Lopo L. Rego, Neil A. Morgan, & Claes Fornell

Reexamining the Market Share–Customer Satisfaction Relationship

Market share and customer satisfaction are often used to assess marketing performance. Despite the widespread assumption of a positive relationship between these two variables, the limited extant empirical literature on the subject indicates either a negative or a nonsignificant relationship. The authors reexamine this relationship over a longer time period than has previously been possible in a representative sample of U.S. consumer markets and find a consistently significant negative market share–customer satisfaction relationship. This is because customer satisfaction is generally not predictive of firms' future market share, but market share is a strong negative predictor of firms' future customer satisfaction. In follow-up analyses, the authors find that a firm's customer satisfaction can predict its future market share when it is benchmarked against that of its nearest rival and customer switching costs are low. In examining why the market share–future customer satisfaction relationship is generally negative, they find strong support for preference heterogeneity as a key mediator in this relationship. They also show that marketing more brands moderates the negative effect of preference heterogeneity on future customer satisfaction. Thus, larger brand portfolios offer a strategy solution for the general market share–satisfaction trade-off.

Keywords: customer satisfaction, market share, marketing performance, empirical generalizations, brand portfolio

As performance outcomes that are intimately connected with the firm's marketing activities, market share and customer satisfaction are central constructs in marketing theory and practice. They are also often viewed as interrelated (e.g., Anderson, Fornell, and Lehman 1994): managers commonly believe that enhancing customer satisfaction is an appropriate strategy for improving market share (e.g., Morgan, Anderson, and Mittal 2005). For example, the widely cited "service–profit chain" logic suggests that improved customer satisfaction should lead to both enhanced retention of a firm's existing customers and positive reputation effects that will attract new customers; therefore, it should be positively related to the firm's future market share (e.g., Kamakura et al. 2002). However, the limited empirical evidence to date suggests that firms' market share and customer satisfaction either are unconnected or have a negative relationship (Anderson, Fornell, and Lehman 1994; Griffin and Hauser 1993). As a result, Fornell (1995) posits a nonpositive association between market share and customer satisfaction as an empirical generalization.

Here, we empirically reassess Fornell's (1995) proposition and answer three primary questions. First, what is the relationship between market share and customer satisfaction over time? It is important to examine a longer time series of data because time-varying effects can significantly influence any relationship involving firms and their market- and customer-level performance. Yet the few prior studies of this relationship had access to only one (Fornell 1995) or two (Anderson, Fornell, and Lehmann 1994) years of customer satisfaction data. Here, using American Customer Satisfaction Index (ACSI) data over a 13-year period, our analyses establish that market share and customer satisfaction have a significant and stable negative association over time. This strengthens Fornell's original nonpositive empirical generalization to negative and shows that although most managers assume that these two key aspects of marketing performance are positively related, under most conditions, this is not the case, and the reverse is true. This finding has important implications for firms' goal setting and performance measurement.

Second, what is the *nature* of the relationship between market share and customer satisfaction? Our analyses reveal that the overall negative association between these two variables is a result of a generally weak and insignificant impact of a firm's current customer satisfaction on its future market share as well as a strong and significant negative impact of a firm's current market share on its future customer satisfaction. We examine two factors that may influence the effect of current satisfaction on future market share: the firm's customer satisfaction relative to its nearest rival and customer switching costs. We find that a firm's customer satisfaction positively predicts its future market share when it is computed relative to that of its nearest rival *and* customer switching costs are low. This finding has important implications for firms' customer feedback system

Lopo L. Rego is Associate Professor of Marketing (e-mail: lrego@indiana.edu), and Neil A. Morgan is PetSmart Distinguished Professor of Marketing (e-mail: namorgan@indiana.edu), Kelley School of Business, Indiana University. Claes Fornell is Donald C. Cook Distinguished Professor (Emeritus) of Business Administration, Stephen M. Ross School of Business, University of Michigan (e-mail: cfornell@umich.edu). The authors gratefully acknowledge insightful comments and suggestions from seminar participants at Arizona State University, Cardiff University, Case Western Reserve University, Indiana University, and Purdue University. They also thank the National Quality Research Center at the University of Michigan for access to the American Customer Satisfaction Index database. Ajay Kohli served as area editor for this article.

ISSN: 0022-2429 (print), 1547-7185 (electronic)

design and identifies when it might be worthwhile for firms to invest in customer satisfaction improvement efforts.

Third, why is market share negatively related to firms' future customer satisfaction? We provide the first empirical examination of the predominant explanation posited for this relationship—that is, greater product/service preference heterogeneity, which is more difficult to satisfy in the customer base of larger market share firms. Our results strongly support this explanation for the negative market share–future customer satisfaction relationship observed in our sample. This finding provides important new insights into the existence of previously unidentified negative feedback effects in the service–profit chain and shows that strategies designed to build market share can have unintended negative consequences for firm performance. Building on this insight, we also suggest a strategy that could enable firms to efficiently deal with the negative effects of such high levels of preference heterogeneity: adoption of larger brand portfolios. We show that marketing a greater number of brands enables firms in our sample to mitigate the negative association between market share and customer satisfaction by reducing the strong negative impact of preference heterogeneity on future customer satisfaction.

Conceptual Framework and Hypotheses

Market share has long been a central issue in the economics, management, and marketing literatures as both a market(ing)-related performance dependent variable and a potential market-based asset driver of brand- and firm-level performance. However, there remains considerable debate surrounding the nature (spurious or real) and magnitude (relatively large or very small) of the relationship between market share and firm profitability (e.g., Ailawadi, Farris, and Parry 1999; Boulding and Staelin 1993; Jacobson 1988). Despite this controversy, researchers and managers still typically view market share as an important indicator of the effectiveness of firms' marketing efforts (e.g., Farris et al. 2006).

In contrast, whereas customer satisfaction has long been a central construct in the consumer behavior, marketing strategy, and theoretical and empirical modeling research streams in marketing, it has generally received much less attention in economics and management. In further contrast to market share, the large and increasing body of evidence linking customer satisfaction with suppliers' financial performance is much less controversial in terms of the nature and magnitude of the relationship (e.g., Luo, Homburg, and Wieseke 2010; Morgan and Rego 2006). Like market share, however, customer satisfaction is also widely used as a key marketing performance indicator (Luo and Homburg 2007).

Given the central importance of both market share and customer satisfaction in the marketing literature as well their widespread use as key performance indicators, the relationship between these two variables has received surprisingly little attention. Much of the marketing literature—along with most managers—adopts an implicit service–profit chain perspective and assumes that customer satisfaction is a driver of subsequent repurchase and recommendation behaviors and is thereby positively associated with a firm's future market share. Furthermore, brand-level researchers have noted that consumers of high-share packaged goods brands tend to purchase in greater amounts and with greater frequency and exhibit greater behavioral loyalty (e.g., Fader and Schmittlein 1993). To the extent that postpurchase attitudes such as satisfaction translate into observed future repeat purchase behaviors, this would also suggest that current-period customer satisfaction should have a positive association with a firm's future market share.

However, the limited empirical evidence does not generally support a significant positive relationship between customer satisfaction and market share (Anderson, Fornell, and Lehmann 1994; Fornell 1995; Griffin and Hauser 1993). This led Fornell (1995) to propose a nonpositive relationship between the two variables as an empirical generalization. The supporting theoretical arguments proposed by Anderson, Fornell, and Lehmann (1994) and Fornell (1995) suggest that, ceteris paribus, a firm's market share reflects the heterogeneity of its customer base, with more heterogeneous needs being more difficult to satisfy. Fornell (1995) therefore posits that whereas customer satisfaction with a supplier is positively associated with customers' repurchase and recommendation behavior, these positive effects on a supplier firm's future market share are counterbalanced—and may even be overwhelmed—by the negative impact of greater heterogeneity in the firm's customer base, which reduces the firm's ability to satisfy its customers' increasingly diverse needs and requirements in the future. Thus, the literature suggests the following:

> H_1: (a) A firm's current period customer satisfaction is positively associated with its future market share, but (b) a firm's current-period market share is negatively associated with its future customer satisfaction.

What Factors May Affect the Customer Satisfaction–Market Share Relationship?

Because the literature has typically assumed a positive relationship between a firm's current-period customer satisfaction and its future market share, attention to factors that may affect the existence or strength of this relationship has been sparse. However, the literature has broadly supported the intuition that the satisfaction of a firm's customers may be more strongly related to the firm's future market share when it is benchmarked against the satisfaction delivered by alternative suppliers rather than calibrated as an absolute value. For example, Mittal and Kamakura (2001, p. 134) find that evaluating customers' "true" satisfaction ratings (i.e., those that will affect their actual repurchase behaviors) requires the value of customers' next-best alternative, which is "based on not only the satisfaction from the brand but also the expected satisfaction from competing brands."

Here, we propose that a firm's nearest rival—the rival that targets the most similar customers and positions its product/service most similarly in terms of quality and price—is the closest alternative supplier to (or from) which customers may switch. Benchmarking the firm's customer satisfaction against that of its nearest rival therefore provides information regarding the relative attractiveness to customers of both suppliers (e.g., Mittal and Kamakura 2001; Ping 1993). This should be a better indicator of the motivation for customers to switch from one firm to the other than the absolute value of satisfaction provided by a single firm (e.g., Fornell 1992). Thus, information that Firm A delivers a low level of satisfaction to its customers may not be sufficient to infer probable customer switching motivation, because it ignores the satisfaction available from the nearest alternative supplier. For example, if Firm A's nearest rival (Firm B) delivers even lower satisfaction to its customers than Firm A, ceteris paribus, the likelihood of Firm A's customers switching to Firm B is low because they have no expectation of finding greater satisfaction by doing so (e.g., Colgate et al. 2007). Thus, we propose the following:

> H_2: A firm's current-period customer satisfaction is more strongly positively associated with its future market share when it is benchmarked as relative to the firm's nearest rival.

As we have argued, benchmarking a firm's customer satisfaction against that of its nearest rival provides insight into customers' motivation to switch suppliers. However, the literature also suggests that customers may vary in the extent to which they are willing or able to switch suppliers, even when they are motivated to do so, due to the presence of switching costs—that is, the perceived costs a firm's customers associate with switching to an alternative supplier (e.g., Mittal and Kamakura 2001; Roos, Edvardsson, and Gustafsson 2004). These may range from simple time, effort, and psychological costs involved in finding and acquiring substitute products/services from a rival supplier (e.g., Burnham, Frels, and Mahajan 2003) to the monetary costs of losing existing loyalty rewards and discounts or breaking service contracts with an existing supplier (e.g., Fornell 1992). To the extent that switching costs for a firm's customers are positive, these costs will likely offset any satisfaction benefits that customers may anticipate from switching suppliers. Thus, if Firm B delivers a higher level of satisfaction to its customers than Firm A, it is likely to gain fewer additional customers from Firm A when switching costs for Firm A's customers are high. This leads us to propose the following:

> H_3: The positive effect of a firm's current-period relative customer satisfaction on its future market share is weakened by the presence of customer switching costs.

Why Might Market Share Negatively Affect Customer Satisfaction?

