Endogenous Sunk Costs and the Geographic Distribution of Brand Shares in Consumer Package Goods Industries*

Bart J. Bronnenberg† Sanjay K. Dhar‡ Jean-Pierre Dubé‡

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Abstract

This paper describes industrial market structure in consumer package goods (CPG) industries using a unique database spanning 31 industries and the 50 largest US metropolitan markets. A general set of stylized facts is documented pertaining mainly to the geographic patterns in brand shares. A connection between the patterns and a model of endogenous sunk costs in advertising is established by testing several predictions of the theory. We establish that concentration is bounded below in advertising-intensive industries even as market size grows large. We also find a fixed number of advertised brands within an industry across markets of varying size. However, we observe a proliferation in the number of non-advertised brands in larger markets. Finally, we collect historic entry dates for two of our industries and find that order of entry has a strong impact on the rank-order of shares in a market. The historic roll-out of brands across markets also introduces spatial covariance within a brand's geographic distribution of shares. A similar spatial covariance pattern emerges in advertising. Alternative explanations for these geographic patterns, including other marketing instruments such as prices, are rejected. The relationship between advertising and market shares suggests a role for advertising in the formation of long-run industrial market structure.

JEL classification: L11, L66, M30, M37, R12

1 Introduction

Little research has studied geographic patterns in the industrial market structures of final branded consumer goods. We describe and test the underlying economics generating the geographic distribution of market shares across large US city-markets for several large consumer packaged goods (CPG) industries. Of particular importance is the understanding of how different marketing variables, such as prices, advertising and promotions, contribute to the formation of market structures

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†UCLA Anderson Graduate School of Management, University of California, Los Angeles

‡Graduate School of Business, University of Chicago

in CPG industries. The theory and empirical evidence suggest a role for advertising, as a long-run marketing strategy to build brands in a competitive environment, versus pricing and promotions, as more temporary competitive tactics. For the remainder of the analysis, we will use the terms brand and firm interchangeably.

A novel feature of this analysis is the comprehensive database collected to study market structure in CPG industries. The basic scanner data consist of longitudinal marketing data for all the brands from 31 CPG industries, covering 39 months in the 50 largest city market areas, as designated by AC Nielsen. A demographic supplement to these data provides information on households in each market. For a subset of 23 geographic markets, we match contemporaneous as well as historic advertising levels from several years prior to the sample. Survey-based data from Young and Rubicam Brands provide additional information on brand quality perceptions and brand attitudes. For two of the industries, we supplement the data with information on entry (the year a brand entered a local market). Finally, for several industries, we obtain the location of the nearest production plant for each brand.

We begin with a description of the market structures observed in our data. We define a geographic market structure for an industry by looking at the observed share levels as well as the rank-order of shares (i.e. concentration and the identities of the largest firms). Three persistent stylized facts about market shares emerge for our 31 CPG industries. First, most of the variation in shares lies in the cross-section of geographic markets, as opposed to the within-market time-series or the cross-section of national retailers. Second, individual brands' shares are highly spatially-dependent: share levels of a brand are similar in markets that are geographically "close." On average, the spatially-dependent component of a brand's shares accounts for roughly 60% of the total variance across markets. Finally, most CPG industries are concentrated as there is typically at least one brand with a non-trivial market share in each geographic market. However, the identity of the leading firm in a CPG industry varies across markets and, hence, the rank-order of brand shares in an industry differs across geographic areas. This fact also indicates that local market structures differ from the national market structure. The robustness of these observations across such a large set of industries is the primary motivation for trying to uncover a systematic theoretical explanation.

As in Sutton's (1991) treatment of advertising as an endogenous sunk cost (ESC), we believe brand advertising constitutes a vital component for building a brand. The investment in advertising is both fixed and sunk in CPG industries. The theory generates several testable predictions for advertising-intensive industries. As market size grows, the theory predicts a competitive escalation in advertising levels. Consequently, in advertising-intensive industries, market concentration levels should be bounded away from zero as market size increases (Shaked and Sutton 1983, 1987, and Sutton 1991). Furthermore, one would not observe a competitive escalation in the number of advertising brands. A caveat to this prediction is that one could nevertheless observe a proliferation of unadvertised "fringe" brands. Extending the theory to accommodate sequential entry generates an additional prediction. A first-mover will try to pre-empt subsequent entry by investing highly in the endogenous sunk cost. In contrast with simultaneous entry, early-movers will invest relatively more in advertising and should garner a sustainable share advantage over later movers, who will not find it profitable to emulate this strategy. Thus, the historic order-of-entry of brands into a market should covary positively with market shares and advertising.

The data exhibit several important characteristics for testing the ESC theory. The identification of a first-mover effect requires a distinction between the impact of a first-mover ("state dependence") and differences in the relative marketing competencies of firms ("heterogeneity"), a problem analogous to the incidental parameters problem (Heckman 1981). The extant literature on the "pioneering advantage," typically uses a single time-series for an industry (see Golder and Tellis 1993 for a historical analysis, and Kalyanaram, Robinson and Urban 1995 for a detailed literature survey). Our identification strategy uses the observed variation in the identities of the first-movers across markets within a given industry. To test for a lower bound in concentration relative to market size, we use the variation in market size across geographic markets. Finally, the observed spatial dependence in brand shares helps rule out several alternative explanations for the geographic patterns in shares. By establishing that spatial dependence accounts for most of the geographic variation in shares, we can test entry against alternative sources of firm asymmetries simply by looking at their spatial densities.

Our empirical results correspond well with the theory. We segment our industries into advertising-intense and non-advertising-intense groups. As predicted by the theory, we find that local concentration is bounded away from zero in the limit for the former. We also find that the lower bound function is steeper for non-advertising-intense industries than for advertising-intense industries. Similarly, we do not observe proliferation in the number of advertised brands as market size grows. In contrast, we do see proliferation in the number on non-advertised products as market size grows. We also find evidence of a lower bound in concentration for the set of advertised brands in an industry, but not for the set of unadvertised brands. These results are consistent with the hypothesis that brand advertising generates a form of vertical differentiation that leads to a different industrial market structure than in settings with horizontal differentiation only.

Focusing on the two industries for which we have entry data, we find that the historic order-of-entry explains both a brand's share level and covariance across markets. For robustness, we also show that entry explains a brand's perceived quality levels across markets. After conditioning on entry, the magnitude of the spatial component of share variation falls by over 50% and, hence, entry accounts for most of the observed spatial dependence. Entry also tends to explain a brand's advertising share ("share-of-voice") across markets. This latter connection supports our prediction that the entry effect reflects early entrants investing aggressively in advertising to build larger brands than subsequent entrants, as predicted by ESC theory. While we only observe historic entry for two industries, the spatial patterns in shares explained by entry are observed in most of our 31 industries, suggesting that our results might be generlizeable.

Surprisingly, we find no systematic geographic correlation between shares and prices or promotions. These marketing variables are found instead to co-move with shares over time, which accounts for a relatively small component of the total variance in shares. Hence, advertising appears to play an important role in the formation of long-run indstrial market structures, whereas prices and promotions may have a more temporary tactical influence[1].

These results contribute to a growing empirical literature testing game-theoretic models of industrial market structure formation. Some of this literature uses structural models, especially when crucial market outcome data are unavailable (Bresnahan and Reiss 1991, Berry 1992). Our work follows a separate stream pioneered by Sutton (1991) who provided several detailed case studies testing the implications of exogenous (e.g. manufacturing plant) and endogenous (e.g. advertising and R&D) sunk costs on market structures in the food industry across international markets. The theory has subsequently been used to describe market structures across US manufacturing industries (Robinson and Chiang 1996), across US MSAs in the supermarket industry (Ellickson 2003) and the banking industry (Dick 2004), across US urban areas for the radio and the restaurant industries (Berry and Waldfogel 2003) and across small rural areas in the banking industry (Cohen and Mazzeo 2004). Our work is also related to the literature studying the geographic Silicon-Valley type agglomeration of manufacturing firms (e.g. Krugman 1991, Ellison and Glaeser 1997, 1999); although the spatial distribution of competing CPG shares appears to be quite asymmetric.

The remainder of this paper is organized as follows. Section two outlines the theory and some comparative static predictions from a model of ESC, including the role of sequential entry. In section three, we describe our data. In section four, we provide a detailed description of the patterns in the data. In section five, we test the comparative static predictions of ESC theory. This section also analyzes the role of historical entry on current market structure. It further serves to rule out several alternative explanations. Section six concludes.

2 Endogenous sunk costs theory

In this section, we motivate the empirical predictions that arise from a model of endogenous sunk costs. We then motivate why advertising represents a crucial fixed and sunk investment for

[1] One must be cautious in interpreting these findings. We do not establish any causation between shares and prices or promotions. We simply document that these three variables co-move strongly in the time series, but not in the geographic cross-section.

building up a successful CPG brand. We also provide some details on the histories of the CPG categories used in our analysis to motivate the role of initial conditions on market structure. The theory generates several testable hypotheses. The first such prediction regards concentration in advertising-intensive industries:

If it is possible to enhance consumers' willingness-to-pay for a given product to some minimal degree by way of a proportionate increase in fixed cost (with either no increase or only a small increase in unit variable costs), then the industry will not converge to a fragmented market structure, however large the market becomes (Sutton 1991, p.47).

The theory generates a related limiting prediction whereby growth in market size does not lead to an escaltion in the total number of firms that invest in the enodgenous sunk cost (advertising). However, if a market can sustain both advertised and non-advertised brands (i.e. firms that invest in the fixed cost and firms that do not), growth in market size will lead to an escalation in the number of the latter in the limit.

While these scenarios are discussed in the context of simultaneous entry, the predictions are robust to environments with sequential entry (Shaked and Sutton 1987; Sutton 1991). However, sequential entry generates a third prediction regarding a first-mover advantage. First-movers can invest aggressively in the endogenous sunk cost to preempt future entry. Hence, we expect the market shares and levels of investment in the fixed cost (advertising) to co-vary with order of entry.

2.1 Theoretical framework

The discussion below re-states the basic framework and results in Shaked and Sutton (1987) and Sutton (1991). Consider a discrete choice model of consumer demand with both horizontal and vertical product differentiation. Define a product x with characteristics (ψ, h) where ψ is vertical and h is horizontal. Assume a consumer h is described by his income, Y_h, where $Y_h \sim f(Y, \alpha)$, and an ideal point in horizontal product attribute space, α_h. If consumer h chooses brand x, he obtains utility:

$$\begin{aligned} U(x) &= u(\psi, |h - \alpha_h|, Y_h - p) \\ &= u(\psi, d, y_h) \end{aligned} \tag{1}$$

where $u_\psi > 0, u_d < 0$, $u_{\psi y} > 0$ and u_y and $|u_d|$ are bounded above. This model is sufficiently general to include many of the popular empirical models used in the brand choice literature such as the multinomial logit and the random coefficients logit.

Firms play the following three-stage game. In the first stage, they decide whether or not to enter a market. In the second stage, they pick product attribute levels (ψ, h) at cost $F(\psi)$ where F is strictly positive and increasing in the level of quality, ψ, and $\frac{F'}{F}$ is bounded above. This latter assumption ensures that as quality levels increase, the incremental costs to raise quality do not become arbitrarily large. In the third stage, firms play a Bertrand pricing game conditional on the product attributes and marginal costs $c(\psi)$, where $c(\psi) < \overline{Y} < \max(Y_h)$. These assumptions imply that higher quality firms also have higher marginal costs. However, marginal costs are bounded above by some income level below the maximum income level and, hence, there will always be some consumers willing to pay for arbitrarily large quality levels. In other words, costs increase more slowly than the marginal valuation of the "highest-income" consumer.

The crucial assumption is that the burden of advertising falls more on fixed than variable costs. This assumption ensures that costs do not become arbitrarily large (i.e. prohibitively large) as quality increases. Consequently, it is always possible to outspend rivals on advertising and still impact demand. This seems like a reasonable assumption for the CPG markets in which advertising decisions are made in advance of realized sales. It is unlikely that advertising spending would have a large influence on marginal (production) costs of a branded good[2]. In more general consumer settings, this assumption may not be innocuous. Berry and Waldfogel (2003) examine the role of this assumption for market structure. In the restaurant industry, where they find that quality is borne mainly in variable costs, they observe the range of quality levels offered rises with market size while market shares fragment with market size. In contrast, for the newspaper industry, where they expect quality to be a fixed cost, they observe average quality rising with market size without fragmentation.

The following propositions are proved in Shaked and Sutton (1987).

Proposition 1 *If $u_\psi = 0$ (i.e. no vertical differentiation), then for any $\varepsilon > 0$, there exists a number of consumers S^* such that for any $S > S^*$, every firm has an equilibrium market share less than ε.*

Essentially, in a purely horizontally-differentiated market, the limiting concentration is zero as market size increases. The intuition for this result is that as the market size increases, we observe a proliferation of products along the horizontal dimension until, in the limit, the entire continuum is served and all firms earn arbitrarily small shares.

