MARKETING SCIENCE
Vol. 28, No. 5, September–October 2009, pp. 810–819
ISSN 0732-2399 | EISSN 1526-548X | 09 | 2805 | 0810

informs®

DOI 10.1287/mksc.1090.0495

The Financial Markets and Customer Satisfaction: Reexamining Possible Financial Market Mispricing of Customer Satisfaction

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We investigate the association between information contained in the American Customer Satisfaction Index (ACSI) metric and future stock market performance. Some past research has provided results suggesting that the financial markets misprice customer satisfaction; i.e., firms advantaged in customer satisfaction are posited to earn positive future-period abnormal stock returns. We reexamine this relationship and find that statistically significant evidence of financial market mispricing of customer satisfaction is limited to firms in the computer and Internet sector. The results suggest that the mispricing anomaly reported in past research appears not to stem from a systemic failure of the financial markets to impound the financial implications of customer satisfaction into current stock price, but rather from abnormal returns achieved by a small group of satisfaction leaders in the computer and Internet sector over the period of study. Analyses based on unconditional risk covariates and analyses using conditional risk covariates estimated from short-window, high-frequency data support this finding.

Key words: marketing metrics; valuation; mispricing; customer satisfaction; financial performance; efficient markets
History: Received: January 12, 2009; accepted: February 17, 2009.

Introduction

Under the efficient market hypothesis, the price of a stock reflects all available information and provides an unbiased estimate of the value of a firm. However, contrary to the efficient market hypothesis, some (e.g., Daniel et al. 1998) have suggested that it may take time for the market to correctly price some types of assets and strategic decisions. Market participants may not take into account the full effects of a strategy on a timely basis, but rather do so later on, when the effects of the strategy have been more fully reflected in other (e.g., accounting) performance metrics. Daniel and Titman (2003, p. 7) conclude that “there is considerable evidence that investors underreact to information conveyed by management decisions.”

Past research has focused on assessing the financial market's ability to immediately and fully impound into the price of a firm's stock the value of some intangible assets. Most notably, several studies report evidence suggesting that under certain conditions, the financial market does not properly value *levels* and *changes* in research and development (R&D). For example, Chan et al. (2001) find that the financial markets are overly pessimistic about R&D-intensive stocks that have performed poorly in the past. They find that these firms earn positive future-term excess returns. Eberhart et al. (2004) examine the long-term performance of firms following substantial unexpected increases in R&D. They conclude that that the market initially underreacts to R&D spending and is slow to recognize the full extent of R&D future-term benefits. Although these findings are consistent with financial market mispricing, alternative explanations to market inefficiency have been offered to explain apparently anomalous results. For example, Chambers et al. (2002) present evidence suggesting that the presumed abnormal returns earned by R&D-intensive firms actually reflect additional risk associated with R&D. The degree to which R&D is mispriced by the financial markets remains an ongoing area of study.

Some have suggested that financial markets similarly underappreciate marketing assets and strategies. Similar to R&D, marketing assets such as customer satisfaction may generate long-term benefits that are not reflected in current-term accounting results (Hauser et al. 1994). The financial markets may not properly price marketing assets having delayed, longer-term effects on firm performance. Marketing assets mispriced by the financial markets (i.e., those that the financial markets respond to on a delayed basis) warrant special attention. Because the absence of an immediate market reaction may be inappropriately viewed as the absence of an effect on firm value, inadequate resources may be devoted to initiatives that the financial markets do not properly value in a timely fashion. A central contribution of anomalies research is that it can help to improve the efficiency of capital markets and managerial activities.

In a thought-provoking study, Fornell et al. (2006) report evidence and conclude that the financial markets misprice customer satisfaction. Although not geared toward providing tests of statistical significance, the analysis finds very large positive future-period abnormal stock returns to the portfolio of top-satisfaction stocks. This finding, which contradicts the efficient markets hypothesis, is consistent with the financial markets not fully appreciating the long-term value implications of customer satisfaction when it occurs or when it is announced. Rather, only in the future, presumably when the effect of satisfaction has impacted some other metric that financial market participants make use of (such as earnings), will the financial markets fully impound the value implications of customer satisfaction into stock price.

Subsequent studies have come to conflicting conclusions as to whether the financial markets undervalue firms with high customer satisfaction. For example, O'Sullivan et al. (2009), analyzing a portfolio based on the top 20% of firms in terms of ACSI relative to their competition, find no statistically significant evidence of mispricing. Aksoy et al. (2008), however, find statistically significant evidence of mispricing for a portfolio formed based on firms simultaneously having customer satisfaction scores both (1) above the national average *level* for that time period and (2) showing a positive *change* (i.e., increase) from the previous period.

Because of these conflicting findings and the fact that empirical assessments of mispricing may be sensitive to, for example, the model for expected return and dependent on sector- and context-specific factors, a reexamination of the possible mispricing of customer satisfaction is warranted. Fama (1998), for example, notes that apparent anomalies are often "chance events" and tend not to be robust to alternative testing methodologies. Establishing evidence of customer satisfaction-based mispricing calls for additional analyses to those undertaken in previous research.