The main explanation scholars have proposed for the possible negative effect of a firm's market share on its future customer satisfaction highlights the mediating role of the level of preference heterogeneity evident in a firm's customer base. Preference heterogeneity pertains to differences among individual customers in how they respond to firms' products and service offerings and associated marketing programs (e.g., Horsky, Misra, and Nelson 2006). The literature has suggested that a firm's market share reflects the number of customers in its customer base and that, ceteris paribus, the greater the number of customers a firm has, the greater the heterogeneity in customer product/service needs and wants the firm consequently faces (Anderson, Fornell, and Lehmann 1994; Hauser, Simester, and Wernerfelt 1994). All else being equal, it is more difficult for a firm to effectively and efficiently satisfy customers who exhibit more heterogeneous product and service preferences (e.g., Griffin and Hauser 1993). Thus, it is likely to be more difficult for larger market share firms to satisfy customers because they face greater preference heterogeneity, which reduces their ability to satisfy customer needs (e.g., Fornell 1995; Griffin and Hauser 1993). This suggests the following:

> H_4: The negative relationship between a firm's current-period market share and the firm's future customer satisfaction is mediated by preference heterogeneity in the firm's customer base.

A Possible Strategy Solution for the Market Share–Customer Satisfaction Trade-Off?

Given the centrality of market share and customer satisfaction in marketing theory and given managers' desire to perform well on both criteria, it is important to identify strategies that may enable firms to accomplish this. The theoretical arguments for H_4 suggest that strategies that reduce the negative satisfaction impact of the greater preference heterogeneity associated with larger market shares are those that are most likely to help firms achieve high levels of both market share and customers' satisfaction. A way to accomplish this is to market a greater number of brands (Aaker 2004). By marketing different brands—each designed to appeal to groups of customers with similar needs and preferences—firms can address varying customer needs and requirements (e.g., Kekre and Srinivasan 1990; Morgan and Rego 2009). Thus, facing a given level of preference heterogeneity associated with its market share, a firm offering more brands is more likely to enable customers to find an offering in the firm's brand portfolio that will be closer to their ideal individual requirements. This should diminish the negative effect of preference heterogeneity on customer satisfaction. Therefore,

> H_5: The mediating role of preference heterogeneity in the market share–future customer satisfaction relationship is moderated by the number of brands marketed by the firm.

Data

The National Quality Research Center at the University of Michigan's Ross School of Business supplied our primary data set, which consists of ACSI data for approximately 200 companies for the period 1994–2006. The ACSI is designed to be representative of the U.S. consumer economy, sampling industries that collectively represent more than 42% of U.S. gross domestic product. The ACSI collects satisfaction data from a national probability sample of consumers of the products and services of the largest firms within each industry that are responsible for more than 70% of total industry sales (for details, see Fornell et al. 1996). More than 800,000 customers were surveyed between 1994 and 2006. The ACSI customer satisfaction score is a latent variable computed annually for each of the 200+ firms in the database (see Fornell et al. 1996) and has been widely used in marketing strategy research. Within our sample, the mean customer satisfaction rating is 77.37 (on a 100-point scale), with a standard deviation of 6.48 and a range between 52.64 and 90.17.

Because unit sales data are not available for most firms, we drew on data from multiple sources to compute market share as the firm's U.S. and ACSI industry-adjusted sales revenue as a percentage of total ACSI industry sales in the United States. Appendix A details the procedure involved in computing market share and data sources. As Table 1 shows, the market shares computed for the firms in our data set ranged from less than 2.1% to 58.9%, with a mean market share of approximately 11.2%. We assessed external validity for our market share measure by comparing our metric with the market share figures provided by *Market Share Reporter* (e.g., Lazich 2006) for the subset of firm-year observations common in both data sets (approximately 15% of our sample). The overall correlation between the two market share measures was .89.

We compute relative satisfaction by benchmarking each firm's customer satisfaction against that of its nearest rival for each firm in our data set in a two-stage process detailed in Appendix A. First, we identified each firm's nearest rival each year using the approach developed by Morgan and Rego (2009). Second, we created a relative satisfaction measure for each firm-year by subtracting the nearest rival ACSI satisfaction score from that of the local firm.

Switching costs are the perceived costs a firm's customers associate with moving to an alternative supplier. The literature has suggested that switching costs are observable when customers exhibit loyalty that cannot be explained by the satisfaction delivered to them by firms' product and service offerings (e.g., Fornell 1992). As described in Appendix A, we therefore measure switching costs as the "unexplained loyalty" exhibited by the firm's customers. Because there are no publicly available direct measures of preference heterogeneity, we use individual consumer-level ACSI data to construct an indirect proxy measure (see Appendix A) that captures diversity in the "ideal" points of each firm's customer base.[1] Appendix B presents four nomological validity assessments that lend strong support to our measures of both switching costs and preference heterogeneity.

Finally, we collected information regarding the number of brands marketed by each firm in our sample from annual 10-K/10-Q filings, supplemented by the Hoovers.com database. To ensure comparability with the rest of our data set, we collected data on only the brands owned by each firm that are marketed in the United States in the specific industry(ies) for which the ACSI collects data from the firm's customers.

We also collected additional firm-level information to obtain a range of control variables for our analyses (see Appendix A). To control for any economies-of-scope effects, we collected information on the number of business segments served from the Hoovers.com database. To control for economies-of-scale effects and firm-level heterogeneity, we used Compustat data on firm size (book value of assets), selling and general administration (SGA) expenses-to-sales revenue ratio, advertising-to-sales revenue ratio, and research and development (R&D)-to-sales revenue ratio. We also collected data on each firm's return on assets (ROA) to control for any possible effect of firms' prior performance. Finally, to control for differences between industries, we computed market growth rates and industry concentration (Herfindahl–Hirschman Index [HHI]) using Compustat data.

Tables 1 and 2 present descriptive statistics and correlations for each of the variables in our data set. After eliminating utilities (e.g., electricity, gas, water), which are typically local monopolies, and deleting firms for which less than three years of data were available, the number of firm-year observations in our data set was 792, covering 104 firms operating in 23 industries (see Appendix C).

Table 3 contains the contemporaneous and one-year lagged bivariate correlations between market share and customer satisfaction and offers preliminary insights into the existence and nature of the association between the two

[1]Although switching costs and preference heterogeneity are often conceptualized as industry- or category-level phenomena, in this study, we adopt a firm-level perspective.

TABLE 1
Summary Statistics (N = 792)

Variable	M	SD	SE	Min	Med	Max
Customer satisfaction	77.37	6.48	.24	52.64	78.81	90.17
Rival customer satisfaction	77.39	6.45	.22	52.64	78.32	90.30
Relative customer satisfaction	–.02	4.00	.16	–15.15	.00	14.24
Market share	11.21%	12.55%	.47%	2.11%	7.42%	58.90%
ROA	5.74%	5.90%	.21%	–38.12%	5.82%	24.37%
Firm size (total assets)	62,502	153,849	5,467	347	12,667	1,459,737
SGA-to-sales	18.95%	12.03%	.43%	.00%	20.49%	45.70%
Advertising-to-sales	3.22%	3.88%	.14%	.00%	1.96%	21.56%
R&D-to-sales	1.00%	1.74%	.06%	.00%	.00%	12.15%
Number of segments	5.36	7.57	.27	1.00	2.00	64.00
Number of brands	16.35	20.29	.72	1.00	8.00	79.00
Market concentration (HHI)	.19	.14	.00	.07	.16	.60
Market growth rate	6.62%	9.49%	.34%	–25.30%	5.66%	61.49%
Switching costs	.00	3.42	.12	–9.29	.04	11.39
Preference heterogeneity	1.00	.07	.00	.72	1.00	1.23

Notes: This table presents descriptive statistics for all variables included in our sample and used in all reported empirical analyses. All variables are defined in Appendix A.

TABLE 2
Correlations (N = 792)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Customer satisfaction	1														
2. Rival customer Satisfaction	.806	1													
3. Relative satisfaction	–.213	.296	1												
4. Market share	–.333	–.263	–.025	1											
5. ROA	.272	.241	–.009	–.137	1										
6. Firm size (total assets)	–.029	.137	.152	.284	–.259	1									
7. SGA-to-sales	.172	.342	.084	–.290	.259	–.049	1								
8. Advertising-to-sales	.336	.286	–.069	–.305	.439	–.311	.475	1							
9. R&D-to-sales	.395	.461	.104	–.143	.128	.309	.165	.200	1						
10. Number of segments	.498	.564	–.014	–.328	.147	–.001	.388	.262	.169	1					
11. Number of brands	.588	.564	.006	–.088	.389	–.113	.355	.446	.270	.476	1				
12. Market concentration (HHI)	–.131	–.146	–.098	.490	.036	.025	–.037	.022	.098	–.233	–.100	1			
13. Market growth	–.118	–.123	–.054	.104	–.031	.112	–.071	–.130	–.041	–.078	–.125	.041	1		
14. Switching costs	.006	.028	.087	.049	.091	.019	–.147	–.026	.028	–.025	.025	.002	.016	1	
15. Preference heterogeneity	–.158	.018	.355	.125	–.034	.208	.016	–.013	.122	–.088	.007	.063	–.088	–.077	1

Notes: Each cell in this table contains the correlation coefficients for all variables included in our sample (as defined in Appendix A). Correlation coefficients greater than |.088| are significant at the $p < .01$ level, while those greater than |.069| are significant at the $p < .05$ level.

TABLE 3
Customer Satisfaction–Market Share Correlations by Year

Year (t)	Observations	Market Share$_{(t)}$ Satisfaction$_{(t+1)}$	Market Share$_{(t)}$ Satisfaction$_{(t)}$	Satisfaction$_{(t)}$ Market Share$_{(t+1)}$
1994	64	–.348	–.388	–.387
1995	65	–.376	–.363	–.383
1996	66	–.323	–.364	–.373
1997	66	–.346	–.311	–.343
1998	49	–.178	–.213	–.118
1999	68	–.406	–.300	–.322
2000	68	–.288	–.376	–.374
2001	68	–.344	–.276	–.302
2002	49	–.193	–.160	–.169
2003	64	–.359	–.332	–.373
2004	56	–.349	–.319	–.401
2005	59	–.429	–.419	–.422
2006	50	—	–.462	–.415
Overall	792	–.332	–.333	–.341

Notes: This table summarizes one-period lagged and contemporaneous correlations between customer satisfaction and market share by year. All correlations are significant at the $p < .05$ level.

variables. These correlations indicate the existence of a negative association between them—both contemporaneously and with market share lagging customer satisfaction one year and vice versa—with an overall correlation ranging between –.332 and –.341.[2] This correlation is also remarkably stable, with annual coefficients ranging between –.160 and –.462 for the 13 years in our data set.

Hypothesis-Testing Approach

To test our hypotheses, we use dynamic panel generalized method of moments (GMM) estimation (Arellano and Bover 1995; Blundell and Bond 1998). This approach deals with common estimation issues in our data set, particularly "small T, large N" panels (i.e., relatively few time periods and many firms), dynamic dependent variables (i.e., share and satisfaction are somewhat "persistent" and dependent on prior-period observations), endogeneity (i.e., regressors that are correlated with prior- and possibly current-period errors), fixed-level firm effects, and heteroskedasticity and serial correlation within but not across firms (Roodman 2009). Dynamic GMM uses the generalized method of moments, empirically generates sample moments from the data, requires no distributional assumptions, and is most useful when the error term and regressor distributions are not independent and instrument variables are needed to produce efficient and unbiased estimators (Baum, Schaffer, and Stillman 2003).

