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The authors study brand-share dynamics among competing brands in new repeat-purchase categories. In such new categories, market shares are strongly affected by retailer distribution decisions. Because a retailer that considers a brand for distribution can take into account the prior performance of that brand with other retailers, the success of a manufacturer in obtaining distribution can depend positively on its brand's market share to date. This creates positive feedback between a brand's market share and its distribution over the growth stage of the category. Temporary positive feedback, along with the way manufacturers influence their brand's market share and distribution, is hypothesized to drive the emergence of the market structure. The authors model this feedback to quantify the evolution of a brand's coupled market share and distribution. Empirical results using data from the U.S. ready-to-drink tea category suggest that positive feedback between market share and distribution exists in the early growth stage of the category. Therefore, early in the life of the new category small short-term changes in market share or distribution may generate larger long-term changes in market share and distribution. Later, such momentum appears absent. In this context, the authors discuss how a late entrant fails to capture a sizeable share of the market.

The Emergence of Market Structure in New Repeat-Purchase Categories: The Interplay of Market Share and Retailer Distribution

Annually, U.S. manufacturers introduce more than 4000 new products into the U.S. market for repeat-purchase or packaged goods (Kahn and McAlister 1997). A substantial

number of these new products are launched in young or new product categories, for example, super-concentrated laundry detergents, ready-to-drink teas, and so forth. Of concern to manufacturers that launch new brands in these categories are the evolution of the market share of their own brand and the dynamics of new-brand entry by competitors.

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Economic research on market structure deals with these topics, that is, with the distribution of market shares or industry concentration (e.g., Davies and Geroski 1997; Shaked and Sutton 1990) and with the evolution of the number of industry participants, that is, entry and/or exit dynamics (e.g., Kadiyali 1996). Several empirical generalizations exist around these two issues for consumer durables (Klepper and Graddy 1990). However, not much is known about the emergence of market shares or entry/exit dynamics in new repeat-purchase categories. In contrast, most of what is known about such categories stems from research on—and applies to—mature markets (for a recent survey, see Dekimpe and Hanssens 1995a). A lacuna therefore exists in the literature on how market shares are formed over time

in repeat-purchase categories. This is unfortunate for two reasons. First, market shares are among the best predictors of long-term profitability (Buzzell and Gale 1987). Second, if truly long-term effects of marketing action exist in repeat-purchase categories, such effects must be sought in how manufacturers influence the evolutionary path that leads to a certain stable division of the market.

This investigation contributes to filling this gap in the literature in three ways. First, it conceptualizes several important influences on how market shares in new repeat-purchase categories evolve. In a nutshell, the formation of shares in new repeat-purchase categories is proposed to be based, in part, on a feedback mechanism. Specifically, retailers' distribution decisions are influenced positively by a brand's market share. This dependence—combined with market-share effects of distribution—creates a temporary positive feedback over the growth stage of the category's life cycle.

However, from the vantage point of the manufacturer, this positive feedback alone is an incomplete perspective on how categories evolve. Manufacturers attempt to influence brand-level dynamics of distribution and market share directly by offering support to retailers through in-store merchandising and by targeting consumers with advertising or price discounts. Such attempts form a separate influence on the way a category develops. In summary, the market structure of the category is proposed to be initially driven by a feedback mechanism that operates during the growth stage of the category. In addition, over all stages of the category's life cycle, manufacturers can directly influence share and distribution with their marketing instruments.

Because of positive feedback, the dynamics of the market are initially characterized by momentum, that is, by the phenomenon that a change in brand-level market share or distribution can result in a larger long-term change in both market share and distribution. One consequence of this view is that the process with which market-structure emerges is hard to reverse after the growth stage of the category's life cycle, in which retailers make most of their distribution decisions, has passed. Another consequence is the existence of a time window beyond which the probability of successful entry sharply drops.

Second, beyond this conceptualization, we formulate a logically consistent model that captures the coupled relation of brand share and distribution and allows for marketing-mix effects on both the push and the pull sides of the market. An analysis of the dynamic properties of this model allows for the quantification of the dynamics of a brand's share.

Third, we provide an empirical application of the model and generate several insights. These can be stated succinctly with the help of Figure 1, which depicts five years (1991–96) of weekly U.S. market-share data of the four largest brands in the ready-to-drink tea category in the grocery channel. First, although we might successfully fit a market-share model to the final year of data by attributing the cross-sectional differences in market shares to brand intercepts, this effectively masks the key object of managerial interest, namely, the evolutionary path that leads to the particular division of the market. In this context, the present study attempts to shed light on where brand intercepts come from. Second, we quantify the longer-term effects of raising

either market share or distribution. These quantifications explain and underscore why, in Figure 1, drifts in shares may last for more than two years. Third, we discuss the implications of this study in the context of a late entrant in this market.

The structure of this article is as follows. In the next section, we conceptualize how new repeat-purchase categories develop over time and are influenced by a market-share retail-distribution feedback and by the manufacturer's marketing action. In the third section, we formalize a model to capture the formation of market shares. This model uses coupled multiplicative competitive interaction (MCI) market-share models. The fourth section contains an empirical application using data from the U.S. ready-to-drink tea category. In the fifth section, we focus on the market-share and distribution dynamics of the estimated system at various stages in the category's life cycle and on the dynamics of marketing-mix effectiveness. We then apply these results to the introduction of a late entrant. In the sixth section, we conclude with managerial insights and directions for further research.

CONCEPTUAL BACKGROUND

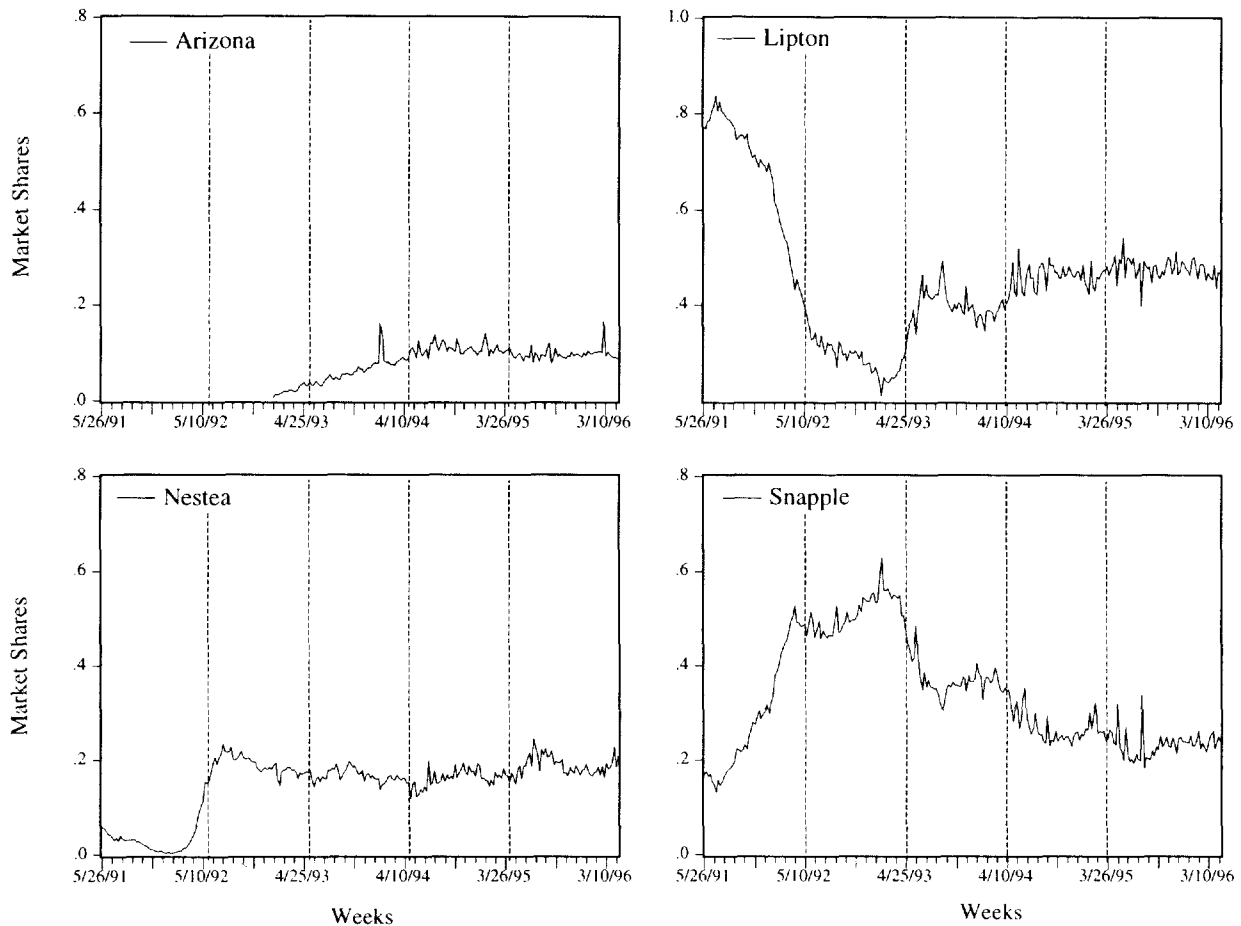
The literature suggests several important forces on the dynamics of market shares in new repeat-purchase categories. These are (1) a temporary positive feedback between brand-level share and distribution, (2) the accumulation in—and instability of—brand-level distribution and market shares, and (3) the manufacturer's action to support its own brand. The conceptualization of how market shares evolve is summarized in the form of hypotheses and is shown in Figure 2.

