Customer Satisfaction and Stock Returns Risk

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Over the last decade, a number of studies have argued that customer satisfaction has high relevance for financial markets because it has a significant impact on stock returns. Little attention, however, is directed at understanding the impact of customer satisfaction on the risk of stock returns. Literature in finance suggests that investors that judge performance only in terms of returns will place more resources than warranted in risky opportunities, forgo profitable opportunities, and apply misguided performance evaluations. Accordingly, this study develops, tests, and finds empirical support for the hypotheses that positive changes in customer satisfaction result in negative changes in overall and downside systematic and idiosyncratic risk. In other words, investments in customer satisfaction insulate a firm’s stock returns from market movements (overall and downside systematic risk) and lower the volatility of its stock returns (overall and downside idiosyncratic risk). The results are robust to concerns related to alternative measures of risk, model specifications, and sample composition criteria raised in some recent studies. The results, therefore, indicate that customer satisfaction is a metric that provides valuable information to financial markets. The robust impact of customer satisfaction on stock returns risk, therefore, suggests that it might be useful for firms to disclose their customer satisfaction scores in their annual report to shareholders.

Key Words: Customer Satisfaction, Relationship Marketing, Systematic Risk, Idiosyncratic Risk, Beta, Analyst Earnings Forecast, Downside Risk
Customer satisfaction is viewed as a measure of the size, loyalty and the quality of the customer base of a firm (Fornell et al. 2006; Morgan and Rego 2006). It is also viewed as a measure of a nation’s economic health (Fornell et al. 1996) and a metric to affirm the fundamental principle of capitalist free markets where investors reward firms that meet customer needs better than competition (Fornell et al. 2006). Not surprisingly, firms have invested considerable resources in measuring customer satisfaction and it is viewed as the largest item of the annual market intelligence budget (Wilson 2002).

The public availability of data from the American Customer Satisfaction Index (ASCI) has seen a large body of work that explores the financial impact of customer satisfaction. Most of these studies show that customer satisfaction has a strong positive impact on both accounting measures of returns (e.g., Gruca and Rego 2005) and stock returns (e.g., Aksoy et al. 2008). There is, however, an ongoing debate whether customer satisfaction provides information for the financial markets (including financial analysts and institutional investors) beyond that reflected in accounting metrics (see Fornell, Mithas and Morgeson 2008; Jacobson and Mizik 2008).

While a large body of literature explores the impact of customer satisfaction on stock returns, little attention is paid to its impact on stock returns risk. Stock returns risk is a key component of shareholder value that matters to financial markets (Barber and Odean 2000) and main street managers (Grinblatt and Titman 1998). Investors that judge performance only in terms of returns will place more resources than warranted in risky opportunities, forgo profitable opportunities, and apply misguided performance evaluations (Markowitz 1952). Not surprisingly, it is a statutory requirement for financial analysts to articulate the risk of investing a stock to investors (SEC 2002). The purpose of this article, therefore is to examine the impact of customer satisfaction on stock returns risk. The study makes the following contributions.
First, this study contributes to the limited literature on the impact of customer satisfaction on stock returns risk (e.g., Aksoy et al. 2008; Fornell et al. 2006; Gruca and Rego 2005) by exploring both dimensions of stock returns risk: **systematic risk**, that is, the degree to which a firm’s stock returns are a function of market returns and **idiosyncratic risk**, that is, the volatility in stock returns that cannot be explained by market movements. While prior studies examine the effect of customer satisfaction on systematic risk, its impact on idiosyncratic risk remains unexplored. Idiosyncratic risk accounts for almost 80% of the variation in a firm’s stock returns and financial analysts tend to use idiosyncratic risk when issuing their rating of the risk of investment in a stock (Lui, Markov, and Tamayo 2007). High idiosyncratic risk can put the survival of a firm at risk, hamper efforts to acquire or divest firm stock, and affect the value of stock options (e.g., Clayton, Hartzell, and Rosenberg 2005). Examining the impact of customer satisfaction on idiosyncratic risk, therefore, is responsive to recent calls for demonstrating the relevance of marketing for financial markets (e.g., Rust et al. 2004).

Second, the current study complements prior literature by exploring the impact of customer satisfaction on **downside** systematic and idiosyncratic risk. Downside systematic risk represents the degree to which stock returns are sensitive to the downturns in stock market (Ang, Chen and Xing 2006). The impact of customer satisfaction on downside systematic risk, therefore, indicates the extent to which investments in customer satisfaction can insulate a firm against stock market downturns (see Petkova and Zhang 2005). Downside idiosyncratic risk represents the volatility in stock returns when the stock returns of a firm are negative. The impact of customer satisfaction on downside idiosyncratic risk, therefore, indicates the degree to which customer satisfaction lowers the volatility of potential losses from investing a firm’s stock.

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1 Since Aksoy et al. (2008) and Fornell et al. (2006) use a portfolio approach, idiosyncratic risk is diversified away and the impact of customer satisfaction on it is not estimated.
(Markowitz 1959). This is important as investors are typically more concerned about the prospect of losses than gains from investments (see Gul 1991; Harvey and Siddique 2000).

Third, this study contributes to the theoretical literature on customer satisfaction by developing hypotheses that outline the impact of customer satisfaction on systematic risk and idiosyncratic risk. As such, this study complements prior literature that investigates customer satisfaction’s impact on stock returns (Morgan and Rego 2006), its attitudinal benefits (Homburg, Koschate, and Hoyer 2005), and organizational outcomes (Luo and Homburg 2007).