Proposition 2 *There exists an $\varepsilon > 0$ such that at equilibrium, at least one firm has a market share larger than ε, irrespective of the market size.*

As market size increases for industries in which firms can make fixed and sunk investments in quality (i.e. vertical attributes), we do not see an escalation in entry. Instead, we see a competitive escalation in advertising spending to build higher-quality products. The intuition for this results

[2]The main driving force for CPG private labels and store brands is the fact that one can frequently mimick the national brand phsyically without the overhead required to build the brand name.

is that a higher quality firm can undercut lower-quality rivals. Hence, the highest-quality firm will always be able to garner market share and earn positive economic profits. At the same time, only a finite number of firms will be able to sustain such high levels of advertising profitably, which dampens entry even in the limit. These two results indicate that product differentiation per se is insufficient to explain concentration. Concentration arises from competitive investments in vertical product differentiation. When firms cannot build vertically-differentiated brands (by advertising) we expect markets to fragment as market size grows. In contrast, when firms can invest to build vertically-differentiated brands, we do not expect to see market fragmentation, but rather an escalation in the amount of advertising and the perseverence of a concentrated market structure.

The results above generate a basic set of predictions for long-run market structure. In industries characterized by substantial endogenous sunk investments, such as advertising, we expect concentration to be bounded below even as the size of the market increases in the limit. However, in the absence of these endogenous sunk investments, we would expect concentration to converge to zero as the market size increases in the limit.

Sutton (1991) discusses a hybrid case that arises in markets where consumers may be segmented according to those who derive utility from the vertical attribute (i.e. brand quality) and those who do not. In such a market, it is possible to sustain firms that do invest in the endogenous sunk cost as well as firms that do not. In the limit, these two subsegments of advertised and non-advertised brands diverge to two independent market structures. As market size grows the former set of firms will have a concentration level bounded below. However, concentration for the latter set of firms will converge to zero. In this respect, the theory provides differential predictions for firms that advertise and firms that do not (see also Ellickson 2004).

2.2 Sequential entry and sunk costs

In the case of CPG industries, many of which originated late in the 19^{th} or early in the 20^{th} centuries, a model of simultaneous entry is unrealistic. Firms more likely entered local geographic markets in sequence as national roll-outs required considerable time to co-ordinate. Interestingly, Shaked and Sutton (1987) have shown that the non-fragmentation results of the previous section continue to hold under sequential entry for a finite number of firms. In addition, Sutton (1991) discusses how sequential entry can lead to order-of-entry effects on market shares (see for example Lane 1980 and Moorthy 1988). Since a first-mover can pre-empt future entry, we expect the advertising level and share of the first-mover to be higher than subsequent entrants. The role of order-of-entry on market structure provides an even more micro set of predictions for market structure as the identities of specific firms becomes relevant. Specifically, if the order in which firms in a given industry enter markets differs across geographic areas, then the theory predicts geographic differences in the rank-order of shares.

A separate literature in consumer psychology has investigated the role of first-mover effects in controlled experimental settings (Kardes and Kalyanaram 1992, Kardes, Kalyanaram, Chandrashekaran and Dornoff 1993). For comparable products, the evidence suggests that subjects systematically recall the attributes of earlier entrants better and are more likely to choose earlier entrant products in future brand choice scenarios. The logic for these findings is based on learning. In our analysis, we cannot rule out these types of inherent first-mover effects on consumer behavior. However, since many of our industries have been around since the mid 19^{th} century, it is unlikely that a firm could sustain such an inherent first-mover advantage for over one hundred years without some additional strategic difference in its behavior relative to its competitors.

3 Data

In this section, we describe the data sources used in the analysis. Our primary data source is AC Nielsen scanner data for 31 CPG industries in the 50 largest AC Nielsen-designated Scantracks[3] as in Dhar and Hoch (1997). These industries collectively account for roughly $26 Billion in annual national revenues. The data are sampled at four-week intervals between June 1992 and May 1995. The CPG industries covered are all large industries representing a wide range of both edible grocery and dairy products. For each industry, we observe sales, prices and promotional activity levels for each of the brands. Brand sales are measured in "equivalent units", which are scaled measures of unit sales provided by AC Nielsen to adjust for different package sizes across brands. We then compute brand shares by taking a brand's share of total equivalent unit sales for the industry within a given market during a given time period. Promotional activity is reported as the decomposition of total local brand sales in terms of the merchandizing conditions under which the product was sold in different retail outlets. These merchandizing conditions include feature advertising, in-aisle displays and price-cuts. Promotion levels in a given market during a given time period are computed as the share of a brand's total sales under any promotional condition. We also have analogous data at the retailer-level for those retailers with local annual revenues exceeding $2MM. There are 67 such retailers in the data, which jointly cover 48 of the 50 Nielsen markets. Matched to these marketing data are advertising intensity levels measured in gross rating points (GRPs)[4] for 23 of the geographic markets. Advertising expenditure levels are computed using the list price (by market and quarter) of GRPs reported in the Media Market Guide. Table A.1 in the Appendix lists examples of some of the CPG food industries covered,

[3]Each Scantrack covers a designated number of counties, with an average of 30 and a range of 1 to 68. All markets include central city, suburban and rural areas.

[4]GRPs are the CPG industry standard for measuring advertising. GRPs are calculated by multiplying reach and frequency. Reach measures the proportion of the target market that has seen the firm's advertising at least once. Frequency measures the average number of times individuals in the target market saw the ad.

brand	average local share	average price per weight equivalent[b]	% volume sales on any promotion	local GRPs per month
Folgers Coffee	0.302 (0.108)[a]	29.216 (2.061)	0.335 (0.069)	1043 (207)
Maxwell House Coffee	0.248 (0.121)	29.312 (2.304)	0.392 (0.078)	795 (106)
Kraft Mayonnaise	0.489 (0.205)	1.180 (0.105)	0.317 (0.068)	467 (99)
Unilever Mayonnaise[b]	0.289 (0.175)	1.261 (0.093)	0.253 (0.067)	352 (38)

[a]Deviations across markets of averages within markets in parenthesis

[b]AC Nielsen's weight equivalent units are industry specific. Comparisons across industries are therefore invalid.

Table 1: Descriptive statistics for the main brands

along with each of the geographic markets and retailers in the database.

We also consider the impact of historic advertising on current sales using additional AC Nielsen GRP data for the years 1989-1993 for all 31 industries. For each of the 23 markets above with contemporaneous sales and advertising data, we construct a market and brand-specific measure of the historic investment in advertising from 1989 to 1993. Table 1 provides descriptive statistics for the two largest brands in each of the ground coffee and mayonnaise industries, for which we will also provide details on entry data below.[5]

Demographic measures for each market are also obtained from two sources. First, based on 1993-1995 census data, Spectra Marketing provide the following variables: "Home Value" is the fraction of households in an area owning homes valued over \$150,000; "Elderly" is the fraction of the population in an area older than 55 years; "Education" is the fraction of households in an area with a four-year college degree; and "Ethnic" is the fraction of black and Hispanic households. "Income>50" measures the local fraction of the households with incomes larger than 50K. Second, additional demographic variables are collected from the 1994 MarketScope book by Trade Dimensions. These variables include "Income," "Hispanic," "Household Size," and "Age." Descriptive statistics are available upon request.

We also construct a proxy for the minimum-efficient-scale in each industry to capture the exogenous set-up cost for a firm to enter a market. The proxy is based on data from the 1997 economic census at the industry-level for the manufacturing sector. We compute the average value of depreciable assets by dividing the reported "Gross Book Value of Depreciable Assets at Beginning of Year" by the reported "Number of Companies". A summary of these data appear in the Appendix in table A.2. We refer the reader to Sutton (1991, Chapter 4) for a detailed discussion of the empirical issues surrounding the measurement of Minimum Efficient Scale in practice.[6]

From Young & Rubicam we obtained the Brand Asset Valuator data for 1993. These data describe local perceptions about product quality and brand attitudes based on surveys from a

[5]Comparable descriptive statistics for the remaining 29 categories are available upon request.

[6]Sutton (1991) uses a different proxy for minimum efficient scale based on the median plant output for an industry as a ratio of total industry output.

national sample of households. We use brand-specific quality perception data for each of the 4 census regions: Northeast, Midwest, South, and West.[7] The quality measures are available for the largest of our 31 industries, and for both industries for which we have collected entry data.

For a select number of industries, we were able to collect information on the exact geographic location of the manufacturing plant. The plant location provides a measure of cost asymmetries for brands in a market based on the distance from the market to the plant. The plant location data were obtained from interviews with managers, websites and other secondary data sources.

Finally, for a select number of industries, we were able to collect data on the year the brand entered each of the geographic markets. These data were obtained from a large number of sources including historic publications (e.g. Encyclopedia of Brands, the Gale Group, 1993, and Pendergast 1999), the trade press, the manufacturers themselves and the Internet, mainly at manufacturer websites. In addition, we consulted the "Hills Brothers" archives at the National Museum of American History, Washington D.C., which contain marketing and sales records from the 19^{th} and early 20^{th} centuries.[8]

4 Documenting the patterns of interest

We now provide a general description of the market structures observed across the 50 geographic markets and 31 industries. The description of the raw market share data generates three distinctive patterns, which are described in detail for the coffee and mayonnaise industries as examples. To generlize these findings, we also report summaries of results across the entire set of 31 industries. First, most of the variation in a brand's market shares lies in the cross-section of geographic markets as opposed to the time-series of months.[9] Second, the identity of the highest-share firm in an industry varies across markets, leading to variation in the rank-order of shares across markets and leading to share asymmetries both within and across markets. Finally, we observe very strong "spatial dependence" across markets in a brand's within-market mean share, but not in deviations from its within-market mean share.

4.1 Decomposition of variance in brand shares

We begin by analyzing the sources of variation in market shares. For many of the industries, the leading products are physically quite similar. For example, in the ground coffee industry, the two leading brands, Folgers and Maxwell House differ primarily in less tangible aspects related

[7] For a mapping of States into census regions see http://www.census.gov/geo/www/us_regdiv.pdf.

[8] For the mayonnaise industry, entry data were frequently available only at a regional level. In these instances, an exact entry date would need to be inferred, for example by interpolation based on geographically "close" markets. For this reason, our entry analysis will focus on whether a firm had "at least a five year entry advantage" instead of using the exact entry date of a brand.

[9] Later we will show that this market effect also explains considerably more of the total share variation than specific retailer effects.

$N = 62$	Brand	Market	Brand+ Market	Brand× Market
min	1%	0%	14%	61%
max	53%	97%	98%	99%
median	21%	25%	55%	96%
mean	23%	33%	56%	92%

Table 2: Summary statistics for R^2 of brand and market fixed effects by brand and industry for the 2 top selling brands in each of 31 industries.

to branding. In the absence of product differentiation, one might anticipate aggressive price competition to eliminate any asymmetries in brand shares within and across markets.

We begin by estimating the within-industry proportion of market share variation for the two largest (at the national level) brands in the brand/market/time data that is explained by brand versus market fixed effects. A summary of the R^2 levels from each of these 31 regressions (one per industry) apprears in Table 2. Despite the physical similarities in products within several of these industries, a strong brand effect emerges across the 2 largest brands in all 31 industries. On average across industries, brands account for 33% of the total share variation. Industry-specific results are also reported in the first three columns of Table A.3. To simplify the presentation, results are only reported for a subset of the industries. In the coffee industry, the brand component captures 19% of the share variation. Interestingly, including separate brand and market effects explains almost half as much share variation as including brand/market interaction effects, 56% versus 92% respectively on average across industries. These results suggest that, within an industry, not only is there heterogeneity across brand shares but there is considerable heterogeneity in a given brand's share across markets.

The next two columns of Table A.3 build on these findings by reporting a separate decomposition of the shares for the top two brands in the same subset of industries by markets and months. A summary of the R^2 levels across each of the top two brands and 31 industries appears in Table 3. For a brand brand, cross-market variation emerges overwhelmingly as the dominant component of market share variation. On average, markets account for nearly 90% of the share variation whereas time accounts for roughly 4%. We conclude that the cross-section of markets captures the majority of the variation in a brand's share.[10]

To illustrate the relative importance of cross-market variation versus time-series variation for brand shares, we use two specific examples. For the top two brands in each of the ground coffee

[10]There are several reason for which one might be cautious in interpreting the dominance of the cross-sectional variation. First, our data is time aggregated to months, which suppresses the temporal variation. For four of our industries, we have analogous sampled at a weekly frequency. In those industries, we observe a similar dominance of cross-sectional variation. A second potential concern is that our time series may appear to be short. In fact, 3 years is considerable longer than typical scanner data bases used in practice, using only a singly market (e.g., one city or one retail chain).

N=62	Market	Time
min	0.505	1.000E-04
max	0.998	0.267
median	0.910	0.019
mean	0.874	0.040

Table 3: Summary statistics for R^2 of market and time fixed effects by brand and industry for the 2 top selling brands in each of 31 industries.

