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COMPETITION BASED MARKET SHARE FORECASTING

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Competition Based Market Share Forecasting

Abstract

While market share forecasting procedures typically focus on the customer, a two-step procedure is developed that uses competition as the forecast's focal point. The focal point is average industry market share, which equals 100 divided by the number of competitors. The market share forecast adjusts average industry market share up or down based on the business's competitive advantages and disadvantages. The forecasting procedure tends to be more effective for mature businesses than for start-up ventures.

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Introduction

Kotler (1988) describes sales forecasts by saying, "All forecasts are built on one of three information bases: *what people say, what people do,* or *what people have done*" (p. 270). While these diverse forecasting procedures often recognize competition, the focal point is typically the customer. Many firms though pay very close attention to competitors. In Day and Nedungadi (1989), 39% of the firms report an orientation that is either competition centered or balanced between competition and customers. This suggests there is potential value for competition based forecasting.

The competition based forecasting procedure that is developed and empirically tested below is conceptually straightforward. It is based on two assumptions. First, in the absence of competitive advantages and disadvantages, each business in a market should have an average industry market share (AVEMS). Second, competitive advantages and disadvantages are the primary forces that explain why a given business deviates from AVEMS.

These two assumptions generate a two step forecasting procedure. In the first step, dividing 100 by the number of competitors yields average industry market share (AVEMS). In the absence of competitive advantages and disadvantages, this is a business's expected market share. In the second step, the market share forecast arises by using the business's competitive advantages and disadvantages to adjust AVEMS up or down. While random factors also influence market share differences, step 2 highlights competitive advantages and disadvantages.

Regression equations are used below to estimate the market share models. The estimates are used to forecast market share in various holdout samples.

Because evaluating the market share impact of various competitive advantages is a standard procedure in sales response functions (see Parsons and Schultz 1976 and Naert and Leeflang 1978), this forecasting procedure's unique aspect is using AVEMS as the forecast's focal point.

This competition based forecasting procedure is applied to cross-sections of start-up ventures and mature manufacturing businesses. Forecasting accuracy tends to be greater for mature businesses than start-up ventures. The relative importance of AVEMS and the competitive advantage variables is also compared. This is similar to Schmalensee (1985) and Wernerfelt and Montgomery (1988) in the sense of assessing the relative impact of business and industry characteristics on business performance.

For established businesses in mature markets, the forecasting accuracy for AVEMS alone is similar to the combined accuracy of the competitive advantage variables. The competitive advantage variables are relative product quality, relative product line breadth, relative marketing expenditures, relative price, and order of market entry. For start-up ventures, the forecasting accuracy for the combined competitive advantage variables is stronger than AVEMS alone. Still, in the start-up ventures' pooled data analysis, AVEMS has the highest level of statistical significance of any single model variable.

Competition Based Market Share Forecasting

Competition is the basis for each step in a two step market share forecasting procedure. Step one uses AVEMS as the forecast's focal point[1], where AVEMS equals 100 divided by the number of competitors. Step two adjusts this level for competitive advantagesa and disadvantages. More details are provided below.

Step One

To calculate AVEMS, the number of competitors only includes survivors. Dead businesses are excluded because they do not influence market share directly. Because of their limited competitive impact, small scale competitors are also excluded. The data below exclude competitors with a market share less than 1%.

Step one is relatively straightforward for a short-term forecast. For example, if an entrant and 9 established competitors have a market share greater than or equal to 1%, AVEMS equals 10%. With rapid entry or exit though, AVEMS can be unstable. When more than 100 firms entered the wine cooler market from 1982 to 1986, AVEMS declined from 100 to 1.

Because entry can destabilize AVEMS, the data analysis examines the interaction with recent entry. A negative interaction can occur when rapid entry

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[1] A second potential focal point is to select a single competitor whose market share can be forecasted with relative certainty and who has similar competitive advantages and disadvantages. For example, a focal point of comparison for the Scripto Ultra-Thin disposable lighter could have been the existing Scripto Mighty Match (<u>Business Week</u> 1982). Because choosing a single competitor is often subjective, this choice can rely heavily on expert opinion.

increases random measurement error for AVEMS. Because random measurement error weakens an estimated relationship, the AVEMS estimate is biased towards zero. As an alternative hypothesis, recent entry signals that the competitors are composed of both recent entrants and established businesses. Because a recent entrant is typically not as challenging as an established business, a greater portion of the market share pie is expected[2]. This generates a positive interaction.

Step one is *not* as straightforward for a long-term forecast. This is because a forecast is also required for net entry, which equals the number of firms that enter less the number that exit. The net entry forecast is very important when the market starts or ends with a limited number of competitors. For example, when the number of competitors increases from 2 to 5, AVEMS decreases by 30 share points. If the number of competitors increases from 20 to 50, AVEMS only decreases by 3 share points.

While the net entry forecast can be highly uncertain, economic research provides some insights. Gort and Klepper (1982) identify five stages that correspond roughly to the first 3 product life cycle stages. They find that most entry occurs in the early growth stage, most exit occurs in the transition from the growth to the maturity stage, and net entry is limited in the introductory, late growth, and maturity stages.

[2] An alternative approach uses a weighted average to calculate the number of competitors. For example, 2 recent entrants could be viewed as equivalent to 1 established competitor. While the dummy variable method adjusts the regression coefficient up, this method adjusts AVEMS up.

Curry and George's (1983) survey reports a regression to the mean effect[3]. Hence, markets that start with relatively few competitors tend to attract entry. The number of competitors tends to be reduced by both merger activity and an increase in the minimum efficient scale of operations.

While industry characteristics are important, net entry is also influenced by incumbents' strategic behavior. In certain extreme instances, aggressive reactions can drive an entrant out of the market. When aggressive reactions create a reputation for "toughness", Milgrom and Roberts (1982) and Kreps and Wilson (1982) show this can deter future entry.