Fourth, this study presents empirical analyses that take into account concerns related to the use of (i) alternate measures of risk, (ii) inclusion of accounting variables, and (iii) sample composition in studies that use stock-market based data (see Bali and Cakici 2008; Fama 1998). We find that customer satisfaction lowers overall and downside systematic and idiosyncratic risk. These results are robust to the concerns highlighted in prior research and indicate that customer satisfaction provides valuable information to financial markets which complements the information contained in accounting measures. The results, therefore, speak directly to the Financial Accounting Standards Board (FASB) which recommends that firms should provide non-financial information to investors that can help them assess the amount, timing, and uncertainty of prospective cash receipts (FASB 1978). As such, customer satisfaction is a valuable metric that should be considered for disclosure in a firm’s annual report and be among the list of key performance drivers in communications to financial markets.

The current study also contributes to the recent efforts at highlighting the relevance of marketing efforts to senior management (Rust et. al 2004). Firms are increasingly using customer satisfaction as an implementation performance metric (Kaplan and Norton 1996) and as a measure of competitive advantage (Morgan, Anderson and Mittal 2005). Financial markets,
therefore, would be interested in knowing if customer satisfaction is a relevant metric given its myriad uses. Moreover, since CEO compensation is also influenced by customer satisfaction (Ittner, Larcker and Rajan 1997), its impact on risk is critical in an environment when pay for performance is increasingly important in the eyes of shareholders.

**Marketing Strategy and Stock Returns Risk**

While there is conceptual recognition that marketing related investments such as brand building serve to reduce risk (e.g., Srivastava, Shervani and Fahey 1997), little empirical work demonstrates this benefit. One early study finds that some marketing strategy variables reduce risk (measured as variance in return on investment), while others inflate it (Bharadwaj and Menon 1993). Madden, Fehle and Fournier (2006) find that a portfolio of strong brands has a much lower systematic risk compared to a portfolio without strong brands. More recently, McAlister, Srinivasan and Kim (2007) find that advertising and R&D investments are associated with lower systematic risk. Finally, Sorescu and Spanjol (2008) find that while incremental innovations are unrelated to risk, breakthrough innovations lead to higher risk.

Three recent studies examine whether customer satisfaction reduces risk. Gruca and Rego (2005) find that customer satisfaction has a negative effect on systematic risk. They, however, do not test whether the impact of customer satisfaction on systematic risk is robust to alternative models used to calculate systematic risk. Such analyses are important as research in finance shows that results of studies that use stock market data tend to depend on the models used to calculate the variables based on stock returns (Fama 1998; also see Aksoy et al. 2008).

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2 Systematic risk is also labeled as market risk or beta. We stay consistent with the marketing literature and label it as systematic risk (McAlister, Srinivasan and Kim 2007).
Fornell et al. (2006) find that a portfolio of firms with above average customer satisfaction and increase in customer satisfaction not only produces excess returns but also produces systematic risk less than one, that is, there is no risk premium. This study, however, does not examine the impact of changes in customer satisfaction on the changes in systematic risk at the individual firm level. Thus, the likelihood that increases in customer satisfaction do not have an impact on a firm’s systematic risk is not ruled out. Indeed, in a recent study, Aksoy et al. (2008) find that there is no difference between the systematic risk of a portfolio of firms with high and increasing customer satisfaction and a portfolio of firms with low and decreasing customer satisfaction. Analysis of the impact of customer satisfaction on systematic risk at the firm level is also important to ascertain whether customer satisfaction provides information beyond accounting variables such as leverage that are likely to affect systematic risk.

To the best of our knowledge, the preceding studies do not investigate the impact of customer satisfaction on idiosyncratic risk. Since high idiosyncratic risk indicates high uncertainty about expected cash flows, it can put the survival of a firm at risk, and therefore matters to managers and employees (Grinbaltt and Titman 1998). Moreover, as incentives are frequently tied to stock returns, managers are concerned about idiosyncratic risk (Pace 1999). High idiosyncratic risk can inhibit strategic moves such as acquisitions and divestures as potential partners are likely to be wary of being acquired by or acquiring a firm with high degree of uncertainty over its future cash flows (see Clayton, Hartzell, and Rosenberg 2005). Not surprisingly, there is substantial empirical evidence which suggests that idiosyncratic risk is a relevant risk metric (e.g., Ang et al. 2006; Guo and Savickas 2008). Indeed, recent research in accounting suggests that financial analysts track a firm’s idiosyncratic risk when issuing their rating of the risk associated with investment in a stock (e.g., Lui, Markov, and Tamayo 2007).
Finally, prior studies do not examine the impact of customer satisfaction on the downside systematic risk and downside idiosyncratic risk. A negative impact of customer satisfaction on downside systematic risk could underline its value as a marketing investment that insulates a firm from market downturns (see Ang, Chen, and Xing 2006). Similarly, a negative impact of customer satisfaction on downside idiosyncratic risk could underscore its value as an investment that lowers the risk of negative stock returns.

**Relating Customer Satisfaction to Stock Returns Risk**

The key theoretical argument for making investments to increase customer satisfaction is that satisfied customers are more likely to reward the firm by staying with it longer. A number of studies show that customer satisfaction enhances customer retention and therefore generates a loyal and stable customer base (e.g., Anderson and Sullivan 1993; Bolton 1998; Fornell 1992; Mithas, Jones, and Mitchell 2004; Mittal and Kamakura 2001). We, therefore, use these results and develop our hypotheses.

*Customer satisfaction and systematic risk.* Firms that are able to cushion themselves from the impact of market movements and deliver consistent cashflows typically enjoy lower systematic risk. We now propose that increases in customer satisfaction engender customer loyalty, which in turn cushions a firm’s cash flows from the impact of market movements.

Higher customer satisfaction engenders customer loyalty because it indicates superior value proposition for the customer (e.g., Mittal and Kamakura 2001). Increases in customer satisfaction also increase product usage, which generates experience with the product and reduces the perceived risk of the customer (Bolton, Kannan and Bramlett 2000). Greater customer loyalty along with the lower perceived risk and superior value proposition facilitate the
formation of close relationships where the customer has higher commitment to the firm (Gustofsson, Johnson, and Roos 2005).