Positive Feedback Between Brand-Level Market Share and Distribution

In the grocery channel, retailers make decisions about which categories and, from those categories, which brands to stock. For new categories and brands, such retailer distribution decisions are not all made at once; that is, at an aggregate level these decisions are spread out over both time and space. The temporal distribution of retailers in making the decision to distribute or carry a new brand creates the possibility that adopting retailers take the past success of a brand with other retailers into account when making their own decisions. The following examples illustrate two avenues through which such feedback takes place:

- Retailers search actively for promising items. In a personal interview, a manager for a large U.S. retailer claimed to search the grocery market actively by using syndicated store data to identify items that are not currently in the retailer's assortment but that sell well in its own or other U.S. markets. Subsequently, these items are evaluated for adoption in a subset of the stores of the retail chain and are adopted broadly conditionally on performing well in the subset.
- Manufacturers bring leading brands to a retailer's attention through advertisements in specialized trade publications, such as *Beverage World*, *National Grocer*, and *Convenience Store News*. A favorite subject of advertising copy in these publications is the announcement that the newly advertised item is a high-share or high-sales item. For example, relevant to our later empirical work, Snapple advertised in 1993 to retailers that it has, "once again, achieved an astounding triple-digit increase in annual case sales" (*Beverage World* 1993, p. 7). Such claims are intended to get distribution by claiming past success.

Figure 1
WEEKLY U.S. SHARES OF THE TOP FOUR BRANDS IN THE READY-TO-DRINK TEA CATEGORY IN THE GROCERY CHANNEL
OVER FIVE YEARS



In addition to the relation from past share to distribution, there is a direct relation in the opposite direction from retailer distribution to share of sales (see also Oliver and Farris 1989; Reibstein and Farris 1995). Conceptually important is that whereas distribution must react to market share with at least some delay for the retailers to observe and act, market share will react to changes in distribution immediately.

H_1 (feedback): Changes in a brand's distribution are positively affected by changes in its past market share, and changes in a brand's market share are positively affected by changes in its current and past distribution.

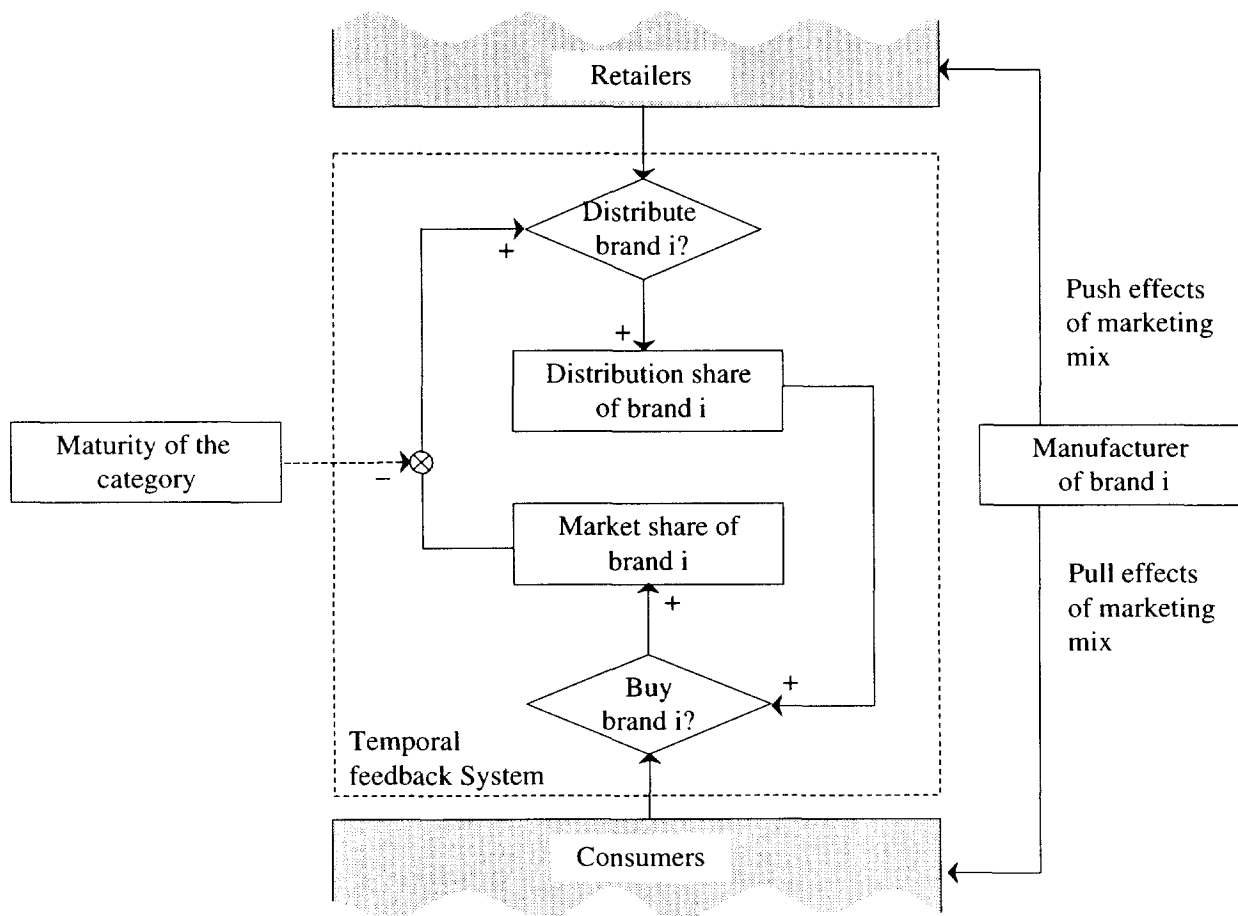
To our knowledge, the presence of this feedback has not been tested. In part, this is because the relationship between market share and distribution has not been studied by using data over time (Reibstein and Farris 1995). Farris and colleagues (1998) suggest in a simulation study that positive feedback may be the result of routinized behavior on behalf of retailers. In a broader sense, the presence of positive feedback in the evolution of market structure has also been suggested in work on network externalities (Arthur 1989; Arthur, Ermoliev, and Kaniovski 1987), which uses conta-

gious nonlinear processes to model the dynamics of market shares.¹

However, positive feedback between market share and distribution in a new category cannot last forever. There is an obvious economic limitation to the number of brands from a single category that a retailer will stock. For retailers, adding an $(n+1)$ th brand to the assortment of a category must be subject to decreasing marginal returns as the number of brands n increases. In contrast, the opportunity cost associated with the scarce nature of shelf space is near-linear because there are many potential other categories to which the shelf space of the $(n+1)$ th item could be allocated. Therefore, as the category matures and n increases, it will be less attractive for the retailer to distribute or carry an addi-

¹The most famous of such processes is the urn scheme—formalized by and named after Pólya (1931)—in which draws of two types of balls from an urn result in replacement of more balls of the same type. Such a process entails positive feedback. Formally, it belongs to a class of processes called "path-dependent" (see, e.g., Eggenberger and Pólya 1923; Freedman 1965; Pólya 1931). Properties of these processes are documented by Johnson and Kotz (1977).

Figure 2
REPRESENTATION OF THE TEMPORAL POSITIVE FEEDBACK THAT DRIVES THE EVOLUTION OF MARKET SHARE IN NEW REPEAT-PURCHASE CATEGORIES



tional brand. The influence of market share on distribution is hypothesized to diminish accordingly.

H₂ (erosion of positive feedback): The positive effect of market share on distribution decreases as the category matures.

This hypothesis implies the existence of a negative interaction of the share-to-distribution effect with time. Similar to H₁, this hypothesis, to our knowledge, has not been tested.

Accumulation of Retailer Distribution and Share of Demand

Another set of forces, which operates on the dynamics of market shares in new repeat-purchase categories, is posed by the mechanisms that make brand-level distribution and market share evolving² variables over the growth stage of

the category. This accumulation is of substantive consequence because it implies that developments in the new repeat-purchase category become more and more difficult to erase as the category evolves toward maturity.

Retailers' distribution decisions are not made frivolously, and they represent the outcome of a costly and deliberate evaluation process (Rao and McLaughlin 1989). When a brand is distributed by a retailer, it will likely be distributed at least long enough to prove itself. Consequently, given the amount of items in the average grocery store, it is too costly for any single retail chain to make decisions about category composition for all categories and items on a frequent basis. For the manufacturer that seeks coverage from many independent retail chains, this implies that distribution in the early category is a cumulative variable. Therefore,

H₃ (accumulation in distribution): Brand-level retail distribution evolves over the life cycle of a new repeat-purchase category.

²Formally, a series of data is evolving if it fails to have a constant mean and/or variance. Intuitively, an evolving series represents the accumulation of past shocks.

Market shares are also hypothesized to evolve. In repeat-purchase categories, consumers learn about brands by buying and using them. This fosters selective sampling if preferences are formed for certain brands (Erdem and Keane 1996) but not for others. Consumers satisfice and are generally less motivated to learn about other brands after they have settled on a satisfactory brand of choice (Carpenter and Nakamoto 1989; Hoyer 1984). In addition, consumers have been found to be subject to inertia in their choices in many repeat-purchase categories (e.g., Givon 1984). These consumer behavior phenomena contribute to the possibility that a change in market share during the early part of the life cycle of the new category may be persistent.

There are various phenomena in the distribution channel that exacerbate this persistence. For example, percentage-of-sales or percentage-of-share budgeting rules by the manufacturer of a brand may also cause changes in market share to have long-term effects (Bass 1969; Dekimpe and Hanssens 1995a; Farris et al. 1998). Furthermore, retailers will generally give better shelf space to market leaders. Also, over the evolution of a repeat-purchase category, various agents, such as wholesalers and brokers in the vertical channel, form habits about which brands to buy, broker, and distribute. From these arguments, again, a change in market share can be expected to be persistent.