In addition, future entry can be deterred by using preemptive investments. These investments are defensive strategies developed prior to entry. While marketing generally focuses on serving the consumer, preemptive investments are at least partly justified by limiting or delaying competition. For example, see Spence (1977) and Salop (1979). Hence, preemptive investments often reduce net entry.

Preemptive investments can fall in any area of the marketing mix. Examples include investments in new product introductions (Prescott and Visscher 1977), sleeping product patents (Gilbert and Newberry 1982), beefing up distribution (Porter 1976, p. 26-35), intensive advertising (Comanor and Wilson 1974) and limit pricing (Scherer 1980).

Step Two

Step two adjusts AVEMS for the competitive advantages and disadvantages that influence market share. Competitive advantages can arise on

[3] Curry and George's survey results address changes in seller concentration. The factors that change seller concentration should typically change the number of competitors as well.

the supply side of the market in the marketing mix or on the demand side of the market in the customer base. Each competitive advantage must be identified, measured, and the market share impact estimated.

For a short-term forecast, competitive advantages can usually be identified. Aaker's (1988) survey results indicate that managers identify competitive advantages "with a high degree of reliability" (p. 206). Various competitive advantage measures are discussed in Parsons and Schultz (1976) and Naert and Leeflang (1978).

A long-term forecast requires insights into sustainable competitive advantages. While environmental changes and competitive actions threaten sustainability, certain types of competitive advantages tend to be more sustainable than others.

For market pioneers, product line breadth advantages are typically more sustainable than product quality advantages (Robinson and Fornell 1985 and Robinson 1988). Cost savings based on scale economies tend to be more sustainable than those based on greater experience (Porter 1980). Brand name advantages are often sustainable. Of the top twenty five consumer brand names in 1923, in 1983 nineteen were still market leaders (Advertising Age 1983).

Once competitive advantages and disadvantages are identified and measured, what options are available to adjust AVEMS? As Mahmoud (1984) says, "Forecasters and managers have a wide choice of ways to forecast, ranging from purely intuitive or judgemental approaches to highly structured and complex quantitative methods." (p. 139). In certain instances, the adjustments can be handled informally by using expert opinion. This could arise early in the new product development process where Urban and Hauser (1980, p. 280) say only a "ballpark" forecast is needed.

In other instances, more accurate adjustments to AVEMS are required. When historical cross-sectional data are available, the market share adjustments can be estimated using a regression equation. A general model specification is:

$$MS_i = \beta_0 + \beta_1 \, AVEMS_i + \beta_2 \, X_{2,i} + \ldots\ldots + \beta_k \, X_{k,i} + \varepsilon_i \qquad (1)$$

where MS is market share, i = 1, 2, ..., n, β_0 to β_k are the estimated parameters, AVEMS is average market share, X_2 to X_k are the competitive advantages and disadvantages, and ε is the random error.

Because variation in AVEMS is required to estimate β_1, this specification is most appropriate for data that cuts across a number of different markets. (The data analysis below estimates the model across broad samples of mature and start-up businesses.) In situations where AVEMS is constant, such as within a given market in a single time period, β_1 can not be estimated. If a market has frequent entry or exit over time, then β_1 could be estimated with time series data. Even so, time series data are not ideal because it is difficult to model the complicated time lags associated with entry and exit.

Equation 1 uses a linear model specification. Because multiplicative and attraction specifications have also been widely used, why was the linear specification selected? (For a brief survey of these alternative specifications, see Cooper and Nakanishi 1988.) The multiplicative specification has the advantage of modeling marketing mix interactions. Logarithms though are used to make the model linear in parameters. Because most of the competitive advantage measures are either dummy variables or categorical variables with negative values, the multiplicative specification is not used.

The attraction specification is generally used within a given market. It is theoretically appealing because it satisfies the range constraint (all market share predictions fall between 0 and 1) and the sum constraint (the sum of the market share predictions equals 1.0). Because evaluating the importance of AVEMS will be done across rather than within markets, the attraction specification is not used. In any case, the linear specification should not distort the forecasting accuracy because the studies surveyed in Cooper and Nakanishi (1988, p. 31) only find marginal forecasting differences across these 3 specifications.

In addition to these model specification issues, the dependent variable in equation 1 could represent the difference between market share and AVEMS. This is because the procedure can be viewed as forecasting the difference between the business's share and the industry average.

There are 4 reasons though why AVEMS is specified as an independent variable. First, the interaction between AVEMS and recent entry can be tested. Second, the discussion above implicitly assumes the impact of AVEMS on market share is linear. Different functional forms test this implicit assumption.

Third, subtracting AVEMS from MS essentially forces $\beta_1 = 1.0$. Depending on the sample, β_1 can be greater or less than 1.0. For example, Urban and Hauser (1980) say that for new products, "Long - run sales are not obtained immediately" (p. 300). While these competitive disadvantages can measured by X_2 to X_k, key variables are often excluded or measured with error. When this occurs, the intercept (β_0) can decline and β_1 can be less than 1.0. In contrast, established Fortune 500 firms tend to have superior skills and resources. When these skills and resources are not effectively incorporated in the competitive advantage measures, the intercept can increase and β_1 can be greater than 1.0.

Fourth, when AVEMS is an independent variable, the relative importance of AVEMS versus competitive advantages and disadvantages can be compared. This follows in the spirit of Schmalensee (1985) and Wernerfelt and

Montgomery (1988) by comparing the relative impact of business versus industry characteristics on business performance.

Data

The competition based model specification in equation 1 is applied to a sample of start-up ventures. Because the data cover the first 2 years of commercialization, this illustrates a short-term forecasting application. The application is potentially useful because start-up ventures often do not have the time and money to invest in marketing research. For example, see Wall Street Journal (1988).

The model is also applied to a cross-section of mature consumer and industrial goods businesses. In the sense that a mature market represents long-term performance[4], this provides a conditional long-term market share forecast. The results are conditional in the sense that managers must condition their forecast on given values of AVEMS and competitive advantages.