When market downturns occur, firms compete more intensely and customers are likely to be tempted by competitive offers. However, highly satisfied customers that have greater commitment to a firm are less likely to consider other firms because the superior value provided by a firm is very valuable for customers during downturns (e.g., Heide and Weiss 1995). This is because during downturns customers are under pressure to secure offerings that provide greater value in terms of better utility or lower costs (see Soberman and Gatignon 2005). Indeed, Noordewier, John, and Nevin (1990) find that customers tend to purchase more from suppliers with whom they have higher commitment especially in conditions of high uncertainty such as market downturns. This suggests that increases in customer satisfaction lower the vulnerability of a firm’s cash flows to market downturns.

In contrast, firms with declining customer satisfaction suffer from insecure cash flows during market downturns because their customers are more likely to switch suppliers if other suppliers offer marginally better offerings or lower prices. This is because declining customer satisfaction scores indicate that a firm’s customers do not perceive it as providing them with a value proposition that is attractive enough to turn down competitive offers that are more likely during market downturns. The firm’s cash flows, therefore, are likely to be severely affected by market downturns. As the stock price is the discounted value of expected cash flows, higher sensitivity of expected cash flows to market returns translates into higher systematic risk. Thus, increases in customer satisfaction are likely to lower the sensitivity of a firm’s stock returns to market movements in general and to market downturns in particular. Therefore, we expect:

\[ H1a: \text{A positive change in customer satisfaction results in a negative change in a firm’s systematic risk.} \]
H1b: *A positive change in customer satisfaction results in a negative change in a firm’s downside systematic risk.*

*Customer satisfaction and idiosyncratic risk.* Since idiosyncratic risk reflects stock returns volatility not explained by systematic factors, it is largely affected by a firm’s actions. We now propose that customer satisfaction facilitates a firm’s ability to understand its customers, which in turn, reduces the volatility in its cost and revenue streams, and therefore lowers its overall and downside idiosyncratic risk.

Increases in customer retention stemming from increases in customer satisfaction foster a stable customer base. Such a stable customer base promotes a firm’s ability to learn about its customers, their unique requirements, and demand patterns (also see Tuli, Kohli, and Bharadwaj 2007). As a firm becomes more familiar with customer demand patterns, it can anticipate the changes in customer demand to adjust its production cycle accordingly and lower the mismatch of firm inventory with customer orders (Bharadwaj, Bharadwaj and Bendoly 2007). Thus, firms that deliver higher customer satisfaction are likely to have lower volatility in inventory costs.

Greater knowledge of the customer base also reduces the variance in a firm’s customer service costs that might occur due to the rejection of unsuitable offerings, a result of a poor understanding of customer requirements (Anderson, Fornell, and Lehman 1994). Such product returns are not trivial as exemplified by the $13.8 billion spent by the U.S. electronics industry in 2007 due to product returns by customers (Lawton 2008). Indeed, firms that increase their customers’ satisfaction have far fewer customer complaints and higher customer retention (Brown et al. 2005; Bolton 1998). Consequently, such firms have lower costs of customer recovery and lower need to discount prices to retain customers.
Highly satisfied customers also provide positive word of mouth for a firm (Lam et al. 2004). Positive word of mouth engenders greater credibility among customers and serves as a low cost channel for retaining customers (Villanueva, Yoo and Hanssens 2008). It may also serve as a countervailing strategy rather than the traditional policy of firms to counter advertising attacks with advertising retaliation (Steenkamp et al. 2005). Thus, positive word of mouth enhances a firm’s advertising and promotional efficiency, which, in turn, reduces its marketing related costs (Luo and Homburg 2007).

Highly satisfied customers are also likely to continue purchasing and/or increase their purchases from a firm (e.g., Rust, Zahorik, and Keiningham 1994, 1995). Lower volatility in costs and greater stability of revenues results in more stable cash flows and is likely to lower idiosyncratic risk. Since customer satisfaction is perceived as a measure of the loyalty and quality of customers, and satisfied customers are likely to increase their purchases from a firm (Mittal and Kamakura 2001), increases in customer satisfaction can be perceived as a signal of higher future revenues. Increases in customer satisfaction, therefore, are likely to allay concerns related to negative cash flows, that is, lower the downside idiosyncratic risk of a firm. Formally,

$$H2a: \text{A positive change in customer satisfaction results in a negative change in a firm's idiosyncratic risk.}$$

$$H2b: \text{A positive change in customer satisfaction results in a negative change in a firm's downside idiosyncratic risk.}$$

**Method**

**Measures**

*Dependent variables.* We use the Fama-French three factor model to obtain the measures of systematic and idiosyncratic risk (Fama and French 1993). For each firm we estimate equation (1) using the daily observations for the four quarters for which customer satisfaction is measured.
In equation (1), $\beta_{mi}$ represents the systematic risk for a firm, while the idiosyncratic risk is obtained by calculating the standard deviation of residuals from this model.

$$\text{(1) } (R_{it} - R_{ft}) = \alpha_{it} + \beta_{mi} (R_{mt} - R_{ft}) + \beta_{si} (SMB)_t + \beta_{hi} (HML)_t + E_{it}$$

Where, $R_{it}$: Daily return on stock of firm ‘i’ on day ‘t’.  
$R_{ft}$: Daily risk free return on day ‘t’.  
$R_{mt}$: Daily return on a value-weighted market portfolio on day ‘t’.  
(SMB)$_t$: Fama-French size portfolio on day ‘t’.  
(HML)$_t$: Fama-French market-to-book ratio portfolio on day ‘t’.

$$\text{(2) } R_{it} = [(D_{it} + P_{it}) - P_{i(t-1)}] / P_{it}$$

$$\text{(3) } R_{mt} = [L_t - L_{(t-1)}] / L_{(t-1)}$$

Where, $D_{it}$: Dividends from stock ‘i’ on day ‘t’  
$P_{it}$: Split adjusted price of stock ‘i’ on day ‘t’.  
$L_{t}$: Market price adjusted index of a value-weighted market portfolio comprising all stocks on NASDAQ, AMEX, and NYSE markets on day ‘t’.