H₄ (accumulation in share): A brand's market share evolves over the life cycle of a new repeat-purchase category.

This hypothesis is not inconsistent with the broad literature on stability of market shares in mature categories (e.g., Dekimpe and Hanssens 1995a; Lal and Padmanabhan 1995; Srinivasan and Bass 1997). It may well be that accumulation in distribution and market shares is limited to only a part of a repeat-purchase category's life cycle. However, this is an empirical issue.

Manufacturer's Influence on Share and Distribution

Manufacturers can directly influence market share with their marketing mix. These effects on market share are the pull effects of the marketing mix. To avoid restating the hypothesis for each variable in the mix, a generic hypothesis is stated. The exact variables taken into account in this study will be specified subsequently.

H₅ (pull effects): A manufacturer's investments in the marketing mix positively affect the market share of its brand.

In addition, the market-share response to a manufacturer's marketing variables may vary over time. Several studies have been concerned with dynamics in price elasticities (e.g., Parker 1992), and alternative mechanisms for such dynamics have been proposed. For example, consumers become more sensitive to price and less sensitive to nonprice interventions by the manufacturer as a consequence of the increased use of promotions (Mela, Gupta, and Lehmann 1997). In addition, the composition of a brand's clientele is not constant over the life cycle of the category. Those consumers who adopt early are generally less price sensitive than those who adopt late (Rogers 1983). Finally, the level of differentiation of brands within categories may decrease over time as a consequence of imitation of the most successful manufacturers. This homogenization may lead to increased sensitivity to price. Price is not the

only instrument that may have dynamic effects. The role of advertising to supply consumers with relevant product information is expected to diminish as consumers gather first-hand user experience through consumption of the category (Little 1979).

H₆ (dynamic effects on share): Market share becomes more responsive to price and less responsive to advertising as the category approaches maturity.

In addition to influencing consumers, manufacturers also try to influence the retailers directly with various marketing variables (e.g., Rao and McLaughlin 1989). Advertisements in trade publications, trade allowances, bill-backs, slot premiums, and sales support of new items at the point of purchase are all used by manufacturers as distribution incentives for the retailer. For example, in the 1992 Snapple advertisement quoted previously, the Snapple brand promises "exciting new promotions and spokespersons" to retailers. These offers are supply effects of marketing mix in that they are direct attempts to create distribution. These effects are the push effects of marketing-mix expenditure.

H₇ (push effects): A manufacturer's investments in the marketing mix positively affect the retailer distribution of its brand.

Similar to the effects on market share, the effects on distribution are proposed to be dynamic over the evolution of the category. Specifically, because retailers face shelf space constraints that become binding as the category matures, we hypothesize the following:

H₈ (dynamic effects on distribution): Distribution will become less sensitive to the variables contained in the marketing mix as the category evolves to maturity.

Of considerable interest for manufacturers in the allocation of marketing dollars is the total effect of a single marketing-driven change in distribution or market share. To determine this total effect, it is necessary to model the dynamics of the market. Namely, a simple comparison of contemporaneous marketing-mix effects on a brand's distribution versus on its share misrepresents the true effects of such marketing action in view of H₁–H₄. Rather, the direct effects of price, promotion, and advertising trigger a sequence of effects between market share and retailer distribution. These effects must be compounded to represent the total effectiveness of marketing intervention.

In summary, the dynamic emergence of a stable distribution of market shares consists of a temporary feedback loop between brand-level share and retail distribution and of the manufacturers' attempts to influence the variables in this loop. Market share and distribution both evolve over the life cycle of the category, and the positive feedback between them is limited to the growth stage of the category. Therefore, the division of the total sales in the market into market shares in a repeat-purchase category is viewed principally as hard to reverse when the growth stage has been passed.

MODEL DEVELOPMENT

To represent the hypothesized mutual causation of market share and retailer distribution and the manufacturer's influence on both of them, it is possible to use two coupled and causally ordered MCI models (Cooper and Nakanishi 1988),

one for market shares and one for the share of distribution.³ The objective for this choice is to model feedback between share of sales and share of distribution, while obeying the cross-sectional sum and range constraints associated with share measures.

The coupled MCI structure can always be transformed to a system of linear equations. It is even possible to write a subclass of the coupled MCI models as a restricted vector autoregressive (VAR) model. This allows for the combination of, on the one hand, the parsimony of logically consistent models with, on the other hand, the use of the literature in multivariate time series (see, e.g., Hamilton 1994; Lütkepohl 1993). The MCI class of models offers the added benefit that it is less heavily parameterized than unrestricted VARs. This is particularly useful with high-frequency data for which high-order systems—with many lags—may be expected.

The MCI Model and Its Linear Form

Consider the MCI representation of a single dependent variable, for example, market shares Y_{lit} of brand $i = [1, \dots, N]$ at time $t = [1, \dots, T]$ with m exogenous variables $X_{i\ell t}$, $\ell = [1, \dots, m]$.⁴ With exogenous effects $b_{\ell i}$ and lagged effects a_{ki} , the attraction model of Y_{lit} is defined by

$$(1) \quad \text{Attr}_{it} = \exp(\mu_i + \epsilon_{it}) \prod_{\ell=1}^m X_{i\ell t}^{b_{\ell i}} \prod_{k=1}^p Y_{lit-k}^{a_{ki}}$$

and

$$Y_{lit} = \frac{\text{Attr}_{it}}{\sum_{j \in J_t} \text{Attr}_{jt}}$$

where μ_i is the brand intercept, ϵ_{it} is the error term, and J_t indexes the available set of brands.⁵ The system defined by Equation 1 has N equations. Because of the sum-constraint—market shares add to one—dependencies across these equations exist that reduce the rank of the system. It is possible to linearize the system in Equation 1 to an equivalent $(N - 1)$ dimensional system of equations. Taking the ratio of Y_{lit} and the share of an arbitrarily fixed Brand 1, Y_{11t} , gives for $i = 2, \dots, N$

$$(2) \quad \frac{Y_{lit}}{Y_{11t}} = \frac{\exp(\mu_i + \epsilon_{it}) \prod_{\ell=1}^m X_{i\ell t}^{b_{\ell i}} \prod_{k=1}^p Y_{lit-k}^{a_{ki}}}{\exp(\mu_1 + \epsilon_{1t}) \prod_{\ell=1}^m X_{1\ell t}^{b_{\ell 1}} \prod_{k=1}^p Y_{11t-k}^{a_{k1}}}$$

For notational convenience, we define log transforms $y_{lit} = \ln(Y_{lit})$ and $x_{i\ell t} = \ln(X_{i\ell t})$, log-ratios $\tilde{y}_{lit} = \ln(Y_{lit}/Y_{11t})$ and $\tilde{x}_{i\ell t} = \ln(X_{i\ell t}/X_{1\ell t})$, and the differences $v_{li} = \mu_i - \mu_1$ and $e_{lit} = \epsilon_{it} - \epsilon_{1t}$. Finally, we define the $[m \times 1]$ vector $x_{it} = [x_{i1t} \dots x_{im1t}]'$ (and \tilde{x}_{it} for the same in log-ratios) and the $[1 \times m]$ vector of coefficients $b_i = [b_{i1} \dots b_{im}]$. Taking the log on both sides of Equation 2 leaves a system for $i = 2, \dots, N$ that is linear in logs.

³The *share of distribution* is defined as the distribution of a given brand divided by the sum of the distribution of all other brands.

⁴This structure allows for lagged effects of the exogenous variables, which can all be arrayed in the vector $X_{i\ell t}$.

⁵The number of brands is allowed to vary over time to accommodate brand entry in the model. This means that N can be time-dependent too and that the sample size for an equation can be brand-specific. These subscripts were suppressed to avoid cluttered notation.

$$(3) \quad y_{lit} - y_{11t} = v_i + b_i x_{it} - b_1 x_{1t} + \sum_{k=1}^p a_{ki} y_{lit-k} - \sum_{k=1}^p a_{k1} y_{11t-k} + e_{lit}$$

All negatively signed terms involving the fixed Brand 1 are common across $i = 2, \dots, N$. These terms enforce the constant-sum constraint of market shares. Their function resembles that of the time dummies in the specification of a homogeneous MCI model in Nakanishi and Cooper's (1982) study. Note that the dependent variable in Equation 3 is the log-ratio of market shares $\tilde{y}_{lit} = \ln(Y_{lit}/Y_{11t})$. Whereas shares are bounded on $[0 - 1]$, the log-ratio \tilde{y}_{lit} is defined on the entire real line.

Recursive Feedback Between Share and Distribution

To simplify the exposition of the coupled system and of its implied dynamics, the restriction of common parameters across brands in Equation 3 is used in this and the next section. This restriction will not be imposed in the empirical part of this study. The effect of the restriction is that the i subscript is dropped from the coefficients a and b and that the right-hand side of Equation 3, similar to the left-hand side, can be expressed in log-ratios. This simplifies Equation 3 to

$$(4) \quad \tilde{y}_{lit} = v_i + b \tilde{x}_{it} + \sum_{k=1}^p a_k \tilde{y}_{lit-k} + e_{lit}$$

Arranging the $N - 1$ equations gives the following representation:

$$(5) \quad \tilde{y}_{it} = V_i + B_i \tilde{x}_t + \sum_{k=1}^p A_{k11} \tilde{y}_{it-k} + e_{it}$$

where V_i and e_{it} are column vectors of size $(N - 1)$, x_t is a column vector of size $(N - 1)m$, B_i is a block diagonal matrix of $(N - 1)$ by $(N - 1)m$, and A_{k11} is a diagonal square matrix of size $(N - 1)$.