For ease of exposition, we begin by summarizing a levels-levels model specification of H_1 in Equations 1a and 1b (Anderson, Fornell, and Rust 1997; Tuli, Bharadwaj, and Kohli 2010) that models the level of customer satisfaction and market share as dependent variables. We control for observable heterogeneity by including known predictors and likely influencers of the customer satisfaction–market share association in our model formulations.

$$\text{(1a)}\quad \text{Market share}_{i(t+1)} = \alpha_0 + \alpha_1\text{Satisfaction}_{i(t)} + \alpha_2\text{Market share}_{i(t)} + \alpha_3\text{ROA}_{i(t)} + \alpha_4\text{Firm size}_{i(t)} + \alpha_5\text{SGA/sales}_{i(t)} + \alpha_6\text{Adv/sales}_{i(t)} + \alpha_7\text{R\&D/sales}_{i(t)} + \alpha_8\text{Segments}_{i(t)} + \alpha_9\text{HHI}_{i(t)} + \alpha_{10}\text{Market growth}_{i(t)} + \text{Year}_{(t+1)} + \eta_i + \varepsilon_{i(t+1)},$$

$$\text{(1b)}\quad \text{Satisfaction}_{i(t+1)} = \beta_0 + \beta_1\text{Market share}_{i(t)} + \beta_2\text{Satisfaction}_{i(t)} + \beta_3\text{ROA}_{i(t)} + \beta_4\text{Firm size}_{i(t)} + \beta_5\text{SGA/sales}_{i(t)} + \beta_6\text{Adv/sales}_{i(t)} + \beta_7\text{R\&D/sales}_{i(t)} + \beta_8\text{Segments}_{i(t)} + \beta_9\text{HHI}_{i(t)} + \beta_{10}\text{Market growth}_{i(t)} + \text{Year}_{(t+1)} + \varphi_i + \zeta_{i(t+1)},$$

where i stands for firm and t for time (year), $\text{Year}_{(t+1)}$ represents a set of mutually exclusive year dummies, η_i and φ_i are time-invariant unobservable firm-fixed effects (e.g., supplier relationships), and $\varepsilon_{i(t+1)}$ and $\zeta_{i(t+1)}$ are random errors representing all unobserved influences on future market share and customer satisfaction, respectively.

Although the inclusion of year dummies combined with a time-invariant error component partially alleviates some heteroskedasticity and unobservable effects estimation concerns, it does not fully resolve these issues, nor does it address all possible sources of endogeneity (Mizik and Jacobson 2004; Tuli, Bharadwaj, and Kohli 2010). Dynamic panel GMM resolves these concerns by first-differencing (thereby eliminating firm-specific fixed effects) and by using two-period or earlier lagged values of all regressors as instrument variables (IVs), thereby alleviating simultaneity and dynamic endogeneity. Thus, we also assess H_1 through a changes-changes model specification, as summa-

[2]To explore possible nonlinearity in this relationship, we tried exponential, logarithmic, polynomial, and power estimations for the association between the two constructs and found no statistical evidence of nonlinearity.

rized in Equations 2a and 2b (Arellano and Bond 1991; Roodman 2009).

$$
\begin{aligned}
\text{(2a) } \Delta\text{Market share}_{i(t+1)} = {} & \alpha_1 \Delta\text{Satisfaction}_{i(t)} \\
& + \alpha_2 \Delta\text{Market share}_{i(t)} + \alpha_3 \Delta\text{ROA}_{i(t)} \\
& + \alpha_4 \Delta\text{Firm size}_{i(t)} + \alpha_5 \Delta\text{SGA/sales}_{i(t)} \\
& + \alpha_6 \Delta\text{Adv/sales}_{i(t)} + \alpha_7 \Delta\text{R\&D/sales}_{i(t)} \\
& + \alpha_8 \Delta\text{Segments}_{i(t)} + \alpha_9 \Delta\text{HHI}_{i(t)} \\
& + \alpha_{10} \Delta\text{Market growth}_{i(t)} \\
& + \Delta\varepsilon_{i(t+1)}, \text{ and}
\end{aligned}
$$

$$
\begin{aligned}
\text{(2b) } \Delta\text{Satisfaction}_{i(t+1)} = {} & \beta_1 \Delta\text{Market share}_{i(t)} \\
& + \beta_2 \Delta\text{Satisfaction}_{i(t)} + \beta_3 \Delta\text{ROA}_{i(t)} \\
& + \beta_4 \Delta\text{Firm size}_{i(t)} + \beta_5 \Delta\text{SGA/sales}_{i(t)} \\
& + \beta_6 \Delta\text{Adv/sales}_{i(t)} + \beta_7 \Delta\text{R\&D/sales}_{i(t)} \\
& + \beta_8 \Delta\text{Segments}_{i(t)} + \beta_9 \Delta\text{HHI}_{i(t)} \\
& + \beta_{10} \Delta\text{Market growth}_{i(t)} + \Delta\zeta_{i(t+1)}.
\end{aligned}
$$

Despite the broad applicability and statistical efficiency of dynamic panel GMM, research has also identified a few weaknesses. These weaknesses involve the inherent decrease in statistical power associated with first-differencing (Levine, Loayza, and Beck 2000), the validity of the instrumentation procedure for the first-differences equations (Arellano and Bover 1995), and the possibility for magnification of gaps in unbalanced panel data sets (Roodman 2009). However, the impact of these shortcomings can be minimized by jointly estimating levels-levels and changes-changes formulations (Arellano and Bover 1995; Blundell and Bond 1998). This enables researchers to obtain additional instruments and increases efficiency (e.g., Mizik and Jacobson 2004, Roodman 2009). Regressors in the changes-changes equation are instrumented using two-period (or earlier) lagged regressor levels, whereas regressors in the levels-levels equation are instrumented using their own lagged first-differences (Roodman 2009). This system of equations is usually referred to as "system GMM."

Several tests enable us to assess the method used as well as the validity of the results. The Wald chi-square statistic is an omnibus test that assesses whether the proposed model specification predicts market share and customer satisfaction. We also examine AR(1) and AR(2) statistics to test for serial correlation in the error terms. Dynamic panel GMM assumes that first-order serial correlation is present in the data but that second-order serial correlation is not present. Therefore, the null hypotheses (i.e., there is no k-order serial correlation) should be rejected for AR(1) and not rejected for AR(2). We also report the Hansen J-statistic, which jointly tests correct model specification and valid instrument overidentification restrictions. Valid instrumentation requires that the J-statistic be consistent in not rejecting the null hypothesis.[3] We also report the C-statistic (i.e., difference-in-Hansen test) as an additional robustness test of instrument validity for the changes-changes model specifications. We also verified that including year dummies improves model fit (Sarafidis, Yamagata, and Robertson 2006) and confirmed that all steady-state lagged dependent variable estimates are less than 1 in absolute value (Roodman 2009).[4]

Finally, we address remaining estimation concerns by testing spurious regression using the Maddala and Wu (1999) Fisher combination test (because our panel data set is slightly unbalanced), and we unequivocally reject the unit-root hypothesis for both market share and customer satisfaction. We also log-transform variables[5] with skewed distributions, Winsorize data at the 1% level to ensure that extreme observations do not drive our results (e.g., Tuli, Bharadwaj, and Kohli 2010), and estimate variance inflation statistics to confirm that multicollinearity does not unduly influence our estimates. We jointly estimate the proposed dynamic panel system GMM model specifications (i.e., we jointly estimate Equations 1a and 2a and then Equations 1b and 2b) and report standardized estimates (z-scores) to facilitate effect size comparison.

To assess H_2 and H_3, we then reestimate the levels-levels and changes-changes model specifications detailed previously but substitute "relative satisfaction" in place of absolute customer satisfaction (labeled "satisfaction") (M3C and M4C) and include the switching costs variable (M3D and M4D) along with the relative satisfaction × switching costs interaction (M3E and M4E). For comparative purposes, we also estimate models using absolute customer satisfaction in the presence of switching costs (M3A and M4A) and the satisfaction × switching costs interaction (M3B and M4B). To test H_2, we combine the parameter estimates and associated (co)variance matrices from M1A and M2A with those from models M3C and M4C into one parameter vector and simultaneous (co)variance matrix. Using seemingly unrelated estimation methods, we then test for cross-model parameter equality for the "absolute" versus "relative" customer satisfaction estimates in models M1A and M3C and models M2A and M4C (Greene 2005).

To test H_4, we follow Baron and Kenny's (1986) logic that if preference heterogeneity mediates the negative effect of current market share on future customer satisfaction, we should observe that (1) market share positively predicts preference heterogeneity, (2) preference heterogeneity negatively predicts future customer satisfaction, and (3) the direct effect of current market share on future customer satisfaction is weaker when the effect of preference heterogeneity is accounted for (i.e., the direct effect is "mediated away"). In assessing the presence of mediation and the statistical significance of our findings with bootstrapping, we follow Zhao, Lynch, and Chen's (2010) approach.

[3]Roodman (2009) cautions that a more conservative *p*-value should be used (e.g., $p > .25$) and also warns that this *p*-value should not equal 1, suggesting that it should be smaller than .90, as a general rule.

[4]As a final robustness check, we follow Bond (2002) and confirm that in our analysis, all main-effects estimates are such that the corresponding estimates for ordinary least squares > GMM > fixed effects.

[5]These variables include market share, customer satisfaction, firm size (assets), and the number of segments. Substantively, our hypothesis testing findings do not change as a result of these transformations.

To assess H_5, we conduct a moderated mediation test of the moderating effect of the number of brands marketed by the firm on the mediating role of preference heterogeneity on the negative relationship between market share and future customer satisfaction hypothesized in H_4. Drawing on Muller, Judd, and Yzerbyt (2005), the moderated mediation test requires simultaneous estimation of the following equations:

$$M = a_0 + a_1 \times X, \text{ and} \tag{3}$$

$$Y = b_0 + b_1 \times M + b_2 \times X + b_3 \times W + b_4 \times M \times W, \tag{4}$$

where M is the mediator variable (preference heterogeneity), W is the moderator variable (number of brands), X is the independent variable (current period market share), and Y is the dependent variable (future customer satisfaction). It can be demonstrated that the conditional indirect effect of X on Y, mediated by M and moderated by W, is given by $a_1 \times b_1 + a_1 \times b_4 \times W$ (Muller, Judd, and Yzerbyt 2005). Thus, for H_5 to hold, the conditional indirect effect of market share (X) on customer satisfaction (Y), estimated as $a_1 \times b_1 + a_1 \times b_4 \times$ number of brands (W), should be such that $a_1 \times b_1$ and $a_1 \times b_4$ are both positive and significant. Preacher, Rucker, and Hayes (2007) show that the distribution of the conditional indirect effect in this test is nonnormal and skewed, requiring bootstrap-estimated efficient standard errors and percentile-based confidence intervals to assess the statistical significance of the indirect conditional effects.

We follow this approach in testing H_5, estimating levels-levels and changes-changes model specifications for the moderation-mediation system of equations outlined previously. For consistency, we also include the same set of control variables in our equations as those used in our prior hypotheses tests. The statistical significance of the conditional indirect effect of market share on customer satisfaction reported is based on 5,000 bootstrap runs for each estimated model and uses percentile-based confidence intervals (Preacher, Rucker, and Hayes 2007).