Downside systematic risk ($\beta_{dmi}$), is obtained from equation (4) for observations where excess market returns are negative (see Ang, Chen, and Xing 2006).

$$\text{(4) } (R_{it} - R_{ft}) = \alpha_{dit} + \beta_{dmi} (R_{mt} - R_{ft}) + \beta_{dsi} (SMB)_t + \beta_{dhi} (HML)_t + E_{dit}, \text{ where } (R_{mt} - R_{ft}) < 0$$

Downside idiosyncratic risk, in turn, is measured as the standard deviation of residuals obtained from equation (5) for observations where excess firm returns are negative. This measure corresponds to the concept of semi-variance, that is, the variance in negative returns from investing in a stock (see Markowitz 1959).

$$\text{(5) } (R_{it} - R_{ft}) = \alpha_{drit} + \beta_{dmi} (R_{mt} - R_{ft}) + \beta_{dsi} (SMB)_t + \beta_{dhi} (HML)_t + E_{drit}, \text{ where } (R_{it} - R_{ft}) < 0$$
Customer satisfaction. We use the American Customer Satisfaction Index (ACSI) database to obtain customer satisfaction scores (see www.theacsi.com). The ACSI collects customer satisfaction data from over 50,000 customers by using telephone interviews. The overall customer satisfaction scores are scaled from 0-100 and have been released in the public domain since 1994 (see Fornell et al. 1996 for a detailed discussion of the ACSI methodology). In the current study we include only those firms that are listed on three US-based stock exchanges (NASDAQ, NYSE, and AMEX). We use the natural logs of customer satisfaction for each firm as this lowers the influence of extreme values (e.g., Anderson, Fornell, and Rust 1997).

Control variables. Appendix Table A1 outlines the control variables, their definitions, and the literature supporting their inclusion in the models. We control for the effects of R&D investments by using the R&D to Total Assets ratio. In addition, we follow research in accounting and finance and use Total Assets, Return on Assets, Dividend Payouts, Financial Leverage, and Liquidity as control variables. To control for competitive activity in an industry we use the Herfindahl concentration index (see Hou and Robinson 2006). In addition, to control for the systematic effects across time, we use year dummies that correspond to the year in which the customer satisfaction score is measured.

Data Collection
We use four different sources to collect data for the current study. The customer satisfaction metric comes from the ACSI database. The ACSI collects and releases data on annual basis, but does so throughout the year in different quarters for firms in different industries. For example, scores for firms in the manufacturing durables are released in the second quarter, while for those in the retail sector are released in the fourth quarter. We obtained the customer satisfaction scores from the fourth quarter of 1994 to the fourth quarter of 2006. Since
our objective is to test the effect of changes in customer satisfaction on changes in risk, and our models control for the lagged values of the dependent variables, we use firms for which at least 3 years of customer satisfaction data are available.

Data for the stock prices for firms was obtained from University of Chicago’s Center of Research on Stock Prices (CRSP). Data for the value-weighted market portfolio, the Fama-French size and market-book ratio factors, Treasury bond rates, and the momentum factor were obtained from the data library maintained by Professor Kenneth French\(^3\). For the accounting measures, we use the Standard and Poor’s COMPUSTAT quarterly data file. Following Jacobson and Mizik (2008), we align the quarterly COMPUSTAT data to the annual ACSI data.

Combining the datasets yields 1318 pooled time series and cross-sectional observations for the customer satisfaction scores, overall and downside systematic risk and idiosyncratic risk. That is, we estimated 1318 regressions using the Fama-French 3 factor model to calculate the dependent variables. In line with literature in finance, we find that on average the Fama-French 3 factor model explains 21% of the variance in stock returns (e.g., Goyal and Santa-Clara 2003). That is, idiosyncratic risk accounts for 79% of the variance in stock returns of the firms in this sample. These observations come from 29 different SIC 2 digit industry groupings. As shown in Table 1, the largest group of observations is from the utilities industry (SIC 49) with 255 observations.

Table 2 outlines the descriptive statistics and correlations between the variables. As shown in Table 2, the correlations between customer satisfaction and systematic risk, downside

\(^3\) http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
systematic risk, idiosyncratic risk, and downside idiosyncratic risk are in the expected direction for both levels and first differences of variables.

[Insert Table 2 Here]

**Model & Estimation Procedure**

We assess the impact of changes in customer satisfaction on changes in risk measures because it lowers the potential problems associated with autocorrelation and removes the impact of time invariant unobservable factors (e.g., Jacobson and Mizik 2008). It is, however, important to note that using a changes model carries a cost of not being able to estimate the effects of levels of customer satisfaction on the levels of risk measures. Subsequently, we test levels models and find that our substantive conclusions are robust to this specification. Since past stock returns risk predicts future risk, we include the lagged differences in the dependent variable in the model (Lui, Markov, and Tamayo 2007). The inclusion of the lagged dependent variable also controls for inertia, persistence, and different initial conditions (see Mizik and Jacobson 2004).