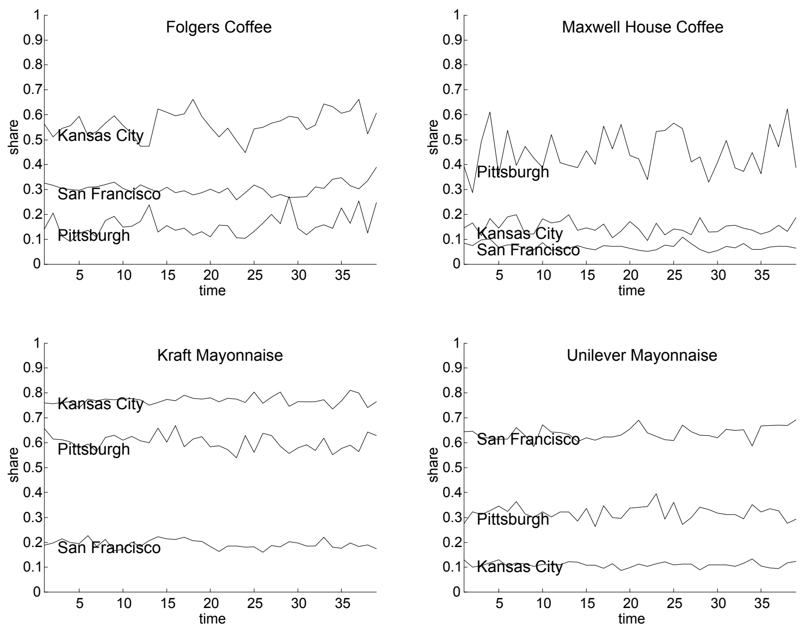

Figure 1: Local time-series variation in shares by brand and several local markets.

and mayonnaise data, we plot each brand's time series for three distinct markets, Kansas City, San Francisco and Pittsburgh, each from a different region of the US. Each of the plots reveals that the variation in a brand's share across these three markets is considerably larger than the variation across time within each market. In fact, the data appear relatively stationary over time.[11] Using the Dickey-Fuller unit root test (e.g., Hamilton 1994) for Folgers and Maxwell House, we reject a unit root for 91 of the 100 local time series (i.e. 50 markets and 2 brands). In the mayonnaise industry, unit roots can be rejected 100% of the time (i.e. for each brand in all 50 markets).

4.2 The geographic dispersion in brand shares

We now examine the distribution of brand shares across markets. First, we look at the coffee and mayonnaise industries. Figure 2 maps the geographic distribution of within-market mean shares for the top two ground coffee and mayonnaise brands across our 50 US markets. Each circle's

[11] A similar observation regarding share stationarity over time has been suggested by Dekimpe and Hanssens (1995).

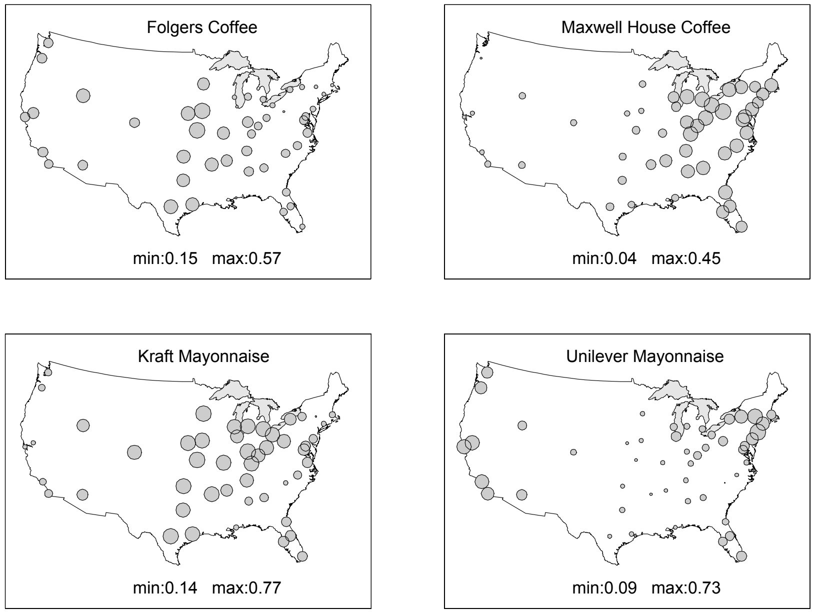

Figure 2: The geographic distribution of share levels across US markets. Circles' radii are proportional to share levels.

radius is proportional to the size of the share in a given market. The maps indicate that brand shares vary considerably across markets. The average market share of Folgers ranges from 0.15 in Pittsburg to 0.57 in Kansas City. For Maxwell House, average local market shares are between 0.04 (Seattle) and 0.45 (Cleveland). The maps also indicate that, within an industry, the rank-order of shares varies considerably across geographic areas. Maxwell House shares are strongest in the northeast, precisely where Folgers is weakest. In general, Folgers clearly dominates the ground coffee industry in the west and north central markets. But, Maxwell House dominates the East Coast. Finally, the distribution of shares across markets is clearly not random as we see strong similarities in brand shares in geographically "close" regions.

The lower half of Figure 2 illustrates similar patterns in the for the two leading mayonnaise brands, Kraft and Unilever. Geographically, shares are even more dispersed than in the coffee data. Local shares for Kraft are between 0.14 in New York and 0.77 in Kansas City. For Unilever, local shares are between 0.09 and 0.73. Spatial patterns also appear in the data insofar as Unilever shares dominate markets in the North East and West Coast, whereas Kraft shares dominate in the central and midwestern markets.

Generalizing across the 31 industries, we observe a fair amount of dispersion in a brand's shares across markets. Using the top two brands per industry, we see an average dispersion of 0.73 (its standard deviation divided by its mean). In general, this dispersion in brand shares leads to considerable variation in the rank-orders of shares across markets. Across industries, we see an average of 8 different brands that are a local share-leader in at least one market, with a range of 1 to 27. In fact, on average across industries, a local leader dominates a maximum of 64% of the markets. In only three industries do we observe a single share-leader: Cereals, Cream Cheese and Frozen Toppings. In both the coffee and mayonnaise industries, we observe four different local leading brands. For coffee, none of the four brands dominates in more than 52% of the markets. In mayonnaise, none of the four brands dominates in more than 72% of the markets. Interestingly, while the largest brands tend to have entered all 50 markets, the average brand in our database has entered only 11.4 markets, on average. Clearly, the local market structure is considerably different from the national market structure for most of these industries.

4.3 Spatial dependence in brand shares

In addition to geographic dispersion in market shares, Figure 2 also illustrates that a brand's shares are spatially dependent i.e., a given brand's shares co-vary positively acros markets. We now provide a more formal description of this spatial dependence in brand shares (see Bronnenberg and Mahajan 2001 and Bronnenberg and Sismeiro 2002 for previous work that has also looked at spatial covariance in market shares using parametric models).

We use the non-parametric approach of Conley and Topa (2002) to estimate the spatial autocorrelation in brand shares as a function of the distance between a pair of markets. Suppose the observed share data, y_m, are indexed by locations m with coordinates ω_m in a Euclidean space. We assume the dependence between the observations is a function of the physical distance between their locations. Thus, two random variables, y_m and $y_{m'}$, become increasingly dependent as the distance between m and m' shrinks (i.e. as they become "close").[12] We define the spatial autocovariance function as:

$$cov\left(y_m, y_{m'}\right) = f\left(D_{mm'}\right) \tag{2}$$

where $D_{mm'} = \|\omega_m - \omega_{m'}\|$ is the Euclidean distance between locations m and m'. The spatial autocovariance function, 2, can be estimated non-parametrically using kernel-smoothing over a grid of distances. At a given gridpoint δ, the estimated spatial autocovariance is:

$$\widehat{f}_y\left(\delta\right) = \sum_{m,m'\neq m} W_N \left\|\delta - D_{mm'}\right\| \left(y_m - \overline{y}\right)\left(y_{m'} - \overline{y}\right), \tag{3}$$

where $W_N \|\delta - D_{mm'}\|$ are weights.[13] To obtain the corresponding spatial autocorrelation function

[12]Formally, we assume our data, y_m, are second order stationary and isotropic (i.e. dependent on distance between two locations and not on direction). See Conley (1999) for a more detailed discussion of the regularity conditions of this model.

[13]We use the uniform kernel with bandwidth $\eta = 200$ miles

$$W_N \left\|\delta - D_{mm'}\right\| = \begin{cases} \dfrac{1}{N_\delta} & \text{if } \left\|\delta - D_{mm'}\right\| < \eta \\ 0 & \text{else} \end{cases}, \tag{4}$$

(ACF), we standardize 5 by the sample variance of y:

$$\widehat{\rho}_y(\delta) = \frac{\widehat{f_y}(\delta)}{var(y)}. \tag{6}$$

Note that the summation in 3 does not include pairs of observations from the same market (i.e. where $D_{mm} = 0$). Decomposing observed shares into two orthogonal components, an i.i.d. component and a dependent component, then our our estimate of the covariance, $\widehat{f}_y$, captures only the latter. Then, by construction, the estimated ACF at zero, $\widehat{\rho}_y(0)$, captures the fraction of total variance in y that is accounted for by the dependent component[14].

We test the statistical significance of our ACF point estimates using the bootstrap procedure of Conley and Topa (2002). The data are re-sampled with replacement from their empirical marginal distributions to create pseudo-samples that are spatially independent. An acceptance region for the null hypothesis of spatial independence is constructed using quantiles of the pseudo-sample estimates of $\widehat{\rho}(y_m, y_m')$.

The empirical distribution of inter-market distances in the data is reported in Figure 3. Given the amount of information in the range of distances between zero and 1000 miles, we estimate the spatial ACF along a grid between 0 and 1000 miles. Figure 4 plots the spatial ACFs for the within-market mean shares in the ground coffee and mayonnaise industries. That is, the ACF is estimated for $\overline{y_{im}} = \frac{1}{T}\sum_t y_{imt}$, where y_{imt} is the market share of brand i in market m during month t. The 95% acceptance region for the null hypothesis of spatial independence is also reported. The spatial ACFs are strikingly similar across each of the brands. In each case, the spatial autocorrelation is positive and significant over a distance of 500-600 miles. A high share in one market coincides with a high share in geographically close markets. Since this dependence arises from the within-market mean shares, we roughly interpret this pattern as a persistent "long-run" phenomenon. Finally, the estimate of ACF at zero, $\widehat{\rho}(0)$, roughly corresponds to the proportion of total cross-market variance in share associated with the spatially-dependent error

where N_δ is the number of location pairs within $\delta \pm \eta$ distance. Defining the *distance class* $\mathcal{D}_{\delta\eta}$ as the combinations of (m, m'), $m > m'$ (because of symmetry), for which $\|\delta - D_{mm'}\| < \eta$, the empirical estimator for the covariance function used in this paper reduces to (Cressie 1993):

$$\widehat{f}_y(\delta) = \sum_{\forall (m,m') \in \mathcal{D}_{\delta\eta}} \frac{(y_m - \overline{y})(y_{m'} - \overline{y})}{N_\delta}. \tag{5}$$

Experimentation with other kernels (e.g. Gaussian and Bartlett) had little impact on our estimates of the spatial ACF.

[14]More formally, suppose that shares can be decomposed into an indiosyncratic as well as a dependent component:

$$y_m = \varepsilon_m + \nu_m$$

where $E(\nu_m \nu_n) = f(D_{mn})$, $E(\varepsilon_m \varepsilon_n) = \begin{cases} \sigma^2, & \text{if m=n} \\ 0, & else \end{cases}$ and $E(\varepsilon_m \nu_n) = 0$. By construction, the estimated ACF at zero is just $\widehat{\rho}_y(y) = \frac{\widehat{f_y(0)}}{\widehat{f_y(0) + \sigma^2}}$ where the denominator is simply the total geographic sample variance in shares.

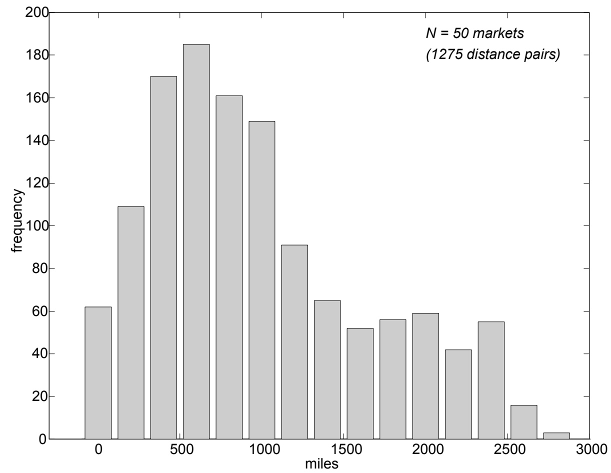

Figure 3: Distribution of inter-market distances in miles.

component. Since $\widehat{\rho}(0)$ exceeds 0.5, we conclude that the co-variation in shares across markets account for a substantial portion of the total cross-market variation in shares.

Next, we estimate the spatial ACF for the within-market deviations from the mean share, $\varepsilon_{imt} = y_{imt} - \overline{y_{im}}$, for brands i, market m and months t. For each month, we then estimate the spatial ACF for geographic cross-section of de-meaned shares, ε_{imt}. Rather than plot the ACF for each brand and month, we instead plot the time-averaged ACF as well as the time-averaged spatial independence region in Figure 5. Our findings fail to reject the null hypothesis of spatial independence in the monthly deviations from the mean market shares for a brand.[15]. Furthermore, looking at the estimated correlation at zero distance, $\widehat{\rho}(0)$, we observe that the variance in deviations from the mean share level within a market account for a very small component of the overall variance in shares across markets. The findings suggest that spatial dependence does not arise from correlated temporal shocks to shares across markets.