Results

Table 4 summarizes the estimates obtained in testing H_1 for the levels-levels model specification (M1A) and changes-changes model specification (M2A). We also examine the possibility that the market share–customer satisfaction relationship may be characterized by longer lag structures and report estimates for model specifications including additional market share and customer satisfaction lags (M1B and M2B). All the instrument validity and identification tests reported in Table 4 support the use of system dynamic panel GMM to estimate the proposed models.

In the relationships of interest in H_1, the main-effects results in Table 4 indicate that in all four model specifications, firms' current-period market share is a significant negative predictor of the following year's customer satisfaction, with beta coefficients ranging from –.164 to –.486 (all p-values < .05). However, we also find in all four models that customer satisfaction is not a significant positive predictor of firms' future market share, with beta coefficients ranging from –.038 to .150 (all p-values > .10). Empirically, the overall negative relationship we observe between the two variables differs from Fornell's (1995) original nonpositive empirical generalization logic in that the negative effect of current market share on future satisfaction in our data is significantly stronger than the (insignificant) effect of current period satisfaction on future market share.[6]

We conducted sensitivity analyses to assess the robustness of our results. First, we performed more aggressive outlier influence tests by Winsorizing our data to the 2.5th and 5th percentiles. Our findings remain substantively unchanged. Second, we reestimated our models to include the contemporaneous association between satisfaction and market share; again, the substantive findings remain unchanged. Third, we also estimate alternative model specifications using a stock market–related measure of financial performance (Tobin's Q) in place of (and also in addition to) the accounting-based financial performance (ROA) used in our models and observed no substantive changes to our main-effects findings. Fourth, we also tested for—and found no supporting evidence of—alternative nonlinear model specifications. Overall, these analyses suggest that the Table 4 H_1 test results are robust and generalizable.

When compared with the equivalent models M1A and M2A (Table 4), our Table 5 H_2 testing results show that controlling for the presence of switching costs (models M3A and M4A) does not lead current-period satisfaction to positively predict future market share with insignificant beta coefficients of .037 and –.189 (both ps > .05), respectively. This remains true when we include the satisfaction × switching costs interaction term in M3B and M4B, with insignificant beta coefficients of .024 ($p > .05$) and –.062 ($p > .05$), respectively. These results also hold when we substitute relative satisfaction into the same equations, as shown in M3C and M4C, in which relative satisfaction does not significantly predict future market share ($\beta = .115$, $p > .05$, and $\beta = .029$, $p > .05$). They also hold when we include switching costs in the relative satisfaction models M3D ($\beta = .116$, $p > .50$) and M4D ($\beta = .030$, $p > .50$).

However, Table 5 also reveals that when we use the relative measure of customer satisfaction and include both the switching costs variable and its interaction with relative satisfaction (models M3E and M4E), the beta coefficient for relative satisfaction becomes positive and significant ($\beta = .126$, $p < .01$, and $\beta = .088$, $p < .05$), switching costs becomes positive and significant ($\beta = .062$, $p < .05$) in the levels-levels model but not in the changes-changes model ($\beta = .021$, $p > .05$), and the interaction term becomes negative and significant in both models ($\beta = –.091$, $p < .05$, and $\beta = –.055$, $p < .05$).[7] Chi-square tests indicate that the dif-

[6]This difference can be inferred from Table 4, which reports standardized estimates (z-scores) obtained using system GMM. We also tested the hypothesis that these two effects are identical in magnitude by imposing a constraint to our model. We found that the negative effect of current market share on future satisfaction is significantly stronger than the effect of current-period satisfaction on future market share ($p < .04$).

[7]As a follow-up analysis, we also examined two alternative "relative-to" satisfaction metrics (industry average and best in industry) and degree of competition (HHI) as an alternative or complement to switching costs, but we found no significant moderating effects for them either independently or in combination with our other moderator variables.

TABLE 4
The Customer Satisfaction–Market Share Relationship

A: Levels-Levels

	Market Share$_{(t+1)}$		Satisfaction$_{(t+1)}$	
Levels-Levels	**M1A**	**M1B**	**M1A**	**M1B**
Satisfaction$_{(t)}$	–.038	.013	.692***	.656***
Satisfaction$_{(t-1)}$		–.032		.266***
Market share$_{(t)}$	.954***	.618**	–.177**	–.164***
Market share$_{(t-1)}$		.533**		.105
ROA$_{(t)}$	.063**	.054*	.001	–.011
Firm size$_{(t)}$	.129**	.081	.010	.011
SGA-to-sales$_{(t)}$	–.023	–.016	–.039**	–.024
Advertising-to-sales$_{(t)}$	.016	.028	.046*	.027
R&D-to-sales$_{(t)}$	.021	.039	.051**	.022
Number of segments$_{(t)}$	–.016	.035	.073**	.043**
Concentration$_{(t)}$	–.100	–.012	.011	.023
Market growth$_{(t)}$	.032	.052**	–.023*	–.023
Model Details				
Observations	792	792	669	669
Parameters	23	25	23	25
Instruments	63	71	41	49
Wald χ^2	211.60***	269.03***	37.94***	102.41***
AR(1)	–2.42**	–2.24*	–4.35***	–4.41***
AR(2)	1.02	–.91	1.47	.92
Hansen J	124.83	129.45	119.02	133.08
Hansen C	26.38	21.32	23.91	18.52

B: Changes-Changes

	ΔMarket Share$_{(t+1)}$		ΔSatisfaction$_{(t+1)}$	
Changes-Changes	**M2A**	**M2B**	**M2A**	**M2B**
ΔSatisfaction$_{(t)}$	.056	.150	.183**	.219**
ΔSatisfaction$_{(t-1)}$		–.009		.166**
ΔMarket share$_{(t)}$	.360***	.434***	–.371**	–.486*
ΔMarket share$_{(t-1)}$		.065		.265
ΔROA$_{(t)}$	.072	–.029	.094	–.022
ΔFirm size$_{(t)}$	.428*	.053	–.237	–.004
ΔSGA-to-sales$_{(t)}$	.123	.189*	–.037	–.077
ΔAdvertising-to-sales$_{(t)}$	–.219	–.302*	.091	.149
ΔR&D-to-sales$_{(t)}$	.075	.078	.239	.372*
ΔNumber of segments$_{(t)}$	–.639*	–.716	.496	–.110
ΔConcentration$_{(t)}$	–.254***	–.091	.107	.268**
ΔMarket growth$_{(t)}$	–.036	–.036	.048	.094*
Model Details				
Observations	792	792	669	669
Parameters	21	23	21	23
Instruments	59	67	27	35
Wald χ^2	5.93***	3.49***	2.38***	4.59***
AR(1)	–2.01*	–2.31*	–3.64***	–3.15**
AR(2)	1.17	1.42	1.58	.76
Hansen J	112.93	119.56	120.93	107.69
Hansen C	23.20	22.57	14.97	16.21

*$p < .05$.
**$p < .01$.
***$p < .001$.

Notes: This table presents regressions of future market share and future customer satisfaction for levels-levels and changes-changes model specifications jointly estimated using system GMM. Models M1A and M1B are levels-levels specifications and models M2A and M2B represent changes-changes specifications. All estimates are standardized. All variables are defined in Appendix A. The focal explanatory variables are the one- and two-period lags of market share and customer satisfaction. Additional explanatory variables included are one-period lags of firm-specific ROA, firm size, SGA-to-sales, advertising-to-sales, R&D-to-sales, number of business segments, industry concentration, market growth, and year dummies. Two-period (or earlier) and up to five-period lags of market share and customer satisfaction are used as GMM-style instruments, while year dummies are used as IV-style instruments. Model fit is assessed through a Wald χ^2 statistic. We tested first- and second-order serial correlations with AR(1) and AR(2) test statistics, respectively. We assessed validity of instruments using Hansen J and difference-in-Hansen C statistics. Values with no asterisks are nonstatistically significant at $p \geq .05$.

TABLE 5
Satisfaction, Relative Satisfaction, and Switching Cost Predictors of Market Share

A: Market Share$_{(t+1)}$					
Levels-Levels	**M3A**	**M3B**	**M3C**	**M3D**	**M3E**
Satisfaction$_{(t)}$	.037	.024			
Relative satisfaction$_{(t)}$			.115	.116	.126**
Market share$_{(t)}$	.962***	.870***	.838***	.843***	.726***
Switching costs$_{(t)}$	–.034	.012		–.008	.062*
Switching costs$_{(t)}$ × satisfaction$_{(t)}$		.049			
Switching costs$_{(t)}$ × relative satisfaction$_{(t)}$					–.091*
ROA$_{(t)}$	–.006	–.016	–.068	–.065	–.066
Firm size$_{(t)}$	–.041	–.010	–.032	–.034	–.048
SGA-to-sales$_{(t)}$	–.123*	–.186**	–.227**	–.226*	–.224*
Advertising-to-sales$_{(t)}$	.075	.159	.127	.128	.103
R&D-to-sales$_{(t)}$	.058	.058	.111	.109	.117
Number of segments$_{(t)}$	–.066	–.067	–.101	–.101	–.093
Concentration$_{(t)}$	–.104	–.148	–.126*	–.128	–.109
Market growth$_{(t)}$	–.055	–.083	–.089	–.089	–.094
Model Details					
Observations	792	792	792	792	792
Parameters	24	25	23	25	25
Instruments	63	67	63	63	67
Wald χ^2	12.04***	8.49***	9.54***	9.34***	9.03***
AR(1)	–2.25*	–1.45	–1.61	–1.50	–1.56
AR(2)	.89	.75	–.34	–.26	–.42
Hansen J	121.93	126.77	128.02	131.39	132.93
Hansen C	10.76	14.02	13.37	16.36	16.67

B: ΔMarket Share$_{(t+1)}$					
Changes-Changes	**M4A**	**M4B**	**M4C**	**M4D**	**M4E**
ΔSatisfaction$_{(t)}$	–.189	–.062			
ΔRelative satisfaction$_{(t)}$			.029	.030	.088*
ΔMarket share$_{(t)}$	.424***	.104	.353***	.352***	.264**
ΔSwitching costs$_{(t)}$	.035	–.018		–.003	.021
Δ(Switching costs$_{(t)}$ × satisfaction$_{(t)}$)		.007			
Δ(Switching Costs$_{(t)}$ × relative satisfaction$_{(t)}$)					–.055*
ΔROA$_{(t)}$	.059	.067	.016	.016	.019
ΔFirm size$_{(t)}$	.059	.062	.251	.252	.258
ΔSGA-to-sales$_{(t)}$	–.029	–.040	.016	.015	.010
ΔAdvertising-to-sales$_{(t)}$	–.294	–.292	–.206	–.206	–.207
ΔR&D-to-sales$_{(t)}$	.083	.065	.082	.083	.083
ΔNumber of segments$_{(t)}$	.451	.529	–.173	–.179	–.182
ΔConcentration$_{(t)}$	–.291***	–.298***	–.305***	–.304***	–.306***
ΔMarket growth$_{(t)}$	–.080**	–.093**	–.043	–.043	–.046
Model Details					
Observations	792	792	792	792	792
Parameters	22	23	21	22	23
Instruments	59	63	59	59	63
Wald χ^2	4.33***	3.27***	9.88***	4.01***	4.01***
AR(1)	–1.56	–1.74	–.79	–.26	–.37
AR(2)	1.47	.53	–.21	–.09	.12
Hansen J	114.03	116.87	113.98	114.47	116.43
Hansen C	9.30	12.89	11.69	15.04	15.35

*$p < .05$.
**$p < .01$.
***$p < .001$.

