concentration are an important input to a myriad of literatures in economics. While we have attempted to verify the internal and external validity of our results, confirming them using other consumption-based data sources seems like a pressing issue.
References


Neiman, Brent, and Joseph Vavra. 2018. “The rise in household spending concentration.” *Available at SSRN 3137782*.


Internet Appendix

A Data Appendix

A.1 Cleaning Kantar Adspender

From the Kantar AdSpender data, we get the brand name, ultimate parent, and product category. Product categories 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 the GFK MRI and Kantar Adspender

We use a fuzzy merging algorithm to match brands from the GFK MRI data to the Kantar Adspender data. The GFK 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 gfk 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 tweak the match, removing around 350 words 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 GFK product markets to Kantar product categories, then run the Stata reclink2 package, created by Wasi and Flaaen (2015) to match GFK 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 GFK product markets to Kantar product categories. We first naively fuzzy-merge the full list of GFK brands to the full list of Kantar brands; we then check, for each GFK product market, the Kantar categories which are matched to the category most often. We hand-check this merge, adding and subtracting some associations which are not well-captured by the algorithm.

Once we have constructed the GFK-Kantar category crosswalk, we re-run reclink2, matching brands from GFK to Kantar 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, a brand is matched to the same 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 GFK 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 502 product markets to 284 product markets. In subsection B.4 we also report
results for the unbalanced panel, including all 502 product markets.

B Robustness Checks

Subsection B.1 compares our results to the Census data and shows that our results are not due to sample selection. Subsection B.2 compares our results to external industry data for automobile and airline sectors and shows that our data replicates concentration trends in industry data. Subsection B.3 uses top-2 and top-4 market shares, instead of HHIs, as our measure of concentration. Subsection B.4 uses the entire unbalanced panel of product markets, instead of dropping markets to balance the panel. Subsection B.5 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 B.6 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.

B.1 Comparison to Census

A number of other papers have shown, using Census data, that concentration has increased over time. To show that our results do not arise due to sample selection, we recalculate concentration in the census data, generate a subsample of the census data that best matches the GFK MRI product market sample, and confirm that concentration rises in any subsample of the census data. We clean the raw census data, which is available in 5 year intervals from 1997 to 2012, following Barkai (2016), to get a year-industry panel corresponding to 2012 6-digit NAICS codes. Then, we hand-match product markets from the GFK MRI to 6-digit NAICS codes. In general, this is a many-to-many mapping. We then use the Census weights to recompute HHIs.

We verify the findings of other papers: using the census 6-digit NAICS codes as definitions of product markets, concentration is increasing over time. Figure A.1 plots changes in C4, which has a better availability than HHI in the census data. Importantly,
Notes. Median C4s using 2012 census 6-digit NAICS codes. All census industries (black), census industries where the NAICS codes do not change in the timeseries (red), and only census industries that we matched to MRI GFK product markets (green).

product market composition does not change the qualitative results. One issue is that NAICS code definitions are shifting over time. To show this is not driving our results, we also conduct the following exercise. We run a simple regression:

\[
HHI_{jt} = \mu_t + \gamma_j + \epsilon_{jt} \tag{14}
\]

where \( j \) indexes NAICS codes, \( t \) indexes periods of 5 years, and \( \epsilon_{jt} \) is an error term which is independent of \( \mu_t \) and \( \gamma_j \). 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 \( \mu_t \) coefficients from specification (14). Effectively, (14) is a fixed-effects specification: the time fixed effects \( \mu_t \) estimate changes in concentration, using only variation within a given NAICS
Table A.1: Census HHI over time, fixed effects specification

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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 GFK product markets. For columns 2 and 4, we also drop any NAICS industry codes that change in the time series.

codes, over time periods in which it is not affected by merger events. Specification (14) is a simple way to use all variation in concentration over time, which is not affected by NAICS code redefinitions. The results of specification (14), for various subsets of the data, are shown in Table A.1. For all census subsamples, we find that the fixed effects $\mu_t$ are increasing uniformly from 1997 to 2012.

### B.2 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 do 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 concentration datasets.

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 A.2. 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 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 GFK MRI, we aggregate the BTS data, by total revenue, to the level of GFK MRI state-groups, and then we calculate HHIs at the state-group level. We define state-groups by origin airport states, but we have verified that the results hold for destination airports 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 A.2. As with the automobile data, the two datasets are very similar in both levels and trends, at both the local and national level.

B.3 C2 and C4 Concentration measures

Figure A.3 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.