The feedback between share and distribution is modeled as a causally ordered system with contemporaneous effects of distribution on share but not vice versa. We write Y_{2it} for the share of retailer distribution of brand i at time t ; define the same transformations as previously, that is, $y_{2it} = \ln(Y_{2it})$ and $\tilde{y}_{2it} = \ln(Y_{2it}/Y_{21t})$; and define the equivalents of the parameter matrices A_{k11} , B_1 , and V_1 as previously. The dependence of market share on retail distribution and vice versa is modeled using two coupled MCI models as in Equation 5, with contemporaneous effects of distribution on market share:

$$(6) \quad \tilde{y}_{it} = V_i + A_{012} \tilde{y}_{2t} + \sum_{k=1}^p A_{k11} \tilde{y}_{it-k} + \sum_{k=1}^p A_{k12} \tilde{y}_{2t-k} + B_1 \tilde{x}_t + e_{it}$$

and

$$\tilde{y}_{2t} = V_2 + \sum_{k=1}^p A_{k21} \tilde{y}_{it-k} + \sum_{k=1}^p A_{k22} \tilde{y}_{2t-k} + B_2 \tilde{x}_t + e_{2t}$$

Taking all contemporaneous endogenous measures to the left-hand side and combining in $2(N - 1)$ dimensional array form gives

$$(7) \quad A_0 \tilde{y}_t = V + \sum_{k=1}^p A_k \tilde{y}_{t-k} + B \tilde{x}_t + e_t.$$

This representation of the system is called its structural form.⁶ The following partitions of the matrices in the structural form are useful for discussion:

$$(8) \quad A_0 = \begin{bmatrix} I_{N-1} & -A_{012} \\ 0 & I_{N-1} \end{bmatrix} \quad A_k = \begin{bmatrix} A_{k11} & A_{k12} \\ A_{k21} & A_{k22} \end{bmatrix} \quad B = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix}.$$

The matrix A_{012} contains the current effect of the share of retail distribution on market share. The diagonal of the matrix A_0 consists of identity matrices I of dimension $N - 1$. The matrix A_{k11} contains the effect of the k -period-lagged market share on the current market share, whereas A_{k12} contains the effect of the k -period-lagged distribution on the current market share. The matrix A_{k21} contains the effect of the lagged market share on the current distribution, and A_{k22} specifies the effect of the k -period-lagged share of retailer distribution on its current values.

The matrix B contains two identically sized and block diagonal matrices B_1 and B_2 . B_1 contains the instantaneous pull effects of exogenous variables on market shares, whereas B_2 contains the instantaneous push effects on shares of retail distribution.

Finally, the innovations in the system, e_t , have a variance-covariance matrix denoted by Σ .

The Dynamics of the Coupled MCI Models: The Ingredients of Brand-Level Momentum

The dynamics of the coupled system can be analyzed by tracing the impact of an innovation on a single endogenous variable, for example, e_{1it} , on the evolution of the entire system. The result of such an analysis is called an "impulse-response function" (see Dekimpe and Hanssens 1995b)⁷ and is computed by transforming Equation 7 in two steps. In the first step, the reduced form of Equation 7 is obtained by pre-multiplying both sides by A_0^{-1} . This form is a VAR process of order p , VAR(p), with zero-parameter restrictions that give the MCI structure. The reduced form has endogenous effects $\Phi_k = A_0^{-1} \times A_k$, exogenous effects $\Theta = A_0^{-1} \times B$, and innovations $\eta_t = A_0^{-1} \times e_t$ with variance-covariance matrix $\Omega = A_0^{-1} \times \Sigma \times A_0^{-1}$ (see also Hamilton 1994, p. 327). Suppressing the intercept terms V for notational convenience, the following equivalent representations are obtained (the structural form is first, the reduced form second):

$$(9) \quad A_0 \tilde{y}_t = \sum_{k=1}^p A_k \tilde{y}_{t-k} + B \tilde{x}_t + e_t \Leftrightarrow$$

$$\tilde{y}_t = \sum_{k=1}^p \Phi_k \tilde{y}_{t-k} + \Theta \tilde{x}_t + \eta_t.$$

In the second step, impulse-response functions of this system are computed by writing the reduced form, or VAR(p), model in its final form. This final form makes the dependent variables a direct function of past unobserved and exogenous shocks by taking all endogenous measures of the VAR(p) model to the left-hand side and dividing out the lag operator (see Lütkepohl 1993, pp. 325–27). This gives an equivalence relation for the VAR(p) model and its final form representation, that is,

$$(10) \quad \tilde{y}_t = \sum_{k=1}^p \Phi_k \tilde{y}_{t-k} + \Theta \tilde{x}_t + \eta_t \Leftrightarrow$$

$$\tilde{y}_t = \sum_{k=0}^{\infty} \Psi_k \eta_{t-k} + \sum_{k=0}^{\infty} \Psi_k \Theta \tilde{x}_{t-k}.$$

In the second member of the dual Equation 10, the matrices Ψ_k contain all the information on how the unanticipated shocks η_{t-k} and the exogenous shocks $\Theta \tilde{x}_{t-k}$ affect the endogenous variables. A plot of the Ψ_k over k is called an impulse-response function of Equation 7. The matrices Ψ_k of the underlying stable VAR(p) process are simple to compute recursively (Hamilton 1994, p. 260).⁸ Finally, the impulse-response function on the $N - 1$ log-ratios of market share and of distribution can simply be transformed back to share measures given the sum constraint.

A concern with impulse-response functions is the legitimacy of tracing the effect of an impulse on a single element of η_t . It is clear that this can only be a good idea when dealing with independent errors. From the reduced-form VAR(p) representation, this is likely not the case because of the transformation $\eta_t = A_0^{-1} \times e_t$. Even if the e_t are independent, the η_t will not be if there are contemporaneous effects of distribution on market share.

The remedy for this problem is to diagonalize the covariance matrix of η_t , that is, to impose an explicit causal ordering on the endogenous variables so that contemporaneous covariance between two or more variables can be attributed uniquely to one of them. The ordering of the distribution and share variables is in accord with H_1 . The ordering between brands is by assumption (see the empirical section). To diagonalize the innovations, we take the Cholesky decomposition of Ω with causally ordered variables. We call this lower-triangular decomposition Γ and its j th column Γ_j . The effects of a standard deviation shock on the j th variable on the other endogenous measures, s periods into the future, are equal to

$$(11) \quad I_j(s) = \Psi_s \times \Gamma_j.$$

A plot of $I_j(s)$ for a given j across $s = 0, 1, 2, \dots$ is called the "orthogonalized impulse-response function" of Equation 7,

⁶To augment this model with brand-specific coefficients, we write out Equation 3 with the cross-effects of share of distribution on share of sales and vice versa to get a matrix form as previously but in the logs of the endogenous measures on the right-hand side as opposed to the log-ratios.

⁷In the differential effects model, these impulse-response functions must be determined through recursive evaluation of Equation 3 augmented with a similar set of distribution equations. The differential effects MCI model does not reduce to a VAR system. Instead, the impulse-responses are a non-linear function of the innovations.

⁸Specifically, $\Psi_s = \Phi_1 \times \Psi_{s-1} + \Phi_2 \times \Psi_{s-2} + \dots + \Phi_p \times \Psi_{s-p}$, where $\Psi_0 = I$ and $\Psi_q = 0$ for any $q < 0$.

which for the remainder of this article is abbreviated simply to the impulse–response function.

In the present context, the impulse–response functions are used to investigate how a change in brand-level market share or distribution affects the subsequent evolution of the entire system. If, for a given brand, small changes in market share or distribution lead to larger changes in both its market share and its distribution in the longer run, this is called “momentum.”

Stability and Parameter Stationarity

Two details round out the exposition of the model of positive feedback between brand-level market share and retailer distribution. First, the econometric translation of H_3 and H_4 is that distribution and share data are econometrically integrated. This means that the effects of past shocks on market share or retail distribution do not fade over time but accumulate instead. Granger and Newbold (1974) have demonstrated that regressions between such integrated variables frequently show illusory effects. The effective remedy against these so-called spurious regressions is to analyze the differenced variables instead of the integrated levels of the variables themselves. The order of differencing in this procedure is the order of integration of the data. Therefore, differenced variables are substituted in Equation 7 for the level variables that are integrated. The meaning of such differenced variables, such as $\tilde{y}_{lit} - \tilde{y}_{lit-1}$, is intuitive. Whereas log-ratios $\tilde{y}_{lit} = \ln(Y_{lit}/Y_{lit-1})$ express the log of relative shares, differences in log-ratios express the log of relative growth, for example,

$$(12) \quad d(\tilde{y}_{lit}) = \tilde{y}_{lit} - \tilde{y}_{lit-1} = \ln\left(\frac{Y_{lit}}{Y_{lit-1}} + \frac{Y_{lit}}{Y_{lit-1}}\right)$$

As with linear additive systems, taking differences in an MCI context maintains the interpretation of modeling growth or decline. Differencing in the MCI model does not lead to violations of the logical constraints in levels.

Second, per H_2 , the strength of the market-share distribution feedback decreases as the category matures. To accommodate such effects in the model formulation, interactions of the effects among the endogenous variables of our system and measures of the maturity of the category must be introduced. These interaction terms can be operationalized as explicit interactions of the matrices A_k with time or as moving-window regressions of the system of equations. Both methods are employed in the empirical application to gauge the dependence of the coupling of market share and retailer distribution on time.

