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The authors document several striking general geographic patterns in the performance of national brands using a large longitudinal scanner database that spans many consumer packaged goods categories and U.S. regional markets. Across markets, they observe that for a typical national brand, the geographic variation in market shares, perceived quality levels, and local dominance is so large that it questions the concept and relevance of a "national brand." Across time, the authors find that the geographic differences in market shares for national brands are persistent and thus are attributed to "long-term" outcomes. The objective of this article is to open a discussion on these surprising stylized findings related to geography in the food and beverage industries. The authors argue that geographically indexed consumer packaged goods data contain rich information about long-term marketing outcomes that offer several new directions for further research.

Consumer Packaged Goods in the United States: National Brands, Local Branding

Consumer packaged goods (CPGs) have been a major focus of empirical research in marketing. The industry is economically important (the food industry totaled $950 billion in 2004). Furthermore, marketing researchers and practitioners have access to high-quality data that are collected and maintained by syndicated data services (e.g., ACNielsen, Information Resources Inc).

Traditionally, research on CPG brands has been dominated by analyses that use data from one or a small number of geographic market areas. Examples of widely used data sets in this regard are the ERIM data, the Dominick's Finer Foods data, and the Stanford Basket data. By design, analyses with these data rely on the time-series variation, which typically spans approximately two years, though the Dominick's data offer an eight-year sample of weekly data. Consequently, much of the general quantitative knowledge about purchase behavior and the effectiveness of marketing-

mix variables in CPG categories is based on information contained in the time series. A selective overview of this literature shows that, in general, market shares for national brands of CPGs are stable (Dekimpe and Hanssens 1995a). A second regularity is that promotions and temporary price cuts typically have higher elasticities than advertising (Assmus, Farley, and Lehmann 1984; Sultan, Farley, and Lehmann 1990). Finally, promotions appear to have mainly short-term effects (Blattberg, Briesch, and Fox 1995; Dekimpe and Hanssens 1995a; Nijs et al. 2003), whereas current advertising has longer-lasting effects across time (Assmus, Farley, and Lehmann 1984; Lodish et al. 1995) and possibly even builds up across time (Dekimpe and Hanssens 1995b).

Perhaps because of the lack of available data, little research in this domain has explored the geographic dimension of CPG categories. A few recent studies have documented patterns in specific categories. For example, market shares have been found to be spatially dependent in the Mexican salsa and tortilla chips categories (Bronnenberg and Mahajan 2001; Bronnenberg and Sismeiro 2002), and in the frozen-entree category, relative marketing investments by competing brands differ across markets (Dubé and Manchanda 2005). The discussion herein explores related geographic patterns across a broad set of CPG categories to establish several general stylized patterns. Ultimately, establishing theories to understand the patterns we document could be the source of a fruitful new research area for quantitative marketers. For now, we discuss several possible research directions based on geography and marketing data.

In our database, shares of CPG brands are empirically dominated by four regularities: (1) persistent share variation within markets and geographic dispersion across markets, (2) temporal stability, (3) broad distribution of local share dominance, and (4) spatial dependence that spans multiple markets (in our case, ACNielsen Scan Tracks).

The magnitudes of the cross–market share variation are sufficient to question whether the general knowledge based on single-market time series generalizes to the case of multimarket data. We note at least two controversial implications about a single-market focus in the analysis of national CPG brands. First, a single-market focus ignores the cross-market dimension in CPG industries and, in doing so, does not focus on explaining the largest source of variation in the market-level performance of national CPG brands. Second, a major goal of quantitative research in marketing is to determine the marginal effects of a firm's marketing investments. If the cross-sectional variation in brand performance is related to such investments, a single-market focus may lead to poor estimation of these marginal effects. Indeed, we conjecture that the cross-sectional variation in market shares may be informative about the long-term effects of marketing investments, such as advertising or distribution, and of strategic marketing decisions about the product, such as local positioning and branding.

In addition to documenting striking new empirical regularities in geographic data, we hope to elicit debate about what we believe are important but overlooked aspects of the domestic CPG industry. Our findings indicate that geographic data may present a novel new source of long-term marketing data. Furthermore, the variation in shares and perceived qualities of national brands raises some questions about the relevance of national brands and national branding. We organize this discussion as follows: First, we discuss the data and summarize the mean geographic and temporal patterns in market shares of CPG brands. Second, we address the notion of a national brand. Third, we put forth several alternative explanations for the cross-sectional patterns in the data. Finally, we conclude.

EMPIRICAL DESCRIPTION OF NATIONAL CPG BRANDS

Data

Our primary data source is scanner data from ACNielsen that span 31 CPG categories in the 50 largest Nielsen-designated Scan Tracks. The three-year data are sampled at 39 four-week intervals between June 1992 and May 1995. The categories span a broad spectrum of food segments: bread and bakery, candy and gum, dairy products, frozen entrees/side dishes, frozen/refrigerated desserts, nonalcoholic beverages, packaged dry groceries, processed canned/bottled foods, and refrigerated meats. Because the U.S. population is agglomerated into geographically concentrated areas, an ACNielsen Scan Track typically embodies a single metropolitan area, such as Boston; Little Rock, Ark.; or Omaha, and its suburban surroundings. In two cases (a coffee data set and a Mexican salsa data set), we were able to supplement our monthly data with weekly data.

In each category, we observe brand-level information, such as sales measured in equivalent units, and several marketing variables.[1] For the subsequent analysis, we construct a brand share measure that is based on equivalent unit sales in a category/market/month.[2] In each category, we focus on the two brands with the largest national market shares. Table 1 contains the means and standard deviations of several descriptive statistics, summarizing the market shares of these 62 products. Specifically, we summarize each brand's national mean market share, its cross–market share dispersion, and its cross–market share range. The upper part of Table 1 pools all 62 products, and the lower part separately analyzes the 47 brands with coverage in all 50 markets and the 15 leading brands without coverage in all 50 markets. A striking feature of the market share data is the high level of share dispersion across markets. Notably, the range and dispersion in a brand's share is similar for products with full national coverage and for products without national coverage. Thus, the high level of dispersion is not merely driven by zero market shares (i.e., brands with no presence in some markets).