Our analysis focuses on the following question: Do the financial markets exhibit a delayed response to information contained in customer satisfaction? That is, we assess the extent to which satisfaction is related to future-period stock returns. Evidence of mispricing would suggest that the financial markets do not appreciate the financial implications of customer satisfaction when it occurs but rather only in some subsequent period, presumably when the financial effects of satisfaction have more fully come to fruition. Consistent with some previous research, we find evidence consistent with the mispricing of satisfaction. However, this mispricing does not appear to be widespread. Rather, the relationship between satisfaction and future-term stock returns appears to stem from the abnormal returns earned by a small group of satisfaction leaders in the Internet and computer sector. Once computer and Internet firms are isolated, we do not find statistically significant evidence of a relationship between satisfaction and future-period abnormal stock return.

Data and Study Setting

The data for our study come from three different sources. The customer satisfaction metric comes from the American Customer Satisfaction Index (ACSI) database available at http://www.theacsi.com. ACSI collects and releases its data on an annual basis, but does so throughout the year in different waves (quarters) for firms in different industries (e.g., health-care firms are assessed in the first quarter and retail firms in the fourth quarter of each year). We use tests that involve monthly and daily stock return data, which come from the University of Chicago's Center for Research in Security Prices (CRSP) database. We obtained values of the risk-free return ($Ret_{risk\,free}$), market (Ret_{mkt}), market size (SMB), book-to-market (HML), and momentum factors (MOM) needed to estimate the Carhart (1997) 4-factor risk model from Kenneth French's data library, posted on his website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

We matched publicly traded firms included in the ACSI survey with the firm's stock returns data from CRSP. This allowed us to form portfolios of firms based on ACSI characteristics. Our initial portfolios were formed based on ACSI data for the third quarter of 1996. Our final rebalancing of the portfolios was based on ACSI data for the first quarter of 2006. The matching yielded 104 firms that had both satisfaction and stock return data for some or all the time period. The final set contains 714 pooled time-series cross-sectional observations, and in terms of abnormal return analyses based on portfolios, this time period covers 117 continuous months for monthly tests and 2,454 continuous trading days for daily tests.

Portfolio Formation

Although we assess a number of different portfolio formation rules, our primary analysis involves categorizing firms into four portfolios based on whether (1) the firm's customer satisfaction score was above or below the national average for that time period and

(2) the firm's customer satisfaction score was increasing or decreasing. This is the same portfolio formation rule as used by Aksoy et al. (2008). The four resulting portfolios are as follows:

	Level of ACSI compared to national average ACSI score	Change in ACSI
Portfolio 1	Greater	Positive
Portfolio 2	Lower	Positive
Portfolio 3	Greater	Negative
Portfolio 4	Lower	Negative

We rebalance portfolios each time after new ACSI data are released. The rebalancing of portfolios occurs for the third month of the quarter for monthly returns tests and in the third week of the second month of the quarter for daily stock returns tests.[1]

Sector-Specific Considerations

The firms in the final sample come from 24 different two-digit major groupings in the standard industrial classification (SIC) system. Table 1 provides information about the distribution of firms included in our analysis across industries. To assess potential context-specific effects, we undertake analysis not just on the aggregate sample but also disaggregate analysis based on three firm groupings. We neither trim nor truncate the sample, but rather assess differential effects across groupings, e.g., undertake Chow tests (Chow 1960). One grouping is "the utility sector," which is comprised of electric, gas, and sanitary service (two-digit SIC 49) firms. As shown in Table 1, it is the largest grouping of firms in the ACSI sample with 193 observations (27% of sample). We separated this grouping not only because of its size but also because of issues related to regulation and monopoly status. We wanted to allow for the fact that customer satisfaction for public utilities firms might have effects that differ from nonutilities. Specifically, while customer satisfaction can play a role in rate setting for utilities, it can be hypothesized to be less important to the financial performance of utility firms, as these firms generally enjoy high barriers to entry, lack of competitive pressure, and high customer captivity. As such, any potential failure of the financial markets to appreciate the long-term benefits of customer satisfaction may be less important for utilities than for nonutility firms. That is, not allowing for a differential effect for utility firms might diminish the estimates of the relation between customer satisfaction and future stock returns in the overall sample.

Table 1 **Distribution of Study Sample Firms Across Major SIC Groups (Two-Digit)**

SIC	SIC major groups	No. of obs
20	Food and kindred products	77
21	Tobacco manufacturers	7
23	Apparel and other textile products	18
28	Chemicals and allied products	9
30	Rubber and misc. plastics products	9
35	Industrial machinery and equipment	35
36	Electrical and electronic equipment	10
37	Transportation equipment	20
42	Motor freight transportation	6
45	Transportation by air	57
48	Communications	50
49	Electric, gas, and sanitary services	193
52	Building materials	6
53	General merchandise stores	57
54	Food stores	39
57	Furniture and home furnishings stores	2
58	Eating and drinking places	17
59	Miscellaneous retail	12
60	Depository institutions	20
62	Security and commodity brokers	7
63	Insurance carriers	15
70	Hotels and other lodging	27
73	Business services	11
99	Miscellaneous	10
	Total	714

Notes. We use firms in SIC 49 as our "public utility" grouping. We have designated firms in SICs 35, 59, and 73 as our "computer/Internet" grouping.