Notes: This table presents regressions of future market share for levels-levels and changes-changes model specifications jointly estimated using system GMM. Models M3A, M3B, M3C, M3D, and M3E are levels-levels specifications, and models M4A, M4B, M4C, M4D, and M4E represent changes-changes specifications. All estimates are standardized. All variables are defined in Appendix A. The focal explanatory variables are one-period lags of market share, customer satisfaction (satisfaction), relative satisfaction, switching costs, the interaction between switching costs and satisfaction, and relative satisfaction. Additional explanatory variables included are one-period lags of firm-specific ROA, firm size, SGA-to-sales, advertising-to-sales, R&D-to-sales, number of business segments, industry concentration, market growth, and year dummies. Two-period (or earlier) and up to five-period lags of market share, customer satisfaction (satisfaction), and relative satisfaction are used as GMM-style instruments, while year dummies are used as IV-style instruments. We assessed model fit using a Wald χ^2. We verified first- and second-order serial correlations with AR(1) and AR(2) statistics and verified instruments with Hansen's J and C statistics. Values with no asterisks are nonstatistically significant at $p \geq .05$.

ference between "absolute" and "relative" satisfaction estimates ($.115^{n.s.}$ vs. $-.038^{n.s.}$) is statistically significant at $p < .05$ in the levels-levels models but not in the changes-changes models ($.029^{n.s.}$ vs. $.056^{n.s.}$). This finding provides partial support for H_2. However, when we add the H_3 switching costs moderator (M3A/M4A vs. M3D/M4D) and interaction terms (satisfaction × switching costs) into the models (M3B/4B vs. M3E/M4E), chi-square tests indicate that the magnitudes of the positive coefficients for "relative" satisfaction are all significantly greater than those for "absolute" satisfaction.

Overall, these results provide partial support for H_2 and strong support for H_3. We also confirmed the H_3 test result in a follow-up split-group analysis in which we found that relative satisfaction is a positive and significant predictor of future market share when switching costs are low ($\beta = .066$, $p < .01$, and $\beta = .087$, $p < .05$) but insignificant when switching costs are high ($\beta = -.021$, $p > .50$, and $\beta = .026$, $p > .50$). Collectively, these results all demonstrate that the presence of switching costs weakens the positive effect of a firm's relative satisfaction on its future market share but that both benchmarking satisfaction relative to the firm's nearest rival *and* the presence of switching costs are necessary conditions to link a firm's current period customer satisfaction positively with its future market share in our data set.

In testing H_4, as we show in Table 6, Panels A and B, model specifications M5A and M6A results are in line with Baron and Kenny's (1986) logic that (1) market share positively predicts preference heterogeneity, with coefficients of .075 ($p < .01$) and .065 ($p < .05$), respectively; (2) preference heterogeneity negatively predicts future customer satisfaction, with coefficients of $-.072$ ($p < .01$) and $-.051$ ($p < .05$), respectively; and (3) the direct effect of current market share on future customer satisfaction is weaker when the effect of preference heterogeneity is accounted for, with insignificant coefficients of $-.035$ ($p > .10$) and $-.037$ ($p > .10$). These results show that preference heterogeneity completely mediates the negative effect of firms' current-period market share on future customer satisfaction, which provides strong support for H_4.

The results of the moderated mediator test presented in models M5B and M6B provide additional support for H_4 because the direct effect of market share on customer satisfaction is nonsignificant in both models M5B ($-.026$, $p > .10$) and M6B ($-.036$, $p > .10$). Panels A and B in Table 6 also provide strong support for H_5 because the estimated conditional indirect effect of market share on customer satisfaction, mediated by preference heterogeneity and moderated by the number of brands, is consistently positive and significant. This finding is true both for the "mediated effect" of market share on customer satisfaction in the levels-levels M5B (.00173, $p < .001$) and changes-changes model M6B specifications (.00195, $p < .001$) and for the "moderated effect" in both models, which is estimated to become more positive as the number of brands in a firm's portfolio increases (.00345, $p < .01$, and .00256, $p < .05$).

Thus, the results reported for models M5A and M6A provide additional strong support for H_4, and the results for models M5B and M6B offer strong support for H_5. Overall, these results show that preference heterogeneity completely mediates the negative effect of current market share on future customer satisfaction but that this mediation effect is moderated by the number of brands marketed by the firm. This finding suggests that a practical strategy for dealing with the general market share–future customer satisfaction trade-off we document may be to adopt a brand portfolio strategy involving the marketing of a greater number of brands.

Implications for Theory and Practice

Our study provides the first comprehensive assessment of an important relationship between two key marketing performance–related variables previously proposed as an empirical generalization. We find support for Fornell's (1995) original proposed nonpositive market share–customer satisfaction relationship using a data set covering a much longer time period than has previously been available. Furthermore, we find robust empirical evidence to strengthen Fornell's (1995) original framing of this relationship from nonpositive to negative. In our sample, we show that as has been previously theorized, market share is a significant negative predictor of future customer satisfaction. However, ceteris paribus, we find no support under most conditions for the notion that customer satisfaction has a positive effect on future market share in our sample. Overall, our results establish (1) the generally negative nature of the association between market share and customer satisfaction and (2) that this negative association is the result of a strong negative effect of current market share on a firm's future ability to satisfy its customers, which is much greater than the generally insignificant effect of a firm's customer satisfaction on its future market share.

We also provide insights into two new factors that, together, significantly strengthen the customer satisfaction–future market share relationship: benchmarking the firm's customer satisfaction relative to that of its closest rival and accounting for the level of customer switching costs. This has two important implications. First, our finding with respect to the firm's customers' switching costs is important because it suggests that for firms trying to increase market share, enhancing customer satisfaction—even relative to that of rivals—may not always be an appropriate strategy. This finding contrasts with the prior literature in this domain that has implicitly adopted a classical theory perspective and failed to examine conditions under which a customer satisfaction improvement strategy may be more or less beneficial for a firm. Second, our findings suggest that managers should calibrate satisfaction improvement efforts relative to those of rivals if their goal is to increase market share. This has important implications for firms' customer feedback system designs, not least in terms of the need to sample competitors' customers as well as the firm's own customers in seeking customer satisfaction data.

Our study also contributes new insights into the causes of the negative market share–future customer satisfaction relationship. Importantly, our results provide strong support

TABLE 6
The Customer Satisfaction-Market Share Relationship Mediated by Preference Heterogeneity and Moderated by Number of Brands

A: Levels-Levels[a]

	Overall	Mediation		Moderated Mediation	
Levels-Levels	**Satisfaction$_{(t+1)}$ M1A**	**Heterogeneity$_{(t)}$ M5A**	**Satisfaction$_{(t+1)}$ M5A**	**Heterogeneity$_{(t)}$ M5B**	**Satisfaction$_{(t+1)}$ M5B**
Satisfaction$_{(t)}$	.692***		.864***		.858***
Market share$_{(t)}$	–.177**	.075**	–.035	.110***	–.026
Preference heterogeneity$_{(t)}$			–.072**		.016
Number of brands$_{(t)}$				.018	.070***
Preference heterogeneity$_{(t)}$ × number of brands$_{(t)}$					.031*
ROA$_{(t)}$	.001	–.015	.006	–.019	–.004
Firm size$_{(t)}$	.010	.184***	–.011	.188***	–.005
SGA-to-sales$_{(t)}$	–.039**	.044	–.035*	.040	–.037*
Advertising-to-sales$_{(t)}$	.046*	.047	.022	.041	.012
R&D-to-sales$_{(t)}$	.051**	.068	.029	.062	.026
Number of segments$_{(t)}$	.073**	–.107**	.057***	–.118**	.040**
Market concentration$_{(t)}$	.011	.002	.027*	.007	.032*
Market growth rate$_{(t)}$	–.023*	–.118***	–.010	–.117***	–.010
Conditional indirect effect of market share$_{(t)}$ on customer satisfaction$_{(t+1)}$ mediated by preference heterogeneity$_{(t)}$ and moderated by number of brands$_{(t)}$				.00173*** + .00345** × Brands$_{(t)}$	

B: Changes-Changes[b]

	Overall	Mediation		Moderated-Mediation	
Changes-Changes	**ΔSatisfaction$_{(t+1)}$ M2A**	**ΔHeterogeneity$_{(t)}$ M6A**	**ΔSatisfaction$_{(t+1)}$ M6A**	**ΔHeterogeneity$_{(t)}$ M6B**	**ΔSatisfaction$_{(t+1)}$ M6B**
ΔSatisfaction$_{(t)}$	.183**		.403***		.373***
ΔMarket share$_{(t)}$	–.371**	.065*	–.037	.095***	–.036
ΔPreference heterogeneity$_{(t)}$			–.051*		.021
ΔNumber of brands$_{(t)}$				.026	.057***
Δ(Preference heterogeneity$_{(t)}$ × number of brands$_{(t)}$)					.027*
ΔROA$_{(t)}$	.094	.032	.012	.037	.017
ΔFirm size$_{(t)}$	–.237	–.218*	–.039	–.177**	–.036
ΔSGA-to-sales$_{(t)}$	–.037	–.081	–.038	–.099	–.037
ΔAdvertising-to-sales$_{(t)}$	.091	.056	–.062	.068	–.064
ΔR&D-to-sales$_{(t)}$	.239	.003	.069	.006	.068
ΔNumber of segments$_{(t)}$	.496	–.111*	.042*	–.104**	.039*
ΔMarket concentration$_{(t)}$	.107	–.043	.041	–.068	.044
ΔMarket growth rate$_{(t)}$	.048	.062	–.022	.046***	–.023
Conditional indirect effect of ΔMarket share$_{(t)}$ on ΔCustomer satisfaction$_{(t+1)}$ mediated by ΔPreference heterogeneity$_{(t)}$ and moderated by ΔNumber of brands$_{(t)}$				.00195*** + .00256* × ΔBrands$_{(t)}$	

*$p < .05$.
**$p < .01$.
***$p < .001$.
[a]Panel A presents mediated-moderation regressions of future customer satisfaction on current preference heterogeneity and number of brands for levels-levels model specifications jointly estimated (with changes-changes) using system GMM.
[b]Panel B presents mediated-moderation regressions of future customer satisfaction on current preference heterogeneity and number of brands for changes-changes model specifications jointly estimated (with levels-levels) using system GMM.
Notes: All estimates are standardized. All variables are defined in Appendix A. The focal explanatory variables are one-period lags of market share, customer satisfaction, preference heterogeneity, number of brands, and the interaction between preference heterogeneity and number of brands. Additional explanatory variables include one-period lags of firm-specific ROA, firm size, SGA-to-sales, advertising-to-sales, R&D-to-sales, number of business segments, industry-specific concentration, market growth, and year dummies. Two-period (or earlier) and up to five-period lags of market share and customer satisfaction are used as GMM-style instruments, while year dummies are used as IV-style instruments. We verified model fit, system GMM assumptions, and instrument validity but do not report these results in this table. We estimated the conditional effect of current market share on future customer satisfaction as proposed by Muller, Judd, and Yzerbyt (2005). We estimated moderated-mediated effects standard errors through bootstrapping (5,000 runs) as detailed in Zhao, Lynch, and Chen (2010) and Preacher, Rucker, and Hayes (2007). Values with no asterisks are nonstatistically significant at $p \geq .05$.

for preference heterogeneity as a key explanation for the observed negative market share–customer satisfaction relationship in our sample. This finding is theoretically important because understanding the causes of empirical generalizations is a central task in knowledge development within any discipline. In addition, such causal understanding provides (1) a stronger platform for the identification and exploration of the most likely boundary conditions to an empirical generalization and (2) a foundation for searching for strategy solutions when—as in this case—the empirical regularity observed involves a trade-off that is problematic for managers.