The results above pertain only to the coffee and mayonnaise industries. As before, to indicate generality, we report spatial dependence findings for the within-market mean shares of the top two brands in a subset of the 31 industries in the final two colums of Table A.3, in the Appendix. The table reports the estimated spatial correlation at zero distance, $\widehat{\rho}(0)$, and the average spatial correlation over the set of grid points between zero and 600 miles. A summary of these findings appears in Table 4. On average, the spatially-dependent component of market shares accounts for over half the total variance. We conclude that understanding the sources of the spatial covariance are important for understanding the geographic distribution of shares. Similarly, we find that the spatial correlation is, on average, about 0.2 for cities up to 600 miles apart. Given the distribution

[15]One can also consider a two-dimensional ACF that considers dependence over time and space. Graphically, we can plot ACF as a surface over the time and geographic distance dimensions. Our findings revealed no patterns of interest in the time-dimension. Hence, we only report dependence patterns in the geographic dimension.

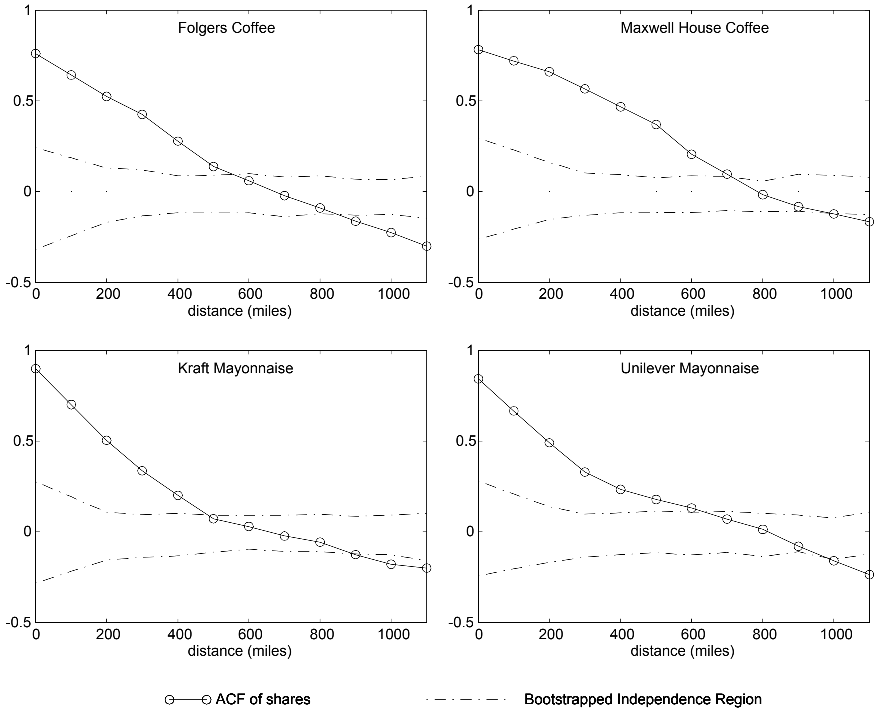

Figure 4: Spatial autocorrelation functions (ACF) for within-market mean shares by brand.

	Correlation at zero distance		Correlation between zero and 600 miles	
	top brand	second brand	top brand	second brand
mean	0.59	0.61	0.20	0.20
median	0.58	0.53	0.20	0.23
min	0.22	0.28	0.01	-0.04
max	1.01	1.32	0.46	0.50

Table 4: Summary of Estimated Spatial Correlation Across Industries

of distances reported in Table 3, this finding suggests that the dependence persists for a large proportion of our geographic markets.

4.4 Sunk costs in CPG industries

In this section we discuss the sources of sunk costs in CPG industries and we motivate the distinction between endogenous and exogenous sunk costs. We also provide some details about two industries to highlight the relevance of the theory: coffee and mayonnaise, for which we were able to collect entry data. We indicate that (1) historically, the dominant brands in each category originated as regional brands; (2) advertising during local launch of these brands was very intense and costly; and (3) local leadership tends persist in absence of major innovations.

Firms in CPG industries incur "start up" costs when launching new brands. Such costs

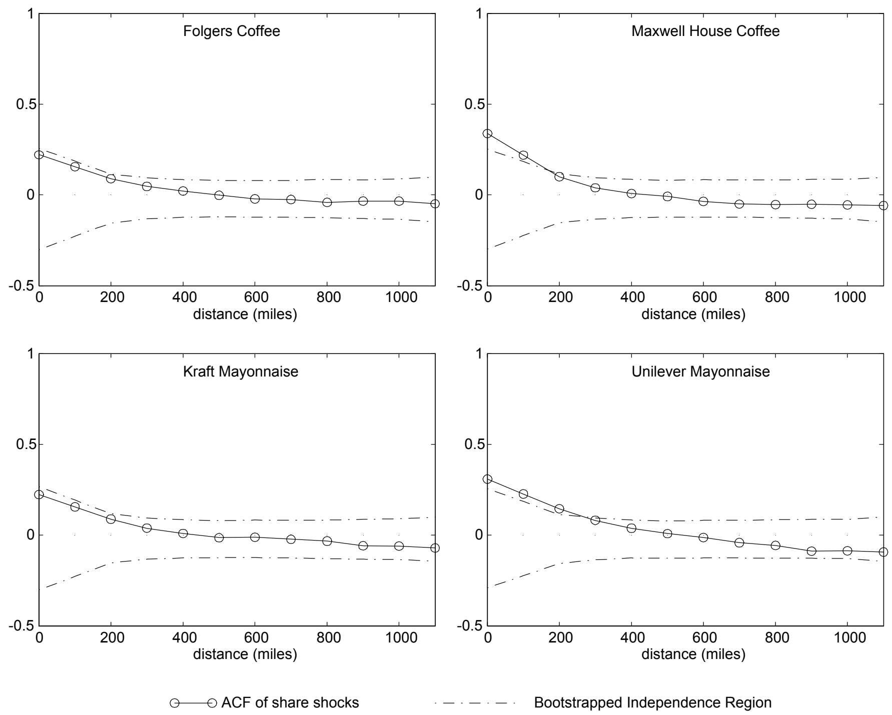

Figure 5: Spatial autocorrelation function (ACF) for the temporal shocks in the share data

are often sunk and cannot be reversed. The magnitude of some of these costs is given by the institutions of an industry rather than being determined strategically by a decision maker. An example of such exogenous fixed costs is the minimal efficient scale of a production facility or plant. Central to this study, however, other launch costs are endogenous. Firms must invest in marketing to "position" their brand and to communicate its quality to potential consumers. Insofar as firms strategically determine the outlays devoted to brand advertising and the image they wish to create, the magnitude of these costs is endogenous. Furthermore, advertising costs are considered to be fixed as they do not vary with the quantity sold but rather with the costs of developing ad copy and the quantity of media time needed. Advertising investments are also sunk in the sense that quality perceptions resulting from the advertising expenditures can not be transferred from one brand to the next.

We now briefly discuss the histories of the two categories for which we obtain historic entry data.

The coffee industry The branded ground coffee industry has a long history in the United States (see e.g., Pendergast 1999). All of the current large national coffee brands originated as local brands in different geographic areas between 1848 and 1900. During this early period, firms relied heavily on advertising to build local market share.[16]

[16]The ubiquity of advertising is evidenced by a news-paper article at the time that noted that unadvertised

Folgers, currently the largest national brand, launched in San Francisco in 1848 and expanded from its San Francisco base eastward. It opened a plant in Kansas City in 1905. Folgers arrived in Chicago by 1959 (30 years after Hills Bros and Maxwell House). There it could not secure a better position than the 3rd spot in the market after Hills Bros and Maxwell House, suggesting that the quality reputation of the two latter firms had become hard to encroach upon. Upon acquisition by Proctor and Gamble, Folgers became subject to a consent decree by the Federal Trade Commission to halt further expansion until 1971. Folgers therefore only became truly national in 1978, when it entered the New England markets.

The second largest national brand, Maxwell House, was launched in Nashville around 1892. Maxwell House first entered the markets in the Southern and South-Atlantic states. Next, in 1921 they entered the New England markets, followed by the West and Mid-West markets in 1924 and 1927 respectively. It was the first coffee brand to have national distribution and relied heavily on advertising during local introduction of their brand (*the Gale Group*, 1999).

Hills Bros is the third largest national coffee brand. It is was launched in 1881 from San Francisco and expanded eastward in the 1920's. It was the first firm to pioneer the use of vacuum packed cans in 1900, an innovation that the rest of the industry was slow to follow. By 1926, Hills Brothers was spending a quarter of a million dollars on advertising (most of it in Western states). It entered the Chicago market in 1930 with an unusually intense marketing including heavy advertising and mailing all Chicago telephone subscribers a half-pound can of vacuum packed Hills Brothers Coffee (Pendergast 1999).[17]

Subsequent innovations in the category, such as the "keyless can" were far less impactful. The vacuum packed can represents the most substantial innovation in the industry during the 20th century. It was adopted by most large competitors by the 1920s and 1930s and remains in use as a standard today.

The mayonnaise industry The mayonnaise industry has traditionally been dominated by few manufacturers. Hellmann's introduced mayonnaise to a mass market on the East Coast in 1912, while Best Foods took the West Coast. Both firms subsequently expanded their trade territories land inward. Best Foods acquired Hellmann's in 1932, but the Hellmann's brand name was maintained in its trade territories. Best Foods was subsequently acquired by Unilever who nowadays informs its customers that "Best Foods is known as Hellmann's east of the Rockies."[18]

Kraft foods is also a substantial participant in the mayonnaise category with such brands as Kraft Real Mayonnaise and Kraft Miracle Whip. Miracle Whip was a major innovation for Kraft in 1933 after it realized that sales of its mayonnaise were slipping and that it needed

products were "the genesis of unsuccessful merchandising" (Pendergast 1999).

[17]The Chicago market up until that time had been a fragmented market with approximately 50 local brands of which only three had more than 25% city-wide distribution (Wilson, 1965).

[18]See for instance http:\\www.mayo.com or http:\\www.hellmanns.com. Hellmann's and Best Foods have the exact same ingredients and in the same quantity order.

a lower priced alternative to mayonnaise in the Depression years. During the introduction of Miracle Whip, Kraft "launched one of the biggest food advertising campaigns [...] and this initial effort led to 22 weeks of almost non-stop advertising, including a weekly two hour radio show."(http:\\www.kraftcanada.com). Thus, as with the coffee brands, advertising investment is high during launch. Despite its late arrival on the market, we hypothesize that Miracle Whip was effectively a substantial innovation for a sizeable segment of consumers. That is, Kraft was able to make Miracle Whip a "new entrant" to consumers because to some it provided a new and to others a better product.

Two smaller manufacturers also have a long history in this category. First, Duke's Mayonnaise was a first mover in South Carolina and was acquired by C.F. Sauer in 1929. The latter still sells the Duke's brand in the Carolina markets. Finally, Blue Plate Mayonnaise is the first major mayonnaise brand in the New Orleans market in 1927, and it still leads in this market.

After the introduction of Miracle Whip, new product innovation in the category has not been very frequent and has met with limited success. The most successful innovations in the category were the introduction of light and cholesterol free mayonnaise in the mid eighties by the incumbent manufacturers. Regular mayonnaise, which remains the bulk of category volume, has remained largely unchanged in appearance and taste since the popularization of the aforementioned brands in the twenties and thirties.

Discussion Historically, most large national CPG brands evolved from regional brands. These regional brands used advertising as a means to enhance their quality image in existing markets. All large national brands today initially launched with large-scale local advertising campaigns. Interestingly, while major shifts in local market shares do not occur in the coffee and mayonnaise categories, there are cases where later entrants (e.g., Folgers in New England) try hard to break into new markets. In such cases, the early entrants generally sustain a strong market share advantage. This suggests that the strategic first mover advantage, which initially is based on pre-emption through advertising investments later is also supported by accumulated advertising investments.

The current market structures (assortment of brands and relative shares) in both the coffee and mayonnaise industries have been in place for a long time. Neither of these categories has seen major successful innovations in the last decennia. An interesting issue is how one defines initial conditions in an industry. The theory we present looks at the product entry date. However, one might consider whether initial conditions can be re-formulated during periods of important product innovation. That is, one might consider comparing the date of product launch versus the date of launch of a radical innovation as two alternative definitions of "entry."

We now present support for advertising as an important endogenous sunk cost in CPG industries.

5 Testing the predictions of ESC theory

In this section, we establish an empirical link between these empirical patterns and the ESC framework mainly by looking at several moments of the empirical distribution of market shares. We proceed in several steps. First, we test the basic predictions of the theory relating concentration levels and market size. Second, we test for a first-mover effect in observed market share levels as well as share co-movements across markets. Third, we attempt to rule out alternative explanations for the main patterns in our data. Finally, we discuss the results in the context of the emergence and sustainability of local oligopolies in CPG markets.

5.1 Concentration and market size

Our first objective is to establish that advertising introduces an element of vertical differentiation by testing for a lower bound in concentration in larger markets for advertising-intense industries, as opposed to non-advertising-intensive industries. The theory predicts a lower bound in the case of ESC because of a competitive escalation in advertising in larger markets amongst a finite number of firms.