B.4 Unbalanced panel

Figure A.4 shows the result of Figure 1 using all 457 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.
Figures A.2: Automobile and Airlines Robustness Check

Notes. The left panel shows the estimated automobile market HHI from the GFK MRI (blue), against the estimated national HHI for the car market, from Ward’s. The right panel shows the estimated HHI from the GFK 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.

B.5 CEX weighting

One concern with our baseline result is that the weights on categories do not reflect consumers’ expenditures in these product categories. We attempt to address this by re-weighting results to reflect expenditure shares across broad product categories from the Consumer Expenditure Survey (CEX). To do so, we manually match each item in CEX to a GFK MRI sector. For example, we match “Cereals and bakery products” to “HoProdFood” and “Nonalcoholic beverages” to “Beverages”. This is a many-to-1 match: CEX items are available in fine subitems, so in general there are many CEX items within each GFK sector. We then aggregate expenditure shares from the 2018 CEX table to GFK MRI sector level, and we use these expenditure shares to weight sectors in our baseline result.

The results are shown in Figure A.5. The results are qualitatively quite similar to results in Figure 1 in the main text. Local and national market-level concentration both decline substantially. Local sector-level concentration increases slightly, while national
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.

sector-level concentration rises and then falls, so it is essentially flat over the entire time horizon.

B.6 Alternative product markets

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 GFK 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 GFK markets to fine Kantar product categories; we then impute 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 457 GFK product markets, 120 Kantar majors, 46 Kantar industries, and 17 GFK sectors.

In Figure A.6, we show how concentration varies at each of these levels of aggregation.
Figure A.4: Median HHI at different market levels 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.

GFK markets are the finest level of aggregation, followed by Kantar majors, Kantar industries, and GFK sectors. The “divergence” trend is relatively uniform. Concentration is decreasing over time at the GFK market level, roughly flat at the Kantar major and industry levels, and increasing over time at the GFK sector level.

B.7 HHI by sector and aggregation level

To complement Figure 4, local product market HHI over time by sector, Figure A.7 shows national product market, local sector HHI, and national sector HHI over time by sector, in addition to local product market HHI.
Figure A.5: CEX Weighting

Notes. Equivalent of Figure 1, where we re-weight sectors, so they reflect expenditure shares from the CEX. Each line shows the CEX-expenditure-weighted median of HHIs. “rh” indicates right-hand axis.
Figure A.6: Median HHI including Kantar major and industry levels

Notes. Equivalent of Figure 1, including Kantar major (green) and industry (blue) levels. MRI GFK product markets (red) and MRI GFK sectors (purple) are identical to Figure 1. rh indicates right-hand axis.
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, for all local markets (top), markets (second row), and local sectors (third row) in a given sector. 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.
C Proofs for Section 4

C.1 Proof of proposition 1

The proof essentially follows directly from Melitz and Ottaviano. Expression (4) for the cost cutoff is (29) in Melitz and Ottaviano, with $L^l = 1$, and using that $\rho \equiv \frac{1}{\tau}$. The technology parameter, $\phi$, is defined on page 304 of Melitz and Ottaviano. Expression (5) is exactly (16) of Melitz and Ottaviano, which applies in the both the single-market and the two-market case. Expressions (6) and (7) are expression (20) of Melitz and Ottaviano, with $L^l = 1$ and $L^h = 1$ and symmetric trade costs.

C.2 Proof of proposition 2

We prove proposition 2 in a few steps. First, claims 1 and 2 characterize two properties of HHIs in the continuous case.

C.2.1 Renormalization properties of HHIs

Claim 1 illustrates how the continuous HHI is analogous to the familiar discrete HHI. If all firms produce identical quantities, the HHI is simply $\frac{1}{N}$, so it is decreasing in the measure of firms which produce. Holding fixed $N$, the HHI is higher when the dispersion of firms’ quantities, measured by the coefficient of variation of $q(c)$, is larger. Expression (15) also holds for discrete HHIs. Thus, the continuous HHI behaves in a way that is qualitatively quite similar to its discrete analog.

Claim 1. Let $H(c)$ represent the distribution of costs among firms producing positive quantities, and let $N$ represent the number of firms producing in a given market. We have:

$$HHI_j = \frac{1}{N} \left(1 + \left(\frac{SD\{q(c)\}}{E[q(c)]}\right)^2\right) \quad (15)$$

Proof. It will be useful to work with, rather than the measure space $i$, the distribution of costs among firms producing strictly positive amounts in each markets. Suppose there are $N$ firms – domestic firms and exporters – which produce positive quantities in each
market. We can disregard firms which produce zero quantity, as they contribute nothing to the HHI integral.