The data are from the Strategic Planning Institute. The start-up business (STR2) data are used for the short-term forecasts and cover the first 2 years of commercialization. The PIMS (Profit Impact of Market Strategies) data are used for the mature markets and are a 2 year average. (The 2 year average provides the closest correspondence to when the number of competitors is measured.)

Each business that submits data to the Strategic Planning Institute is encouraged to form a data gathering team composed of marketing,

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[4] The maturity stage is selected because Polli and Cook (1969) report it tends to be the longest product life cycle stage and market share levels are relatively stable.

manufacturing, finance, and R&D managers. Each observation describes the entry strategy, entered market, competition, operating results, and balance sheet information. Because detailed and confidential information is divulged, the business and industry are anonymous.

Certain data limitations should be recognized. First, the sample is self-selected with most business units belonging to Fortune 500 firms. Because the sample tends to be more successful, better managed, and better financed than a typical random sample of businesses, β_1 may be greater than 1.0.

Second, the sample is limited to survivors because managers are not interested in submitting data on "dead businesses". For example, see Biggadike (1976, p. 39). Because the market share forecasts are conditional on survival, expected market share in a given time period equals forecasted market share times the expected probability of survival. [5]

Samples

For the mature businesses, model estimation uses roughly 50% of each sample. Forecasting validation uses the remainder. The estimation sample examines the following AVEMS functional forms: the simple linear AVEMS functional form, AVEMS plus a squared term, the square root of AVEMS, and the logarithm of AVEMS. The best fitting results are used for the forecast validation.

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[5] While the market share forecast is estimated and validated across survivors, it can provide insights into the expected probability of survival. This is because empirical studies generally find "smaller firms have higher exit probabilities" (Lieberman 1989, p. 4). The result is robust across growing, mature, and declining industries.

The forecast and estimation samples are based on the data's last calendar year. For example, the consumer goods estimation sample ends in 1976. The forecasting sample covers 1977 thru 1986. The consumer goods estimation sample size is 299 and the forecasting sample size is 294. The industrial good sample sizes are 727 and 560.

Selecting the start-up data estimation and forecasting samples is not as straightforward. This is because the sample is heterogeneous and relatively small. To improve sample homogeneity, the sample selection is based on Robinson (1989). Market pioneers that were first to enter, major innovators that "attempted" to serve customer needs for the first time, and markets without any competitors in the year prior to entry are deleted. Nonmanufacturing businesses and entrants that did not submit a full set of variables for the regression analysis are also deleted[6]. The deletions reduce the sample size from 198 to 143. Even with these deletions, the data are relatively heterogeneous in the sense that they are composed of roughly 75% industrial and 25% consumer goods businesses.

With only 143 observations, it is not effective to split the start-up data into estimation and forecasting halves. This is because the results are 1) sensitive to the data split and 2) important inconsistencies arise between the forecasting and estimation results. Hence, a resampling approach is used where the model is estimated over 142 observations and the results are used to predict the remaining

[6] Four observations with extreme values that may have resulted from respondent error, data entry error, or a unique situation are deleted also. One late entrant reports a market share of 100%, one early follower reports a market share of 62% while facing 24 competitors, and two entrants report average per-unit prices at less than 7% of competitors' average prices.

observation[7]. (Cooil, Winer, and Rados 1987 discuss other resampling options.) This approach is followed for each of the 143 observations. It has the advantage of using the data extensively for forecasting, but the disadvantage of not having an estimation sample to examine different AVEMS functional forms.

Variables and Definitions

The variables are defined in Table 1. Market share is defined as the business unit's dollar share of sales in the served market. The served market covers "only the specific products or services, customer types, and geographic areas in which a business actually competes" (PIMS Data Manual 1978, p. 1-2). The served market essentially represents the target market.

AVEMS equals 100 divided by the estimated number of competitors. Competitors with a market share less than 1% are ignored. Since the number of competitors is a categorical variable, the true number is estimated by the category range mean. Because the number of competitors in the start-up data is measured in the year prior to entry, it is increased by 1.0 to reflect the entrant.

For the mature businesses, an important adjustment to the number of competitors is possible. Based on the market share levels of the 3 leading competitors, the category with 5 or fewer competitors is divided into 2, 3, and 4 or

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[7] Because a resampling program is not available for use with this proprietary data, a resampling program was written by Paul Chussil at the Strategic Planning Institute.

TABLE 1

Variable Definitions

Variable	Definition[a]
Market Share	The entrant's dollar sales divided by total served market dollar sales.
Average Industry Market Share	100 divided by the estimated number of competitors. Competitors with less than 1% of the served market are ignored. 50 = 2 competitors, 33 = 3 competitors, 22 = 4 or 5 competitors, 13 = 6 - 10 competitors, 6 = 11 - 20 competitors, 3 = 21 - 50 competitors, and 1 = 51 or more competitors.
Entry * Ave. Industry Market Share	Entry equals 1.0 if any competitor with at least a 5% market share entered during the last 5 years, 0.0 otherwise. Multiply the entry variable by average industry market share.
Relative Product Quality	Estimate the percentage of this business's sales volume accounted for by products and services that, *from the perspective of the customer*, are assessed as "superior," "equivalent," and "inferior" to those available from the three leading competitors. Relative product quality is the percentage superior less the percentage inferior.
Relative Product Line Breadth	Relative to the weighted average of the product lines of the three largest competitors, estimate the breadth of the product line of this business. -1: Narrower 0: Same +1: Broader

TABLE 1 (Cont.)