**Systematic Risk Model**

\[
\Delta \beta_{miT} = \gamma_{m1}[\Delta \beta_{mi(T-1)}] + \gamma_{m2}[\Delta CS_{iT}] + \gamma_{m3}[\Delta R&D_{iT}] + \gamma_{m4}[\Delta X_{iT}] + \Delta \epsilon_{iT}
\]

Where,
\[
\Delta \beta_{miT} = \beta_{miT} - \beta_{mi(T-1)}
\]
\[
\beta_{miT} = \text{Systematic Risk of firm i for year (T)}
\]
\[
CS_{iT} = \text{Log of Customer Satisfaction Score of Firm i for year (T)}
\]
\[
R&D_{iT} = \text{R&D Scaled by Total Assets of Firm i for year (T)}
\]
\[
X_{iT} = \text{Control variables for Firm i for year (T)}
\]
\[
\epsilon_{iT} = \text{Random error term}
\]

**Downside Systematic Risk Model**

\[
\Delta \beta_{dmiT} = \gamma_{dm1}[\Delta \beta_{dmi(T-1)}] + \gamma_{dm2}[\Delta CS_{iT}] + \gamma_{dm3}[\Delta R&D_{iT}] + \gamma_{dm4}[\Delta X_{iT}] + \Delta \zeta_{iT}
\]
Where, \[ \Delta \beta_{\text{dmi}T} = \beta_{\text{dmi}T} - \beta_{\text{dmi}(T-1)} \]
\[ \beta_{\text{dmi}T} = \text{Downside Systematic Risk of firm } i \text{ for year } (T), \text{ and other symbols have usual meanings} \]

**Idiosyncratic Risk Model**

(8) \[ \Delta IR_{\text{IT}} = \gamma_1[\Delta IR_{i(T-1)}] + \gamma_2[\Delta CS_{\text{IT}}] + \gamma_3[\Delta R&D_{\text{IT}}] + \gamma_4[\Delta X_{\text{IT}}] + \Delta \Phi_{\text{IT}} \]

Where, \[ \Delta IR_{\text{IT}} = \text{Idiosyncratic Risk of firm } i \text{ for year } (T) \]
\[ IR_{\text{IT}} = \text{Log of Customer Satisfaction Score of Firm } i \text{ for year } (T) \]
\[ CS_{\text{IT}} = \text{R&D Scaled by Total Assets of Firm } i \text{ for year } (T) \]
\[ X_{\text{IT}} = \text{Control variables for Firm } i \text{ for year } (T) \]
\[ \Phi_{\text{IT}} = \text{Random error term} \]

**Downside Idiosyncratic Risk Model**

(9) \[ \Delta DIR_{\text{IT}} = \gamma_{d1}[\Delta DIR_{i(T-1)}] + \gamma_{d2}[\Delta CS_{\text{IT}}] + \gamma_{d3}[\Delta R&D_{\text{IT}}] + \gamma_{d4}[\Delta X_{\text{IT}}] + \Delta \eta_{\text{IT}} \]

Where, \[ \Delta DIR_{\text{IT}} = \text{Downside Idiosyncratic Risk of firm } i \text{ for year } (T) \text{ and other symbols have usual meanings} \]

**Addressing Endogeneity**

A key benefit of using a panel dataset is that it allows us to control for the potential endogeneity. Equations (6) to (9) include three variables that are likely to be endogenous.

*Lagged dependent variable.* The lag of the dependent variable in equation 6 \( (\Delta \beta_{\text{m}(T-1)}) \) is correlated with the error term \( (\Delta \varepsilon_{\text{IT}}) \). This is because term \( \varepsilon_{i(T-1)} \) is present in the differenced error term \( \Delta \varepsilon_{\text{IT}} \) and is a component of the lag of the dependent variable. For example:

(10) \[ \Delta \beta_{\text{m}T} = \gamma_{m1}[\Delta \beta_{\text{m}(T-1)}] + \gamma_{m2}[\Delta CS_{\text{IT}}] + \gamma_{m3}[\Delta R&D_{\text{IT}}] + \gamma_{m4}[\Delta X_{\text{IT}}] + \Delta \varepsilon_{\text{IT}} \]
(11) \[ \Delta \beta_{\text{m}(T-1)} = \beta_{\text{m}(T-1)} - \beta_{\text{m}(T-2)} \]
(12) \[ \beta_{\text{m}(T-1)} = \gamma_{m1}[\beta_{\text{m}(T-2)}] + \gamma_{m2}[CS_{i(T-1)}] + \gamma_{m3}[R&D_{i(T-1)}] + \gamma_{m4}[X_{i(T-1)}] + \varepsilon_{i(T-1)} \]
(13) \[ \Delta \varepsilon_{\text{IT}} = \varepsilon_{\text{IT}} - \varepsilon_{i(T-1)} \]

Similarly, the lagged dependent variables in equations (7) to (9) are endogenous.
Customer satisfaction. There are compelling arguments which suggest that customer satisfaction should be treated as endogenous. For example, a firm’s investments in relationship building activities such as customer loyalty programs and training of customer service employees can affect customer satisfaction (e.g., Srinivasan and Moorman 2005). These factors also require dedication of substantial resources, which in turn can influence a firm’s stock returns risk. As such, customer satisfaction is highly likely to be correlated with the error term. In addition, one can argue that the lack of stability in a firm’s operations could impact its performance with the customer and lower its customer satisfaction score. That is, riskier firms are likely to underperform their less risky counterparts and have lower customer satisfaction. Customer satisfaction, therefore, is likely to be endogenous.

R&D. As managers may be forward looking, R&D investments are endogenous in a model with stock returns risk as the dependent variable (McAlister, Srinivasan, and Kim 2007).