Our second grouping is firms in the computer and Internet sector. Because our data sample time period covers the period of the "Internet bubble"—the rapid growth, collapse, and subsequent recovery of some of the Internet firms—we wanted to allow for the possibility that this group may exhibit differential effects as well. Pástor and Veronesi (2007) discuss a literature stream highlighting that during technological revolutions (railroads in the 1800s, biotechnology firms in the 1980s, and Internet and computer firms in the 1990s–2000s), the stock price of innovating firms may display high volatility and "bubble-like" patterns. Although scholars differ as to whether this behavior reflects investor irrationality, the behavior of these firms may differ from "old-economy" firms. Our concern is that the behavior of these firms may mask or induce associations in the aggregate analysis (i.e., findings based on aggregate results would not reflect widespread relationships but rather be dependent on a small subsample of firms).

We identify firms in our sample that would fall in the computer and Internet industries. These firms are all based in either SICs 35, 59, or 73. Thus, we group all firms covered by ACSI and included in SICs 35,

[1] We also undertook additional analyses involving different rebalancing periods (e.g., allowing the financial markets to make some adjustments prior to the release of ACSI information based on more timely metrics reflective of customer satisfaction). We found results in close correspondence to those based on rebalancing directly aligned with ACSI release dates.

59, and 73 into our computer and Internet grouping. Ten firms comprise the sample we use for analysis of the computer and Internet grouping: Apple, Dell, Gateway, Google, Hewlett-Packard, Barnes & Noble, Amazon.com, 1-800-Flowers, eBay, and Yahoo!. One notable Internet/computer firm, Microsoft, is not included in our study sample because ACSI began to track Microsoft only in 2006. As one element of our portfolio formation criteria involves differences of the satisfaction metric, the first time Microsoft would be placed in a portfolio is 2007 (i.e., after its second satisfaction score is tracked). We have a total of 58 observations in the computer and Internet grouping (8% of sample).

The third grouping consists of the remaining firms (463 observations, 65% of total sample), i.e., neither utilities nor computer and Internet firms. Firms in this grouping include a wide range of some of the most well-known firms in the country (e.g., American Airlines, Starbucks, Wal-Mart, Ford, MetLife). To the extent that customer satisfaction is unappreciated and mispriced by the financial market, it is this group of firms (i.e., the sample excluding the special cases of regulated utilities with a monopoly position, and computer and Internet firms subject to a "bubble period") that provides evidence as to how widespread any potential mispricing of customer satisfaction might be.

Methodological Approaches for Assessing Financial Market Mispricing

A number of different approaches for assessing the presence of financial market mispricing exist. As noted by, for example, Barber and Lyon (1997) and Fama (1998), no one methodology will be superior under all conditions, and a variety of issues can impact performance of alternative approaches used to generate estimates of abnormal returns. Each approach relies on certain assumptions and has advantages and disadvantages. However, it is also the case that the different approaches share common characteristics or can be modified to addresses some issues and constraints imposed by a given method. As such, different approaches can (and most often do) yield results in close correspondence.

The Calendar-Time Portfolio Approach

One of the more commonly used approaches to assess mispricing is the calendar-time portfolio approach, which was used both by Aksoy et al. (2008) and O'Sullivan et al. (2009). This approach involves forming a portfolio of firms based on some characteristic or a set of characteristics, and then estimating a risk model for the portfolio. The intercept term in the risk model provides the estimate of the abnormal return. Consider a Carhart (1997) 4-factor risk model of the following form:

$$\begin{aligned}\mathrm{Ret}_{pt} - \mathrm{Ret}_{\text{risk free},\,t} &= \alpha_p + \beta_p(\mathrm{Ret}_{\text{mkt},\,t} - \mathrm{Ret}_{\text{risk free},\,t}) + s_p(\mathrm{SMB}_t)\\ &\quad + h_p(\mathrm{HML}_t) + m_p(\mathrm{MOM}_t) + \varepsilon_{pt},\end{aligned} \tag{1}$$

where Ret_{pt} is the value-weighted portfolio p raw return in period t. The statistical significance of the intercept term α_p can be assessed to test for mispricing. Under the null hypothesis of no mispricing, the intercept will not be significantly different from zero.

A central aspect of this approach is the assumption that the portfolio risk factor loadings are constant over time. Barber and Lyon (1997) note that this assumption is a disadvantage of the portfolio approach since portfolio risk characteristics oftentimes change over time. Indeed, this assumption is not tenable for portfolios rebalanced based on satisfaction scores, since the composition of firms in a portfolio changes over time. For example, firms such as eBay, Yahoo!, and Amazon.com were not publicly traded in the initial years of the ACSI data collection, for this reason, they cannot be included in any portfolio in these early years. Once these firms became public, they came into the analysis.