We define the advertising-intensity of an industry by looking at the total advertising investment during and before the sample, 1989 to 1995, scaled by total in-sample industry revenues, 1993 to 1995. The upper and lower quartiles of industry advertising-intensity designate the sets of advertising-intense versus non-advertising-intense industries[19]. We measure concentration using the share of the largest-share brand, C_1, in each industry and geographic market.[20] We also consider two measures of market size based on the natural logarithm of the total revenues for an industry within a market as well as the natural logarithm of the population of a geographic market. The revenue and population data are first normalized by an industry's minimum efficient scale (MES as defined in the data section) to control for the exogenous fixed set-up costs associated with entering into a given industry.[21] In the case of population, the use of a dollar-value normalization is not as intuitive, but we retain this measure to demonstrate robustness of our results.

The escalation in advertising for larger markets is clear in Figure 6, which plots total industry advertising expenditure between 1993 and 1995 against market size measured as the logarithm of revenues over MES. The figure drops the bottom quartile of industries based on advertising-intensity as advertising expenditures tend to remain either zero or close to zero across markets in these industries. A regression of the logarithm of industry advertising in a market on the

[19]This may not an ideal measure of advertising intensity as it is based on equilibrium outcomes of advertising and sales. A preferable approach would be to use some measure of the marginal effectiveness of advertising in an industry. But, such measures are not readily available.

[20]Our substantive results comparing advertising-intensive to non-advertising-intensive results are comparable if we consider a 2,3 or 4-firm concentration ratio.

[21]The results in this section are qualitatively similar if we disregard the minimum efficient scale measures and proceed as if ESC are the only relevant fixed costs and we relate concentration to the logarithm of revenues.

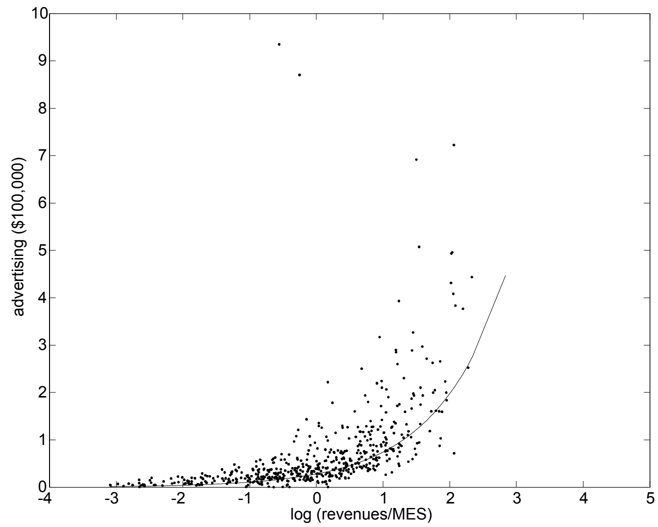

Figure 6: Advertising expenditure per month versus market size excluding the bottom quartile industries based on advertising intensity. The solid line corresponds to the predicted advertising levels from a regression of log-advertising on industry fixed-effects and market size.

logarithm of market size and industry fixed-effects generates a statistically significant market-size elasticity of advertising of roughly one. We plot the predicted advertising levels in the figure to visualize this escalation.

We now test whether this advertising escalation leads to a lower bound in concentration, as predicted by the theory. In Figure 7, we provide a scatterplot of observed concentration levels and market size across industries and geographic areas in our raw data. We provide plots for both advertising-intensive and non-advertising-intensive industries. For the advertising-intensive industries, there is little evidence of a linear correlation between concentration and market size. Furthermore, even in the largest markets, concentration seldom falls below 20%. Although not reported, a regression of concentration on market size reveals a statistically significant concave relationship under both market size definitions.[22] In contrast, there is less evidence of a bound in non-advertising-intensive industries where we observe concentration levels as low as 5%. A regression of concentration on market size reveals a downward-sloping linear relationship in the case of non-advertising-intensive industries.

To test the theory, we need to formalize our analysis of the lower bound. We use the same approach as the extant literature (e.g. Sutton 1991 and Robinson and Chiang 1996) by estimating a lower bound function using the statistical approach of Smith (1994). One can think of the share of the largest firm, C_1 as an extreme value of the distribution of brand shares. Since

[22]Sutton (1991) also finds similar evidence of a non-monotonic relationship between concentration and market size for advertising-intensive industries. This non-monotonicity is consistent with the theory.

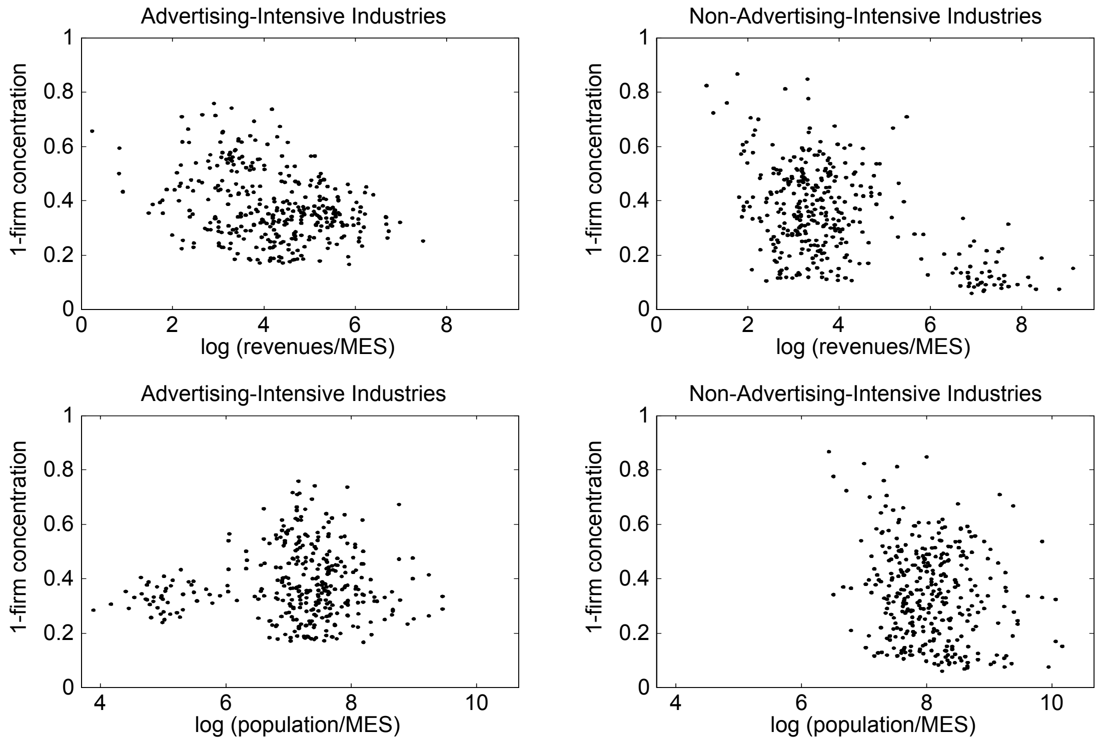

Figure 7: Concentration versus Market Size in relatively advertising-intensive and non-advertising-intensive industries.

we are interested in testing for a bound, we assume C_1 is drawn from a Weibull distribution, which is bounded below. Formally, we assume concentration in market m has the following form: $C_{1m} = B\,(\text{market size}_m) + \omega_m$, where $B\,(\text{market size}_m)$ is a parametric function of observed market size that characterizes the lower bound. The random variable ω_m is distributed according to the Weibull distribution with shape parameter α and scale parameter β. Since C_1 is constrained to lie between zero and one, we instead use a logit transformation, $\widetilde{C}_{1m} \equiv \log\left(\frac{C_{1m}}{1-C_{1m}}\right)$. Finally, since we expect concentration to be inversely-related to market size in smaller markets, we follow the literature and specify $B\,(\text{market size}_m)$ as a quadratic polynomial in the inverse of market size:

$$\widetilde{C}_{1m} = a + \frac{b}{\text{market size}_m} + \frac{c}{(\text{market size}_m)^2} + \omega_m. \tag{7}$$

This parametric formulation also provides us with a characterization of the limiting concentration as the market size approaches infinite: $a = \log\left(\frac{C_{1\infty}}{1-C_{1\infty}}\right)$ when market size approaches infinite.

We estimate the parameters for the bound function, $(a, b, c)'$, and the Weibull distribution, $(\alpha, \beta)'$, using the two-step procedure suggested by Smith (1994).[23] Standard errors are computed using the simulation method discussed in Smith (1994).

[23] In the first stage, we estimate $(a, b, c)'$ from (7) using a simplex search subject to the constraint $\widetilde{C}_{1m} - a - \frac{b}{\text{market size}_m} - \frac{c}{(\text{market size}_m)^2} \geq 0$. In the second stage, parameters $(\alpha, \beta)'$ are estimated by fitting the first-stage prediction errors to a Weibull distribution.

	Concentration versus revenues/MES				Concentration versus population/MES			
	Ad-Intensive		Non-Ad-Intensive		Ad-Intensive		Non-Ad-Intensive	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
a	-1.74	0.07	-3.07	0.22	-1.90	0.21	-7.48	1.15
b	0.63	0.22	2.22	0.71	1.56	1.48	39.02	10.92
c	-0.02	0.04	0.00	0.19	4.77	1.54	0.01	29.26
α	1.18	0.03	1.90	0.05	1.19	0.04	2.10	0.05
β	1.97	0.07	2.34	0.09	1.91	0.08	2.36	0.10
$C_{1\infty}$	0.15	0.01	0.044	0.023	0.13	0.05	0.01	0.01
log-likelihood	271.18		395.45		279.97		429.86	

Table 5: Estimated Lower Bound Functions for concentration in advertising-intensive and non-advertising-intensive industries.

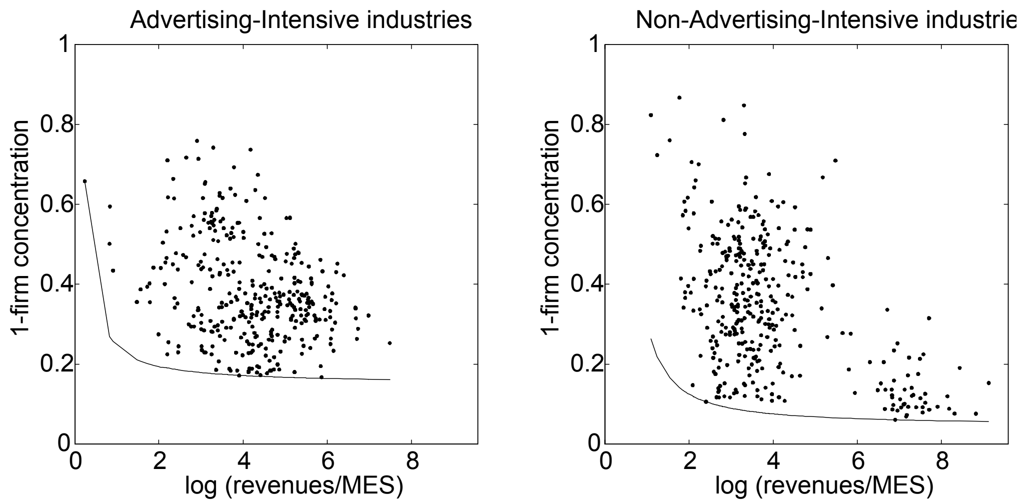

Figure 8: Estimated lower bounds on concentration for ad-intensive versus non-ad-intensive industries (using log revenues)

Estimation results are reported in Table 5. In general, we observe a steeper bound function for non-advertising-intensive industries, driven mainly by the linear as opposed to the quadratic term. To illustrate, we plot the estimated bound functions in Figure 8, using revenues as market size, and in Figure 9, using population as market size. Furthermore, the estimated limiting bounds reported in Table 5, $C_{1\infty}$, are much lower for non-advertising-intensive than for advertising-intensive industries (about 15% and less than 5% respectively). The estimated limiting bounds are not statistically different from zero at the 95% confidence level in the case of non-advertising-intensive industries. These results are all consistent with the theory. Our findings suggest that concentration is bounded away from zero in advertising-intensive industries, but not in non-advertising-intensive industries.