Variable	Definition
Relative Marketing Expenditures	Relative marketing expenditures is the mean of relative salesforce, relative advertising, and relative promotion expenditures as a percent of sales. -2 = Much less -1 = Somewhat less 0 = About the same 1 = Somewhat more 2 = Much more
Relative Price	The percentage above or below the average level of selling prices of this business's products and services, relative to the average level of the three largest competitors.
Market Pioneer	At the time this business first entered the market, was it: 1 = one of the pioneers in first developing such products or services, 0 = otherwise.
Early Follower	Same as above, except an early follower of the pioneer(s) in a still-growing, dynamic market. (In the regression analysis, the early follower category is excluded.)
Late Entrant	Same as above, except a late entrant in a more established market situation.

a) The variable definitions are from the PIMS Data Manual (1978). They apply directly to the mature businesses and are similar, if not identical to the start-up business definitions.

5 competitors[8]. The adjustment is important because these categories provide key variation in AVEMS. (Because of data limitations, the start-up businesses measure only yields categories for 2 and 3 to 6 competitors.)

The entry interaction multiplies entry by AVEMS. For a mature business, entry equals 1.0 if any entrant achieved at least a 5% market share during the last 5 years, 0.0 otherwise. For a start-up venture, entry equals 1.0 if any other entrant had the "potential" to achieve at least a 5% market share, 0.0 otherwise[9].

The competitive advantage variables are identical for the two mature business samples. The only differences versus the start-up ventures are that 1) the PIMS product quality measure is replaced by two relative product advantage dummy variables and 2) a product patent dummy variable is added (see Robinson 1989).

The competitive advantage variables included in each model follow Robinson and Fornell (1985) and Robinson (1988). They are relative product line breadth, relative marketing expenditures, relative price, and order of market entry. Each variable is coded so that a level comparable to the 3 leading

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[8] PIMS includes market share levels for each of the 3 leading competitors and sets a minimum value for each variable. The minimum value for the largest competitor is 5 share points. The minimum value for the second and third largest competitors is 1 share point. When 1 share point is reported for the second or third leading competitor, they are <u>not</u> counted as competitors. When the largest competitor reports a market share of 5 points, it is assumed they are a significant competitor. This is because monopolies in mature markets are unusual. Based on these assumptions, the first PIMS category of 5 or fewer competitors is expanded to 2, 3, and 4 or 5 competitors.

[9] The other entrant must have entered after the start-up venture and before the data forms were completed. This is generally during the start-up's first 4 years of commercialization.

competitors equals zero, a competitive advantage is positive, and a competitive disadvantage is negative.

Order of market entry is measured by the market pioneer, early follower, and late entrant categories. Based on Robinson and Fornell (1985) and Urban et al. (1986), market pioneers should have competitive advantages and late entrants competitive disadvantages. Assuming early followers have no competitive differences, they are the excluded dummy variable category.

Estimation Results

Is the impact of AVEMS on market share linear or nonlinear? While the theoretical arguments above point to a linear relationship, this is tested by examining four different AVEMS functional forms: the simple linear AVEMS functional form, AVEMS plus a squared term, the square root of AVEMS, and the logarithm of AVEMS. The entry * AVEMS interaction is also examined. Because the estimation results are used in the forecasting stage, these results help narrow down the number of potentially useful models.

The models are estimated using ordinary least square (OLS). A limitation of the OLS results is that White's (1980) test indicates that the regression error terms are heteroskedastic. Generalized least squares (GLS) was used in an attempt to correct for the heteroskedasticity. Because White's test indicates that the mature market GLS error terms remain heteroskedastic, the OLS results are presented. While heteroskedasticity does not bias the OLS coefficient estimator, the standard errors and the statistical significance tests are biased[10]. Hence, when the estimation results are presented, statistical significance is conservatively based on two - tail tests.

Because the main data analysis focus is on prediction, would predictions based on OLS differ dramatically from GLS? For the start-up ventures, this is unlikely because the start-up venture estimation results in Robinson (1989) are similar for OLS and GLS. For the mature businesses, the sample sizes are 299 for consumer goods and 727 for industrial goods. With these large samples, the GLS efficiency gains should be modest. These conclusions are also consistent with Brodie and de Kluyver (1984) who report, "no significant differences can be observed between the predictive performance of OLS and GLS-based specifications" (p.199-200).

The mature business explained variation results are shown in Table 2. For consumer goods, AVEMS alone explains 25.5% of the market share variation. For industrial goods, it is 27.9%. The full model specification results though, which include the competitive advantage variables, are the most important. For consumer goods, adding AVEMS squared explains virtually as much market share variation as the square root functional form and more variation than the logarithmic functional form. For industrial goods, the addition of AVEMS squared yields the highest explained variation for the alternative functional forms. Thus, this indicates that the most general alternative to the linear model adds AVEMS squared to the specification. It should also be noted that, across

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[10] Even though White (1980) derives a consistent estimator of the the OLS coefficient standard errors in the presence of heteroskedasticity, this estimator is not available in the AQD computer package that is available for use with the proprietary PIMS data.

TABLE 2

Explained Market Share Variation for Various Average Industry Market Share Functional Forms

	Explained Market Share Variation			
	Mature Consumer Goods (n=299)		Mature Industrial Goods (n=727)	
	Additional Independent Variables			
Average Industry Market Share (AVEMS) Functional Forms	None	Competitive Advantage Variables	None	Competitive Advantage Variables
	(%)	(%)	(%)	(%)
1) AVEMS	25.5	56.6	27.9	46.8
2) AVEMS plus Squared AVEMS	26.4	57.7	28.0	47.0
3) Square Root AVEMS	27.2	57.8	26.7	46.3
4) Logarithm AVEMS	25.7	56.4	22.4	43.0
5) AVEMS plus Entry* AVEMS	26.4	57.3	28.6	47.1

both samples, adding the entry*AVEMS interaction term increases explained variation by less than 1%.

Since the explained variation gains versus the simple linear AVEMS model are modest, should market share forecasting even consider AVEMS squared and the entry * AVEMS interaction? The regression results in Table 3 provide additional insights. For both consumer and industrial goods, the squared AVEMS term is negative and statistically significant. AVEMS relationship may turn down because of the measurement error for large AVEMS values. (As described above, measurement error arises because the number of competitors must be estimated from categorical data.) Also, both entry interaction terms are positive and statistically significant.