Firms in a given customer satisfaction portfolio will change over time not only because they were not publicly traded or were not tracked by ACSI over the entire study period, but also because of shifts in customer satisfaction scores. A firm may not have ACSI scores below or above the national average for the entire study period. Furthermore, even more frequent shifts of firms across portfolios will occur if inclusion in a given portfolio is based on the change in satisfaction in anyway. A firm is unlikely to have consistently positive or negative *changes* in customer satisfaction scores for the entire duration of the analysis. Indeed, as the time-series properties of customer satisfaction scores are much like those of a random walk, changes in satisfaction will be approximated by a white noise series and, as such, will have an equal probability of being positive or negative in a given period.

As a result, the composition of firms included in a given portfolio changes over time. For example, only approximately 30% of firms included in the top customer satisfaction portfolio at the end of the analysis would be included in the top portfolio in the initial period of the analysis. Because firms in a portfolio change over time, the risk profile of the portfolio changes and the risk factor loadings of the portfolio can be expected to change over time as well. As such, the risk factor loadings need to be treated as time varying (Fama 1998, p. 298).

Firm-Specific Risk Models

Another approach for assessing mispricing, advocated by, for example, Fama (1998, p. 295), involves first obtaining an estimate of abnormal returns by firm (i.e., estimating firm-specific risk models), aggregating the abnormal returns into a portfolio by time period, and then determining whether the mean abnormal return for firms in a given portfolio is significantly different from zero. That is, a risk model, e.g., a 4-factor Carhart (1997) model, can be estimated at the individual firm i level:

$$\begin{aligned}\mathrm{Ret}_{it} - \mathrm{Ret}_{\text{risk free},\,t} &= \alpha_i + \beta_i(\mathrm{Ret}_{\text{mkt},\,t} - \mathrm{Ret}_{\text{risk free},\,t}) + s_i(\mathrm{SMB}_t)\\ &\quad + h_i(\mathrm{HML}_t) + m_i(\mathrm{MOM}_t) + \varepsilon_{it}. \end{aligned} \tag{2}$$

The abnormal return for each firm i and each time period t can then be computed as

$$\begin{aligned}\mathrm{abnRet}_{it} = \mathrm{Ret}_{i,\,t} - [&\mathrm{Ret}_{\text{risk free},\,t} + \hat{\beta}_i(\mathrm{Ret}_{\text{mkt},\,t} - \mathrm{Ret}_{\text{risk free},\,t})\\ &+ \hat{s}_i(\mathrm{SMB}_t) + \hat{h}_i(\mathrm{HML}_t) + \hat{m}_i(\mathrm{MOM}_t)]. \end{aligned} \tag{3}$$

The estimated abnormal returns can be value-weighted and aggregated into portfolios based on the portfolio selection criteria. The statistical significance of the mean abnormal return for the portfolio can then be assessed. This approach assumes firm-specific risk factor loadings are constant over time for a given firm but does not require portfolio risk factor loadings to be time invariant. As such, the approach provides a means to assess abnormal portfolio returns when the composition of firms in a portfolio changes over time.

Time-Varying Risk Factor Loadings

However, the assumption of time-invariant firm risk may be violated. As conditions change and the firm changes over time, so too may the risk factor loadings. To take into account the possibility of changing risk covariates, an alternative approach to the calendar-time portfolio approach and firm-specific risk modeling is needed.

A common approach in risk models is to estimate "unconditional" risk factor loadings that use the full time series of returns (typically measured at monthly increments) for each firm or portfolio, and to restrict the parameters to be constant across the entire sample period. In contrast, "conditional" risk covariates are allowed to vary over time. One approach to obtaining conditional estimates is to use a systematically varying parameter model that allows the parameters to vary as a function of some set of observed variables. The limitation of this approach is the inability to accurately determine and model which characteristics cause the risk covariates to vary.

Instead of requiring conditioning information, an alternative approach is to directly estimate conditional risk factor loadings using short-window regressions (Lewellen and Nagel 2006). Rather than estimating the risk model over the entire sample using the full time series, the model can be estimated with high-frequency (e.g., daily) data over a shorter time period. The implicit assumption here is that the risk factor loadings are stable over this shorter time period so that they can be treated as constant for that period. As such, conditional risk factor loadings can be directly obtained by estimating the parameters for the risk model separately for each period.

Lewellen and Nagel (2006) note that although the use of daily data (as opposed to monthly data, for example) can yield more precise estimates, analysis using daily data is not without its limitations. They note, in particular, that nonsynchronous prices (i.e., a delay in a response to common effects) can have a major impact on short-horizon risk covariates. To account for this, they suggest the inclusion of both current and lagged risk factors in the daily risk models. The risk factor loadings are calculated as the sum of the coefficients for the current and lagged values.