Following Arellano and Bond (1991), we use the lagged level values of endogenous variables as instruments for their first differences (for applications of this method see Gupta 2005; Narasimhan, Dutta, and Rajiv 2006). For example, in equation (6), $\beta_{mi(T-2)}$ and other lags can be used as an instrument for $\Delta \beta_{mi(T-1)}$ under the condition (Arellano and Honore 2001):

(14) \[ E [\varepsilon_{it(T-1)}, \varepsilon_{it(T-2)}] = 0 \]

This is because,

(15) \[ \beta_{mi(T-2)} = \gamma_{m1}[\beta_{mi(T-3)}] + \gamma_{m2}[CS_{it(T-2)}] + \gamma_{m3}[R&D_{it(T-2)}] + \gamma_{m4}[X_{it(T-2)}] + \varepsilon_{it(T-2)} \]

And under condition (14), $\beta_{mi(T-2)}$ is a valid instrument for $\Delta \beta_{mi(T-1)}$ because

a) it is correlated with $\Delta \beta_{mi(T-1)}$, as $\Delta \beta_{mi(T-1)} = \beta_{mi(T-1)} - \beta_{mi(T-2)}$,

b) but it is not correlated with the error term $\Delta \varepsilon_{iT}$ in (6) because $\Delta \varepsilon_{iT} = \varepsilon_{iT} - \varepsilon_{iT-1}$, i.e., it does not contain $\varepsilon_{it(T-2)}$.
Similarly, $CS_{mi(T-1)}$ and further lags can be used as instruments for $\Delta CS_{miT}$, and $R&D_{mi(T-1)}$ and further lags can be used as instruments for $\Delta R&D_{miT}$. We test for the validity of instruments by using the Hansen test of over-identifying restrictions (Hansen 1982). The null hypothesis in this test is that the model specification meets the moment condition specified in equation (14) and, therefore, instruments are valid. After selecting the instruments, we use the Generalized Method of Moments (GMM) estimator as it yields unbiased and consistent estimates (see Arellano and Bond 1991; Arellano and Honore 2001).

Results

Table 3 outlines the results of the models. Since we use first differencing and the lagged values of dependent variables, the sample size for overall and downside systematic and idiosyncratic risk models is 806 observations (129 firms). As shown in Table 3, across models we fail to reject the null hypotheses for the Hansen test. The instruments used in the estimation, therefore, are valid.

[Insert Table 3 About Here]

Overall and downside systematic risk. Results support H1a and H1b, that is, a positive change in customer satisfaction results in a negative change in systematic risk (-1.88, p < 0.05) and in a negative change in downside systematic risk (-3.76, p < 0.01). Results of control variables are largely in line with prior work in marketing and finance. We find that high financial leverage enhances systematic risk (0.76, p < 0.05) and downside systematic risk (0.89, p < 0.10). This supports the argument that firms with greater financial strength (i.e., lower leverage) are less affected by market downturns and hence are likely to have lower systematic risk (see Lie
We also find that the changes in R&D investments have a significant effect on systematic risk (-3.10, p < 0.01) and downside systematic risk (-7.80, p < 0.01).

We find that changes in ROA lower systematic risk (-1.21, p < 0.05) and dividend payouts tend to enhance the downside systematic risk (4.75, p < 0.05). This suggests that financial markets do not reward firms that are not willing to reinvest their earnings to secure future cash flows in market downturns. Finally, we find that increasing industry concentration lowers systematic risk (-1.30, p < 0.01) and downside systematic risk (-1.26, p < 0.05).

Idiosyncratic risk and downside idiosyncratic risk. Consistent with H2a and H2b, we find that a positive change in customer satisfaction results in a negative change in idiosyncratic risk of a firm (-3.42, p < 0.05) and a negative change in downside idiosyncratic risk (-2.31, p < 0.01). The results for the other control variables are largely in line with literature in finance. We find that increases in leverage increase the perceptions of financial concerns and therefore increase idiosyncratic risk (4.06, p < 0.01) and downside idiosyncratic risk (3.64, p < 0.01). Similarly, increases in a firm’s earnings (ROA) soothe investor’s concerns and therefore lower idiosyncratic risk (-5.36, p < 0.01) and downside idiosyncratic risk (-3.02, p < 0.01).

We find that increases in industry concentration increase idiosyncratic risk (1.80, p < 0.05) and downside idiosyncratic risk (1.18, p < 0.05). One explanation could be that increases in industry concentration indicate that a number of firms are exiting an industry (e.g., Dobrev, Kim, and Carroll 2002). Moreover, as industries become more concentrated, they become likely targets for government scrutiny and regulation. This, in turn, could raise concerns about the attractiveness of an industry and uncertainty over future earnings of firms in it. As a result, firms in such industries are likely to have greater idiosyncratic risk.

Sensitivity Analyses
In order to draw policy implications and communicate the value of marketing actions to financial markets, we assess the robustness of our results. This is especially important as prior work in finance shows that conclusions drawn from an analysis of abnormal returns and risk measures can change when factors such as sampling aspects and models used to measure returns and/or risk are changed (see Bali and Cakici 2008; Fama 1998).

Removal of potential outliers. To test whether results are driven by outliers, we removed observations with residuals in the top and the bottom five percentiles. As shown in Table 4, there are no changes in the substantive conclusions the current study.

Removing stocks with price less than $2. Low priced stocks tend to exhibit behavior that is contrary to the normal behavior of the majority of stocks (Ball, Kothari, and Shanken 1995; Hertzel et al. 2002). To address this issue we conducted the analyses by removing those stocks from the sample that had a year end stock price of less than $2. As shown in Table 4, our substantive conclusions do not change when we remove these observations from our sample.

Using a level’s model. While we use the changes model along with the GMM estimator, we also test to see if our conclusions are robust to the use of levels models:

\[
\begin{align*}
\beta_{miT} & = \gamma_{m1}[\beta_{mi(T-1)}] + \gamma_{m2}[CS_{iT}] + \gamma_{m3}[R&\&D_{iT}] + \gamma_{m4}[X_{iT}] + \epsilon_{iT} \\
\beta_{dniT} & = \gamma_{dm1}[\beta_{dni(T-1)}] + \gamma_{dm2}[CS_{iT}] + \gamma_{dm3}[R&\&D_{iT}] + \gamma_{dm4}[X_{iT}] + \zeta_{iT} \\
IR_{iT} & = \gamma_{1}[IR_{i(T-1)}] + \gamma_{2}[CS_{iT}] + \gamma_{3}[R&\&D_{iT}] + \gamma_{4}[X_{iT}] + \Phi_{iT} \\
DIR_{iT} & = \gamma_{d1}[DIR_{i(T-1)}] + \gamma_{d2}[CS_{iT}] + \gamma_{d3}[R&\&D_{iT}] + \gamma_{d4}[X_{iT}] + \eta_{iT}
\end{align*}
\]

In addition to removing the potential outliers, we also test the sensitivity of our conclusions to recent research which indicates that customer satisfaction has little effect on stock returns once firms from the computer and internet sector (SIC 37, 59, and 73) and the utilities sector (SIC 49) are removed from the sample (Jacobson and Mizzik 2008). Our results are largely consistent when we use such sensitivity analyses.
We test our hypotheses by estimating equations (16) to (19) using seemingly unrelated regressions (SUR) approach that allows for correlations between error terms across these models (Wooldridge 2006). As shown in Table 4, our substantive conclusions remain unchanged if we use the levels model as opposed to the changes model.