In addition to the scanner data, we use information on perceived brand qualities that Young & Rubicam (Y&R) collect through annual surveys for its Brand Asset Valuator database. Quality metrics are computed using the survey respondents' binary assessments of a brand's qualitative characteristics, such as whether a brand is "Trustworthy" or "Prestigious." We use two of these survey questions to

[1]"Equivalent units" are scaled measures of unit sales provided by ACNielsen to adjust for different package sizes across brands.

[2]We also have access to several promotion and price variables. We currently focus on introducing and discussing the patterns in local brand share performance, not on explaining them. Thus, we do not include a lengthy discussion of price and promotion variables.

Table 1
DESCRIPTION OF THE TOP-SELLING BRANDS ACROSS 31 CATEGORIES

	Average Share	Dispersion[a]	Range	Minimum	Maximum
All leading brands (N = 62)					
M	.216	.722	.399	.070	.469
SD	.151	.729	.179	.099	.205
Leading brands with coverage in all 50 markets (n = 47)					
M	.263	.433	.402	.092	.494
SD	.142	.185	.173	.104	.202
Leading brands without coverage in all 50 markets (n = 15)					
M	.069	1.633	.391	.000	.391
SD	.040	1.018	.201	.000	.201

[a]Between-markets standard deviation in local market shares divided by national share.

measure perceived brand quality: "High Quality" and "Best Brand in Category." We compute our measures of perceived brand quality as the percentage of respondents in a geographic area who rate the product as High Quality and Best Brand in Category. Intuitively, the High Quality measure captures the absolute quality level of the brand itself. The Best Brand in Category measure captures the rank order of the brands in terms of perceived quality within the category. Our sample of Brand Asset Valuator data was collected in 2004 and is available for each of nine Census divisions.[3]

The Geography of Brand Performance in CPG Industries

We now discuss the main empirical characteristics of the CPG brand share data by investigating their properties across brands, markets, and time. We focus on the two brands in each category with the largest national market shares. Thus, for each of the 31 categories, our data cover two brands, 50 markets, and 39 months.

Local and geographic dispersion of brand shares. We first inspect the raw market share data to identify the dominant sources of variation. We decompose the shares into time, market, and brand fixed effects, as well as an interaction between market and brand. Table 2 reports the R-square for each of the effects across the 31 industries.[4] Examining the main effects, we immediately notice the surprising disparity between the main effects of market and those of time. Variation across geography explains considerably more of the share variance than variation across time. Equally striking is the finding that the interaction between market and brand effects explains considerably more than the sum of their main effects. The contrast with the interaction with the main effects indicates two phenomena: share dispersion within a market and share dispersion across markets. On average and across all industries, this interaction explains almost all the share variation, indicating the typically small role of time in explaining total variance in brand shares. Geography accounts for considerably more of the share variation than time. This relatively large geographic component of brand shares is surprising and novel.

We now check the robustness of the large geographic component (versus the temporal component) in relation to the sampling frequency of our data. The time aggregation into monthly sales could potentially "oversmooth" the time-series variation in shares. To rule out time aggregation, we use the two weekly multimarket data sets. Using 158 weeks of data on the U.S. coffee category across the same 50 markets (from a slightly later time window [1996–1998]), we find that the R-square of the market × brand interactions is .81. Using another data set on the Mexican salsa category at the weekly level across 64 markets and 104 weeks in 1995–1996, the R-square of the market × brand interactions is .94. In both cases, geography, not time, accounts for the overwhelming majority of the variation in shares.

There are two implications of the large market × brand interactions in Table 2. First, a brand's market shares vary more across geographic markets than across time. To visualize this cross-market dispersion, Figure 1 plots a brand's local shares against its national share. Panels A and B illustrate the share dispersion for each of the 62 brands. The panels highlight the coffee data for illustrative purposes. In the coffee category, the shares for Folgers and Maxwell House vary across markets over a range of 15%–56% and 4%–45%, respectively. We observe these patterns in varying degrees for each of the categories. The most striking feature of these graphs is the large disparity between a brand's national share and its local shares in specific Scan Track markets. This geographic dispersion casts doubt on the extent to which a brand's performance can be analyzed accurately on the basis of a single geographic market. Moreover, the dispersion leads to the question whether the national performance of a brand is predictive of the brand's local performance in specific geographic areas. Without an underlying explanation for the dispersion, a single geographic market may provide limited information about a brand's overall performance.

We now try to rule out the explanation that dispersion in a brand's share is simply a reflection of differences in the competitive environment across markets. For example, a strong private-label program in a local retail chain can have a large impact on the category (Dhar and Hoch 1997). In Figure 1, Panel C, we plot the shares of the private label across markets. Dispersion in the private-label share is not surprising because different retailers have different private-label programs. However, in most categories, the dispersion in private-label share is too small to account for the dispersion in the national brand shares. Focusing again on the coffee category, we find that the private-label share varies from approximately 0% to 20%, which is insufficient to account for the national brand dispersion we reported previously. In general, it does not appear that strong local private labels generate the geographic dispersion.

The second implication is that the pattern of cross-market dispersion is brand specific, which indicates within-market variability in brand shares. To illustrate this variability, Panel D of Figure 1 plots the log-share-ratio for the two brands in each of the 31 categories across markets. We use

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[3]For definitions, see http://www.census.gov/geo/www/us_regdiv.pdf.