We use this short-horizon, high-frequency estimation approach to modify the portfolio approach and the firm-specific risk modeling so as to allow for time-varying risk factor loadings.

Portfolio Approach with Time-Varying Risk Factor Loadings. A time-varying portfolio approach can be undertaken by forming portfolios as in the standard portfolio approach, but the risk factor loadings can be allowed to vary for each rebalancing period in the analysis. This method accounts for the varying portfolio risk associated with rebalancing (i.e., the firms in the portfolio change every time new ACSI data are released). The intercept term (α_p) in this model represents the estimated abnormal returns of the portfolio.

That is, we can estimate the following daily returns portfolio model, which includes both current and lagged risk factors, so as to incorporate the Lewellen and Nagel (2006) correction for high-frequency data:

$$\begin{aligned}&\mathrm{Ret}_{pt} - \mathrm{Ret}_{\text{risk free},\,t}\\ &= \alpha_{pf} + \sum_{q=2}^{Q} \alpha_q (Q_q - Q_1)\\ &\quad + \Bigg[\sum_{q=1}^{Q}\sum_{\tau=0}^{1}[\beta_{\tau pq}(\mathrm{Ret}_{\text{mkt},\,t-\tau} - \mathrm{Ret}_{\text{risk free},\,t-\tau}) + s_{\tau pq}(\mathrm{SMB}_{t-\tau})\\ &\qquad + h_{\tau pq}(\mathrm{HML}_{t-\tau}) + m_{\tau pq}(\mathrm{MOM}_{t-\tau})]\Bigg] * Q_q + \varepsilon_{pt}, \end{aligned} \tag{4}$$

where Q_q is a set of indicator variables that are equal to one when the rebalancing period is q, and zero otherwise.

Firm-Specific Risk Models with Rolling Data Window Risk Factoring Loadings. Another approach allowing for time-varying risk factor loadings involves estimating firm-specific risk models but allowing the risk covariates to change over time through the use of a rolling data window. McAlister et al. (2007), for example, made use of a rolling window approach to allow for intertemporal variation in the systematic risk coefficient in a capital asset pricing model. We undertake estimation using a rolling window of 240 trading days (approximately one year) of data with a one-day step. We estimate Carhart's (1997) 4-factor asset pricing model for each firm (i) and each day (t) separately using the $[t-240; t]$ data sample to obtain firm-day–specific risk factor loadings. Again, we include current and lagged risk factors to incorporate the Lewellen and Nagel (2006) correction for high-frequency data.

This approach allows for the risk of the firm to change over time. Once the model is estimated, a value-weighted abnormal return can be computed each day for a given portfolio and its mean assessed.

Results of Empirical Analyses

Analyses Based on Monthly Returns Data: Calendar-Time Portfolio Approach

Table 2, panel A provides estimates of abnormal returns obtained using the calendar-time portfolio approach. The table presents results from aggregate analysis and then the disaggregate analysis where the sample is separated into utility firms, computer and Internet firms, and the remaining firms.

The first row of Table 2, panel A provides estimates of abnormal returns for the four ACSI portfolios formed on the basis of firms being either above or below the national average ACSI score, and also whether the firms ACSI score increased or decreased. For the top ACSI portfolio (i.e., firms with an ACSI score above the mean and showing an increase in the score from the previous wave), the estimated abnormal monthly return for the sample as a whole is 0.0052 with a t-statistic of 1.82. Although not significant at the 5% level, the estimated abnormal return for the top ACSI portfolio is significant at the 10% level and suggestive of possible mispricing. Although the estimated t-statistic is lower than that reported by Aksoy et al. (2008), the estimate of abnormal returns is in near exact correspondence with the estimate they report (0.0050) for the abnormal return from their estimated 4-factor model.[2] For the other three portfolios,

Table 2 Abnormal Returns for Portfolios Formed Based on the Firm being Above or Below the Average Level of Satisfaction and Showing an Increase or Decrease in Satisfaction, Value-Weighted Returns (Monthly Data, December 1996 to August 2006)

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
Panel A: Calendar-time portfolio approach				
All firms	0.0053	0.0039	0.0024	−0.0012
	[1.82]	[0.81]	[0.75]	[−0.35]
No utility or computer/ Internet firms	0.0045	0.0032	0.0010	−0.0035
	[1.42]	[0.86]	[0.25]	[−0.73]
Utility firms	0.0017	0.0017	−0.00080	−0.0019
	[0.38]	[0.38]	[−0.18]	[−0.38]
Computer/ Internet firms	0.027*	0.0071	0.0075	0.0039
	[2.25]	[0.41]	[0.73]	[0.44]
Panel B: Portfolios formed from firm-specific risk models				
All firms	0.007*	0.0035	0.0012	−0.00078
	[2.22]	[1.03]	[0.34]	[−0.23]
No utility or computer/ Internet firms	0.00421	0.0049	−0.00020	−0.0023
	[1.12]	[1.29]	[−0.05]	[−0.62]
Utility firms	0.0022	−0.0012	−0.0013	0.0018
	[0.53]	[−0.27]	[−0.31]	[0.43]
Computer/Internet firms	0.032**	0.00031	0.0096	0.0073
	[2.98]	[0.03]	[0.88]	[0.68]