While the Table 3 results are statistically significant, are they also economically significant? Economic importance is assessed by comparing expected market share with and without theses variables in the model. In Table 4, expected market share is based on the Table 3 regression estimates that include the additional explanatory variables. It assumes the business is an early follower and has no competitive advantages or disadvantages.

To assess the importance of adding AVEMS squared to the consumer goods model, the relevant Table 4 comparison is the difference between the first and second columns. The difference across the AVEMS range of 1 to 22 is 2.1 share points or less. The range covers 93% of the sample. For industrial goods, the nonlinear relationship is even less pronounced. Hence, economic significance

TABLE 3

Estimation Results for Mature Markets

	Market Share					
Variable and Expected Sign	Mature Consumer Goods (n=299)			Mature Industrial Goods (n=727)		
Constant (+/-)	10.36[a] (6.86)***	5.58 (3.46)***	3.07 (1.60)	11.41 (11.76)***	7.86 (6.57)***	6.32 (4.33)***
Industry Variables						
Average Industry Market Share (+)	.94 (10.07)***	.79 (10.78)***	1.20 (6.02)***	.99 (16.76)***	.96 (18.57)***	1.16 (8.54)***
Average Industry Market Share Squared (+/-)[b]			-1.31 (-2.46)**			-.60 (-1.89)*
Entry * Average Industry Market Share (+/-)			.19 (1.88)*			.14 (1.97)*
Competitive Advantage Variables						
Relative Product Quality (+)		.12 (4.39)***	.12 (4.60)***		.13 (6.56)***	.13 (6.61)***
Relative Product Line Breadth (+)		5.75 (6.03)***	5.59 (5.94)***		4.60 (6.69)***	4.51 (6.56)***
Relative Marketing Expenditures (+)		1.03 (1.18)	1.44 (1.67)***		2.50 (3.87)***	2.50 (3.89)***
Relative Price (-)		.16 (1.99)**	.13 (1.54)		-.01 (-.12)	-.01 (-.10)
Market Pioneer (+)		8.01 (4.93)***	7.65 (4.77)***		3.58 (3.11)***	3.66 (3.19)***
Late Entrant (-)		-4.34 (-2.11)**	-4.69 (-2.31)**		-4.79 (-3.11)***	-4.64 (-3.02)***
R^2	.25	.57	.58	.28	.47	.47

a) The values in parentheses are z-statistics. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

b) The coefficient estimate is multiplied by 100.

TABLE 4

Expected Market Share for Different Average Industry Market Share Functional Forms

Average Industry Market Share (AVEMS) (%)	Expected Market Share[a]					
	Consumer Goods Independent Variables			Industrial Goods Independent Variables		
		AVEMS, AVEMS Squared, and Entry * AVEMS			AVEMS, AVEMS Squared and Entry * AVEMS	
	AVEMS (%)	Entry=0 (%)	Entry=1 (%)	AVEMS (%)	Entry=0 (%)	Entry=1 (%)
1	6.4	4.3	4.5	8.8	7.5	7.6
3	8.0	6.6	7.1	10.7	9.8	9.3
6	10.3	9.8	10.9	13.6	13.1	13.9
13	15.9	16.5	18.9	20.3	20.4	22.2
22	23.0	23.1	27.3	29.0	28.9	32.0
33	31.7	28.4	34.7	39.5	38.1	42.7
50	45.1	30.3	39.8	55.9	49.3	56.3

a) Expected market share is based on the Table 3 coefficient estimates that include the competitve advantage variables. Expected market share assumes the business is an early follower and has no competitive advantages or disadvantages.

across the vast majority of the sample is modest[11].

Is the entry * AVEMS interaction term economically significant? Economic significance is assessed by comparing expected market share with and without entry. For consumer goods, economic significance equals .19 times AVEMS. (In Table 4, this is the difference between the second and third columns.) When AVEMS equals 6, expected market share increases by roughly 1 share point. When AVEMS equals 33, it increases by roughly 6 share points. The industrial goods magnitudes are similar. This indicates the interactions are economically significant when AVEMS is relatively high.

Since a case can be made that both variables generate at least modest economic significance, why are the R^2 values at the bottom of Table 3 only increased by 1% or less?

This seems to occur because each variable is economically significant for only a small portion of each sample. As mentioned above, the economic significance for AVEMS squared is 2.1 share points or less for 93% of the consumer goods sample. Also, the entry interaction results are economically significant when AVEMS is relatively high, say 20 or higher. This applies to 29% of the consumer goods sample. Because only 23% of these businesses report recent entry, the product of these 2 percentages suggests the interaction is economically meaningful for roughly 7% of the consumer goods sample. The industrial goods figure is 6%.

Given these results, which model specifications should be used to forecast market share? For mature businesses, the results suggest that a marginally more

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[11] Economic significance is clearly meaningful when AVEMS equals 50. Even so, these estimates may not be accurate because AVEMS equals 50 for only 1% of the consumer goods sample and only 2% of the industrial goods sample.

complicated specification, which includes AVEMS squared and the entry interaction, performs marginally better than the simple linear specification. While these 2 additional variables are probably more important in hypothesis testing than in forecasting, their incremental forecasting value is evaluated below.

Forecasting Results

Comparing forecasting accuracy across different model specifications provides insights into the incremental forecasting gains. For example, with limited resources, should a manager attempt to forecast AVEMS or the competitive advantage variables? Do the incremental forecasting gains associated with having a full model specification exceed the incremental costs of forecasting the entire set of the independent variables?

Five model specifications provide insights into incremental forecasting gains. The naive or benchmark model specification only has one independent variable, AVEMS. The second model includes the 3 AVEMS variables: AVEMS, AVEMS squared, and the entry interaction term. The third model is naive in the sense that it only includes the competitive advantage variables. The fourth includes both AVEMS and the competitive advantage variables. The final model includes the 3 AVEMS variables and the competitive advantage variables.