[4]In a few cases, not all top brands are present in all 50 markets or 39 periods. In such cases, we have computed the fixed effect models (1) as balanced analyses of variance (ANOVAs) by deleting markets or periods in which one of the brands was not available, (2) as ANOVAs in which zero market share was used as data, and (3) as unbalanced ANOVAs in which only the observations with zero share were deleted. In all three cases, the results are substantively identical.

Table 2

SUMMARY OF THE PERCENTAGE OF VARIANCE EXPLAINED BY MARKET, BRAND, AND TEMPORAL COMPONENTS IN THE CATEGORY-LEVEL DATA

N = 31	Market	Brand	Time	Brand + Market + Interaction
M	.32	.31	.01	.92
Minimum	.03	.00	.00	.63
Maximum	.99	.93	.09	.99
SD	.23	.28	.02	.08

Figure 1

NATIONAL MARKET SHARES PLOTTED AGAINST LOCAL MARKET SHARES ACROSS 31 CPG CATEGORIES (WITH THE COFFEE CATEGORY HIGHLIGHTED)

A: Top National Brand

B: Second National Brand

C: Private Label

D: Share Ratio of Top Brands
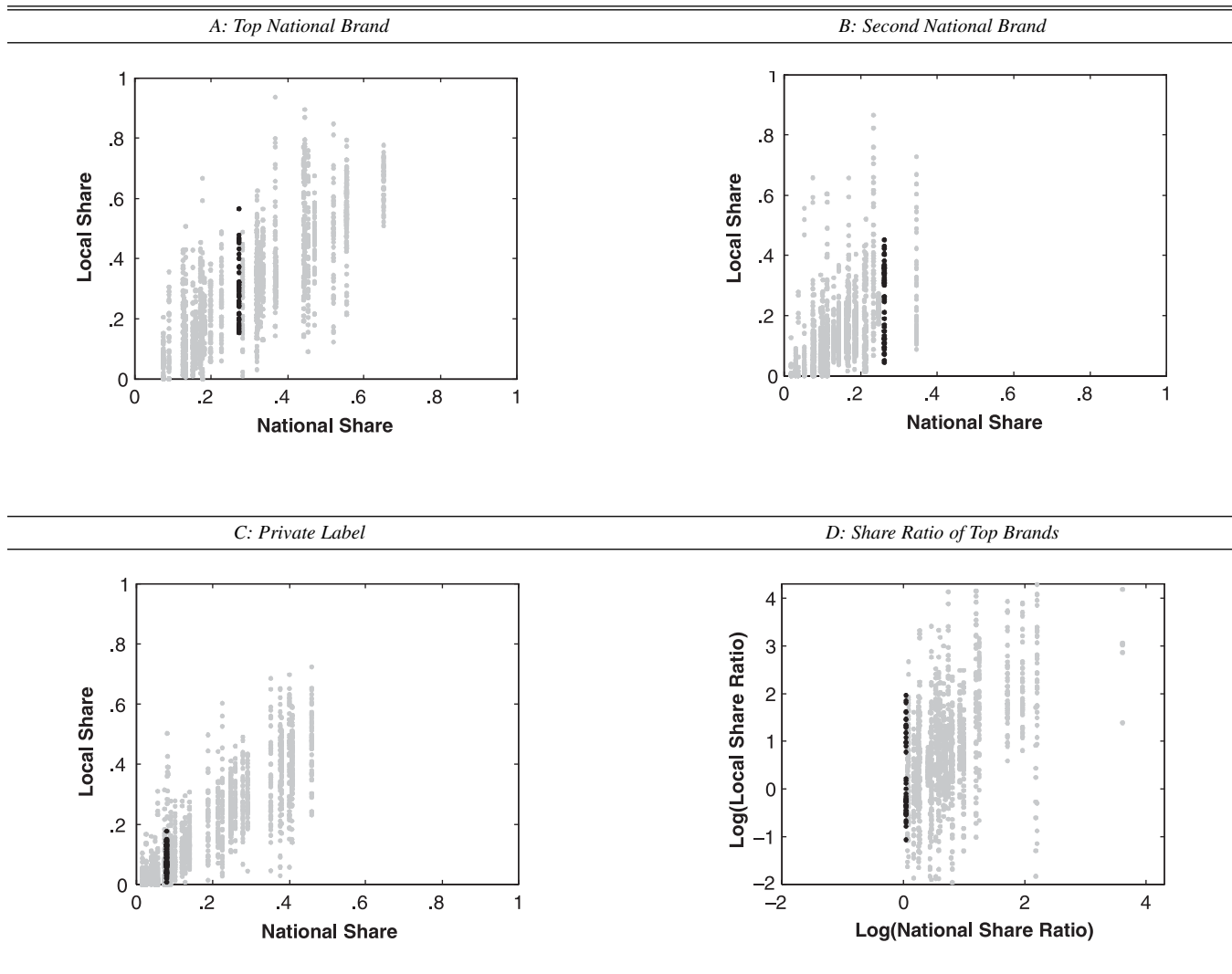
logarithms to offset the scale concerns that arise when one of the two brands has a small share, leading to large share ratios. For many categories, the national share ratio (horizontal axis) is close to 1 (0 on the log scale). However, we observe a wide range of share ratios across geographic areas (vertical axis). For example, the national share ratio in the coffee industry is close to 1 (0 in logs); that is, both Folgers and Maxwell House have equal shares (approximately 26% each). At the local market level, however, we observe a ratio of shares ranging from roughly .37 to 7 (–1 and 2 on the log scale). The range of log-ratios across markets suggests that there is a stronger tendency for one brand to dominate (in terms of shares) in local markets than in the national market. In general, a category's national market structure differs from its local market structure. Focusing on either the national market or a single geographic market may limit not only the information about a given brand's performance but also the information about the category as a whole. For example, although the national market for coffee appears to be a symmetric duopoly, most local markets exhibit a strong dominant firm with more market power. The same holds for

many other categories. Therefore, future research could benefit from a better theoretical and empirical understanding of the sources of these local share differences.