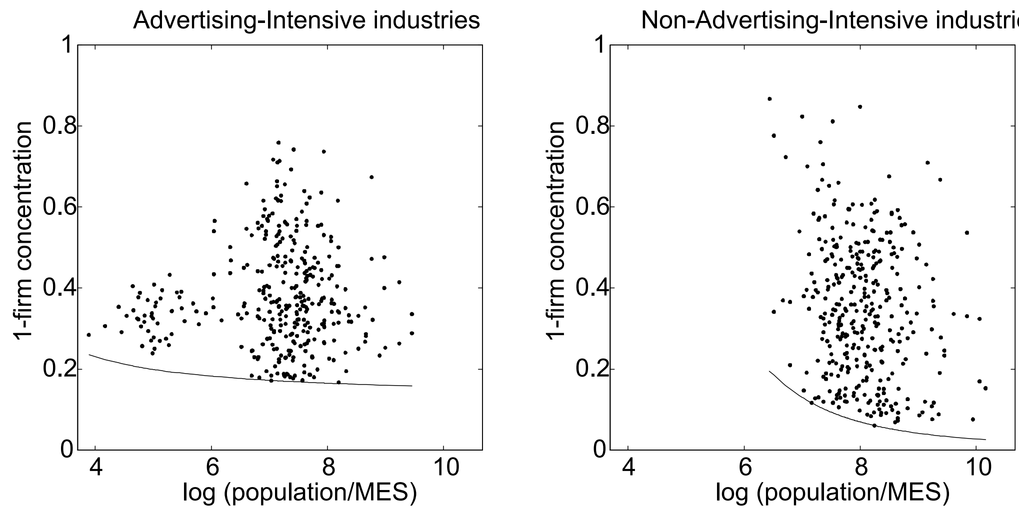

Figure 9: Estimated lower bounds on concentration for ad-intensive versus non-ad-intensive industries (using log population)

5.2 Brand proliferation

The concentration results documented above relate directly to the observed escalation in industry advertising in larger markets. The theory generates a related prediction placing an upper bound on the number of advertised brands as market size grows. However, we may nevertheless observe a proliferation in the total number of brands if the market can sustain non-advertised "fringe" brands, which will increase in number as market size grows. Ellickson (2004) documents evidence of a similar two-tiered market structure with dominant and fringe firms in the context of supermarkets. He finds that the number of high quality supermarkets remains fixed across markets of varying size, whereas the number of low-quality supermarkets increases in larger markets.

In our data, we observe a co-existence across markets and industries of brands that advertise and brands that do not. In table A.4, in the Appendix, we report the average (across markets and time) number of brands and market share levels for advertised versus non-advertised brands in each of the industries. For these results, we drop the private labels to focus on the proliferation of small local brands; although adding private labels would merely strengthen our results below. We summarize these findings in table 6. We use the historic advertising as a proxy for investment in the sunk cost. Hence, our classification of advertising versus non-advertising brands is based on whether a brand invested in advertising (i.e. the sunk cost) during the years 1989-1993.[24] The typical market for any given industry has considerably more non-advertised brands than

[24]For the results reported, we define an advertising brand as one that advertises during each year in our data. A non-advertising brand is defined as one that never advertised during the sample years. Although not reported, all of our results are robust to less conservative definitions that consider brands that "occasionally" advertise (i.e. up to less than half the time) and brands that "occasionally" do not advertise (i.e. less than half the time).

	market share			number of brands		
	mean	min	max	mean	min	max
Advertising Brands	0.27	0.06	0.68	1.39	0	6.04
Non-Advertising Brands	0.07	0.02	0.21	8.14	1.26	19.22

Table 6: Summary of advertising versus non-advertising brands across all 31 industries

	Number of Brands versus log(revenues/MES)				Number of Brands versus log(population/MES)			
	Advertising Brands		Non-Advertising Brands		Advertising Brands		Non-Advertising Brands	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
intercept	0.89	0.14	1.58	0.09	0.95	0.13	1.70	0.09
log(market size)	0.07	0.06	0.11	0.02	0.02	0.06	0.10	0.03
log-likelihood	-615.82		-1577.04		-616.50		-1579.82	

Table 7: Brand proliferation and market size. The log(market size) terms are included in deviations from their mean level. Each regression also includes industry fixed-effects.

advertised brands. The number of non-advertised brands can be as large as 19, whereas the number of advertised brands never exceeds 6, on average. Interestingly, the mean share of an advertised brand is considerably larger than that of an non-advertised brand, on average. In this respect, our distinction between the former and the latter seems to be catpuring a distinction between large brands and a “fringe”.

We next test the proliferation prediction by pooling our 31 industries and 23 geographic markets for which we observe advertising. Since the the number of brands is a count variable, we run a Poisson regression of the number of advertised brands in an industry and geographic market on industry fixed-effects and market size.[25] We then run the same regression using the number of unadvertised brands as the dependent variable. Results are reported in Table 7, where market size is approximated as either the natural logarithm of the ratio of population to minimum efficient scale or as the natural logarithm of the ratio of revenues to minimum efficient scale. As expected, we find a statistically insignificant relationship between market size and the number of advertising brands. However, we do find a statistically significant relationship between market size and the number of fringe brands. These findings are robust to both our definitions of market size. These results suggest that the number of non-advertising brands increases with market size, while the number of advertising brands does not.

[25] Formally, we assume the number of brands of a given type t (t =advertise or no advertise) in an industry i and market m, N_{imt}, are distributed Poisson with mean λ_{imt} where:

$$\lambda_{imt} = \exp\left(X_{im}\beta_t\right)$$

and X_{imt} are characteristics of industry i which is of type t in market m.

	Advertising brands		Non-Advertising Brands	
	coefficient	s.e.	coefficient	s.e.
a	-1.73	0.17	-4.80	0.64
b	9.9*e-4	0.94	7.57	4.51
c	5.7*e-4	1.92	-1.51	7.39
α	1.26	0.06	1.39	0.06
β	1.99	0.12	2.24	0.15
$C_{1\infty}$	0.15	0.05	8.2*e-3	0.01
log-likelihood	117.33		136.94	

Table 8: Estimated bound function for advertised versus non-advertised brands in the advertising-intensive industries.

Finally, we revisit the lower bound on concentration by estimating a separate bound within the segment of advertised brands and the segment of non-advertised brands. In each case, we use the maximum share within a segment-industry-market. We also restrict our attention to the advertising-intensive industries, as defined in the previous section. Parameter estimates are reported in Table 8 and graphical results are reported in figure 10. As expected, the estimated bounds function is steeper for the non-advertised brands. In fact, just looking at the raw data we can see that concentration falls with market size for the segment of non-advertised brands. Furthermore, the limiting bound appears to be much lower than that of the advertised brands. In Table 5, we report the limiting lower bounds in each case finding a lower bound of 0.15 for advertising-intensive industries and 0.0082 for non-advertising-intensive industries. These results confirm that in advertising-intensive industries, the set of non-advertised brands fragments while the set of advertised brands does not. Thus, non-advertised brands develop a sub-market-structure ressembling the prediction of an exogenous sunk costs market.

5.3 Order of entry effects

We now investigate the impact of historic order-of-entry on the geographic distribution of market shares. Unfortunately, historic entry data are not readily available for all 31 industries (in contrast with current share and marketing data) and need to be collected manually. We focus this analysis on two industries, coffee and mayonnaise, for which we collected entry patterns from various sources. Whereas our analysis thus far has generalized across 31 industries, focusing on two industries limits the generalizeability of our results on order-of-entry. Nevertheless, the spatial patterns explained by order-of-entry are observed across other advertising-intensive industries and, hence, our analysis in this section can be seen as a preliminary attempt to explain a general phenomenon.

Figure 11 contains a plot of the US geographic maps for the two leading brands in each of the ground coffee and mayonnaise industries. To indicate the order-of-entry patterns, we use a shaded

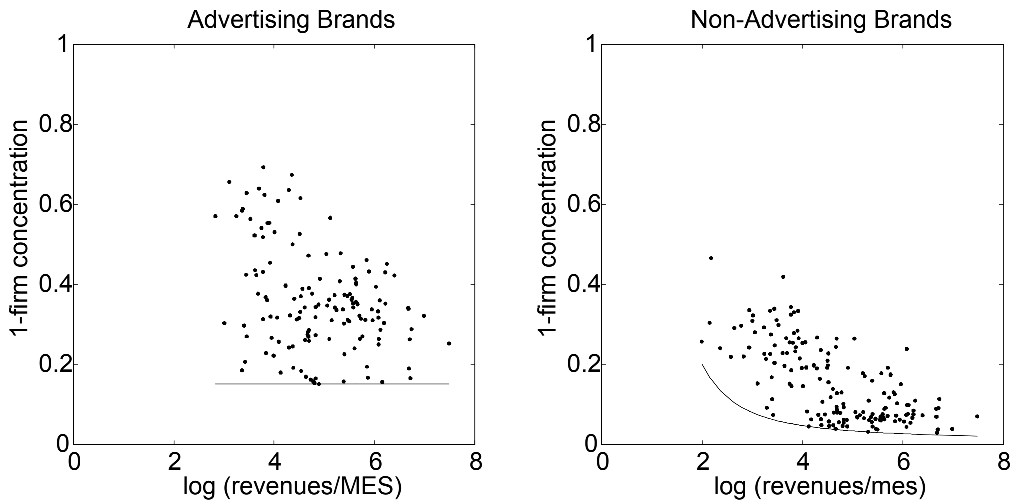

Figure 10: Estimated lower bounds on concentration in the advertising-intensive industries for advertised versus non-advertised brands.

circle for markets where the brand had at least a 5 year entry advantage and an open circle for markets where it did not. Hence, the maps give a graphical representation of the joint distribution of a brand's shares and early entry status across markets. For example, Folgers started in the West and moved East whereas Maxwell House started in the East and moved West. The maps also reveal a strong positive correlation between a brand's share level and its early entry status. Entry status also appears to exhibit a similar spatial covariance as a brand's shares.

We now look at the relationship between shares and entry more formally. The main objective is to test whether early entry status explains the observed share levels across markets. Unlike Mazzeo and Cohen (2003), we treat historic entry as exogenous[26]. In the coffee category, we include a third brand, Hills Brothers, to ensure that we always have the top two brands in each market. In table 9, we report regression results, by industry, for share levels on brand and early entry status. The dependent variable is the within-market mean share for each brand. We define "FirstEntry" as an indicator for whether or not a brand had at least a 5 year first entry advantage in a market. We report results from four models. In the first, we include only entry; in the second we include only brand effects; in the third we inlclude both brand and entry; and in the fourth we include demographic variables.[27] In both industries, we find that entry alone explains a non-trivial portion of the total cross-sectional variation in shares, 44% in coffee and 58% in mayonnaise. Conditioning on both entry and brand accounts for 76% of the variation in

[26]Since the brands we study originated during the mid to late 19^{th} century, it is unlikely that technology at the time would have been adequate to coordinate a national role-out. Similarly, it is unlikely that a firm selected an "optimal" target market to initialize the diffusion of its brand across the US.

[27]The demographic variables control for exogenous market-specific characteristics to reflect local demand conditions.

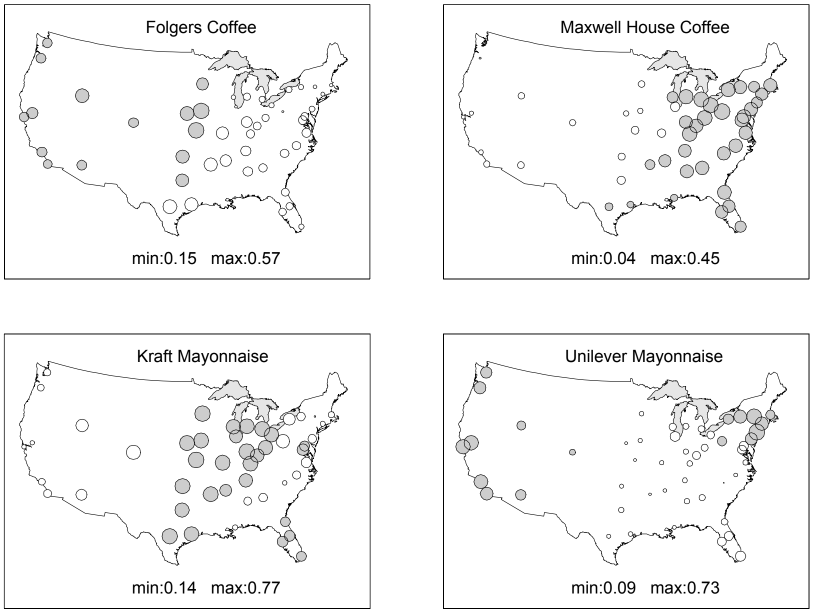

Figure 11: The joint geographic distribution of share levels and early entry across US markets. Circles are proportional to share levels. Shaded circles indicate a brand locally moved first.

coffee and 68% in mayonnaise. In coffee, early entry status appears to generate roughly a 17% benefit to share level. In mayonnaise, early entry generates a 29% share benefit. The entry effects are fairly robust both to the inclusion of brand effects and the inclusion of demographic variables. However, the brand effects are sensitive to the inclusion of entry as, in both industries, the brand effects fall once entry is accounted for. Finally, the magnitude of the entry effects are such that the rank-order of shares for the top brands will be influenced by the order of entry.

To check the robustness of our entry effect, we now investigate the impact of entry on perceived quality levels for these brands. Unlike market share, which is an outcome of the ESC investment, the perceived brand quality is a more direct measure of the ESC investment itself. The Y&R measures of perceived brand quality for each brand and market serve as the dependent variable. Results appear in table 10. As before, entry explains a substantial portion of the total variation in perceived brand quality across markets in both coffee and mayonnaise (23% in both industries). The scale of these measures is really ordinal in nature, so we do not attribute much importance to the levels of our parameter estimates. Nevertheless, as before, conditioning on entry does slightly lower the expected quality differentials across brands within a market.