EMPIRICAL APPLICATION

Data

Weekly U.S. grocery data from the ready-to-drink tea category supplied by Information Resources Inc. were used for an empirical example. A few historical notes about this category are appropriate. Lipton introduced canned iced tea in 1972 and started the category. For all practical purposes, it monopolized the market for a long time. In 1987, Snapple reformulated the category with its introduction of “real brewed tea,” which came in three flavors: lemon, mint, and raspberry–peach. In 1991, the category began growing as Lipton formed a tea partnership with Pepsico. Another early

entrant in the industry was Nestea, which started in 1992 as a joint venture between Nestlé and the Coca-Cola Company. These were the three largest brands on the still small market in early 1992. Arizona was introduced in May 1992, and Fruitopia entered the grocery channel late, in Spring 1995.⁹

The observation window covers 257 weeks, or almost five years, from May 26, 1991, to April 21, 1996. Over this observation period, the category volume grew by more than 700%. The sharpest growth was realized in 1992–93, after which the growth rate of the category volume declined steadily but remained positive through 1996. The data used are U.S. aggregates from INFOSCAN. They have been assembled from a nationwide sample of approximately 3000 stores in 64 regional markets. Five brands were selected—Arizona, Fruitopia, Lipton, Nestea, and Snapple—which jointly account for more than 80% of category volume in the grocery channel. The remainder of the category is highly fragmented into many small and mostly regional brands.

For each brand, data are available about volume sales, dollar sales, all-commodity value (ACV)–weighted distribution, and ACV-weighted feature.¹⁰ These were matched with Competitive Media Reporting’s weekly spot-advertising expenditures summed over all U.S. markets. Price is computed as the dollar sales divided by the volume sales. At the U.S. level of aggregation, the variability in the exogenous measures is predominantly attributable to the actions of manufacturers as opposed to those of retailers. The following definitions of variables are used in the empirical analysis. *Market share* refers to share of volume. *Price* is relative price; that is, it is the price measure defined previously divided by the average price on the market. *Distribution* is defined as share of distribution, that is, as the ACV-weighted distribution of a given brand divided by the sum of ACV-weighted distributions of all the brands on the market. *Feature* is defined as the ACV-weighted level of featuring divided by the ACV-weighted distribution.¹¹ *Advertising* is measured in transformed units of expenditures for reasons of confidentiality. In Table 1 we give the essential descriptive statistics of the data.

Hypothesis Testing

To test the eight hypotheses of how new repeat-purchase categories evolve over time, the following empirical analyses are performed. We first tested for unit roots in the market-share and distribution data (H_3 and H_4).

Then we tested H_1 , regarding the presence of positive feedback, by estimation of the reduced form of Equation 7 and by testing for positive effects of lagged market share on current distribution. We tested the dynamics of these effects, as in H_2 , by using interactions with time and by moving-window regressions. The feedback between market share and retailer distribution is additionally visualized by the impulse–response functions at various points in time.

We tested H_5 and H_7 , about marketing-mix effects on market share and distribution, through estimation of the ma-

⁹The moment of introduction is defined in our data by the moment when a brand has 1% share of distribution for the first time.

¹⁰ACV-weighted may be interpreted as weighted by store size; that is, 80% ACV-weighted distribution means that a given brand is sold in supermarkets that collectively account for 80% of all volume sold.

¹¹This is done to erase the identity that, at the aggregate level, featuring presumes distribution.

Table 1
DESCRIPTION OF THE WEEKLY U.S. DATA OF THE READY-TO-DRINK TEA CATEGORY

Variable	Statistic	Arizona	Fruitopia	Lipton	Nestea	Snapple
Share of sales	mean	.084	.004	.462	.148	.333
	minimum	.006	.000	.212	.004	.133
	maximum	.165	.018	.837	.245	.628
	standard deviation	.032	.003	.139	.063	.117
Share of distribution	mean	.142	.067	.373	.234	.283
	minimum	.010	.012	.250	.023	.134
	maximum	.214	.090	.715	.319	.405
	standard deviation	.069	.020	.149	.077	.059
Relative price	mean	1.142	1.128	.756	.953	1.152
	minimum	.815	.830	.631	.682	.911
	maximum	1.297	1.253	.866	1.134	1.277
	standard deviation	.084	.090	.041	.101	.061
Store feature	mean	.030	.061	.096	.022	.065
	minimum	.000	.000	.003	.000	.000
	maximum	.139	.152	.251	.079	.259
	standard deviation	.026	.040	.065	.020	.049
Advertising expenditures ^a	mean	.00 ^b	10.96	22.98	30.05	65.49
	minimum	.00	.00	.00	.00	.00
	maximum	.00	110.65	325.60	373.40	444.60
	standard deviation	—	27.17	51.91	74.48	109.61
Observations (weeks)		172	56	257	257	257

^aAdvertising expenditures have been transformed to undisclosed units for reasons of confidentiality.

^bNo advertising data were recorded for Arizona, which did not use spot-television advertising over the observation period.

trices of exogenous effects on share of sales and share of distribution, respectively. Finally, we tested H_6 and H_8 , about the time dependence of the effectiveness of marketing mix on share and distribution, respectively, through a series of moving-window regressions.

Preliminary Analysis

Unit-root testing. To test the hypotheses of integration of the endogenous variables, we used the augmented Dickey-Fuller (ADF) test. Dekimpe and Hanssens (1995a) provide a detailed account of how to implement the ADF test. Here, only the essentials are stated. The ADF test uses ordinary least squares to estimate equations of the form $\Delta y_t = \alpha y_{t-1} + \sum_{v=1}^w \beta_v \Delta y_{t-v} + \zeta_t$, where Δy_t is the time series in differences, α and β_v are response parameters, and ζ_t is the error term. Of interest is the significance of the coefficient α . If it is negatively significant, the null hypothesis of a unit root in y is rejected. The appropriate number, w , of lagged terms Δy_{t-v} in the ADF test is determined by the Schwarz criterion. MacKinnon (1991) gives recently tabulated critical values of the t-test on α .

In Table 2 we present the results of the unit-root tests for the log-ratios of the data, that is, for the logs of the ratios of the data relative to the data of a fixed brand (Lipton). Unit roots can be rejected neither for the share data nor for the distribution data of any brand at the 1% significance level (except for the distribution log-ratio of Arizona, but this result is sensitive to the number of augmentation terms). This result accords with the visual impression of the data in Figure 1. Additional ADF tests for the integration of exogenous measures also could not be rejected. Prices, featuring, and advertising are therefore also evolving variables. Finally, unit-root tests were performed on the log of the series (for

the differential effects model) with the same general results as in Table 2.

Structural breaks. Perron (1990) suggests that the presence of exogenous structural breaks in the data biases the results of the unit-root tests in favor of finding unit roots (but see also Banerjee, Lumsdaine, and Stock 1992). To eliminate this bias, Perron suggests a test for unit roots in the presence of structural breaks. This test was applied to all endogenous series around three candidates for structural breaks (see also Figure 1): the jump in share of Nestea around January 5, 1992; the introduction of Arizona around January 10, 1993; and the introduction of Fruitopia around April 2, 1995. The structural-break tests were applied to the log-ratios and the logs of the endogenous variables. The results are that in only one case the test results of the Perron test disagree with the test results of the ADF test over the same time period. Therefore, the evidence for unit roots does not appear to be an artifact of the presence of possible structural breaks.

Unit roots in moving windows. It is possible that unit roots only hold over part of the data. This would especially be true if market shares stabilized over the latter part of the observation period. To test for this possibility, the ADF tests were performed on moving windows of data of 52 weeks shifted by 4 weeks at a time. This gives a total of 50 different ADF statistics per series, which allows for the detection of trends in the strength of evidence for unit roots. The tests were performed on the endogenous measures in logs and log-ratios. The general result of these tests is that the evidence for unit roots remains constant for the retail-distribution data over the entire observation period. The evidence for unit roots in the share data becomes less strong toward the end of the data horizon; however, in no single window of data is the unit-

Table 2
AUGMENTED DICKEY-FULLER UNIT-ROOT TEST ON THE LOG-RATIOS

Variable	Brand	Lags	ADF Statistic	1% Critical t	5% Critical t	Outcome ^a
Share of sales	Arizona	2	-2.56	-3.47	-2.88	u-u
	Fruitopia	1	-1.66	-3.58	-2.93	u-u
	Nestea	5	-2.87	-3.46	-2.87	u-u
	Snapple	2	-2.35	-3.46	-2.87	u-u
Share of distribution	Arizona	1	-9.27	-3.47	-2.88	r-r
	Fruitopia	4	-0.00	-3.58	-2.93	u-u
	Nestea	9	-2.10	-3.46	-2.87	u-u
	Snapple	3	-3.32	-3.46	-2.87	u-r
Relative price	Arizona	3	-2.91	-3.47	-2.88	u-r
	Fruitopia	0	-3.93	-3.58	-2.93	r-r
	Nestea	2	-1.45	-3.46	-2.87	u-u
	Snapple	3	-2.28	-3.46	-2.87	u-u
Store feature	Arizona	7	-2.72	-3.47	-2.88	u-u
	Fruitopia	1	-2.48	-3.58	-2.93	u-u
	Nestea	4	-2.31	-3.46	-2.87	u-u
	Snapple	6	-3.62	-3.46	-2.87	r-r
Advertising expenditure	Arizona	—	—	—	—	—
	Fruitopia	5	-3.13	-3.58	-2.93	u-r
	Nestea	5	-1.01	-3.46	-2.87	u-u
	Snapple	4	-1.65	-3.46	-2.87	u-u

^au = unit root not rejected; r = unit root rejected; the first character gives the outcome of the test at 1% significance; the second character gives the outcome of the test at 5% significance.

root hypothesis rejected in the market-share data for all brands at the same time.¹²

On the basis of these joint test results, with unit roots in the series in whole and in part, all the variables in Equation 7 are replaced with their first differences. Even if the market data at the end of the observation horizon is not integrated, this does not lead to biased estimates (see Plosser and Schwert 1977, who show that even with overdifferencing the parameters of the system are unbiased). In contrast, the danger of making wrong inferences from underdifferenced data is greater in view of Granger and Newbold (1974).