The persistent nature of geographic patterns. On average, the market × brand interaction in Table 2 accounts for 92% of the share variation, which also indicates that brand shares are stable over time. In this respect, the within-market mean brand share may be a good measure of a brand's long-term share. We test the stability of the within-market shares over time using the Dickey–Fuller test for stationarity (e.g., Hamilton 1994). For the national brands in our data, we find that a unit root in the local market shares can be rejected in 80% of cases. These findings are consistent with those of Dekimpe and Hanssens (1995a). To check the sensitivity of our stationarity results to the length of our panel, we rerun the Dickey–Fuller test using six years of data from the coffee category. Of the 100 time series (two brands and 50 markets), a unit root in shares is rejected in 99 cases. The persistence of the geographic share differences can also be observed graphically. Figure 2 plots six years of coffee brand shares (Folgers and Maxwell House) for three geo-

Figure 2
MARKET SHARES IN THE COFFEE INDUSTRY REMAIN RELATIVELY STABLE FROM 1992 TO 1998
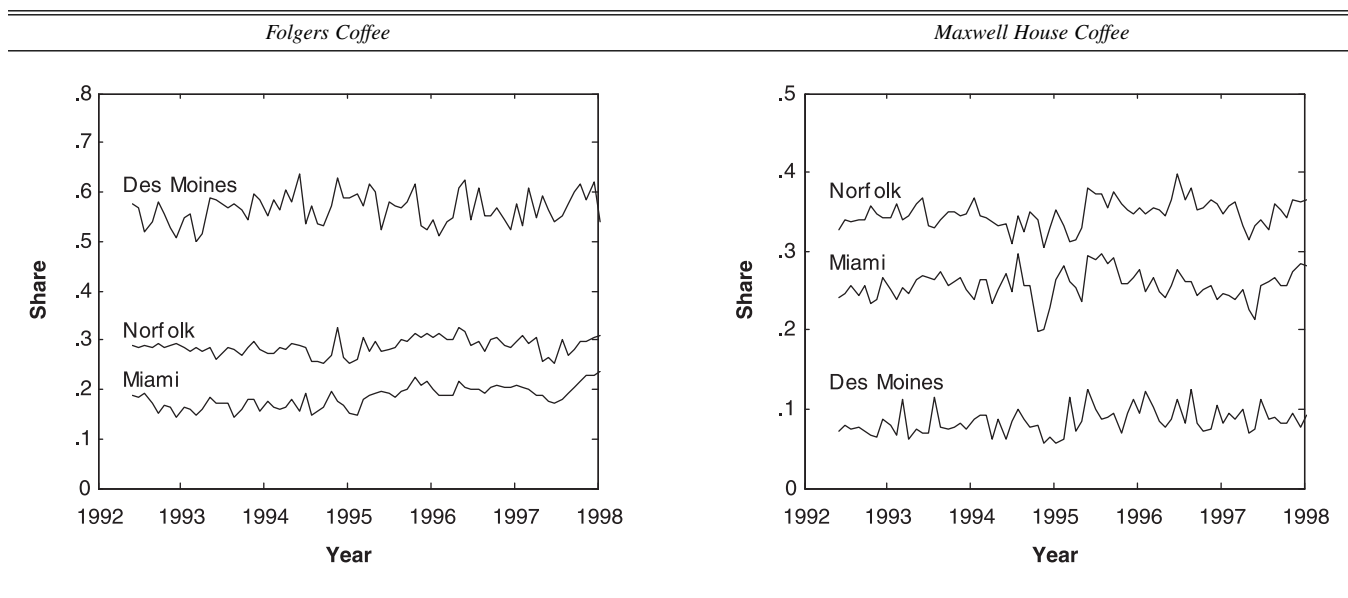
graphically distinct markets (Des Moines, Iowa; Miami; and Norfolk, Va.). The graphs indicate that the extent of time-series variation differs across markets (e.g., Folgers shares are more volatile in Des Moines than in Miami). Effectively, the graph indicates an interaction effect between time and market. Nevertheless, the cross-time variation is small compared with the extremely stable differences in a brand's mean share across markets. The graphs also indicate the equally stable differences in shares across brands within a market (e.g., in Des Moines, Folgers's share is five times the size of Maxwell House's share).

The stationarity tests show that the geographic patterns are a long-term phenomenon, which in turn makes them of strategic interest. Furthermore, the geographic share variation may provide a rich resource for studying the long-term effects of marketing investments. As we discussed previously, the time-series variation in our data appears to capture only a minor component of share variance. It is also often difficult to obtain sufficiently long time-series databases to measure long-term effects.[5] Therefore, inferences about the impact of marketing variables based on a short time series of market shares could be either imprecise or, given the patterns in our database, biased to capturing short-term tactical benefits rather than long-term strategic effects. A related problem is that the dispersion in brand shares across markets may imply that marketing effectiveness differs across markets. For example, Boatwright, Dhar, and Rossi (2004) find that the marginal effectiveness of promotions and prices varies considerably across retail accounts from around the country. Recognizing these limitations of single-market time-series data suggests some limitations on our current general knowledge of the marginal effectiveness of marketing variables. Insofar as long-term information

can be obtained from a cross-section of markets, geographic variation may be a highly underutilized resource in the field. The cross-section of markets offers a large number of realizations of the long-term outcome of marketing investments within a category on market shares. Experimenting with cross-sectional geographic data and contrasting findings with single-market time-series data may be a novel way to advance current knowledge of marketing effectiveness, and thus this line of inquiry constitutes an important direction for further research.