Finally, we show that entry has a similar predictive ability for a brand's advertising intensity (in GRPs) across markets. We measure a brand's advertising intensity in a market as its "share of voice" (its share of total advertising GRPs for the industry). Results are reported in Table 11, where a separate entry coefficient is estimated for each brand. For most of the brands, we

Coffee	Share, N=150							
	Entry Effect		Brand Effects		Entry and Brand Effects		Entry, Brand and Demo-graphic Effects	
Variables	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
Intercept	0.135	0.011	0.057	0.014	0.050	0.010	0.355	0.370
Folgers			0.245	0.020	0.200	0.015	0.200	0.014
MaxwellHouse			0.191	0.020	0.086	0.017	0.086	0.016
Hills Bros								
FirstEntry	0.202	0.019			0.170	0.015	0.170	0.014
R^2	0.440		0.536		0.756		0.776	
Mayonnaise	Share, N=100							
	Entry Effect		Brand Effects		Entry and Brand Effects		Entry, Brand and Demo-graphic Effects	
Variables	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
Intercept	0.245	0.019	0.289	0.027	0.187	0.019	0.066	0.797
Kraft			0.200	0.038	0.141	0.025	0.142	0.025
Unilever								
FirstEntry	0.327	0.028			0.298	0.025	0.293	0.025
R^2	0.577		0.220		0.681		0.688	

Table 9: Impact of entry on share levels

Coffee	Perceived Quality, $N = 150$							
Variables	Entry Effect		Brand Effects		Entry and Brand Effects		Entry, Brand, and Demo-graphic Effects	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
Intercept	0.116	0.003	0.094	0.003	0.093	0.003	0.163	0.104
Folgers			0.061	0.005	0.055	0.005	0.055	0.004
Maxwell House			0.041	0.005	0.025	0.005	0.025	0.005
Hills Bros								
FirstEntry	0.036	0.005			0.026	0.005	0.026	0.004
R^2	0.229		0.527		0.615		0.706	
Mayonnaise	Perceived Quality,$N = 100$							
Variables	Entry Effect		Brand Effects		Entry and Brand Effects		Entry, Brand, and Demo-graphic Effects	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
Intercept	0.485	0.004	0.473	0.003	0.465	0.003	0.494	0.134
Kraft			0.054	0.005	0.049	0.004	0.049	0.004
Unilever								
FirstEntry	0.034	0.006			0.024	0.004	0.026	0.004
R^2	0.227		0.570		0.680		0.685	

Table 10: Impact of Entry on Perceived Quality Levels

	Coffee, $N = 69$ Entry and Brand Effects			Mayonnaise, $N = 46$ Entry and Brand Effects	
Variables	Coefficient	s.e.	Variables	Coefficient	s.e.
Intercept	0.024	0.006	Intercept	0.400	0.014
Folgers	0.329	0.009	Kraft	0.104	0.021
Maxwell House	0.255	0.010	Unilever		
Hills Bros			Entry Kraft	0.073	0.022
Entry Folgers	-0.024	0.011	Entry Unilever	0.074	0.022
Entry MH	0.022	0.011			
Entry HB	0.011	0.019			
R^2	0.969		R^2	0.645	

Table 11: Impact of entry on advertising levels

observe a positive impact of entry on advertising intensity. An exception is Folgers, which has a significantly negative coefficient. Folgers tends to advertise in markets where the coffee category is relatively large. In effect, Folgers advertises more strongly in markets where the category development index (CDI) is high.[28] In contrast, Maxwell House, Unilever and Kraft all advertise more aggressively where their respective brand development indeces (BDI) are high.[29] Marketing practitioners routinely use CDI and BDI to help allocate marketing resources across geographic areas (see Kotler 2000, pages 124-25 for a discussion). In the data, the correlation between BDI (CDI) and advertising share of voice in the coffee industry is 0.33 (0.15) and 0.41 (0.04) for Folgers and Maxwell House, respectively. In the mayonnaise industry the correlation between BDI (CDI) and advertising share of voice is 0.86 (0.03) and 0.77 (-0.07) for Kraft and Unilever, respectively. Since entry has a strong impact on shares, it is therefore not surprising to observe a strong correlation between entry and advertising for BDI-driven firms. In fact, standard practice of BDI-based advertising decisions is entirely consistent with the equilibrium in our model of ESC with sequential entry. Although we do not observe entry data for other industries, we do observe an average correlation between share of voice and BDI (CDI) of 0.36 (-0.03) for the 2 largest brands and the 31 industries. This finding suggests most firms allocate advertising resources in a manner that protects their strong markets.

We now examine the impact of entry on the co-variation in shares across markets. We estimate a spatial autocovariance function for the residuals from the share regression in column four of Table 9 which capture the variation in shares net of entry and market demographics. Standardizing by the variance of the residuals gives us the spatial auto-correlation of the residuals. As before, the spatial auto-correlation at zero indicate the proportion of variance in the residuals accounted for

[28]The category development index (CDI) measures the importance of a geographic market to an industry as that market's share of the national industry revenue, relative to the market's share of national grocery dollar volume.

[29]The brand development index (BDI) in a market is defined that market's share a manufacturer's brand revenue relative to that market's share of the national industry revenue.

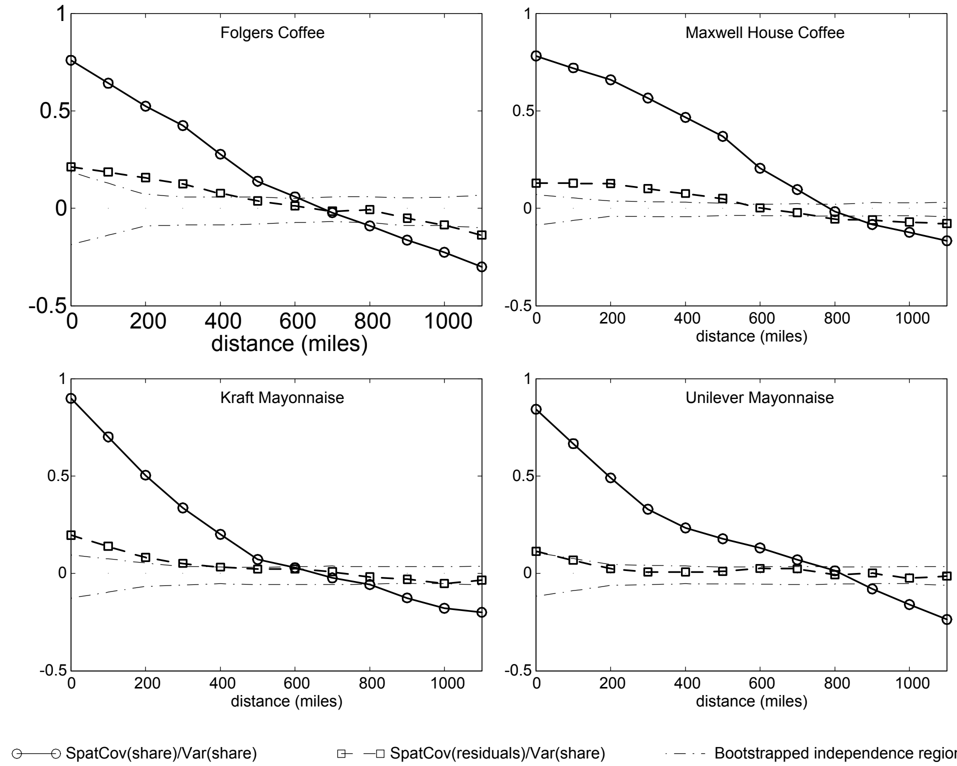

Figure 12: Accounting for spatial covariation using Entry.

by a spatially-dependent component. A plot of the estimates appears in Figure 12, indicated by the squares. The dotted lines correspond to the 95% acceptance region for independence. We also plot the original ACF of the raw shares, indicated by the circles. The results indicate that, after conditioning on entry, the dependent component of shares becomes very small relative to the total variance. In both industries, the share of variance accounted for by the dependent component falls by over 50%. We conclude that entry accounts for a sizeable proportion of the spatial dependence observed in the data.

The theory predicts that order-of-entry will influence the rank-order of market shares in advertising-intensive industries. For two of our industries, we find that entry is a very good predictor for a brand's share levels, accounting for a large proportion of the total geographic variance in shares. In fact, the rank-order of shares appears to be directly influenced by entry status, even after controlling for brand-specific effects. Furthermore, we have shown that entry accounts for a large proportion of the geographic covariance in a brand's shares across markets. We find that the proportion of total share variance accounted for by the dependent component across markets falls over 50% once entry is accounted for. Thus, the historic geographic diffusion of brands across geographic markets appears to be a good predictor of the observed spatial dependence in current market shares. We have also shown that early entrants advertise more aggressively for firms using BDI advertising allocation rules. These results are consistent with the prediction of the theory whereby an early entrant advertises more aggressively and, in turn, garners a higher market share in equilibrium.

5.4 Alternative explanations

In the previous sections, we establish a connection between the the asymmetric share patterns, for coffee and mayonnaise, and historic entry patterns. In this section, we test several potential sources of firm heterogeneity that could also explain these patterns. First, we consider geographic cost advantages based on a brand's proximity to its production plant (Greenhut and Greenhut 1988). Second, we test for relationships with specific multi-market retailers. Manufacturers frequently pay slotting allowances to retailers to obtain premium shelf space for their products (*Federal Trade Commission* 2001, Israilevich 2004, Sudhir et al. 2004). Third, we look for parent company effects in the case that specific food companies might possess regional advantages that are passed-on to each of its brands. In addition to firm heterogeneity, we also look at alternative strategic asymmetries that could explain these patterns. Specifically, we look at the role of prices and promotions in explaining the cross-market share patterns.

In table 12, we continue the analysis of share levels across markets for coffee and mayonnaise as we did with entry in table 9. In the first column, we repeat the brand-only effect. In the second column, we add the distance of each brand to its nearest manufacturing plant. The distance effect is insignificant in both industries, suggesting that proximity to production facilities does not engender a strategic advantage in either industry.

In the third and fourth columns, we look at the correlation between shares and the log of prices and promotions, respectively, after controlling for brands. In both industries, these effect sizes are very small and, in the case of promotions, insignificant. One must be cautious in interpreting these effects as there is clearly a simultaneity problem since firms set prices and promotions in anticipation of their respective impacts on shares. Nevertheless, it is surprising how relatively uncorrelated prices and promotiones are with the cross-section of shares.[30] Although not reported, we also computed the ratio of the estimated spatial covariance in the residuals of the regression of shares on prices (and on promotions) to the variance of shares. At a zero distance, we obtain values of roughly 0.70 for prices and 0.83 for promotions. These results indicate that very little of the spatial covariance in market shares is accounted for by either of these two marketing variables. The lack of a promotinal effect is particularly interesting since promotions represent a form of

[30]In contrast, price and promotion variables are often strongly related to the within-market temporal differences in brand shares. We run a separate regression of shares on prices and/or promotions for each of the top two brands in each industry and each of the 50 markets. That is, we run 100 regressions per indstry (2 brands and 50 markets). On average, the R^2 of price is 0.21, for promotion it is 0.27 and for both combined it is 0.37. It is clearly not possible to interpret causation from such regressions. Our objective here is merely to indicate that prices and promotions do appear to co-move with shares over time, even though they do not across markets.

Coffee	Brand		Distance		Price		Promo		All	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Intercept	0.057	0.014	0.062	0.019	1.247	0.269	0.107	0.034	1.158	0.454
Folgers	0.245	0.020	0.246	0.020	0.283	0.020	0.265	0.023	0.255	0.021
Maxwell House	0.191	0.020	0.191	0.020	0.231	0.021	0.202	0.021	0.123	0.021
Hills Bros										
FirstEntry									0.161	0.015
MinDistToMnfr			-0.009	0.024					-0.034	0.016
log(Price)					-0.364	0.082			-0.122	0.074
log(Promo)							0.063	0.039	0.108	0.035
R^2	0.536		0.536		0.590		0.544		0.796	
Mayonnaise	Brand		Distance		Price		Promo		All	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Intercept	0.289	0.027	0.306	0.040	0.438	0.056	0.312	0.112	0.366	0.750
Kraft	0.200	0.038	0.200	0.038	0.157	0.039	0.197	0.042	0.090	0.027
Unilever										
FirstEntry									0.273	0.024
MinDistToMnfr			-0.024	0.039					-0.105	0.036
log(Price)					-0.652	0.218			-0.576	0.166
log(Promo)							0.016	0.077	0.061	0.052
R^2	0.220		0.223		0.285		0.220		0.737	

Table 12: Impact of various firm asymmetries on share levels

awareness advertising. Typical promotions include feature ads in newspapers and in-aisle displays in the retail stores that do not contain any specific product or brand quality information, in contrast with television advertising. In the final column, we pool all the various effects, including entry and demographics. Comparing back to the previous section, we can see that the entry effect is very robust to these other explanations. Overall, we conclude that entry seems to be a considerably better predictor both of expected share levels and of the spatial covariation in a brand's share levels across markets.