Testing for cointegration. Finally, the procedure of replacing levels with their differences in the system is not appropriate if cointegration plays a major role in the dynamics of the system. This is so because, in a cointegrated system, the levels of one variable contain information about the levels of other variables. Differencing the data suppresses this information. Thus, there is a need to test for cointegration. We carried out tests for cointegration between market share and share of distribution, paying special attention to the possibility that cointegration is present in the first years of observation but not later. In the Appendix, results from the two principal tests to detect cointegration indicate that cointegration between market share and share of distribution is absent from our data. Therefore, the system is estimated with differenced variables.¹³

¹²In addition, the spikes in the last year of share data (see Figure 1) are related to promotions and contribute to a rejection of unit roots in the normal operationalization of the ADF test (see also Franses and Haldrup 1994).

¹³Other ways in which cointegration could occur among other variables early in the data collection were not explored. Testing for cointegration in short windows of time is subject to low power.

Estimation and Model Selection

Choices must be made with respect to different specifications of the system.¹⁴ To guide these, model testing was conducted using the Schwarz criterion for model selection (Lütkepohl 1993) separately on the share of sales equations and the share of distribution equations. These models can be estimated using the seemingly unrelated regressions (SUR) estimator (see, e.g., Bultez and Naert 1975; for a closely related discussion, Johnston 1984, pp. 331ff.), which does not rely on equal sample sizes for each equation. This makes it suitable for estimation in the context of new product introductions, for which sample sizes are by definition not equal across equations. Details about the SUR estimator used and the computation of the Schwarz criterion for the multivariate time series problem considered here appear in the Appendix. The following conclusions were drawn from an analysis of this criterion across alternative model specifications:

- *Intercepts.* The Schwarz criterion selects models without intercepts over models with intercepts. Little cross-brand variance is left unaccounted for when the differenced endogenous variables of the system are allowed to affect one another.
- *Interaction terms.* The Schwarz criterion selects a model with time-dependent endogenous effects.
- *Differential effects.* The Schwarz criterion suggests that there is no evidence for brand-specific effects in either the endogenous or the exogenous measures. This holds for the market share as well as for the share-of-distribution equations. However, even with common effects, brands with different entry times will have different share-distribution effects because of the interactions of these effects with time.

¹⁴In the model specification tests, diagonal matrices A_k were used. Although such a diagonal structure is not necessary (e.g., Foekens 1995), it is clear that without imposing structure on the matrices A and B, the number of parameters quickly becomes overwhelming.

•*Order of the system.* An endogenous lag structure in the distribution model of five weeks was selected. Although there are more positive and significant lagged effects between distribution and share, the Schwarz criterion does not select such specifications. The number of lags for the endogenous measures is driven by the distribution equations.

•*Lags on exogenous measures.* The exogenous measures have a system-relevant history of three weeks. The number of lags for the exogenous measures such as price and feature is driven by the share equations.

In view of these results, in the remainder of this article we report on a system with differenced variables; an order of five; contemporaneous, one- and two-period lagged exogenous measures but no intercepts; and homogeneous effects.

Estimation Results

In view of the specification results, the parameters of the $2(N - 1)$ -dimensional system can easily be estimated from the reduced form of Equation 7 using the SUR estimator (Hanssens, Parsons, and Schultz 1990). The reduced form of Equation 7 is equivalent to that model without the contemporaneous effects of distribution on market share. The instantaneous effects of distribution on market share are contained in the variance-covariance matrix of the innovations e_t . (For a similar discussion around this issue, see Dekimpe and Hanssens 1995b.)¹⁵ Two types of results are discussed. First, to test the hypotheses of the coupling of market share and distribution in the growth stage of the new category and their uncoupling later on, we present the estimation results of the reduced form of Equation 7 with explicit time dependence of the feedback. Estimation of these interactions offer a direct test of the erosion in the positive feedback. Second, we use repeated estimations with a moving window of data to infer the changes in the implied dynamics of the coupled system in more detail.

Results from the model with explicit time interactions. Estimation results of the distribution equations and the market-share equations of the reduced form of Equation 7 with time interactions appear in Table 3, Parts A and B, respectively.

- Feedback.* In support of H_1 , Table 3, Part A, shows that distribution is positively influenced by past market share. It is not the first lag of market share that has the greatest effect on distribution. Instead, it takes a while before distribution responds to changes in market share, which seems consistent with the causal ordering assumed in their coupling. According to the estimation results, most of the effect of a change in market share on distribution takes place four to five weeks after the change.
- Erosion in feedback.* From Table 3, Part A, the influence of market share on distribution diminishes with time. Of five interaction terms, all five are negative, and moreover, four are significant. This suggests that the positive feedback between market share and distribution erodes over time.
- Effects of marketing mix on share.* From Table 3, Part B, the effects of marketing variables on share are important. This supports H_3 , that marketing-mix expenditures have a strong positive influence on the evolution of brand-level market share. The only instrument that has no effect on shares is advertising.¹⁶

¹⁵Also, note that estimating the structural form of the model, that is, Equation 7, requires identifying restrictions on the correlations among the stochastic shocks.

¹⁶Advertising appears to have effects on category expansion as well as on brand sales.

•*Effects of marketing mix on distribution.* There is some evidence for marketing-mix effects on distribution. Specifically, feature advertising positively affects distribution. This effect seems to confirm H_7 , that marketing-mix expenditures have a positive effect on distribution.¹⁷

Moving-window regressions: dynamics in the parameters. The reduced form of Equation 7 can be estimated with relatively small windows of weekly data. This permits characterization of the dynamics of the parameters. We discuss these dynamics subsequently for several key parameters and derive them from a total of 50 repeated estimations of the system using a moving window of 52 weeks at four-week increments.

•*The influence of share on distribution.* In Figure 3, we show the influence of lagged share on distribution in some detail for three- and four-week lags. The effects of lagged share on distribution first increase and next decrease. One interpretation of this interesting pattern is that the sensitivity of distribution to market share increases with the size of the category at first and then declines as shelf space constraints at the retailer level become binding. The sensitivity of distribution to share has diminished to almost zero around the 20th estimation of the system. In the time frame prior to this erosion, 1991–93, the growth in the category is steep. Therefore, in this empirical application, the positive effect of share changes on distribution changes seems to be restricted to the early growth stage.

•*Price sensitivity.* At the same time, as can be seen in Figure 4, price sensitivity of market share shows a negative (enforcing) trend. For the first estimations, the price parameter is around -1 , next rapidly drops to a value less than -2 , and stabilizes around that value. The pattern supports the speculation in H_6 that price becomes more important as the category matures.

Other dynamics of the parameters in the category suggest that there are no clear trends in the sensitivities of marketing-mix effects on distribution and that the advertising effects remain insignificant over the entire observation horizon. H_8 is therefore not supported.

IMPLICATIONS FOR THE READY-TO-DRINK TEA CATEGORY

The Dynamics of Momentum: Impulse-Response at Different Points in Time.

An important issue from a managerial point of view is how brand share and distribution build on each other. In this section, the moving-window estimation results of the previous section are used to compute the impulse-response functions of market share and distribution at various stages of the new category's life cycle. Specifically, the matrices Φ_k in Equation 9 are computed from the estimation results of the first and the last of the moving-window regressions of the reduced form of Equation 7 and are next compared.¹⁸ We use the Nestea brand in this section as an exemplar. The causal ordering imposed on the data to derive the im-

¹⁷The fit or tracking statistics of this model are high. Given the reported fit statistics in difference equations in Table 3, it is not surprising that the model in levels fits well (R^2 s are more than 95% for share, better for distribution). The model anticipates responses to price- and promotion-induced variation well.

¹⁸Because Equation 7 is estimated in differences, we report the accumulated impulse-response functions (see Lütkepohl 1993, p. 48). Impulse-response functions have been transformed back from the log-transform that was used to linearize the MCI model. The vertical axis therefore gives share points; that is, .01 denotes a one-point share change.