Spatial dependence. Given the large potential quantity of information contained in geographic data, it is surprising how little is currently known about the geographic distribution of market shares. A recent stream of literature has documented spatial dependence in a couple of categories (see, e.g., Bronnenberg and Sismeiro 2002). The spatial dependence implies that the shares for a given brand are correlated across markets; a brand's shares are similar in geographically close markets. Quantifying the extent of spatial dependence enables us to measure the information content of a cross-section of markets. In general, the magnitude of spatial covariance may point toward yet another direction for further research that seeks to understand sources of intermarket linkages.

To measure the spatial dependence in market shares, we estimate each brand's spatial autocorrelation function (ACF) nonparametrically using Conley and Topa's (2002) approach. The ACF measures the correlation coefficient between a brand's shares in two markets as a function of the geographic distance between them. We estimate the ACF for each brand using the 50 within-market mean share observations. For estimation, we use a uniform kernel with a bandwidth of 180 miles. Figure 3 displays the distribution of the distance at which the spatial ACF crosses zero. Loosely interpreted, this is equal to the typical distance between two cities at which the data become spatially independent. Typically, a brand's shares appear to be correlated in markets separated by up to 500 miles. This effect has been observed in other categories, but we show that it is

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[5]In some exceptional cases, authors have obtained access to proprietary databases that span much longer time horizons than the usual two to three years (e.g., ERIM database). For example, Mela, Gupta, and Lehmann, (1997) use eight years and three months from one category to measure long-term effects of advertising and promotions.

Figure 3
THE DISTRIBUTION OF INTERCITY DISTANCE UNTIL SPATIAL
INDEPENDENCE IS OBTAINED (I.E., WHERE THE SPATIAL ACF
CROSSES ZERO) ALONG WITH THE BEST-FITTING WEIBULL
DISTRIBUTION (HATCHED LINE)
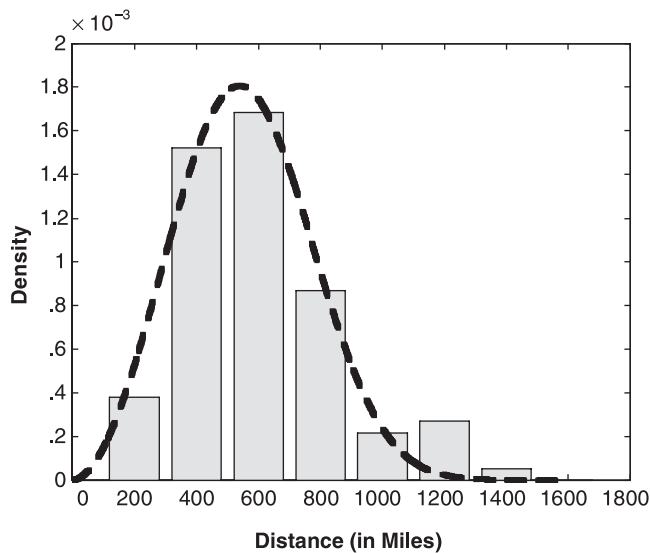
general across categories. The magnitude of spatial correlation estimated in these categories implies that a typical geographic sample of 50 markets is equivalent to approximately 10–20 independent realizations.[6] Given the short duration of most readily available time-series databases, even 10–20 independent geographic realizations of a long-term outcome in a market presents a useful resource for quantitative research. Figure 4 reports the spatial ACF for several individual brands, along with a 95% acceptance region for "spatial independence." The acceptance region for spatial independence is constructed using a bootstrap procedure that resamples the data from the marginal distributions (for details, see Conley and Topa 2002). The general pattern of spatial dependence could raise some debate about what is the geographic scope of a market. The spatial ACFs indicate that most ACNielsen Scan Tracks are considerably smaller than the spatial scale of market shares. Empirical studies examining the correct scope of a geographic market should constitute an important area for further research.

Perceived brand quality. Thus far, we have focused only on a brand's market share to measure performance. For robustness, we also examine analogous geographic patterns in perceived brand-quality measures. Using the Y&R data at the Census division level, we look for cross-market variation in quality perceptions for the same brand. From the 62 brands (top 2 brands in each of the 31 categories' national markets), we are able to match perceived quality data for 35 brands. To compare the cross-market dispersion in market

shares with dispersion in perceived quality, we again use the coefficient of variation—that is, the ratio of the cross-market standard deviation of perceived quality over the mean of perceived quality for a given brand. Table 3 reports the descriptive statistics of dispersion levels across categories for each of the two perceived quality measures and for market shares. The quality perception data exhibit comparable levels of dispersion as the market share data.[7] For example, the coefficient of variation for Best in Category is .34, whereas for shares it is .36. The slightly lower dispersion for the High Quality measure probably reflects the fact that consumers in the Y&R survey are asked to rate whether the brand is High Quality rather than its degree of quality. In the coffee category, the Y&R scores for Folgers being the Best Brand in Category range from 9% to 22% of respondents (the national mean is 15%), whereas for Maxwell House, the scores range from 3% to 20% (the national mean is 10%). The dispersion of these beliefs is surprising given the limited degree of physical product differentiation among the top coffee brands. The clear lack of a consistent quality perception across markets further erodes the concept of a national brand.

Conclusion. To summarize our discussion thus far, shares of CPG brands are empirically dominated by four regularities: (1) dispersion within markets and dispersion across markets, (2) temporal stability, (3) wide distribution of local leadership, and (4) spatial dependence that spans multiple Scan Tracks. These geographic patterns are striking because they force us to reconsider whether generalized knowledge based on single-market time-series data captures the most relevant aspects of marketing impact. Insofar as geography leads to different conclusions about the effectiveness of marketing variables, it could suggest that there is still much to learn. Moreover, the geographic patterns suggest that national performance is not representative of local performance for a brand. This observation then raises the fundamental question, What is the relevance of a national brand?