This research also provides several important new insights for managers. First, we show that firms aiming to enhance market share and customer satisfaction simultaneously will generally have a more difficult time than those that try to maximize only one of these objectives. The knowledge that such trade-offs generally exist is not trivial, particularly when many firms are installing "marketing dashboards" that frequently monitor both customer satisfaction and market share as key marketing metrics. Managers often assume that different dimensions of marketing performance are generally positively correlated, and yet our results show that this is not the case for market share and customer satisfaction. Managers must be aware of this probable trade-off when designing marketing strategies and programs and when drawing inferences about their success and failure using market share and customer satisfaction as metrics.

Second, we provide new insights into key linkages posited in the widely used service–profit chain framework. Our results show that such simple causal theories positively linking customer satisfaction with future market share omit key boundary conditions that may have a significant impact on whether and how managers should act. In addition, the service–profit chain framework misses an important and countervailing negative feedback effect. Failure to account for such feedback effects may lead managers to design marketing programs that have unintended and unexpected negative consequences for the firm. For example, in contrast to the service–profit chain logic, our results indicate that focusing on enhancing customer satisfaction may not be an appropriate strategy for increasing market share, depending on the customer satisfaction of the firm's rivals and the switching costs faced by the firm's customers. Likewise, strategies designed to increase the firm's market share may have unintended negative consequences for customer satisfaction unless managers are able to manage the resulting increase in customer heterogeneity through the use of larger brand portfolios or some other (yet-to-be-discovered) mechanism.

Third, we reveal that when aiming to increase market share, managers should adopt relative-to-rival customer satisfaction metrics. This finding has important customer feedback system design and budget implications. Notably, it suggests that managers must competitively benchmark their customers' satisfaction, which may necessitate collecting satisfaction data from rivals' customers in addition to those of the firm. This is not a trivial task given that customer feedback research already consumes the largest proportion of most firms' market research budgets and that data collection costs are the single most-expensive line item of customer feedback system costs. Yet our results show that such additional data collection costs may be worthwhile if they enable managers to better pinpoint the likely impact of customer satisfaction improvement initiatives and therefore better allocate scarce marketing resources.

Limitations and Further Research

Several limitations of our study must be considered when assessing our results. First, although we use a sample of U.S. firms operating in consumer markets that is designed to be representative of the majority of the U.S. consumer economy, this is, by definition, biased toward larger, publicly traded firms. We also have no data covering firms operating in either non-U.S. consumer markets or business-to-business markets. In addition, we have no data relating to markets in which alternative explanations for some of the relationships we observe in our study may also be salient. For example, in categories such as luxury goods, another reason market share may be negatively related to future customer satisfaction is that perceptions of exclusivity are reduced (e.g., Hellofs and Jacobson 1999).

Second, we do not have direct measures of the preference heterogeneity variable that we examine as the key cause of the negative market share–future customer satisfaction relationship. Although our validity checks (Appendix B) provide some evidence that our proxy indicator captures the underlying variable, direct measures would be preferable.

Third, consistent with other studies using ACSI data, our analyses are at the firm level, and we do not have brand-level market share or customer satisfaction data to assess whether our results hold at the brand level. A follow-up subgroup analysis comparing corporate (single-brand) firms with multibrand firms suggests that we should expect the negative market share–customer satisfaction relationship to hold at the brand level. However, we do not have the brand-level data to assess this empirically for firms marketing more than one brand.

Beyond the need to address these limitations, our study also raises several important new questions for further research. First, we establish a robust and generalizable negative impact of a firm's market share on future customer satisfaction. However, depending on market size, intuition suggests that this effect may be weaker at low levels of market share. For example, in a post hoc analysis (Appendix D), we split our data into market share quintiles and reestimated our H_1 changes-changes model. The results show that the effect of market share on future customer satisfaction is insignificant in the lowest two market share–level quintiles (in which market shares range from 2.1% to 6.7%), becomes strongly negative at average and above-average levels of market share (market shares ranging from 6.7% to 13.4%), and weakens in the highest market share quintile. In combination with our hypothesis testing results, these findings raise several important research questions. For example, are there threshold effects on effect of market share on customer satisfaction? What drives any threshold levels, and are the levels and their drivers different in different industries?

Second, we uncover new factors that significantly affect the customer satisfaction–future market share relationship. However, we do not have the data to conduct an extensive exploration of possible moderators of this relationship. Having begun to establish factors that strengthen or weaken customer satisfaction's role in driving market share, we believe it is worthwhile for further research to examine additional potential moderators of this important marketing relationship. For example, is it possible that the costs of delivering higher levels of customer satisfaction lead firms to raise prices, which in turn dampens customer demand and offsets any positive share gain benefits? If so, is customer price sensitivity an additional boundary condition?

Third, our analyses indicate the importance of managing heterogeneous customer preferences in explaining firms' ability to enhance their market share and highlight larger brand portfolios as a way to deal with such preference heterogeneity. However, our "number of brands" measure provides a somewhat coarse picture. Further research exploring more detailed aspects of how a firm's brand portfolio strategy affects its ability to manage preference heterogeneity is required. For example, our results suggest that larger brand portfolios may benefit firms even more, to the extent that firms can position each brand as having different features that appeal to different segments in their customer base. Is this the case? Likewise, the impact of different brand portfolio architectures may also be important. For example, how effective and efficient are subbrands versus completely different brand names in managing customer preference heterogeneity? Does a well-known or prominently displayed corporate parent name diminish the effectiveness of larger brand portfolios in delivering satisfaction to diverse sets of customers? These theoretically and managerially significant questions are worthwhile avenues for further research.

Fourth, there is an increasing body of evidence linking customer satisfaction with stock market performance, but evidence regarding the level and significance of the performance benefits of market share is far from conclusive. In light of our findings identifying the common trade-off between these two marketing performance aspects, does this suggest that investors may value customer satisfaction more than market share? Thus, if forced to make a trade-off—as our results suggest is likely for many firms—should managers emphasize customer satisfaction at the expense of market share? Moreover, what are the financial performance implications of achieving *both* higher levels of market share and customer satisfaction? On the one hand, industrial organization economics suggests that when faced with two performance objectives that may have inherent trade-offs, managers should aim to maximize one objective (i.e., either customer satisfaction or market share) or risk getting "stuck in the middle" (e.g., Rust, Moorman, and Dickson 2002). On the other hand, the resource-based view posits that successfully executed value-creating strategies that are complex and difficult to achieve—such as management of potential trade-offs between actions and resource deployments that increase customer satisfaction and market share simultaneously—are also more difficult to imitate and, therefore, provide a significant source of sustainable competitive advantage and superior long-term financial performance (e.g., Mittal et al. 2005). Which viewpoint is correct with respect to market share and customer satisfaction?

Conclusions

Most managers and much of the literature assume that market share and customer satisfaction are positively related indicators of marketing performance. Our comprehensive analyses on an extensive time series of data indicate a significant, stable, and robust negative association between market share and customer satisfaction. We show that this is the result of a strong negative effect of market share on future customer satisfaction coupled with a generally insignificant effect of customer satisfaction on future market share. We also find that the effect of a firm's customer satisfaction on its future market share is strengthened by both benchmarking it relative to the firm's nearest rival and considering the firm's customers' switching costs. In addition, building on our finding that greater preference heterogeneity is a key cause of the negative firm market share–future customer satisfaction relationship, we identify marketing multiple brands as a condition under which this negative association does not hold. Thus, building larger brand portfolios that may more closely align different brands with the needs and desires of customers in different segments is a strategy by which firms may be able to manage the market share–customer satisfaction trade-off revealed in our data.

REFERENCES

Aaker, David A. (2004), *Brand Portfolio Strategy*. New York: The Free Press.

Ailawadi, Kusum L., Paul W. Farris, and Mark E. Parry (1999), "Market Share and ROI: Observing the Effect of Unobserved Variables," *International Journal of Research in Marketing*, 16 (1), 17–33.

Anderson, Eugene W., Claes Fornell, and Donald R. Lehmann (1994), "Customer Satisfaction, Market Share, and Profitability," *Journal of Marketing*, 58 (July), 53–66.

———, ———, and S. Mazvancheryl (2004), "Customer Satisfaction and Shareholder Value," *Journal of Marketing*, 68 (October), 172–85.

———, ———, and Roland T. Rust (1997), "Customer Satisfaction, Productivity, and Profitability: Differences Between Goods and Services," *Marketing Science*, 16 (2), 129–45.

Arellano, Manuel and Stephen Bond (1991), "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *Review of Economic Studies*, 58 (2), 277–97.

——— and Olympia Bover (1995), "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics*, 68 (1), 29–51.

Baron, Reuben M. and David A. Kenny (1986), "The Moderator–Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations," *Journal of Personality and Social Psychology*, 51 (6), 1173–82.

Baum, Christopher F., Mark E. Schaffer, and Steven Stillman (2003), "Instrumental Variables and GMM: Estimation and Testing," *Stata Journal*, 3 (1), 1–31.

Blundell, Richard and Stephen Bond (1998), "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87 (1), 115–43.

Bond, Stephen R. (2002), "Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice," *Portuguese Economic Journal*, 1 (2), 141–62.

Boulding, William and Richard Staelin (1993), "A Look on the Cost Side: Market Share and the Competitive Environment," *Marketing Science*, 12 (2), 144–66.

Burnham, Thomas A., Judy K. Frels, and Vijay Mahajan (2003), "Consumer Switching Costs: A Typology, Antecedents, and Consequences," *Journal of the Academy of Marketing Science*, 31 (2), 109–126.

Colgate, Mark, Vicky Thuy-Uyen Tong, Christina Kwai-Choi Lee, and John U. Farley (2007), "Back from the Brink: Why Customers Stay," *Journal of Service Research*, 9 (3), 211–28.

Fader, Peter S. and David C. Schmittlein (1993), "Excess Behavioral Loyalty for High-Share Brands: Deviations from the Dirichlet Model for Repeat Purchasing," *Journal of Marketing Research*, 30 (November), 478–93.

Farris, Paul W., Neil T. Bendle, Phillip E. Pfeifer, and David J. Reibstein (2006), *Marketing Metrics: 50+ Metrics Every Executive Should Master*. Philadelphia: Wharton Publishing.

Fornell, Claes (1992), "A National Customer Satisfaction Barometer: The Swedish Experience," *Journal of Marketing*, 56 (January), 6–21.

——— (1995), "The Quality of Economic Output: Empirical Generalizations About Its Distribution and Relationship to Market Share," *Marketing Science*, 14 (3), 203–211.

———, Michael D. Johnson, Eugene W. Anderson, Jaesung Cha, and Barbara Bryant (1996), "The American Customer Satisfaction Index: Description, Findings, and Implications," *Journal of Marketing*, 60 (October), 7–18.