Table 3
ESTIMATION RESULTS

A: Distribution Equations ^a								
Variable	Lag	Size of the Effects			Interaction with Time			
		Parameter	(s.e.)		Parameter	(s.e.)		
Share	1	.045	(.020)	** c	-.240E-03	(.104E-03)	**	
	2	.030	(.021)		-.170E-03	(.114E-03)		
	3	.071	(.020)	***	-.330E-03	(.117E-03)	***	
	4	.140	(.020)	***	-.751E-03	(.115E-03)	***	
	5	.104	(.019)	***	-.561E-03	(.104E-03)	***	
Distribution	1	.290	(.060)	***	-1.817E-03	(.610E-03)	***	
	2	-.029	(.061)		.715E-03	(.608E-03)		
	3	.321	(.056)	***	-.918E-03	(.541E-03)	***	
	4	.032	(.058)		.636E-03	(.530E-03)		
	5	-.199	(.057)	***	2.112E-03	(.518E-03)	***	
Price	0	.004	(.019)					
	1	-.006	(.026)					
	2	-.015	(.025)					
Feature	0	1.867E-03	(.967E-03)	*				
	1	2.266E-03	(1.089E-03)	**				
	2	.951E-03	(.962E-03)					
Advertising	0	.002E-03	(.284E-03)					
	1	-.001E-03	(.302E-03)					
	2	-.001E-03	(.283E-03)					

B: Share Equations ^b								
Variable	Lag	Size of the Effects			Interaction with Time			
		Parameter	(s.e.)		Parameter	(s.e.)		
Share	1	-.024	(.063)		-2.528E-03	(.377E-03)	***	
	2	.299	(.065)	***c	-3.135E-03	(.422E-03)	***	
	3	.227	(.064)	***	-1.990E-03	(.422E-03)	***	
	4	.205	(.065)	***	-1.414E-03	(.414E-03)	***	
	5	.122	(.062)	*	-.742E-03	(.375E-03)	**	
Distribution	1	.270	(.185)		1.932E-03	(2.469E-03)		
	2	-.055	(.184)		2.038E-03	(2.419E-03)		
	3	.349	(.172)	**	-1.348E-03	(2.258E-03)		
	4	.235	(.182)		-1.112E-03	(2.270E-03)		
	5	-.579	(.176)	***	4.195E-03	(2.277E-03)	**	
Price	0	-2.113	(.071)	***				
	1	-.768	(.112)	***				
	2	-.308	(.112)	***				
Feature	0	.022	(.003)	***				
	1	.020	(.004)	***				
	2	.010	(.003)	***				
Advertising	0	-.156E-03	(1.056E-03)					
	1	.721E-03	(1.095E-03)					
	2	-.160E-03	(1.053E-03)					

^aThe average R² across the N - 1 independent equations on the first difference in distribution is .455.

^bThe average R² across the N - 1 independent equations on the first difference in share is .484.

^cSignificance levels are *-.10 level, **-.05 level, ***-<.01 level.

pulse-response functions is as follows: Distribution precedes market share. Nestea precedes the other brands. The latter assumption is motivated by Nestea's expanding its position aggressively in the 1991-92 window, which may suggest that Nestea took initiative as a new entrant. Other than that, the assumption is arbitrary, but the results for Nestea are robust across different causal orderings. We present the results in Figure 5.

The two panels on the left show the impulse-response on the dynamics of distribution, whereas the two panels on the right present the same for share. The two upper panels apply to the first year of observations, whereas the two lower panels apply to the last year of observations.

The solid line in the upper left-hand panel shows that an impulse of one standard deviation of distribution initiates a

further positive evolution of distribution. This evolution combines the direct effect of distribution on itself and its indirect effects through market share. The dashed line shows the effect of a standard deviation shock of market share on distribution. Furthermore, the upper right-hand panel shows how market share reacts to shocks in distribution and in share. An increase in market share is followed by an immediate decrease, after which market share steadily climbs. The effects of distribution on market share also show a steady buildup over time.

The counterparts of these graphs in the lower panels show that the coupling of share and distribution is no longer present for Nestea in 1995-96. Note that the effects of market-share changes on distribution changes are absent. Also, the upward market-share evolution in response to changes in ei-

Figure 3
DYNAMIC EFFECT OF SHARE ON DISTRIBUTION OVER THE EVOLUTION OF THE CATEGORY

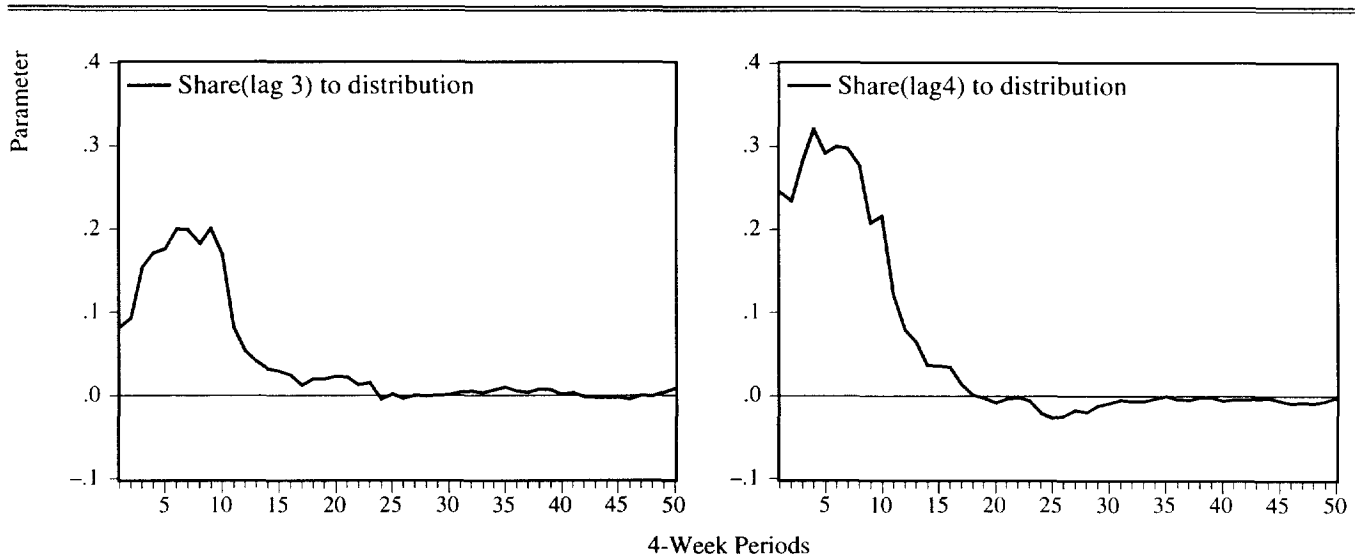
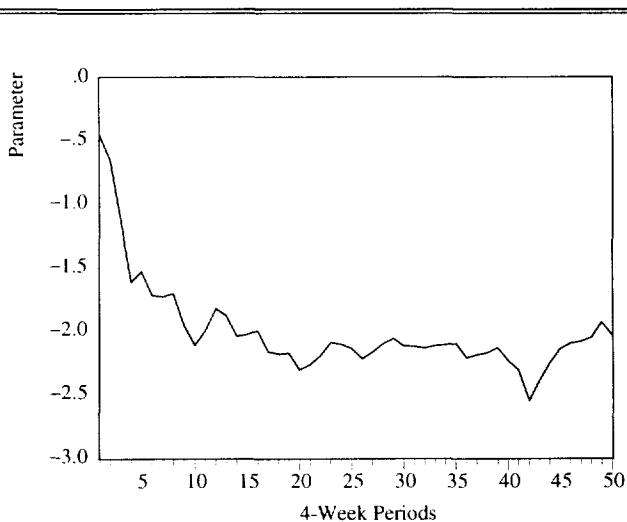


Figure 4
DYNAMIC EFFECTS OF PRICE ON SHARE OVER THE EVOLUTION OF THE CATEGORY



ther endogenous variable is no longer present. The lower panels suggest that evolution of market share and distribution is no longer characterized by momentum in 1995–96.

Was Fruitopia Too Late?

Fruitopia failed to seize noticeable market share upon its introduction in 1994. Its market share in 1995–96 averaged less than half a percentage point and never exceeded two percentage points in the grocery channel. Over the 15-month period it took Fruitopia to get to this level, Arizona and Nestea took 10%–15% of the market two years earlier. The empirical application closes by interpreting this difference in success in the context of the model and its estimates.

The bottom graphs in Figure 5 suggest that by the time Fruitopia was introduced, the effect of share increases on distribution increases had eroded. This implies that Fruitopia would have more difficulty obtaining retailer distribution and market share than previous entrants. More interesting, in a *Wall Street Journal* (1998) article, a manager for Snapple stated that in 1998 “There’s not a lot of inherent momentum in this business.” This accords with the bottom graphs of Figure 5.

In addition, Fruitopia is an expensive brand and was introduced at a point in time when market shares were sensitive to price (see Figure 4). Fruitopia could gain share by aggressive pricing, but this would be inconsistent with its premium image.

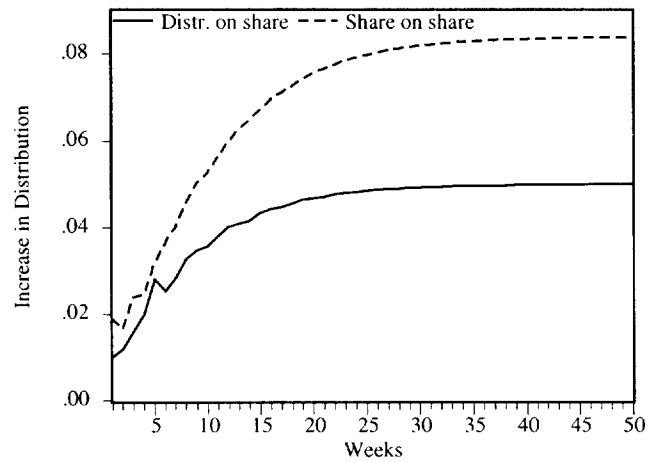
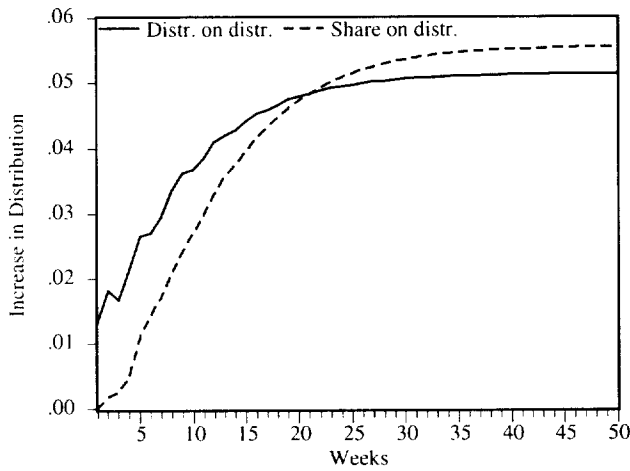
CONCLUSION

We present a model of how brand shares evolve over time for new repeat-purchase categories. This model contains a temporary positive feedback between brand-level market share and share of distribution. We hypothesized that because of this feedback changes in market share and distribution amplify each other, but only during the growth stage of the category’s life cycle and not during later stages. Brand shares can therefore be volatile in a young category but are expected to settle down when retailers have decided which brands to carry. A particular division of the market is harder to change after this point than before it.