Defining the probability distribution \( H(c) \) of costs of firms who produce positive quantities, and \( G(c) \) the distribution of costs among firms that produce, we have, for any function \( f(\cdot) \), that:

\[
\int f(c) \, d\bar{i} = N \int_0^\infty f(c) \, dG(c)
\]  

(16)

Hence, we can write the HHI in terms of the firm cost distribution as:

\[
HHI_j = \frac{\int_0^N (s_j(c))^2 \, dG(c)}{\left( \int_0^N q_j(c) \, dG(c) \right)^2} = \frac{N \int_0^{CM} (q_j(c))^2 \, dG(c)}{\left( N \int_0^{CM} q_j(c) \, dG(c) \right)^2} = \frac{1}{N} \left( \int_0^{CM} q_j(c) \, dG(c) \right)^2
\]

(17)

Expression (17) expresses \( HHI_j \) in terms of the first and second moments of the quantity distribution among producing firms, and the total number of producing firms \( N \). We can further rearrange (17) to:

\[
= \frac{1}{N} \left( \frac{E[q(c)]^2 + Var(q(c))}{E[q(c)]^2} \right) = \frac{1}{N} \left( 1 + \frac{Var(q(c))}{E[q(c)]^2} \right) \]

\[
= \frac{1}{N} \left( 1 + \left( \frac{SD(q(c))}{E[q(c)]} \right)^2 \right)
\]

as desired.

C.2.2 The SVI

First, we show that the difference between the HHI of an aggregated market, and the weighted average of HHI’s in submarkets, is related to the variance of market share.
vectors in submarkets. In particular, consider the following quantity.

**Definition 2.** Define the continuous SVI (submarket variation index) as:

\[
\text{SVI} \equiv \int_0^N \sum_j \frac{Q_j}{\sum_j Q_j} \left( s_j(i) - s(i) \right)^2 \, di \tag{18}
\]

Intuitively, equation (18) calculates, for each firm, the \(Q_j\)-weighted average of deviations of the firm’s market shares in each market from the firm’s global average market share, then we take the integral of this average across all firms. Claim 2 states that the submarket variation index is equal to the \(W_j\)-weighted average of local market HHI\(_s\), minus the global HHI. The SVI is thus a simple measure of the divergence between local and global HHI\(_s\).

**Claim 2.** The quantities SVI, HHI\(_j\), and HHI satisfy:

\[
\text{SVI} = \left[ \sum_j \frac{Q_j}{\sum_j Q_j} \text{HHI}_j \right] - \text{HHI} \tag{19}
\]

**Proof.** Take the RHS of (18), and substitute for \(s(i)\) using (9), to get:

\[
= \int_0^N \sum_j \frac{Q_j}{\sum_j Q_j} \left( s_j(i) - \frac{\sum_j Q_j s_j(i)}{\sum_j Q_j} \right)^2 \, di
\]

Expanding, we have

\[
\int \sum \left( \frac{Q_j}{\sum_j Q_j} (s_j(i))^2 - 2 \frac{Q_j}{\sum_j Q_j} (s_j(i)) \left( \frac{\sum_j Q_j s_j(i)}{\sum_j Q_j} \right) + \frac{Q_j}{\sum_j Q_j} \left( \frac{\sum_j Q_j s_j(i)}{\sum_j Q_j} \right)^2 \right) \, di
\]

This simplifies to:

\[
\left[ \int \left( \frac{\sum_j Q_j s_j(i)}{\sum_j Q_j} \right)^2 \, di \right] - \int \left( \frac{\sum_j Q_j s_j(i)}{\sum_j Q_j} \right)^2 \, di
\]
Now, recalling that the definition of $s(i)$ in (9), we have:

$$\int_{i} \left( \frac{\sum_{j} Q_j s_j(i)}{\sum_{j} Q_j} \right)^2 \text{di} = \int_{i} (s(i))^2 \text{di} = HHI$$

And,

$$\int_{i} \left( \frac{\sum_{j} Q_j (s_j(i))^2}{\sum_{j} Q_j} \right) \text{di} = \sum_{j} \frac{Q_j}{\sum_{j} Q_j} \int_{i} (s_j(i))^2 \text{di} = \sum_{j} \frac{Q_j}{\sum_{j} Q_j} HHI_j$$

This proves (19), and thus claim 2.