Greene, William H. (2005), *Econometric Analysis*, 5th ed. Upper Saddle River, NJ: Pearson Education.

Griffin, Abbie and John R. Hauser (1993), "The Voice of the Customer," *Marketing Science*, 12 (4), 1–27.

Gruca, Thomas P. and Lopo L. Rego (2005), "Customer Satisfaction, Cash Flow, and Shareholder Value," *Journal of Marketing*, 69 (April), 115–30.

Hauser, John, Duncan I. Simester, and Birger Wernerfelt (1994), "Customer Satisfaction Incentives," *Marketing Science*, 13 (4), 327–50.

Hellofs, Linda L. and Robert Jacobson (1999), "Market Share and Customers' Perceptions of Quality: When Can Firms Grow Their Way to Higher Versus Lower Quality?" *Journal of Marketing*, 63 (January), 16–25.

Horsky, Dan, Sanjog Misra, and Paul Nelson (2006), "Observed and Unobserved Heterogeneity in Brand-Choice Models," *Marketing Science*, 25 (4), 322–35.

Jacobson, Robert (1988), "Distinguishing Among Competing Theories of the Market Share Effect," *Journal of Marketing*, 52 (October), 68–80.

——— and Natalie Mizik (2009), "The Financial Markets and Customer Satisfaction: Reexamining Possible Financial Market Mispricing of Customer Satisfaction," *Marketing Science*, 28 (5), 810–19.

Kamakura, Wagner, Vikas Mittal, Fernando de Rosa, and Jose Mazzon (2002), "Assessing the Service-Profit Chain," *Marketing Science*, 21 (3), 294–317.

Kekre, Sunder and Kannan Srinivasan (1990), "Broader Product Line: A Necessity to Achieve Success?" *Management Science*, 36 (10), 1216–31.

Lazich, Robert S., ed. (2006), *Market Share Reporter: Annual Compilation of the Reported Market Share Data on Companies, Products and Services*. Detroit: Gale.

Levine, Ross, Norman Loayza, and Thorsten Beck (2000), "Financial Intermediation and Growth: Causality and Causes," *Journal of Monetary Economics*, 46 (1), 31–77.

Luo, Xueming and Christian Homburg (2007), "Neglected Outcomes of Customer Satisfaction," *Journal of Marketing*, 71 (April), 133–49.

———, ———, and Jan Wieseke (2010), "Customer Satisfaction, Analyst Stock Recommendations, and Firm Value," *Journal of Marketing Research*, 47 (December), 1041–58.

Maddala, G.S. and Shaowen Wu (1999), "A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test," *Oxford Bulletin of Economics and Statistics*, 61 (S1), 631–52.

McAlister, Leigh, Raji Srinivasan, and MinChung Kim (2007), "Advertising, Research and Development, and Systematic Risk of the Firm," *Journal of Marketing*, 71 (January), 35–48.

Mittal, Vikas, Eugene W. Anderson, Akin Sayrak, and Pandu Tadikamalla (2005), "Dual Emphasis and the Long-Term Financial Impact of Customer Satisfaction," *Marketing Science*, 24 (4), 544–55.

——— and Wagner Kamakura (2001), "Satisfaction, Repurchase Intent, and Repurchase Behavior: Investigating the Moderating Effect of Customer Characteristics," *Journal of Marketing Research*, 38 (February), 131–42.

Mizik, Natalie and Robert Jacobson (2004), "Are Physicians 'Easy Marks'? Quantifying the Effects of Detailing and Sampling on New Prescriptions," *Management Science*, 51 (12), 1704–1715.

Morgan, Neil A., Eugene W. Anderson, and Vikas Mittal (2005), "Understanding Firms' Customer Satisfaction Usage," *Journal of Marketing*, 69 (July), 131–51.

——— and Lopo L. Rego (2006), "The Value of Different Customer Satisfaction and Loyalty Metrics in Predicting Business Performance," *Marketing Science*, 25 (5), 426–39.

——— and ——— (2009), "Brand Portfolio Strategy and Firm Performance," *Journal of Marketing*, 73 (January), 59–74.

Muller, Dominique, Charles M. Judd, and Vincent Y. Yzerbyt (2005), "When Moderation Is Mediated and Mediation Is Moderated," *Journal of Personality and Social Psychology*, 89 (6), 852–63.

National Quality Research Center (2003), *American Customer Satisfaction Index: Methodology Report*. Ann Arbor, MI: National Quality Research Center, University of Michigan Business School.

Ping, Robert A. (1993), "The Effects of Satisfaction and Structural Constraints on Retailer Exiting, Voice, Loyalty, Opportunism, and Neglect," *Journal of Retailing*, 69 (3), 320–52.

Preacher, Kristopher J., Derek D. Rucker, and Andrew F. Hayes (2007), "Addressing Moderated Mediation Hypotheses: Theory, Methods, and Prescriptions," *Multivariate Behavioral Research*, 42 (1), 185–227.

Roodman, David (2009), "How to Do xtabond2: An Introduction to Difference and System GMM in Stata," *Stata Journal*, 9 (1), 86–136.

Roos, Inger, Bo Edvardsson, and Anders Gustafsson (2004), "Customer Switching Patterns in Competitive and Noncompetitive Service Industries," *Journal of Service Research*, 6 (3), 256–71.

Rust, Roland T., Christine Moorman, and Peter R. Dickson (2002), "Getting Return on Quality: Revenue Expansion, Cost Reduction, or Both?" *Journal of Marketing*, 66 (October), 7–24.

Sarafidis, Vasilis, Takshi Yamagata, and Donald Robertson (2006), "A Test of Cross-Section Dependence for a Linear Dynamic Panel Model with Regressors," working paper, University of Cambridge, (accessed June 11, 2013), [available at http://www.econ.cam.ac.uk/faculty/robertson/HCSDtest14Feb06.pdf].

Tsui, Anne. S., Terri D. Egan, and Charles A. O'Reilly (1992), "Being Different: Relational Demography and Organizational Attachment," *Administrative Science Quarterly*, 37 (4), 549–79.

Tuli, Kapil R., Sundar G. Bharadwaj, and Ajay K. Kohli (2010), "Ties That Bind: The Impact of Multiple Types of Ties with a Customer on Sales Growth and Sales Volatility," *Journal of Marketing Research*, 47 (February), 36–50.

Zhao, Xinshu, John G. Lynch Jr., and Qimei Chen (2010), "Reconsidering Baron and Kenny: Myths and Truths About Mediation Analysis," *Journal of Consumer Research*, 37 (2), 197–206.

APPENDIX A
Variables: Definitions, Measurement Details, and Sources

Variables	Measurement Details	Data Source/Literature
Customer satisfaction	Firm-level latent variable capturing customers' cumulative satisfaction with their product/service consumption experience from an annual national representative sample of 65,000+ consumers from 200+ U.S. firms.	ACSI; Fornell (1995); Fornell et al. (1996)
Relative customer satisfaction	The difference between a focal firm's satisfaction score and that of its nearest rival—that is, the firm in the same ACSI industry targeting the most similar customers whose products/services are perceived by those customers as being positioned most similarly to those of the focal firm. We use each firm's ACSI respondent demographics (gender, age, income, education, and household size) to compute a demographic dissimilarity score between each pair of firms in each ACSI industry for each year to assess the degree to which each pair of firms targets similar customers. Following Morgan and Rego (2009), we use ACSI data to calculate the similarity of customers' quality and price perceptions of the product/service offering of each pair of firms in each ACSI industry for each year to estimate positioning similarity. We then "collapse" the demographic similarity and positioning similarity scores into a single similarity factor (explaining 82% of variance) using principal components analysis. For each ACSI industry, we identify a focal firm's nearest rival as the firm with the highest similarity factor score. We assessed the external validity of this approach by comparing the rival identified with that selected by two independent raters for a subset of our data and found the correlation between the two approaches was .92. We pair focal firms with nearest rivals for every year and for each firm within each ACSI industry, and we compute our measure as follows: $\text{Relative satisfaction}_{(t)} = \text{Focal firm customer satisfaction}_{(t)} - \text{Nearest rival customer satisfaction}_{(t)}$	ACSI (firm-year-level aggregation of individual-level respondent survey response and demographic data); Morgan and Rego (2009); Tsui, Egan, and O'Reilly (1992)
Preference heterogeneity	Preference heterogeneity involves differences among individual customers in how they respond to the firm's product/service offerings. Firms facing more heterogeneous customer preferences must deal with a greater range of "ideal points" in terms of what their customers would ideally like in the firm's product/service offering. We therefore use individual-level ACSI respondent data and identify the variance (standard deviation) among each firm's customers in how closely they report that the firm's product/service comes to their ideal product/service preference to capture ideal point heterogeneity in a firm's customer base. We control for the potential impact of inconsistent product/service delivery by the firm on the ideal point variability reported by customers using ACSI data on the perceived reliability of the firm's product/services. Therefore, we estimate preference heterogeneity as the residual of regressing the standard deviation of how closely customers report the firm's product/services come to their ideal points onto the perceived reliability of the firm's offerings, aggregated to the firm-level, controlling for industry and time. $\text{SD Close-to-Ideal}_{(it)} = \alpha_0 + \alpha_1 \times \text{Perceived Reliability}_{(it)} + ID_{(it)} + YD_{(it)} + \zeta_{(it)}$, where $ID_{(it)}$ and $YD_{(it)}$ are industry and year dummies and $\zeta_{1(it)}$ is the residual of this regression and is used as our measure of estimated preference heterogeneity.	ACSI (firm-year-level aggregation of individual-level respondent survey response data); Fornell (1995)
Switching costs	Switching costs are perceived costs the firm's customers associate with switching to an alternative supplier. We calibrate these costs as the degree to which customers exhibit loyalty to a firm that cannot be explained by the level of satisfaction delivered by the firm's offerings. Using ACSI data, we estimate customer-level loyalty as a latent factor comprising variables that capture customers' repurchase intentions and price sensitivity. Satisfaction is the ACSI measure detailed previously. We estimate switching costs for each firm-year as the residual of regressing each firm's customer loyalty onto its customers' satisfaction, controlling for industry and time: $\text{Loyalty}_{(it)} = \beta_0 + \beta_1 \times \text{Satisfaction}_{(it)} + ID_{(it)} + YD_{(it)} + \varepsilon_{(it)}$, where $ID_{(it)}$ and $YD_{(it)}$ are industry and year dummies, respectively, and $\varepsilon_{(it)}$ is the residual of this regression and is used as our estimate of switching costs, which are firm and year specific.	ACSI (firm-year-level aggregation of individual-level respondent survey response data); Fornell (1992)