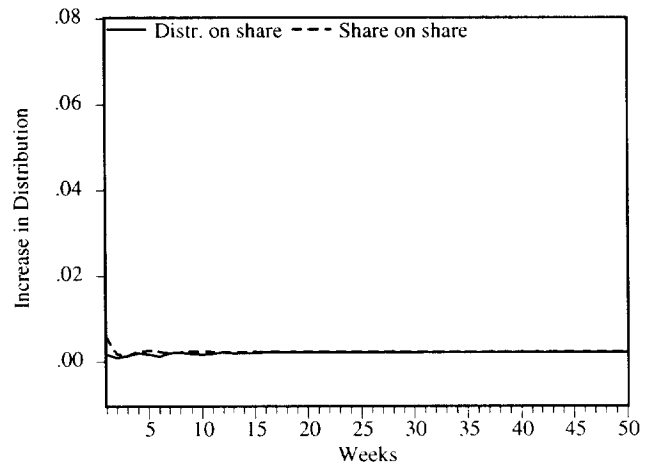
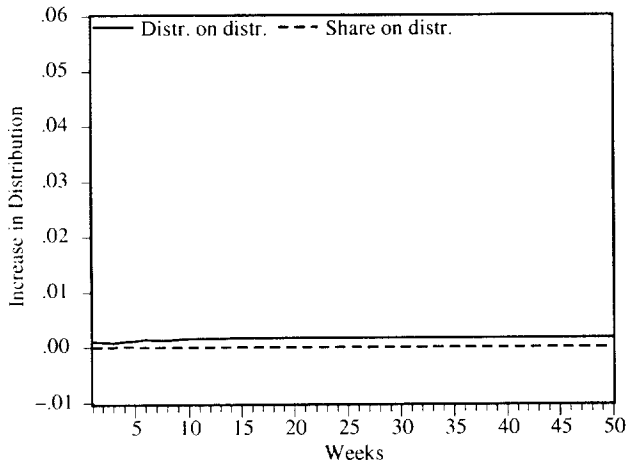
The feature of managerial significance in this context is the long-term share impact of manufacturers’ marketing actions. During the category’s growth stage, changes in either market share or distribution are proposed to trigger a chain of subsequent causes and persistent effects. Marketing-mix investments, if they create such changes, may therefore have long-term effects in new or young categories. The accumulation of these long-term effects codetermines future baseline shares. After the feedback erodes, marketing-mix effects are no longer permanent, and market shares can only be altered temporarily. At this point, stable baseline shares are, in

Figure 5
TOTAL IMPULSE-RESPONSE FUNCTIONS FOR NESTEA

A: 1991-92: Coupled share-distribution dynamics, momentum



B: 1995-96: Uncoupled share-distribution dynamics, no momentum



part, the result of the accumulated effects of marketing-mix expenditures over the growth stage of the category. With this approach we therefore propose that the baseline shares are history-dependent and attribute a distribution of baseline shares in part to the cumulative marketing investments.

Our operationalization of the conceptual framework of the emergence of market structure is a set of coupled MCI models, one for brand-level market shares and one for share of retailer distribution. These models accommodate the logical-consistency constraints associated with share measures.

From an empirical application of the model, it appears first that the dynamics of category share and distribution are initially characterized by the presence of momentum; that is, a single percent increase (decrease) in either share or distribution generates long-term increases (decreases) in both share and distribution that are greater than 1%. However, after the category's early growth stage, share and distribution are no longer coupled, as is illustrated by the bottom panels

in Figure 5, and long-term effects on market share are absent or greatly diminished.

Second, somewhat in contrast to articles focusing on mature categories, we find that market shares can evolve. This evolution is present not only in market shares but also in relative market shares (log-ratios) and in measures of retailer distribution.

Third, marketing mix influences market shares and, to some extent, retailer distribution. The influence of price on market share becomes more important as the category matures. These results suggest that initially the dynamics of the market are driven by the interlocked dynamics of share and distribution, which cause long-term swings in market share (see Figure 1), whereas later the dynamics of market share seem more exogenously determined.

Finally, the empirical analysis suggests that in this category entrants fight an uphill battle after the positive effect of market share on distribution has eroded. This is because successes in lead markets are no longer leveraged into distribu-

tion in other markets so that all distribution must be earned the hard way. At the same time, the market is more responsive to price, so, all else being equal, new entrants face either low margins or low demand.

Taken together, our results suggest that it is hard for new brands to enter the market profitably after the category approaches maturity. Late entrants should regenerate or redefine the category and thereby almost effectively start a new category themselves. The *Wall Street Journal* (1998) article quoted previously comments on how this industry is particularly active in new product introductions. In the face of such ongoing activity, it is interesting that there appears to be a strong trend toward stability in this industry (see Figure 1).

Two avenues for further research seem particularly worth pursuing. First, given the perhaps broad appeal of the concept that momentum for brands exists—at least locally in time—in new categories, there is value in a theoretical study on how and to what extent the dynamics of this model can be controlled by manufacturers. Such a study could offer results on how to mix pull and push effects. Second, it seems important to study the spatial aspects of the evolution of categories, in which, for example, neighboring markets affect one another more than distant markets. Such spatial structure may affect a manufacturer's choice of lead markets in introducing its brands in new repeat-purchase categories.

APPENDIX

Tests for Cointegration

Cointegration is defined as the empirical phenomenon that a linear combination (the cointegrating equation) of two integrated variables is itself not integrated. More broadly, it implies that a system is attracted to a reduced dimensional linear subspace. The number of reductions in the dimensions of the system space is equal to the number of cointegrating equations. This is called the cointegrating rank of a system. Engle and Granger (1987) provide the first formal test for cointegration. This test is based on the definition that a cointegration equation cannot be integrated itself. The Engle-Granger test for cointegration therefore amounts to testing for a unit root in the cointegrating equation. It works well if the cointegrating equation is known. In contrast, Johansen (1991) offers an approach that simultaneously estimates the cointegrating equations and tests for the cointegrating rank.

Tests were performed for cointegration between share and distribution using the Johansen likelihood ratio test and four lags in the endogenous variables. The results, with special attention to the hypothesis of cointegration in the early parts of the series, are listed in Table A1.

Estimation Issues

It is possible to use Zellner's (1962) method for equations that have different sample sizes. Stacking the data by time series, we write the matrix of exogenous variables as X , of endogenous variables as Y , and the covariance matrix of the errors in the equations as Σ_c . Then the SUR estimator is given by

$$(A1) \quad b_{SUR} = [X'(\hat{\Sigma}_c^{-1} \otimes I)X]^{-1}X'(\hat{\Sigma}_c^{-1} \otimes I)Y,$$

Table A1

JOHANSEN COINTEGRATION TEST BETWEEN SHARE AND DISTRIBUTION

Brand	1991-92	1992-93	1991-93	1991-96
Arizona	— (—)	— (—) ^c	— (—) ^c	1 ^{a,b} (167) ^d
Fruitopia	— (—)	— (—)	— (—)	0 (51)
Lipton	0 (49)	0 (52)	0 (101)	0 (252)
Nestea	0 (49)	0 (52)	0 (101)	0 (252)
Snapple	0 (49)	1 (52)	0 (101)	0 (252)

^aCointegrating rank (zero means rejection of cointegration).

^bThere is weak evidence for cointegration from the Johansen test. However, we cannot reject a unit root in the cointegrating equation. Thus there was no cointegration from the Engle-Granger (1987) test.

^cOnly 16 observations.

^dNumber of observations.

where a typical element of the consistent estimator Σ_c of the matrix Σ_c is computed as

$$(A2) \quad \hat{\sigma}_{ij} = (y_i - X_i b_{OLS})'(y_j - X_j b_{OLS}) / \max(T_i, T_j).$$

This procedure can be used with unbalanced data because of the max-function, and, provided the missing values are asymptotically negligible, a consistent estimator of Σ_c is obtained (see also Johnston 1984, p. 338).

The Computation of Schwarz's Criterion

We computed the Schwarz criterion from the log-likelihood function of the system equations assuming a multivariate normal distribution of the innovations. To deal with product introductions, we computed the log-likelihood function for subsamples that contained a constant set of brands. Using T_i to mark time and $(N_i - 1)$ for the size of the set of innovations between T_{i-1} and T_i , we computed the log-likelihood of the innovations in the system of equations for any sample i with

$$(A3) \quad L_i = -\frac{(T_i - T_{i-1})(N_i - 1)}{2}(1 + \log 2\pi) - \frac{(T_i - T_{i-1})}{2} \log |\hat{\Sigma}_i|,$$

where $|\hat{\Sigma}_i|$ is the determinant of the variance-covariance matrix of the innovations associated with the brands on the market in sample i . The total log-likelihood L is the sum of the L_i over all i . The Schwarz criterion is computed as $-2L/T + k \log(T)/T$, where T is the total sample size and k is the number of parameters.

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