### THE RELEVANCE OF A NATIONAL BRAND

Several findings in the preceding sections suggest an ambiguous role of the so-called national brand. Thus far, we have focused on brands that garner the largest shares of a category's national market. However, we observe considerable regional variation in market share, perceived quality, and share dominance. This requires some reflection as to why the term "national brand" is used and what it implies. In this section, we expand the set of brands we study to include all local share leaders across categories and to investigate whether being a national brand carries with it an inherent benefit in terms of local performance.

In the academic literature, the term "national brand" is typically used to distinguish branded goods (e.g., advertised) from private labels (e.g., Blattberg and Wisniewski 1989; Dhar and Hoch 1997). However, as we observed in Panel C of Figure 1, cross-market (and -category) variation in the private-label share is insufficient to drive the geographic patterns observed in the various categories. Local private-label performance cannot account for the large dis-

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[6]Specifically, Clemen and Winkler (1985) note that if the $N \times N$ (spatial) correlation matrix of the observations is denoted as $\boldsymbol{\Gamma}$, the number of equivalent independent observations is equal to $\mathbf{e}' \boldsymbol{\Gamma}^{-1} \mathbf{e}$, where $\mathbf{e}$ is an $N \times 1$ vector of 1s. This number is equal to N if $\boldsymbol{\Gamma} = \mathbf{I}$ (the identity matrix). However, it is less than N if the spatial autocorrelation is positive.

[7]Because the Y&R data are reported for nine Census divisions, we also show the share dispersion using the same spatial aggregation.

Figure 4

FOUR EXAMPLES OF SPATIAL ACFS SHOWING THE SMOOTHNESS OF MARKET SHARES ACROSS SPACE

Lenders Bagels

Smucker's Fruitspread

Country Crock Spread

Tombstone Pizza
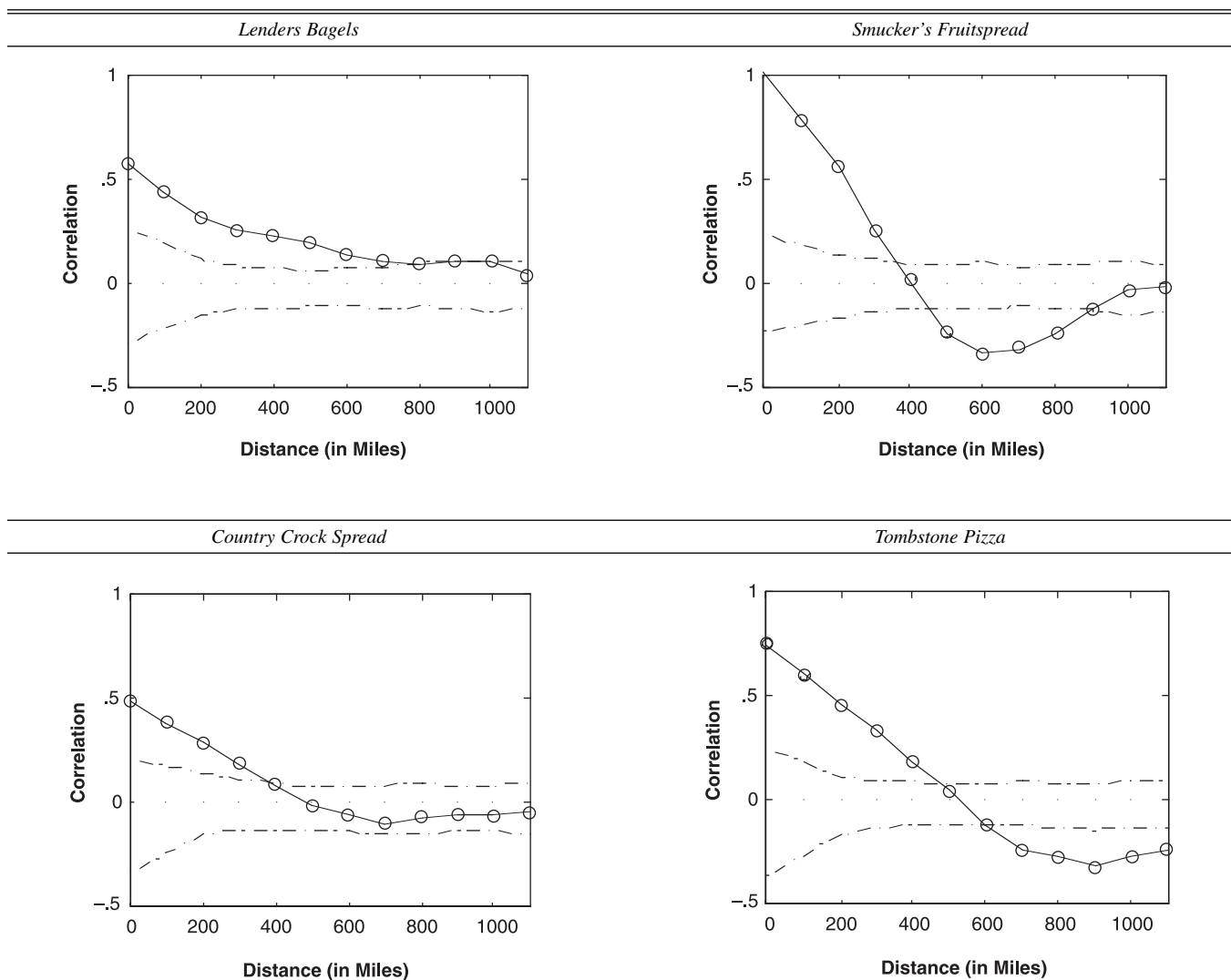
Notes: Spatial autocorrelation indicates the correlation in market shares at various distances. We observe strong autocorrelations over a range typically up to 500 miles.