Notes. Portfolios are rebalanced every time new ACSI data are released and are composed based on the following rule: Portfolio 1 has a greater level of ACSI compared to national average ACSI and a positive change in ACSI, portfolio 2 has a lower level of ACSI compared to national average ACSI and a positive change in ACSI, portfolio 3 has a greater level of ACSI compared to national average ACSI and a negative change in ACSI, and portfolio 4 has a lower level of ACSI compared to national average ACSI and a negative change in ACSI. $N = 117$ continuous trading months; t-statistics are in brackets.
*Significant at the 5% level; **significant at the 1% level.

the estimated abnormal returns are both smaller in magnitude and statistically insignificant.

Disaggregate analysis highlights the primary source of the apparent mispricing. For utility firms, for each of the four portfolios, the estimated abnormal return is small and statistically insignificant. For example, the estimated abnormal return for the top satisfaction portfolio is 0.0017 with a t-statistic of 0.38. The estimated abnormal return for a top satisfaction portfolio for nonutility, noncomputer, and non-Internet firms is larger in magnitude (0.0045), but it too is not statistically significant (i.e., it has a t-statistic of 1.42). It is the computer and Internet firms where we see substantial abnormal returns for the top satisfaction portfolio. The estimated monthly abnormal return for computer and Internet firms is much larger (0.027) than observed for any other portfolio. It is statistically

[2] Although our results are similar to those obtained by Aksoy et al. (2008), we could not obtain exact replication of their findings. We can speculate that the source of the difference might be due to the selection of firms from the ACSI database to match with the CRSP data. The difficulty in obtaining an exact replication is consistent with the analysis and conclusions of Dewald et al. (1986). Nonetheless, the similarity of the point estimates using the portfolio approach across the entire data sample suggests considerable correspondence across the data in our study and that of Aksoy et al. (2008).

different from zero and from the estimated abnormal returns for the noncomputer and non-Internet portfolios. Furthermore, and consistent with the premise that these firms have characteristics that differ from other firms, the risk factor loadings (i.e., covariates) for the top satisfaction computer and Internet portfolio are substantially and statistically different from the risk loadings for the noncomputer and non-Internet portfolios. Nonetheless, it is only for the top satisfaction portfolio of computer and Internet firms that abnormal returns are evident. Abnormal returns for computer and Internet firms not in the top satisfaction portfolio are statistically insignificant for each of the other three satisfaction portfolios.

Analyses Based on Monthly Returns Data: Portfolio Analysis Formed from Firm-Specific Risk Models

As discussed previously, the calendar-time portfolio approach rests on the assumption of constant risk factor loadings (i.e., covariates) across the sample period, an assumption that is unlikely to hold given that the composition of firms in the portfolio changes over time. To see how the results are affected by relaxing this assumption, we undertake analysis based on abnormal return estimates from firm-specific risk models. We estimate firm-specific 4-factor risk models, calculate the abnormal returns as a deviation of realized return for the firm from its expected return, and then compute the value-weighted abnormal return for the satisfaction portfolios. Table 2, panel B presents the results of this analysis.

Conclusions drawn from this analysis mirror those of Table 2, panel A. Namely, the estimate of abnormal monthly return is positive (0.0076) for the sample as a whole and, furthermore, is statistically significant at the 5% level. However, the source of this apparent mispricing appears not to be widespread but rather stems from the large positive abnormal returns earned by firms in the top satisfaction portfolio for computer and Internet firms, which has an estimated abnormal return of 0.0325 with a t-statistic of 2.98.[3] For utilities and the remaining firms in the sample, the estimated abnormal returns for the top satisfaction portfolio are substantially smaller (0.0022 and 0.0042, respectively) and not statistically significant. Interestingly, for nonutility, noncomputer, and non-Internet firms, the return for portfolio 2 (firms with an increase in satisfaction but with a level of satisfaction below the mean), the estimated abnormal return is about the same (0.0049) as the estimated return for firms in the top satisfaction portfolio.

As such, consistent with the results based on the calendar-time portfolio approach, an analysis using firm-specific risk models finds that statistically significant evidence of mispricing appears to exist only for computer and Internet firms.

Analyses Based on High-Frequency (Daily) Returns Data: Calendar-Time Portfolio Approach Allowing for Time-Varying Risk Factor Loadings

To allow for time-varying risk factor loadings, we shift the analysis from using monthly data to analysis using daily data. Panel A of Table 3 provides estimates from the calendar-time portfolio approach using short-horizon, high-frequency data that allow the risk covariates to vary every quarter when the portfolio is rebalanced. Once again, we find results that suggest abnormal returns are limited to the top satisfaction portfolio of firms in the computer and Internet sector. The estimated abnormal daily return for computer and Internet firms in the top portfolio is 0.0010 with a t-statistic of 1.89. The estimated abnormal return for the top satisfaction utility firms and the portfolio of top satisfaction other firms (i.e., excluding utility and computer and Internet firms) is small (0.00012 and 0.0001, respectively) and statistically insignificant.