APPENDIX A
Continued

Variables	Measurement Details	Data Source/Literature
Market share	Firms' sales revenue as a proportion of total sales in the industry. First, for the 104 ACSI-tracked public firms in our sample, we first use Compustat's quarterly data to collect annualized quarterly sales data and align it with the closest quarter of ACSI-collected satisfaction data for that industry. Second, we use Compustat's segments data and the Hoovers.com database to identify the proportion of revenues for each firm that is derived from U.S. sales, and we use the Securities and Exchange Commission (SEC) Edgar database and Hoovers.com to estimate the portion of U.S. revenues that are specific to the ACSI industry to align the firm sales data with the ACSI industry satisfaction data. Only four firms in our data (General Electric, IBM, Nestlé, and Unilever) report less than 15% of their revenue as being derived from the industry for which the ACSI collects their data, whereas 75% of our sample firms derive more than 70% of their revenue from the industries for which the ACSI collects data. Sources used for these first two steps did not always produce the data items for particular firm-years required for our computations. In these cases, we "backfilled" the required data using alternative sources (e.g., trade journals, analyst forecasts) and, in a few cases, estimated the missing data using data from preceding and/or following years. For the 68 ACSI-tracked private (or mutual) firms included in our calculation of total industry sales, we followed the aforementioned two steps but use several alternative sources of data, including Mergent Online, Mergent Web Reports (formerly Moody's Manuals), Thomson Research (formerly Global Access), and Lexis-Nexis databases. Jointly, these multiple sources of private-firm financial information enabled us to collect each firm's annual sales data, adjusted to represent U.S. and ACSI industry-specific sales revenues. Third, we use the primary Standard Industrial Classification (SIC) codes as reported in the *ACSI Methodology Report* (2003) for each ACSI industry to identify other non-ACSI-tracked public competitors in each ACSI industry and replicate the process described in the first two steps for as many of these firms as possible. These data represent a greater number of smaller-sized firms, and consequently, data availability for some of them does not match that of larger ACSI-tracked public firms. Although the U.S. and/or industry sales adjustments for some of these smaller firms is not available, because these firms represent smaller operations, they are also less likely to have multi-industry or multinational operations, which reduces the likely measurement error of including their sales when computing total market size. Furthermore, measurement error is likely to be of similar magnitude for all such small firms within a given industry, and because we compute market share relative to cumulative industry sales, the influence of measurement error is probably small. Because financial data are virtually nonexistent for small non-ACSI-tracked private firms, we excluded them from our estimate of total industry sales. Fourth, we sum the U.S. sales in each industry of all ACSI-tracked and public non-ACSI-tracked firms to compute the total sales in the ACSI industry. As a validity check on our total market sales estimates, we compared this with the comparable market sales revenue computed from the First Research database using the SIC codes listed in the *ACSI Methodology Report* (2003) for the four years that overlapped with our data. The overall correlation between our estimated cumulative adjusted industry sales and the cumulative industry sales reported by the First Research database is .93. In addition, the estimated absolute percent error between both measures is never greater than 11%, with a mean absolute percent error of approximately 4%. Finally, for each ACSI-tracked firm, we then compute the firm's market share as the firm's sales as a percentage of the total industry sales. The correlation between our measure of market share and that provided in *Market Share Reporter* for the 15% of firm-years that overlap with our data set is .89, which suggests excellent face validity. In addition, we also compared our market share measure with an alternative measure in which we dropped all smaller public firms for which U.S.-only and/or ACSI industry–specific sales data were not available from our market size computation. Although both measures had similar correlations with the available *Market Share Reporter* estimates, the absolute magnitude of difference in the estimates was greater if these firms were excluded, suggesting that their inclusion produces more accurate market shares.	ACSI, Compustat quarterly database, Compustat segments database, SEC Edgar database, Hoovers.com, Mergent Online, Mergent Web Reports, Thomson Research, Lexis-Nexis; Fornell et al. (1996)

APPENDIX A
Continued

Variables	Measurement Details	Data Source/Literature
Number of brands	Absolute number of brands marketed by each firm in the ACSI industry for which we have data, obtained from annual 10-K/10-Q filings, supplemented by the Hoovers.com database.[a]	SEC Edgar database, Hoovers.com; Aaker (2004); Kekre and Srinivasan (1990); Morgan and Rego (2009)
ROA	Ratio of the firm's operating income to its book value of total assets. Following accounting norms, we use prior-year assets and current-year operating income to compute ROA (items IBQ and ATQ).	Compustat quarterly data; Jacobson and Mizik (2009)
Firm size	The firm's reported total assets (item ATQ).	Compustat quarterly data; Gruca and Rego (2005)
SGA-to-sales	Annual selling and general administration expenses divided by annual sales revenue, computed using annualized metrics from quarterly measures aligned with the ACSI reporting quarter (items XSGAQ and SALEQ).	Compustat quarterly data; Morgan and Rego (2009)
Advertising-to-sales	Annual advertising expenses divided by annual sales revenue. Aligned such that the fiscal year-end is closest to the ACSI reporting schedule because advertising data is reported annually rather than quarterly (items XADV and SALE).[b]	Compustat annual data; McAlister, Srinivasan, and Kim (2007)
R&D-to-sales	Annualized R&D expenses divided by annualized sales revenue, based on equivalent quarterly measures and aligned with the closest ACSI reporting quarter (as previously; items XRDQ and SALEQ).	Compustat quarterly data; Luo and Homburg (2007)
Number of business segments	Business segments data obtained from the firms' annual 10-K/10-Q filings, accessed using the SEC Edgar database and supplemented using the Hoovers.com database.	SEC Edgar database, Hoovers.com; Morgan and Rego (2009)
Market concentration (HHI)	Assessed using the HHI, calculated as the sum of the squared market shares (see "Market share" details) for all firms in each industry. The HHI is industry and year specific.	Compustat quarterly data, Compustat segments data; Anderson, Fornell, and Mazvancheryl (2004)
Market growth rate	Computed for each ACSI industry using cumulative industry sales revenues for the previous five years and estimated as an annualized average industry sales growth. To capture overall industry conditions, we use sales revenue data for all public firms in that ACSI industry, available from the Compustat database (item SALE).	Compustat annual data; Morgan and Rego (2009)

[a]We assessed measure reliability by comparing it with the number of brands as reported in "Brands and Their Companies" (Gale Cendage Group) for a common subset of firms. The correlation between both metrics is .96.
[b]We verified the robustness of our hypothesis testing results to this alignment of the annual advertising-to-sales data with the ACSI data in our data set by testing alternative alignment procedures (i.e., calendar year and multiyear weighted averages), and our results remain substantively unchanged.

APPENDIX B
Nomological Validity Assessment of New Measures

Variable	Validity Assessment Rationale	Indicator Validity Assessment Results
Preference heterogeneity	Because preference heterogeneity is generally greater for firms facing greater demand (Fornell 1992), it should be correlated with firm size.	The correlation between preference heterogeneity and firm size is .208 (significant at $p < .05$) in our sample.
	Preference heterogeneity is likely to be lower for categories in an industry in which price is the main driver of demand versus industries in which this is not the case.	Among retailers, preference heterogeneity for discount stores (–.660) is significantly lower (t-tests significant at $p < .05$) than for supermarkets (.164) or department stores (.235).
	Preference heterogeneity should be associated with age diversity in a firm's customer base (Andersen et al. 1994).	Preference heterogeneity is positively correlated (.116, $p < .05$) with the standard deviation of the age of consumers in a firm's customer base.
	Preference heterogeneity should be associated with diversity in customers' expectations of the firm's products and services.	Preference heterogeneity is positively correlated (.376, $p < .001$) with the standard deviation of customer expectations of the firm's products/services.
Customer switching costs	Due to the higher downside risk associated with purchasing products of unknown quality, switching costs should be higher for durable than for non-durable products.	The mean switching costs for durable products firms (.091) is significantly higher ($p < .05$) than for those producing nondurable products (–.107).
	Because it is associated with brand choice, switching costs should be positively correlated with brand salience.	The correlation between switching costs and brand salience (EquiTrend) for the firms in our data set is .163 ($p < .05$).
	Switching costs should be higher for categories in which location can create quasilocal monopolies (e.g., retail) than those for which products/services may be supplied through multiple channels (e.g., food and beverage).	The mean switching costs in supermarket retailing (1.20) and discount retailing (.95) are significantly higher (t-tests significant at $p < .05$) than those for processed foods (.36) and soft drinks (.03).
	Switching costs should be higher in categories known for high behavioral loyalty (e.g., cigarettes) versus relatively lower behavioral loyalty (e.g., automobiles, apparel).	The mean switching costs in the cigarette category is 1.39 versus a mean level of –1.74 for automobiles and –.032 for apparel (t-tests significant at $p < .05$).

Notes: We compute preference heterogeneity and customer switching costs measures at the firm-year level. For some validity tests, measures are aggregated to the average category level where such aggregation is required.

APPENDIX C
ACSI Industries included in the Sample

ACSI Industry Code	ACSI Industry Label	Primary SIC Code(s) Associated with ACSI Industry	ACSI Industry Code	ACSI Industry Label	Primary SIC Code(s) Associated with ACSI Industry
1001	Food Processing—All Others	203, 203	2004	Automobiles	371
1004	Food Processing—Cereal	204	3001	Express Mail	4215, 4513
1005	Food Processing—Baked	205	3003	Airlines	4512
1007	Beverages—Beer	2082	4001	Department Stores	531
1008	Beverages—Soft Drinks	2086	4002	Discount Stores	531
1009	Tobacco—Cigarettes	2111	4003	Supermarkets	541, 5411
1010	Apparel	23	4004	Fast Food	581, 5812
1011	Athletic Shoes	302	5001	Banks	602, 603, 606
1013	Personal Care Products	284	5002	Life Insurance	631
1014	Gas—Stations	5541	5003	Property Insurance	633
2001	Personal Computers	357	6001	Hotels	701
2002	Appliances and Electronics	363			

APPENDIX D
Customer Satisfaction–Market Share Relationship at Different Levels of Market Share

Panel Changes-Changes	Low Market-Share ΔSatisfaction $_{(t+1)}$	Below-Average Market Share ΔSatisfaction $_{(t+1)}$	Average Market Share ΔSatisfaction $_{(t+1)}$	Above-Average Market Share ΔSatisfaction $_{(t+1)}$	High Market Share ΔSatisfaction $_{(t+1)}$	Full Sample M2B ΔSatisfaction $_{(t+1)}$
ΔSatisfaction$_{(t)}$	.776***	.598***	.200	.105	.323	.183
ΔMarket share$_{(t)}$	.254	.278	–.448**	–.628*	–.180	–.371*
Observations	**(n = 159)**	**(n = 158)**	**(n = 159)**	**(n = 158)**	**(n = 158)**	**(n = 792)**
Average market share	3.27%	5.41%	8.33%	11.97%	25.97%	11.21%
Minimum market share	2.11%	4.40%	6.67%	10.79%	13.45%	2.11%
Maximum market share	4.39%	6.67%	10.77%	13.42%	58.90%	58.90%

*p < .05.
**p < .01.
***p < .001.
Notes: This table presents regressions of future customer satisfaction for a changes-changes model specifications jointly estimated (with levels-levels) using system GMM. We created panels using levels of future market share, sorted by firm and year. We report the number of observations, range, and average level of market share for each panel, including the full sample (i.e., M2B). All estimates are standardized. All variables are as defined in Appendix A. The focal explanatory variables are one-period lags of market share and customer satisfaction. Additional explanatory control variables (not reported in this table) were one-period lags of firm-specific ROA, firm size, SGA-to-sales, advertising-to-sales, R&D-to-sales, number of business segments, industry concentration, market growth, and year dummies. We used two-period (or earlier) and up to five-period lags of market share and customer satisfaction as GMM-style instruments. We used year dummies as instrument variable (IV)-style instruments. We verified model fit, system GMM assumptions, and instrument validity as detailed in Tables 4 and 5, but we do not report them in this table. Values with no asterisks are nonstatistically significant at $p \geq .05$.