To evaluate forecasting accuracy, the economic loss associated with a given forecast error must be considered. For example, see Mahmoud (1984) and Kennedy (1985). Because different decision makers often suffer different economic losses for a given forecast error, multiple methods are needed to evaluate forecast accuracy.

The R^2 value from regressing actual market share on forecasted market share measures the percent of true market share variation explained by forecasted market share. The absolute share point forecast error and absolute percentage forecast error are also calculated[12]. Because the R^2 value is based on least squares estimation, it assumes that economic costs are positively related to the squared forecast error. This weights large forecast errors more heavily than the 2 linear methods. The results are shown in Table 5.

How does the forecasting accuracy for the naive AVEMS model compare for start-up ventures versus mature businesses? For start-up ventures, the AVEMS forecast explains 12.5% of the market share variation. The mature consumer and industrial goods results though are roughly twice as large at 25.7% and 28.6%. Even though the absolute share point forecast error is higher in mature markets, this is because the average market share is roughly three times higher. A more accurate comparison across markets is the absolute percent forecast error. Again, the AVEMS forecasting results are clearly stronger in mature markets.

How does the forecasting accuracy for the naive AVEMS model compare to the naive competitive advantage model? For start-up ventures, the R^2 value for the naive AVEMS is 12.5% versus 25.3% for the naive competitive advantage model. Thus, the competitive advantage variables alone explain roughly twice the market share variation of AVEMS alone. While forecasting differences for the absolute forecast errors are not as extreme, the competitive advantage specification generally provides superior forecasting accuracy.

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[12] For the absolute percentage forecast error, the minimum market share value in the denominator is set equal to 1.0. This reduces the influence of extreme values for very low share start-up ventures.

TABLE 5

Market Share Forecasting Accuracy Results

Model Specifications	R^2	Market Share Forecasting Accuracy: Absolute Share Point Forecast Error		Absolute Percent Forecast Error	
		Mean	Median	Mean	Median
	(%)			(%)	(%)
I. Start-Up Ventures (n=143)					
A) AVEMS	12.5	7.0	4.1	200	85
B) Three AVEMS Variables[a]	12.9	6.9	4.1	201	85
C) Competitive Advantage Variables	25.3	6.7	4.0	188	75
D) AVEMS and Competitive Advantage Variables (A+C)	30.5	6.3	4.0	171	82
E) Full Model (B+C)	30.8	6.4	4.1	172	76
II. Mature Consumer Goods (n=294)					
A) AVEMS	25.7	12.6	11.2	152	51
B) Three AVEMS Variables	25.8	12.6	10.9	149	49
C) Competitive Advantage Variables	20.7	12.8	10.7	130	54
D) AVEMS and Competitive Advantage Variables (A+C)	41.8	10.5	8.6	98	43
E) Full Model (B+C)	42.7	10.4	8.3	93	41
III. Mature Industrial Goods (n=560)					
A) AVEMS	28.6	12.4	10.2	122	46
B) Three AVEMS Variables	31.5	12.2	10.0	119	44
C) Competitive Advantage Variables	24.2	12.6	10.6	108	46
D) AVEMS and Competitive Advantage Variables (A+C)	49.7	10.2	7.9	88	40
E) Full Model (B+C)	51.6	10.0	7.7	85	39

a) The three AVEMS variables are AVEMS, AVEMS squared, and the entry* AVEMS interaction term.

This conclusion though does *not* hold for the mature market samples. This is because the forecasting accuracy is roughly equivalent for the naive AVEMS and the naive competitive advantage models. (Relative to start-up ventures, the naive AVEMS impact is higher while the naive competitive advantage impact is roughly equal.)

Are AVEMS and the competitive advantage variables complements or substitutes? Because the forecasting accuracy is uniformly strongest for the model specification which includes with both AVEMS and the competitive advantage variables, the 2 naive models appear to be complementary. (The conclusion is especially true for the mature market samples.) This is not surprising because an industry characteristic should not be a close substitute for business characteristics measured relative to competition.

Is forecasting accuracy improved by deviating from the simple linear AVEMS functional form? This is tested by adding AVEMS squared and the entry interaction term to the model. In each sample, these 2 variables marginally increase forecasting accuracy. For example, the R^2 value in the naive start-up venture model increases from 12.5% to 12.9%. Because it is not clear that the modest forecasting gains offset the costs of a more complicated model specification, only certain forecasting applications may benefit by deviating from the simple linear functional form.

Pooled Data Analysis

The final estimation results pool the estimation and forecasting samples. As Brodie and de Kluyver (1984) point out, "differences in parameter estimates can have important implications for normative uses of the different models, e.g., in setting marketing budgets" (p. 195).

For start-up ventures, Table 6 shows that the AVEMS squared variable and the entry interaction term are not significant. To compare the statistical significance of individual variables, the linear AVEMS specification is appropriate because the AVEMS impact is not spread across 3 variables. AVEMS has the highest level of statistical significance of any model variable with z = 3.20. The market pioneer dummy variable is second with z = 2.39[13].

For mature markets, Table 7 shows the magnitudes for AVEMS squared are similar to the estimation model. For the entry * AVEMS interaction term, the consumer goods magnitude though declines from .19 in the estimation results to .10 in the pooled results. While positive, .10 is no longer statistically significant. For industrial goods, the main difference versus the estimation results is also the entry interaction term. The estimate increases from .14 to .24. Thus, the entry interaction estimate is weaker for consumer goods, but stronger for industrial goods. To compare the statistical significance of individual variables, the AVEMS z value is clearly the largest in both consumer and industrial markets.