C.2.3 Computing local HHIs

We know that the distribution of costs (inclusive of trade costs) among producing firms, both domestic firms and exporters, is such that $\frac{1}{c}$ is Pareto distributed, with shape parameter $k$ and minimum $\frac{1}{c_D}$. Also, the quantity $q_j(c)$ is proportional to the difference $c_D - c$

Expression (17) implies that $HHI_j$ is invariant to scaling $q_j(c)$; that is, if we multiply all firms’ quantities by some constant $k$, $HHI_j$ is unchanged. We will thus scale firms’ quantities such that a firm with cost 0 has quantity 1. We can also change variables to work with indexed costs

$$x \equiv \frac{c}{c_D}$$

if $\frac{1}{c}$ is Pareto distributed with minimum $\frac{1}{c_D}$, then $\omega = \frac{1}{x}$ is Pareto distributed, with minimum 1 and shape parameter $k$. Thus, define the rescaled quantity $\tilde{q}(\omega)$; a firm with productivity $\omega$ has rescaled quantity:

$$\tilde{q}(\omega) = 1 - \frac{1}{\omega}$$
Thus, we have:

$$E \left[ \left( 1 - \frac{1}{\omega} \right)^2 \right] = \frac{2}{(1 + k)(2 + k)}, 
E \left[ 1 - \frac{1}{\omega} \right] = \frac{1}{1 + k}$$

thus, plugging into (17), we have:

$$HHI_j = \frac{2 \left( 1 + k \right)}{N \left( 2 + k \right)}$$

(21)

Where \( N \) is the number of firms producing in a given market, including both local firms and exporters. This proves \([12]\) of proposition \([2]\)

Now, let \( M \) be the number of entering firms with cost below \( c_D \) in one market; this is:

$$N = M \left( 1 + \frac{G_c \left( \frac{c_D}{c} \right)}{G_c (c_D)} \right)$$

In renormalized space, we have:

$$\left( 1 + \frac{G_c \left( \frac{c_D}{c} \right)}{G_c (c_D)} \right) = \left( 1 + G_c \left( \frac{1}{\tau} \right) \right) = 1 + \left( 1 - G_w (\tau) \right) = 1 + \frac{1}{\tau^k}$$

Hence, the local HHI is:

$$HHI_j = \frac{1}{M \left( 1 + \frac{1}{\tau^k} \right)} \frac{2 + 2k}{2 + k}$$

C.2.4 Computing the SVI

Suppose that there are a measure \( M \) domestic firms that produce positive quantities in each market. Note that \( M < N \), since \( N \) counts both domestic and exporting firms. In particular, since the \( N \) firms active in a given market consist of importers as well as a fraction \( \frac{1}{\tau^k} \) of exporters; hence, we have:

$$N = M \left( 1 + \frac{1}{\tau^k} \right)$$

(22)
First, the SVI expression simplifies in the two market symmetric case. This is because:

\[
SVI \equiv \int_0^{2M} \sum_j \frac{Q_j}{\sum_j Q_j} \left( s_j(i) - s(i) \right)^2 di = \int_0^{2M} \frac{1}{2} \left( s_1(i) - \frac{s_1(i) + s_2(i)}{2} \right)^2 di
\]

\[
SVI = \frac{1}{4} \int_0^{2M} (s_1(i) - s_2(i))^2 di
\]

Applying (16) from the proof of claim 1, we can express this as:

\[
SVI = \frac{1}{4} \int_0^{c_D} \left( \frac{q_1(c)}{\int q_1(c) \left[ \frac{M(1 + \frac{1}{\tau})}{M(1 + \frac{1}{\tau})} \right] dG(c)} - \frac{q_2(c)}{\int q_2(c) \left[ \frac{M(1 + \frac{1}{\tau})}{M(1 + \frac{1}{\tau})} \right] dG(c)} \right)^2 2M dG(c)
\]

Now, by symmetry, the distributions of \(q_1\) and \(q_2\) are identical, so we can write this as:

\[
SVI = \frac{1}{4} \int_0^{c_D} \left( \frac{q_1(c)}{\int q_1(c) \left[ \frac{M(1 + \frac{1}{\tau})}{M(1 + \frac{1}{\tau})} \right] dG(c)} - \frac{q_2(c)}{\int q_2(c) \left[ \frac{M(1 + \frac{1}{\tau})}{M(1 + \frac{1}{\tau})} \right] dG(c)} \right)^2 \frac{2M dG(c)}{(E[q_1])^2}
\]

Analogous to (17), expression (23) expresses SVI in terms of moments of the joint distribution of \(q_1\) and \(q_2\). It is also invariant to scaling, so we will again scale firms’ quantities to have maximum 1, and index firms by their cost index, \(\omega \equiv \frac{c_D}{c}\), to get:

\[
SVI = \frac{1}{2M \left( 1 + \frac{1}{\tau} \right)^2 (E[q_1])^2} \int_0^{c_D} \left( q_1(c) - q_2(c) \right)^2 dG(c)
\]

(24)

where \(\omega\) is Pareto distributed, with shape \(k\) and minimum 1. Firms export only if \(c < \frac{c_D}{\tau}\), which is equivalent to \(\omega > \tau\).