Table 3

GEOGRAPHIC DISPERSION OF PERCEIVED QUALITY AND SHARES AT THE CENSUS DIVISION LEVEL

N = 9	High Quality	Best Brand	Shares
M	.21	.34	.36
Mdn	.19	.32	.32
Minimum	.06	.11	.05
Maximum	.51	.58	.95

parities between regional market shares and national market shares. Therefore, the mere distinction between a private label and a branded good sheds little light on the geographic patterns we observed.

Perhaps a better reference point for understanding the potential meaning of a national brand is to work with a definition based on geography. The American Marketing Asso-

ciation uses a definition based mainly on the geographic coverage of a brand's distribution:

> A national brand is a brand that is marketed throughout a national market. It contrasts with regional brand and local brand. It usually is advertised and usually is owned by a manufacturer, though neither is necessary for the definition because Kmart's brands, for example, are obviously national, even international. (Bennett 1995)

Notably, the American Marketing Association also distinguishes a national brand from a regional brand and a local brand. The former refers to brands that have distribution in multiple geographic areas but do not have national distribution. The latter refers to a brand whose distribution is confined to a single market. For the purposes of this analysis, we define a national brand as one with distribution in all 50 Scan Tracks.

Using these definitions, we observe an average of 2.5 national brands per category in the 31 categories. Only 2 of the categories—bread and cottage cheese—have no nationally distributed brands. Both categories have strong regional brands and private labels. Pooling across the 50 markets and 31 categories, we observe 1550 market–category pairs. In 75% of these 1550 pairs, a national brand garners the highest market share. Nevertheless, if we examine the set of 249 unique brands that lead (i.e., highest share) in at least one of these 1550 market/category pairs, only 21% are national brands. Most of the leading brands are regional: 54% are active in fewer than 15 markets, and 25% are active in fewer than 5 markets. On average, a category has 8 unique local leaders across the 50 geographic markets, ranging from 1 (cream cheese) to 27 (cottage cheese).

Although national brands tend to lead in multiple markets, it appears that the geographic scope needed to create and defend local leadership in CPG industries is surprisingly small. In the coffee category, for example, the leader in New Orleans is a brand called Community. The brand is available only in the Louisiana markets. Yet it is capable of sustaining its advantage against much larger competitors, such as Folgers and Maxwell House. Similarly, Duke's mayonnaise dominates sales in the South Carolina markets, and Blue Plate mayonnaise dominates in New Orleans, even though all other U.S. markets are split between Kraft and Unilever. Surprisingly, many local brands have been able to defend their market shares over time against national brands owned and marketed by large international CPG firms.

To examine the role of national brands, we use the distribution of maximum shares within a category across markets. Consistent with the brand-share dispersion results documented in the previous section, we also observe dispersion in a category's maximum share across markets. Across the 31 categories and 50 markets, the range of maximum shares has a mean of 40%; the smallest range is only 18% (margarine), and the largest range is 72% (cheese slices). For example, in the cheese-slices category, one of the markets has a leader with a 22% share, whereas another market has a leader with a 94% share. One potential national brand effect consists of testing whether national brand leadership generates a higher maximum share than regional or local brand leadership. In the raw data, the market share of the category/market leader is significantly higher when the leading brand is a national brand than when it is a regional brand (.39 versus .26, t = 13.5), implying a 12% share differential.

To test for the national brand effect more carefully, we run a series of pooled regressions using 1550 maximum shares as the dependent variable. We report the results in Table 4. In Column 1, we include only a national brand dummy variable (indicator for whether the leading brand is nationally distributed). The results indicate approximately a 12% national brand share advantage. Thus, when a national brand leads in a market, it tends to lead with 12 more share points than a local or regional brand. In Column 2, we also include category dummy variables to control for the mean share levels differing across categories. After we control for category effects, we immediately observe that the national brand effect shrinks from 12% to less than slightly more than 2%. Although this differential is statistically significant, it has a much smaller economic magnitude.

Perhaps not surprisingly, many national brands are owned by large marketing firms with considerable financial resources and experience. For each of the leading brands, we have collected the identity and revenues of the parent company that owns the brand. The identities of parent companies were obtained from the Internet. The revenues of the parent companies were obtained from Hoover Online Pro for 1995. We define a "large" parent company as one whose annual revenues exceed the median level in our sample (i.e., $528.6 million in 1995 revenues). Among the 391 local leaders that are not nationally distributed, 231 are owned by a small parent company, and 160 are owned by a large company (i.e., 41%). In contrast, among the national brands, 174 are owned by small companies, and 985 are owned by large companies (i.e., 85%). In Column 3 of Table 4, we include a dummy variable for whether the parent company is large, based on whether its 1995 revenues exceed $114.8 million. Similarly, in Column 4, we use a dummy variable for whether the parent's revenues exceed the median level of $528.6 million. In both cases, we find that the national brand effect is robust to the size of the parent company. Again, the magnitude of the national brand effect is still relatively small at approximately 2%. A potential concern is the collinearity in national distribution and ownership by a large parent company. An interesting direction for further research might be to try to analyze major marketing companies, such as Kraft, Unilever, and Procter & Gamble, and to study more precisely the role of joint ownership of a portfolio of brands.