Using unanticipated changes in independent variables. Since customer satisfaction is highly auto-correlated (0.91, p < .001), changes in it are likely to be unexpected changes (Mizik and Jacobson 2008). An alternate method to measure unexpected changes is to regress a variable on its lags and use the residuals as a measure of unanticipated changes (see Jacobson 1987). We calculate unanticipated values of customer satisfaction and the control variables using this method and use the following models:

\[
\begin{align*}
(20) \quad & \beta_{miT} = \gamma_{m1}[\beta_{mi(T-1)}] + \gamma_{m2}[\delta CS_{iT}] + \gamma_{m3}[\delta R&D_{iT}] + \gamma_{m4}[\delta X_{iT}] + \epsilon_{iT} \\
(21) \quad & \beta_{dmiT} = \gamma_{dm1}[\beta_{dmi(T-1)}] + \gamma_{dm2}[\delta CS_{iT}] + \gamma_{dm3}[\delta R&D_{iT}] + \gamma_{dm4}[\delta X_{iT}] + \zeta_{iT} \\
(22) \quad & IR_{iT} = \gamma_1[IR_{i(T-1)}] + \gamma_2[\delta CS_{iT}] + \gamma_3[\delta R&D_{iT}] + \gamma_4[\delta X_{iT}] + \Phi_{iT} \\
(23) \quad & DIR_{iT} = \gamma_1[DIR_{i(T-1)}] + \gamma_2[\delta CS_{iT}] + \gamma_3[\delta R&D_{iT}] + \gamma_4[\delta X_{iT}] + \eta_{iT}
\end{align*}
\]

Where, \(\delta CS_{iT}\) = unanticipated changes in customer satisfaction  
\(\delta R&D_{iT}\) = unanticipated changes in R&D  
\(\delta X_{iT}\) = unanticipated changes in control variables

Consistent with the preceding analyses, these models are estimated using a SUR approach. As shown in Table 4, our substantive conclusions remain unchanged if we use this method.

Taking momentum into consideration. Studies in finance routinely use the Carhart (1997) model that includes the momentum factor, to assess the robustness of their results to the use of Fama-French 3 factor model (outlined in Equation (1)). The momentum factor is defined as the difference in the returns of firms with high and low prior stock performance (“up” minus
“down”) during day ‘t’ (Carhart 1997). Specifically, the following model is used to measure systematic and idiosyncratic risk (as opposed to Equation (1)):

\[
(R_{it} - R_{ft}) = \alpha_{it} + \beta_{mi}(R_{mt} - R_{ft}) + \beta_{si}(SMB)_t + \beta_{hi}(HML)_t + \beta_{ui}(UMD)_t + \epsilon_{it}
\]

Where, \( (UMD)_t \): Momentum factor on day ‘t’, and other symbols have usual meanings.

As shown in Table 4, our substantive conclusions do not change when we use the Carhart (1997) model to calculate the risk measures.

**Taking aggregate volatility into consideration.** Recent work in finance argues that aggregate volatility, that is, volatility in market movements is an additional factor that should be included in CAPM based models (e.g., Ang et al. 2006):

\[
(R_{it} - R_{ft}) = \alpha_{it} + \beta_{mit}(R_{mt} - R_{ft}) + \beta_{vit}(dVIX)_t + \beta_{si}(SMB)_t + \beta_{hi}(HML)_t + \beta_{ui}(UMD)_t + \epsilon_{it}
\]

Where, \( (dVIX)_t \): Changes in Market Volatility on day ‘t’, \( \beta_{mit} \): Systematic risk and other symbols have usual meanings.

As shown in Table 4, our substantive conclusions do not change when we use the Ang et al. (2006) model to calculate the risk measures.

**Using the Boulding and Staelin (1995) method.** An alternative method for addressing the endogeneity arises from the work of Boulding and Staelin (1995). This method involves first differencing and rho differencing the variables and using the lagged values of the differences of endogenous variables as instruments (see p. G227-G230, Boulding and Staelin 1995). Since we use the differences between lagged values as instruments (as opposed to levels of lagged values) the effective sample size in these models is 660. We follow this approach and find that our substantive conclusions remain unchanged (see Table 4).
Non-CAPM based risk measures\(^5\). Risk measures used in this study are based on CAPM-based models. While widely used, some assumptions underlying CAPM can be considered as too restrictive. For example, CAPM assumes that investors have unrestricted access to capital and there are no transaction costs in buying and selling stocks. It can be argued that the effects of customer satisfaction on multiple dimensions of risk observed in this study are bound by the assumptions of CAPM. We, therefore calculate non-CAPM based measures of overall risk, that is, the standard deviation of a firm’s excess returns \((R_{it} - R_f)\) in year \((t)\). The downside risk is calculated as the standard deviation of a firm’s negative returns in year \((t)\). As shown in Table 4, our substantive conclusions do not change if we use the non-CAPM measures of risk.