Now, the value of the SVI integrand,

\[
(\bar{q}_1(\omega) - \bar{q}_2(\omega))^2
\]

differs depending on whether a firm is an exporter or not. For firms in region 1 that do not export, we have

\[
\bar{q}_1(\omega) = 1 - \frac{1}{\omega}, \quad \bar{q}_2(\omega) = 0
\]

48
For firms that do export, we have

\[ q_1(\omega) = 1 - \frac{1}{\omega}, \quad q_2(\omega) = 1 - \frac{\tau}{\omega} \]

We can thus write (24) as:

\[
SVI = \frac{1}{2M \left( 1 + \frac{1}{\tau} \right)^2 (E[q_1])^2} \left[ \int_1^\tau \left( 1 - \frac{1}{\omega} \right)^2 dG_\omega(\omega) + \int_\tau^\infty \left( \left( 1 - \frac{1}{\omega} \right) - \left( 1 - \frac{\tau}{\omega} \right) \right)^2 dG_\omega(\omega) \right]
\]

We can write this as:

\[
SVI = \frac{1}{2M \left( 1 + \frac{1}{\tau} \right)^2 (E[q_1])^2} \left[ \int_\tau^\infty \left( \left( 1 - \frac{1}{\omega} \right) - \left( 1 - \frac{\tau}{\omega} \right) \right)^2 dG_\omega(\omega) + \int_1^\infty \left( 1 - \frac{1}{\omega} \right)^2 dG_\omega(\omega) - \int_\tau^\infty \left( 1 - \frac{1}{\omega} \right)^2 dG_\omega(\omega) \right]
\]

Now, by properties of the Pareto distribution, we have:

\[
\int_1^\infty \left( 1 - \frac{1}{\omega} \right)^2 dG_\omega(\omega) = \int_\tau^\infty \left( 1 - \frac{1}{\omega} \right)^2 dG_\omega(\omega) = \frac{2}{(k+1)(k+2)}
\]

\[
\int_1^\infty \left( 1 - \frac{1}{\omega} \right) dG_\omega(\omega) = \frac{1}{k+1}
\]
hence,

\[
SVI = \frac{(k + 1)}{M \left(1 + \frac{1}{\tau^2}\right)^2 (k + 2)} - \frac{(k + 1)^2}{2M \left(1 + \frac{1}{\tau^2}\right)^{\frac{3}{2}}} \int_{\tau}^{\infty} \left(1 - \frac{\tau}{\omega}\right) \left(2 \left(1 - \frac{1}{\omega}\right) - \left(1 - \frac{\tau}{\omega}\right)\right) dG_\omega(x)
\]  

Factoring, and using (22), we get:

\[
SVI = \frac{k + 1}{N \left(1 + \frac{1}{\tau^2}\right)(k + 2)} \left[1 - \frac{1}{2} (k + 1)(k + 2) \int_{\tau}^{\infty} \left(1 - \frac{\tau}{\omega}\right) \left(2 \left(1 - \frac{1}{\omega}\right) - \left(1 - \frac{\tau}{\omega}\right)\right) dG_\omega(x)\right]
\]  

(25)

Applying claim 2, we get (13) of proposition 2.

To prove that SVI is increasing in \(\tau\), we have:

\[
\frac{\partial}{\partial \tau} \left(1 - \frac{\tau}{\omega}\right) \left(2 \left(1 - \frac{1}{\omega}\right) - \left(1 - \frac{\tau}{\omega}\right)\right) = \frac{2 - 2\tau}{\omega^2}
\]

which is weakly negative for \(\tau \geq 1\). Hence, as \(\tau\) increases, the (negative) integral term in (26),

\[
\frac{1}{2} (k + 1)(k + 2) \int_{\tau}^{\infty} \left(1 - \frac{\tau}{\omega}\right) \left(2 \left(1 - \frac{1}{\omega}\right) - \left(1 - \frac{\tau}{\omega}\right)\right) dG_\omega(x)
\]

decreases in magnitude. Also, the coefficient term

\[
\frac{k + 1}{N \left(1 + \frac{1}{\tau^2}\right)(k + 2)}
\]

decreases in magnitude. Thus, the SVI is increasing in \(\tau\). This completes the proof of proposition 2.