Analyses Based on High-Frequency (Daily) Returns Data: Portfolio Analysis Formed from Firm-Specific Risk Models with Rolling Data Window Risk Factor Loadings

Panel B of Table 3 reports abnormal daily return estimates based on a firm-specific 4-factor risk model using daily data and a rolling window of 240 trading days with one-day step estimation of risk covariates. This framework allows the risk covariates to vary over time for each individual firm. The estimates of abnormal returns obtained from this approach are very similar to those obtained from the approach based on time-varying portfolio risk covariates (i.e., Table 3, panel A results). For the top satisfaction portfolios, only for computer and Internet firms is the estimated abnormal return suggestive of potential mispricing. The estimated abnormal daily return is 0.00098 and statistically significant at the 10% level, but not at the 5% level. The estimated abnormal return for both utility firms (0.0001) and the other (i.e., excluding computer and Internet and utilities) firms (0.00007) is both small and statistically insignificant.

Interestingly, for both estimation methods allowing for time-varying risk factor loadings (i.e., panels A and B of Table 3), we find that for nonutility, noncomputer, and non-Internet firms, portfolio 2 (firms with

[3] Simulation analysis that takes into account the fact that the risk factor loadings are estimated rather than known with certainty confirms that the null hypothesis of no abnormal return for computer and Internet firms can still be rejected even when additional sources of error are considered.

Table 3 Abnormal Returns for Portfolios Formed Based on the Firm Being Above or Below the Average Level of Satisfaction and Showing an Increase or Decrease in Satisfaction, Value-Weighted Returns (Daily Return Data; November 15, 1996 to August 31, 2006)

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
Panel A: Calendar-time portfolio with time-varying portfolio risk covariates				
All firms	0.00019	0.00015	0.000031	−0.000079
	[1.18]	[0.61]	[0.19]	[−0.44]
No utility or computer/ Internet firms	0.00010	0.00038	−0.00012	−0.00013
	[0.54]	[1.47]	[−0.61]	[−0.59]
Utility firms	0.00012	−0.000034	−0.00012	0.000058
	[0.49]	[−0.13]	[−0.45]	[0.27]
Computer/ Internet firms	0.0010	−0.00067	0.00079	−0.000018
	[1.89]	[−0.81]	[1.56]	[−0.03]
Panel B: Portfolios formed from firm-specific rolling window risk covariates				
All firms	0.00015	0.00024	0.000020	−0.000045
	[0.86]	[1.42]	[0.12]	[−0.27]
No utility or computer/ Internet firms	0.000072	0.00034	−0.000090	−0.00015
	[0.38]	[1.80]	[−0.48]	[−0.80]
Utility firms	0.00010	−0.000066	0.000010	−0.000028
	[0.48]	[−0.29]	[0.05]	[−0.13]
Computer/ Internet firms	0.00098	0.000053	0.00046	0.00068
	[1.86]	[0.09]	[0.86]	[1.32]

Notes. Portfolios are rebalanced every time new ACSI data are released and are composed based on the following rule: Portfolio 1 has a greater level of ACSI compared to national average ACSI and a positive change in ACSI, portfolio 2 has a lower level of ACSI compared to national average ACSI and a positive change in ACSI, portfolio 3 has a greater level of ACSI compared to national average ACSI and a negative change in ACSI, and Portfolio 4 has a lower level of ACSI compared to national average ACSI and a negative change in ACSI. $N = 2{,}454$ continuous trading days; t-statistics are in brackets. *Significant at the 5% level; **significant at the 1% level.

an increase in satisfaction but with a level of satisfaction below the mean) has a higher estimated abnormal return than does portfolio 1. The differences, however, are not statistically significant. This consideration, nonetheless, makes is difficult to advance an argument that the empirical evidence suggests that satisfaction leaders have future-term returns higher than any other satisfaction-based portfolio grouping.

Sensitivity Assessments

As noted by, for example, Barber and Lyon (1997) and Fama (1998), no one methodology will be superior under all conditions, and a variety of issues can impact performance of alternative approaches used to generate estimates of abnormal returns. A host of issues make this a difficult area to study; e.g., results can be sensitive to estimates of expected return (i.e., the "bad models" problem) and may exhibit intertemporal instability. As such, we undertook a number of additional tests using alternative testing methods. These alternative methods generated results in close correspondence to those reported in Tables 2 and 3.