Since the simple linear functional seems adequate for the majority of the mature businesses, is the impact of AVEMS on market share significantly different from 1.0? If the impact is roughly equal to 1.0, then adjusting AVEMS for competitive advantages is relatively straightforward. If the estimate differs from 1.0, then the market share forecast requires an additional adjustment.

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13 Because the excluded category is an early follower rather than a late entrant, the market pioneer dummy variable estimate is reduced. When a late entrant is excluded, the market pioneer z value increases to 2.90.

TABLE 6

Pooled Data Results for Start-Up Ventures

Variable and Expected Sign	Market Share: Years 1 & 2 (n=143)		
Constant (+/-)	3.31 (2.41)**[a]	5.75 (2.30)**	4.68 (1.60)
Industry Variables			
Average Industry Market Share (+)	.36 (4.57)***	.25 (3.20)***	.40 (1.75)*
Average Industry Market Share Squared (+/-)[b]			-.31 (-.69)
Entry * Average Industry Market Share (+/-)			-.01 (-.12)
Competitive Advantage Variables			
Major Product Advantage (+)		6.04 (2.06)**	6.26 (2.08)**
Moderate Product Advantage (+)		.60 (.31)	.62 (.32)
Product Patent or Trade Secret (+/-)		-3.18 (-1.70)*	-3.34 (-1.76)*
Relative Product Line Breadth (+)		2.67 (2.19)**	2.75 (2.24)**
Relative Marketing Expenditures (+)		1.11 (1.27)	1.15 (1.31)
Relative Price (-)		-.02 (-1.08)	-.02 (-1.13)
Market Pioneer (+)		5.38 (2.39)**	5.52 (2.41)**
Late Entrant (-)		-1.00 (-.49)	-.97 (-.44)
R^2	.13	.31	.31

a) The values in parentheses are z-statistics. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

b) The coefficient estimate is multiplied by 100.

TABLE 7

Pooled Data Results for Mature Markets

	Market Share					
Variable and Expected Sign	Mature Consumer Goods (n=593)			Mature Industrial Goods (n=1287)		
Constant (+/-)	9.94[a] (9.01)***	6.55 (5.11)***	3.16 (2.03)**	11.18 (15.11)***	7.47 (8.40)***	5.44 (4.97)***
Industry Variables						
Average Industry Market Share (+)	.96 (14.25)***	.85 (15.18)***	1.37 (8.82)***	1.00 (22.45)***	.96 (25.15)***	1.22 (11.72)***
Average Industry Market Share Squared (+/-)[b]			-1.37 (-3.75)***			-.78 (-3.33)***
Entry * Average Industry Market Share (+/-)			.10 (1.21)			.24 (4.62)***
Competitive Advantage Variables						
Relative Product Quality (+)		.11 (5.47)***	.11 (5.60)***		.14 (9.27)***	.14 (9.20)***
Relative Product Line Breadth (+)		5.89 (7.95)***	5.89 (8.05)***		5.11 (10.02)***	5.00 (9.90)***
Relative Marketing Expenditures (+)		2.05 (3.20)***	2.37 (3.72)***		2.53 (5.05)***	2.53 (5.10)***
Relative Price (-)		.10 (1.70)*	.09 (1.43)		.03 (.53)	.04 (.58)
Market Pioneer (+)		5.38 (4.22)***	5.30 (4.21)***		3.60 (4.25)***	3.58 (4.27)***
Late Entrant (-)		-2.72 (-1.79)*	-2.89 (-1.92)*		-4.48 (-3.94)***	-4.37 (-3.88)***
R^2	.26	.50	.51	.28	.48	.49

a) The values in parentheses are z-statistics. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

b) The coefficient estimate is multiplied by 100.

The most appropriate specification to test whether the linear AVEMS estimate is different from 1.0 is the model that includes AVEMS and the competitive advantage variables. For start-up ventures, the AVEMS estimate in Table 6 is .25. Because start-up ventures often face critical problems in the early years of commercialization, it is not surprising that the estimate is well below 1.0.

For mature businesses, the consumer goods AVEMS estimate in Table 7 is .85. This is significantly less than 1.0. The industrial goods estimate is .96, which is not statistically or economically different from 1.0. This indicates that a) the superior skills and resources of these Fortune 500 businesses are largely picked up by the intercept and the competitive advantage variables and b) the AVEMS measurement error is not large. Given these results, the assumption that the AVEMS impact equals 1.0 is reasonable for the industrial businesses and is not far off the mark for consumer businesses.

The pooled data also generate insights into differences between the start-up and mature business results. Recall the start-up venture linear AVEMS estimate is .25, which is far below 1.0. Also, the start-up venture pooled estimates for AVEMS squared and the entry * AVEMS interaction term are not even close to being significant.

How can these relatively weak results be explained? Recall the AVEMS measure for start-up ventures lumps 3 to 6 competitors in a single category. The mature business measure though distinguishes between 3, 4 or 5, and 6 to 10 competitors. Thus, one explanation is that greater random measurement error for AVEMS weakens the empirical results. Also, the start-up sample size is only 143, versus 593 consumer and 1287 industrial goods businesses. Hence, a second explanation is that the smaller sample size weakens the results. Can these 2 factors explain the relatively weak results?

While these problems can not be resolved for start-ups, they can be imposed on the mature businesses. This is done by lumping 3 and 4 or 5 competitors in a single category and estimating the models over various samples of size 150. This yields 8 industrial goods samples and 4 consumer goods samples. (The fourth consumer goods sample has 143 observations.)

Are these start-up data limitations responsible for the relatively small AVEMS estimate of .25? This seems unlikely. In the models with AVEMS and the competitive advantage variables, the 8 industrial goods estimates range from .84 to 1.13. (The results are not shown.) The 4 consumer goods estimates range from .62 to 1.05.

Are these start-up data limitations responsible for AVEMS squared not being statistically significant? In the full model specification, (with all 3 AVEMS variables and the competitive advantage variables) only 2 of the 8 industrial goods estimates are statistically significant at the 10% level or better. Only 1 of the 4 consumer goods estimates are significant. These results indicate that the start-up data can not effectively test the importance of AVEMS squared.