Despite the preponderance of categories/markets with nationally distributed share leaders, we do not observe a meaningful inherent national brand effect. We observe numerous cases in which local brands have been able to secure leadership with little spatial scale. The type of share garnered by a local brand leader is only marginally lower than that of a national brand leader. Given the large differ-

Table 4

THE EFFECT OF NATIONAL BRAND AND LARGE PARENT STATUS ON LEADING SHARE IN A MARKET

Covariates	1		2[a]		3[a]		4[a]	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Intercept	.265	.008	.539	.016	.544	.017	.538	.017
National brand	.124	.009	.025	.008	.020	.009	.026	.009
Parent (25th percentile)					.017	.009		
Parent (Mdn)							−.003	.008
Observations	1550		1550		1550		1550	

[a]These results include category fixed effects.

ences in share (and perceived quality) performance of national brands across markets, these additional findings further contribute to the puzzle of the significance of a "national brand."

POSSIBLE EXPLANATIONS AND RESEARCH OPPORTUNITIES

In this section, we discuss a selection of possible explanations for the patterns we have discussed. Again, our purpose is not to provide answers but rather to suggest several potential directions for new research based on our descriptive findings. To give some structure to the possible explanations, we focus on the agents in the distribution channel: consumers, retailers, and manufacturers.

Consumer-Focused Explanations

Some of the geographic findings could potentially be demand driven. For example, differences in market shares across geographic areas could simply reflect differences in consumer preferences. Similarly, spatial correlation could arise if preferences are similar in geographically close markets. To some extent, the role of the demand-side explanation requires a more precise definition of preferences. Many of the categories we used herein consist of physically fairly homogeneous goods. Thus, preferences may be a reflection of perceptions of the brands themselves, as opposed to the physical characteristics of the goods. Brand preferences are complicated to analyze because they may indirectly reflect firms' marketing efforts. If brand tastes are endogenous to firms' marketing activities, the geographic patterns we observe in market shares may reflect differences in how firms market their products across U.S. cities.

Retailer-/Distributor-Focused Explanations

Geographic patterns may also be a reflection of differences in the decisions of local retailers. For example, manufacturers may set retailer-specific (rather than market-specific) contracts on point-of-purchase selling efforts. Specific manufacturers or distributors could establish exclusive arrangements with local retailers. Recent research on "category captains" (Foer 2001; Klein and Wright 2004) could possibly explain the cross-market dispersion patterns documented herein. Retail trade areas are often larger in scope than the ACNielsen Scan Tracks. Similarly, distribution centers frequently service a broader set of downstream retailers than those within a Scan Track. Both scenarios could generate spillovers across markets, which in turn would generate the spatial covariance patterns observed across categories.

Manufacturer-Focused Explanations

Given the persistence (long run) in the geographic patterns, these may also be the outcome of manufacturer marketing strategy. The theoretical literature offers two possible explanations, one collusive and one strategic. A collusive explanation for the geographic patterns could arise if competition is reduced, in part, because firms meet in multiple local markets (Bernheim and Whinston 1990). Such collusion could take the form of geographic turf division (Karnani and Wernerfelt 1985) or "spheres of influence" (Bern-

heim and Whinston 1990). Although it seems unlikely that tacit collusion could persist undetected across such a broad range of industries, this explanation cannot be ruled out.

For two of the categories, Bronnenberg, Dhar, and Dubé (2006) explore an alternative explanation for geographic patterns as the outcome of a competitive game with strategic entry advantages in which early entrants build larger brands through advertising. They explore the historic role-out strategies of firms in the coffee and mayonnaise categories to test whether historic order-of-entry differences account for the geographic patterns in shares. In both categories, order of entry accounts for a large component of the variance in share levels and the spatial covariances in shares. Although entry appears to generate a strong prediction for share patterns in these two categories, it is unclear whether these results will generalize across categories. Their data are also unable to measure the exact process through which the persistence of the entry effect is sustained over time. For example, will early entrant advantages persist in categories with frequent product innovations? Similarly, although Bronnenberg, Dhar, and Dubé focus on advertising-based explanations for the entry advantage, in other categories, comparable advantages could arise from other sources, such as relationships with retailers to obtain premium shelf space (Corstjens and Corstjens 1995; Fazio, Powell, and Williams 1989). The critical feature of each of these explanations is that such "state-dependent" explanations cannot be tested in a single market. It is only by pooling across geographic markets, thus making it possible to control for heterogeneity across firms, that a test for state dependence can be identified. These examples further highlight the potential opportunities for further research that arise from the information content on long-term marketing outcomes contained in geographic data.

CONCLUSION

In this discussion article, we noted that the geography of CPG industries is an understudied area with several important potential directions for further research. Indeed, the degree of spatial dispersion in brand shares and perceived quality levels is sufficiently prominent in the data that the concept and relevance of a national brand or national branding may be questioned. Furthermore, the relatively small role of time may cast doubt on the current general knowledge of marketing effectiveness based on single-market time-series data.

We conjecture that studying the geographic patterns of demand for national CPG brands will generate renewed interest in the importance of the product instrument in the marketing mix (e.g., national product development and local speed to market). Indeed, the dominance of promotion and price in academic marketing research is likely because there are excellent measurements of variation in price and promotion. In contrast, the influence of the product has often been banished to the "brand intercept." The geography of CPG industries provides variation in "brand intercepts," which we posit as an area for research. The geographic cross-section provides a sample of long-term brand outcomes with which to study product relative to (and in conjunction with) other marketing instruments, such as advertising and promotions. In a companion article

(Bronnenberg, Dhar, and Dubé 2006), we study historic entry as a potential explanation for variation in relative brand performance across markets. In this discussion, we also suggest several alternative theories that could be considered to help understand the geographic patterns observed in the data. Our hope is that the stylized findings we presented herein and the subsequent discussion will stimulate academic debate about the sources of these patterns and subsequent research into the geography of brands and the role of product strategy. We also hope that the debate will lead to the provision of broader marketing databases that span wider geographic scope and, possibly, longer time horizons.

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