We also assessed different trading rules. Rather than basing portfolio formation on firms being above or below the average level of satisfaction and showing an increase or decrease in satisfaction, we also undertook analysis where portfolios were formed based on (1) the *level* of satisfaction quartiles, (2) the *change* in satisfaction quartiles, (3) whether the firm was the customer satisfaction leader (compared to its two-digit SIC counterparts) in terms of the *level* of satisfaction, and (4) whether the firm was the customer satisfaction leader (compared to its two-digit SIC counterparts) in terms of the *change* in satisfaction. For each of these four different portfolio formation criteria, we found no evidence to contradict the findings from Tables 2 and 3. Statistically significant evidence of potential financial market mispricing of customer satisfaction is not widespread, but rather is limited to firms in the computer and Internet sector.

Conclusions and Directions for Future Research

Some researchers (e.g., Fama 1998) are dismissive of all efforts and results relating to mispricing. The fact that the estimated abnormal return is not statistically significant at the 5% level for any sector when time-varying risk covariates are used (although it is significant at the 10% for the computer and Internet sector) may be taken by some as evidence fully supportive of efficient markets. Although we are sympathetic to the power of the efficient market hypothesis, we are also sympathetic to the view that financial market inefficiencies, with important strategic implications, may be present (see, e.g., Mizik and Jacobson 2007). We also are appreciative of the fact that it is difficult to assess mispricing, as a host of issues come into play.

Our results suggest that financial market mispricing of customer satisfaction is not widespread but rather, if it exists, is limited to firms in the computer and Internet sector. Why this might be taking place and whether the mispricing extends to other sectors or contexts is a direction for future study. Indeed, the mispricing may not be directly related to a customer-satisfaction based anomaly but rather to issues associated with the computer and Internet sector during the 1995–2006 time period; this is an area for future research.

Explaining the existence of marketplace anomalies (e.g., the relationship between satisfaction and future-term returns) is speculative. It is the nature of anomalies research that a number of different explanations might potentially give rise to the empirical findings. Past research has offered explanations ranging from inappropriate risk adjustment to financial market irrationality to explain apparently anomalous empirical findings. For example, our finding that customer satisfaction is predictive of future-term returns for computer and Internet firms might reflect the market's inability to accurately value customer satisfaction in this sector. It might be that not until the effects of satisfaction are reflected in other metrics, such as earnings, will the markets fully value the financial implications of satisfaction. A literature stream in finance provides support for such an interpretation. Daniel and Titman (2003), for example, conclude that the financial markets are oftentimes slow to incorporate financial implications of strategic decisions. Rather than immediately impounding the financial implications of a strategy into the price of the stock, this research stream suggests that it may take years for the market to correctly price some types of strategic decisions.

Alternatively, the findings of apparent mispricing can also be linked to an efficient markets literature stream that shows that anomalous results can be attributed to the changing nature of the uncertainty and market's learning during technological revolutions. This certainly applies to the computer and Internet sector during our study period. For example, Pástor and Veronesi (2007) observe that during technological revolutions with high uncertainty and fast adoption (such as the introduction of railroads in the United States in the 1800s and the Internet in the late 1900s), stock prices of innovative firms tend to exhibit bubble-like patterns. Pástor and Veronesi (2007) develop a general equilibrium model based on the assumptions that the average productivity of a new technology and the probability of adoption of a technology on a large scale are uncertain ex ante. As the market learns about the productivity for technologies that are eventually adopted, the nature of the uncertainty changes from idiosyncratic to systematic. This leads stock prices to fall after an initial run-up. The authors note that the resulting "bubbles" are observable ex post but are unpredictable ex ante. Our findings, however, are consistent with the market's mispricing not being uniform across all firms in the computer and Internet industry, but rather potentially related to customers' satisfaction with the firm.

Whether the abnormal returns earned by satisfaction leaders in the computer and Internet sector were a transitory phenomenon, stem from an inadequate modeling of expected return, reflect a misvaluation that will persist into the future, or reflect special conditions that can be generalized to extend to some firms that are not in the computer and Internet sector is an area for future research.

We should note that these results have little, if anything, to say about the effect of customer satisfaction on financial market valuation of firms. Financial markets may well have correctly impounded information about satisfaction into the price of the stock. The absence of *mispricing* related to a given metric does not imply the absence of impact of that metric (which is the focus of this study) on financial market valuation. For example, the ongoing debate over the existence of post-earnings announcement drift (i.e., the most stable and widely studied market anomaly related to earnings mispricing) does not call into question the effect of earnings on stock prices. The debate is merely over whether the value implications of earnings information are immediately and fully reflected in stock price when earnings information is released to the market, or whether a portion of the reaction occurs with some delay.

We should also note that this study does not preclude the existence of some alternative customer satisfaction-based trading rules, other than the ones we examined, from yielding abnormal returns. Furthermore, financial anomalies may well appear or disappear during different time periods. Because financial market participants are self-interested agents, they can be expected to and do dissipate trading rules when they become aware of them. Some, for example, have suggested that this is currently taking place with respect to the abnormal accounting accruals anomaly. A lack of result stability is an inherent property of research into mispricing. Whether this has or will take place with respect to any customer satisfaction-based anomaly in the computer and Internet sector remains another topic for further research.

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