We now consider the potential role of multi-market retailers in influencing the geographic distribution in brand shares. The practice of slotting-fees could enable a manufacturer to establish a relationships with specific retail chains, which could in turn generate regional advantages in distribution. We can test this effect by checking whether brand share variation exhibits a retail account component in the retail account-level data. A retail account is a combination of a retail chain and a geographical market. This data cannot separately identify a retailer and a market effect for retailers operating in a single geographic market. Instead, retail account effects are tested using dummy variables for retail chains operating in multiple geographic markets (e.g. Albertsons, Safeway and Krogers). For each of the top two brands in each of the 31 industries, we pool all the retail accounts, markets and months and decompose the variance. In general, the

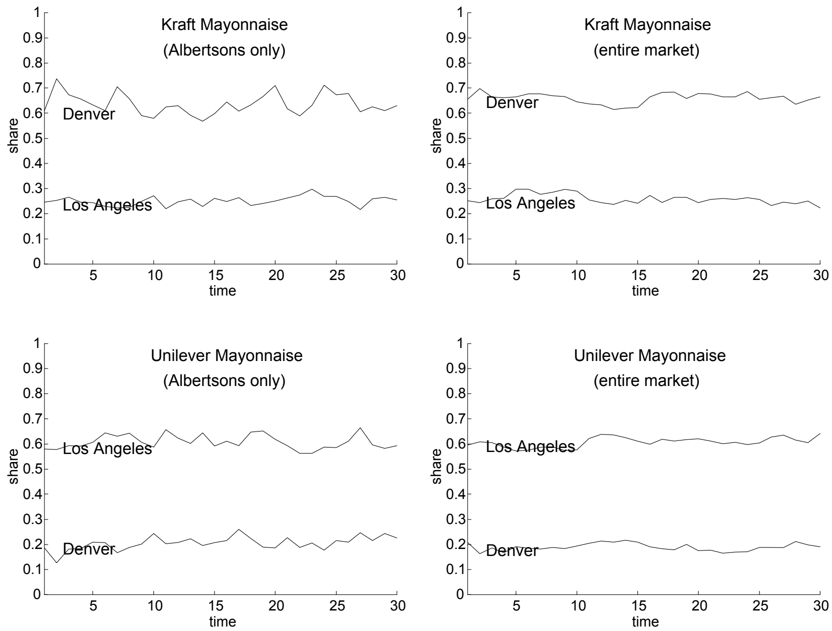

Figure 13: Brand shares in the mayonnaise industry with retailers and in markets

R^2 from retail account fixed-effects are very small compared to market fixed-effects. For instance, market fixed-effects and retailer fixed-effects explain 62% and 14% of the variation in market shares respectively. Similarly, in the mayonnaise industry, market and retailer effects explain 85% and 5% of the share variation respectively. For a few of the smaller industries, retailer effects are larger due to the fact that not all retailers carry them (e.g. refrigerated pasta) or that private labels are strong in some chains and not others. Across all industries, the retail component accounts for 20% of share variation, on average, whereas the market component accounts for more than 51%.

To illustrate these findings, we focus on the retailer Albertsons, which has presence in the West and South regions of the United States. Albertsons' operations in the Denver and Los Angeles markets are sourced by the same buying office. Hence, the Albertsons data for these two markets reflect not only the same retailer, but also the same purchasing agent. In Figure 13, we plot the time series of the Kraft and Unilever brand shares in the mayonnaise industry, the two dominant products in the industry. On the left panels, we report the share history of each brand within Albertsons by market. On the right panels, we report the share history of each brand for the entire market (i.e. all retailers in the market) by market. In the graph, we can see that the market-specific component of the share histories is considerably more influential than the retailer or time components. The within-Albertsons panels correspond very closely to the market-level results. Also, the week-to-week fluctuations in shares are extremely small relative to the cross-market fluctuations.

Overall, we conclude that none of these alternative explanations is capable of explaining the geographic patterns we observe in our brand shares. Furthermore, the entry effect appears to be robust, even after controlling for these various alternative firm asymmetries.

6 Conclusions

We test the implications of a model of endogenous sunk advertising costs using brand data for 31 CPG industries. Consistent with the theory, the results indicate a lower bound on the relationship between concentration and market size for advertising-intense industries. However, in the case of non-advertising-intense industries, no such lower bound is established and, in larger markets, these industries tend to fragment. Similarly, we observe a positive relationship between the number of un-advertised brands and market size, suggesting a proliferation of "fringe" brands in larger markets. However, we do not observe a relationship between market size and the number of advertised brands, suggesting no proliferation of advertised brands in larger markets. Overall, our results suggest that for industries that rely on brand advertising, advertising levels escalate in larger markets, leading to a concentrated structure that is invariant to the market size. In this respect, advertising appears to establish a form of vertical differentiation between competing brands.

For two industries, we also test for a an early-mover effect on current shares. In each of these industries, we find that entry impacts the levels and rank-orders of market shares for the top brands in a market. A comparable entry effect emerges for perceived brand quality, which is also consistent with the theory. In addition, we find that for the most of the brands studied, we observe a strong first-entry effect on advertising "share of voice." Our entry effects can only be established for two industries. However, we find that entry explains almost all of the spatial dependence in market shares. The incidence of spatial dependence does generalize across most of our 31 industries, representing a large component of total share variation. Furthermore, BDI advertising policies appear to be used in all of our 31 industries. In the case of sequential entry, BDI advertising is entirely consistent with the equilibrium in the ESC model.

To further support our findings regarding entry and the geographic patterns in our shares, we look at several alternative potential sources of firm asymmetry across markets. Proxies for several sources of firm heterogeneity, including geographic cost asymmetries (distance to plant) and relationships with retailers that could generate distributional advantages, do not appear to explain much of the geographic patterns in shares. Surprisingly, marketing variables such as prices and promotions do not appear to provide any insights into the geographic patterns in market shares. Instead, they appear to co-move with shares over time, within a market. Hence, promotional awareness tactics do not appear to play a role in the formation of industrial market structure. This finding is in stark contrast with our results connecting advertising and the geographic distribution of market shares. These findings are suggestive of an important relationship between advertising strategy and the long-run industrial market structure of an industry.

The analysis herein relies on entry patterns for only two industries. Ideally, collecting entry patterns for a broader set of CPG industries would allow us to test directly an additional implication of the theory. Mainly, for non-advertising-intense industries, the entry effect should die-out as market size grows. In larger markets, non-advertising-intense industries will tend to fragment, off-setting the potential benefits of early entry.[31] With only two industries with entry information, it was not possible to test this additional implication.

Another interesting extension of the results would be to establish why the degree of advertising-intensity varies across CPG industries. In the current paper, we use the advertising-to-sale ratio to measure advertising, which is based on equilibrium outcomes. A preferable approach would be to use a measure of the marginal effectiveness of advertising. An interesting direction for future research in this area would be to add more structure to the empirical analysis. Our current descriptive models help us identify evidence of a long-run effect of advertising on industrial market structure. However, the estimation of a structural demand system, by industry, could further enable one to measure the marginal effect of advertising on sales and to analyze the implications for equilibrium advertising levels in contrast with prices and promotions. Such an approach might also provide some insights into why CPG industries differ to such a degree in their advertising intensities.

[31] In a model of horizontal product differentiation, an early entrant could establish an advantage through its location choice (Lane 1980). However, as market size grows, this advantage would be offset as competitors gradually cover the entire horizontal continnum.

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A Additional tables

Industries	Bread, Cereal, Coffee, Cream Cheese, Dinner Sausage, Frozen Topping, Fruit Spreads, Margarine, Mayonnaise, Pizza, Yoghurt[a]
Markets	Albany, Atlanta, Baltimore, Birmingham, Boston, Buffalo, Charlotte, Chicago, Cincinnati, Cleveland, Columbus, Dallas, Denver, Detroit, Des Moines, Grand Rapids, Harrisburg, Houston, Indianapolis, Jacksonville, Kansas City, Los Angeles, Louisville, Little Rock, Memphis, Miami, Milwaukee, Minneapolis, Nashville, New Orleans/Mobile, New York, Oklahoma City/Tulsa, Omaha, Orlando, Philadelphia, Phoenix, Pittsburg, Portland, Raleigh/Durham, Richmond/Norfolk, Sacramento, San Antonio, San Diego, Seattle, San Francisco, St. Louis, Syracuse, Tampa, Washington
Retailers	A & P, Super Fresh, ABCO, ACME, Albertson's, Almac's, AWG, BiLo, Big Bear, Bruno's, Del Champs, Demoulas Market Basket, Dominick's, Eagle Food Centers, Farm Fresh, Farmer Jack, Fiesta Mart Inc., Food4Less, Food Lion, Food Mart, Fred Meyer, Gerland's, Giant, Giant Eagle, Grand Union, Great American, H.E.B., Harris Teeter, Harvest Foods, Homeland Food Stores, Hughes Market, Hy Vee Foods, Jewel Food Stores, Kash N Karry, King Soopers, Kohl's, Lucky, Lucky Stores, Minyard Food Stores, National, Omni, P&C, Pathmark, Publix, Purity Markets, Raley's, Ralphs, Randall's, Riser Foods Inc., Safeway, Save Mart, Schnuck's, Schwegmann, Sentry Markets, Shaw's, Shoprite, Smith's Food and Drug Centers, Smitty's, Star Market, Stop and Shop, Super Fresh, Kroger, Tom Thumb, Tops Markets, Vons, Waldbaum's, Wegman's Food Markets, Winn Dixie

[a]To simplify the presentation, we report industry-specific results for a subset of the 31 industries in our database.

Table A.1: The dimensions of the data set

Industry	Manufacturing Sector	Gross Book Value Assets (K$)	Number of Companies	M.E.S. ($1,000)
Bread	Commercial Bakery	6500667	2403	2705.23
Cereal	Breakfast Cereal	3651150	48	76065.63
Coffee	Coffee and Tea	1871625	215	8705.23
Cream Cheese	Cheese	3392545	398	8523.98
Dinner Sausage	Rendering and Meat Byproduct Processing	1154038	137	8423.64
Fruit Spreads	Fruit and vegetable Canning	5113600	663	7712.82
Frozen Toppings	Frozen Specialty Foods	3211837	364	8823.73
Mayonnaise	Mayonnaise and Sauces	1615470	294	5494.80
Margarine	Creamery Butter	150155	32	4692.34
Pizza	Frozen Specialty Foods	3211837	364	8823.73
Yogurt	Fluid Milk	4330098	405	10691.60

Table A.2: 1997 Economic Census Data used to proxy for Minimum Efficient Scale for a subset of our industries.

	ANOVA of brand/ market/time data[a]			ANOVA of market/time data[b]		Spatial Autocorrelation[c]	
	Market	Brand	Market/ Brand Interaction	Market	Time	at 0 distance	average 0-600 M distance
Bread	53%	22%	97%	95%	0%	0.25	-0.02
Cereal	12%	64%	90%	67%	15%	0.56	0.33
Coffee	19%	5%	93%	93%	2%	0.77	0.42
Cream Cheese	1%	97%	99%	88%	3%	0.54	0.03
Dinner Sausage	41%	10%	92%	92%	0%	0.34	0.05
Fruit Spreads	23%	46%	92%	77%	4%	0.85	0.15
Frozen Toppings	2%	93%	99%	82%	6%	0.57	0.17
Mayonnaise	13%	22%	99%	98%	0%	0.87	0.31
Margarine	49%	8%	81%	80%	7%	0.46	0.21
Pizza	42%	5%	85%	85%	3%	0.64	0.26
Yogurt	31%	36%	96%	93%	2%	0.58	0.15
Average across 31 industries	23%	33%	92%	87%	4%	0.60	0.21

[a] R^2 reported

[b] average R^2 across the two top selling national brands

[c] averages spatial autocorrelation across the top two selling national brands

Table A.3: Spatial description of a subset of the 31 industries.

	market share		number of brands	
Category	non-advertising	advertising	non-advertising	advertising
Bread	0.05	0.06	10.30	1.78
Cereal	0.07	0.14	1.26	6.04
Coffee	0.04	0.14	5.22	4.52
Cream Cheese	0.09	0.68	3.35	1.00
Dinner Sausage	0.04	0.10	13.83	2.09
Fruit Spreads	0.07	0.32	7.30	1.00
Frozen Toppings	0.06	0.56	6.61	1.00
Mayonnaise	0.04	0.41	3.52	2.00
Margarine	0.06	0.11	5.09	4.30
Pizza	0.04	0.11	13.87	0.91
Yogurt	0.06	0.22	5.26	2.57

Table A.4: Summary of advertising versus non-advertising brands by industry across a subset of the 31 industries. For each industry, we report the mean across geographic markets.

Category	mean	standard deviation	minimum	maximum
Bread	0.13	0.06	0.05	0.31
Cereal	0.33	0.05	0.24	0.43
Coffee	0.37	0.07	0.25	0.57
Cream Cheese	0.65	0.07	0.51	0.78
Dinner Sausage	0.26	0.10	0.11	0.59
Fruit Spreads	0.32	0.09	0.15	0.63
Frozen Toppings	0.55	0.06	0.42	0.69
Mayonnaise	0.57	0.14	0.31	0.77
Margarine	0.20	0.04	0.13	0.32
Pizza	0.20	0.05	0.12	0.32
Yogurt	0.33	0.08	0.19	0.60

Table A.5: One Firm Concentration statistics for a subset of the 31 industries ($N = 50$ markets)