Are these start-up data limitations responsible for the entry interaction term not being statistically significant? Because the pooled model results are only significant for industrial goods and roughly 75% of the start-up sample are industrial entrants, the industrial results provide the best insights. In the full model specification, 6 of the 8 industrial goods estimates are statistically significant at the 12% level or better. (Only 1 of the 4 consumer goods estimates is statistically significant at the 10% level or better.) Given the robustness of the industrial results and a pooled start-up interaction estimate that virtually equals zero (-.01), it does not appear that recent entry is meaningful for start-up ventures.

Why does the entry interaction differ between start-up ventures and mature businesses? While the cause is not clear, it may relate to a difference in the entry definition. The start-up data entry measure requires an entrant to have the "potential" to achieve a 5% market share. Even when an entrant has this "potential", it may be too small in the first two years of commercialization to have a meaningful competitive impact. In contrast, the mature market measure requires a recent entrant to have already achieved a 5% market share. This is a more stringent test.

Summary and Conclusions

The competition based market share forecasting procedure described above is based on two key assumptions. First, in the absence of competitive advantages and disadvantages, each business in a market should have an average market share. This is the forecast's focal point. Second, competitive advantages and disadvantages are the primary forces that move a business away from the market share average.

Is this market share forecasting potentially useful? For established businesses in mature markets, forecasts based on AVEMS alone explain as much market share variation as forecasts based on all of the competitive advantage variables combined. The competitive advantage variables are relative product quality, relative product line breadth, relative marketing expenditures, relative price, and order of market entry. For start-up ventures, the competitive advantage variables tend to be more important than AVEMS alone. Still, in the start-up ventures' pooled data analysis, AVEMS has the highest level of statistical significance of any single model variable.

In forecasting, should the raw AVEMS value itself be adjusted up or down? To support this straightforward adjustment, the impact of AVEMS on market share should be linear with an estimated coefficient equal to 1.0. For start-up ventures, the estimation results support the linear functional form. Because the pooled regression coefficient is only .25, it is clear that AVEMS should be adjusted down for start-up ventures.

For the larger and richer mature businesses samples, there is some evidence of a nonlinear relationship that tails off in markets where AVEMS equals 33% or 50%. Theoretically, it is not clear why this relationship tails off. There is also evidence that the AVEMS impact increases in markets with recent entry. (This can arise because AVEMS classifies a recent entrant on par with an established business, even though it is generally not as challenging.) The entry interaction is economically significant in relatively high AVEMS markets, say 20 or higher. These 2 deviations from the simple linear specification though do not have an important impact on overall market share forecasting accuracy. This is because each variable is economically significant for less than 10% of each sample.

In contrast to start-up ventures, the linear AVEMS coefficient estimate in mature markets is typically close to 1.0. In industrial markets, the estimated coefficient is not significantly or economically different from 1.0. In consumer markets, the estimated coefficient is .85. Thus, an AVEMS adjustment is generally not necessary for mature industrial businesses in Fortune 500 firms. A modest adjustment may be appropriate for mature consumer goods.

Limitations

The start-up venture data suffer from clear measurement and sample size limitations. Because 3 to 6 competitors are lumped into one category, it lumps markets together whose AVEMS values range from 17% to 33%. Also, the sample size of 143 observations may not be large enough to effectively estimate the AVEMS squared relationship. Better data are needed to test the value of competition based forecasting for start-up ventures.

While the mature markets data have larger samples and a more accurate AVEMS measure, the sample is dominated by businesses based in Fortune 500 frims. Would similar results arise from a more heterogeneous sample?

Also, the mature market model provides forecasts that are conditional on competitive advantages and the market's AVEMS. Hence, any long-term forecast is conditional on independent variable values that must be forecasted 10 or 20 years down the road. While this process is based on a great deal of uncertainty, long-term customer based forecasting faces a similar problem. For example, how would a target customer respond when asked; what brand will you buy in 20 years?

Implications

When a long-term market share forecast is needed, the relative importance of AVEMS in mature markets suggests that managers should forecast net entry. Japanese managers may find these long-term results especially useful. This is because Japanese managers often have a longer time horizon and are more market share driven than U. S. managers. For example, see Fortune (1989).

Of course, competition based forecasting does not rule out using a customer based approach. Wind (1982) recommends, "The inclusion of at least two forecasting methods at each stage of the new product development process"(p. 460). With consistent forecasts, managerial confidence in the results increases.

Even with inconsistent forecasts, an amalgamated or an average forecast is often more accurate than any individual forecast. Kennedy (1985) says, "Research has indicated that the 'best' forecast is one formed as an average of a variety of forecasts, each generated by a completely different technique" (p. 207). Hence, a competition based forecasting procedure may provide a more useful complement to a customer based forecast than a second customer based forecast.

For example, to estimate purchase intentions for a new brand, the brand must be described to potential consumers. Consumers may be less likely to learn about a new brand in a crowded product category, such as breakfast cereals, toothpaste, or shampoos. Even when a consumer plans to try a new brand, it is more difficult to locate when the supermarket aisle is filled with many similar brands. Hence, purchase intentions may be biased upwards in markets with a relatively large number of brands. Competitive insights could reduce this potential bias.

Conclusions

Competition based market share forecasting is typically more effective for mature businesses than for start-up ventures. This is consistent with conventional wisdom that points to a greater emphasis on market share in mature markets. For example, Naert and Leeflang (1978) say, "When products are in the saturation phase of their life cycle - characterized by relative stability in product class sales - firms turn their attention to keeping or increasing their brand's market share" (p. 155).

Using competition as the forecast's focal point though breaks with conventional wisdom that emphasizes the customer. Because an average forecast that draws on different information sources is often more accurate than any individual forecast, competition based forecasting may provide an important complement to conventional customer based forecasting.

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