In addition, we follow accounting literature and measure the perceived risk (or uncertainty) of a firm’s stock as the standard deviation of analyst’s earnings forecast (e.g., Lang and Lundholm 1996). This requires that a firm be followed by at least 4 analysts in a given fiscal year. As result, the sample size for this risk measure is 733 (122 firms). Following prior literature in accounting we also use the number of analysts following a firm as a control variable (e.g., Jones 2007). As shown in Table 4, our substantive conclusions remain unchanged if we use the dispersion in analyst’s earning forecast, a non CAPM metric, as a measure of risk.

**Discussion, Implications & Future Research Directions**

A recent survey of Chief Marketing Officers (CMO) finds marketing accountability and customer orientation among the top three requirements for a successful CMO (Rooney 2008). This study explores both of these issues. Research on customer orientation outcomes measured as customer satisfaction has occupied a prominent status in marketing. Recently, the research has

\(^5\) We thank an anonymous reviewer for suggesting the use of non-CAPM based measures of risk.
expanded to link marketing related actions that drive customer satisfaction to financial outcomes such as stock returns (e.g., Anderson, Fornell, and Mazvancheryl 2004) and cash flows (e.g., Gruca and Rego 2005) addressing the accountability requirement of CMOs. Research in marketing, however, seldom looks at the impact of customer satisfaction on different dimensions of stock returns risk, a key aspect of shareholder value. We take the first step in this direction and contribute to the research on the marketing-finance interface. The current study has several implications for recent efforts at communicating the value of marketing strategy to the financial markets as well as main street managers.

The current study contributes to the recent debate on the value relevance of customer satisfaction beyond the accounting measures (e.g., Fornell, Mithas and Morgeson 2008; Jacobson and Mizik 2008). The current study presents results which show that customer satisfaction is a relevant metric for financial markets as it lowers a firm’s overall and downside systematic and idiosyncratic risk. Recent research in accounting shows that financial analysts tend to use risk metrics such as systematic and idiosyncratic risk when issuing the risk rating of stocks (Hong and Sarkar 2007; Lui, Markov, and Tamayo 2007). As a result, identifying factors that influence these metrics is important as financial analysts can also use customer satisfaction to assess the risk of a stock. The results of the current study can be also used by portfolio managers when analyzing firms to be included in a portfolio. For example, as customer satisfaction reduces both overall and downside systematic risk, firms that increase their customer satisfaction can be used to reduce a portfolio’s exposure to market movements. Similarly, investors who seek average but consistent returns (e.g., pension funds, government funds) can invest in firms that increase their customer satisfaction scores.
The focus of the current study on multiple dimensions of risk suggests that the empirical literature in marketing needs to go beyond systematic risk and take into consideration idiosyncratic risk along with downside systematic and idiosyncratic risk. Senior managers actively seek to manage idiosyncratic risk because it has a direct impact on a firm’s survival and the value of its stock options (e.g., Pace 1999). Idiosyncratic risk also matters to investors as high idiosyncratic risk lowers subsequent returns (see Ang et al. 2006). Downside systematic risk and idiosyncratic risk are also important as they reflect the value of a stock in hedging investments from market downturns. In analyzing the impact of marketing initiatives on stock performance, future research should therefore take into account the multiple dimensions of risk.

The robust nature of customer satisfaction’s impact on multiple measures of risk also speaks to the Financial Accounting Standards Board (FASB). FASB recommends that firms provide non-financial information to investors that can help them assess the amount, timing, and uncertainty of future cash receipts (FASB 1978). This study presents customer satisfaction as a metric that affects the systematic and idiosyncratic risk, and therefore can provide valuable information for investors above and beyond the accounting measures. This suggests that perhaps firms should report customer satisfaction in their annual report and in communications to financial analysts (e.g., Wiesel, Skiera, and Villanueva 2008).

Prior research documents the myriad uses of customer satisfaction including its use as a management control tool and in determining CEO bonus contracts. The financial markets are also interested in CEO compensation and performance since they influence the value of their investment. The findings of the study should provide succor to main street managers as their investments in measuring and monitoring customer satisfaction are worthwhile. By communicating to financial markets the firm’s performance on customer satisfaction, managers
now have a chance to influence the investment community about the quality of the customer base and the management that delivers such a customer base. Consequently, this should enable the firm to earn higher multiples and improve the compensation of senior management.

Limitations & Conclusions

Since we use secondary data compiled from multiple sources, some limitations must be kept in mind. The study uses SIC classification as an indicator for industry. A potential drawback is that SIC classification may include firms that are not direct competitors, leading to missaggregation of firms. However, this missaggregation is unlikely to be systematically different across industries, and therefore unlikely to bias results (Aggarwal and Samwick 1999).

The current study develops hypotheses to examine the impact of customer satisfaction on multiple dimensions of risk and uses data from multiple secondary data sources to test these hypotheses. Results across multiple methods and sensitivity analyses strongly suggest that customer satisfaction contributes to the creation of shareholder wealth by lowering the overall and downside market and idiosyncratic risk. Given the importance of risk to managers and financial markets, this study could serve as a springboard for future research.
### Table 1
Sample Distribution Across Industries

<table>
<thead>
<tr>
<th>SIC Code</th>
<th>Industry Name</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>Agriculture Production Crops</td>
<td>9</td>
</tr>
<tr>
<td>20</td>
<td>Food and Kindred Products</td>
<td>188</td>
</tr>
<tr>
<td>21</td>
<td>Tobacco Products</td>
<td>7</td>
</tr>
<tr>
<td>22</td>
<td>Textile Mill Products</td>
<td>6</td>
</tr>
<tr>
<td>23</td>
<td>Apparel and Other Finished Products</td>
<td>30</td>
</tr>
<tr>
<td>27</td>
<td>Printing, Publishing, and Allied</td>
<td>10</td>
</tr>
<tr>
<td>28</td>
<td>Chemicals and Allied Products</td>
<td>43</td>
</tr>
<tr>
<td>29</td>
<td>Petroleum Refining and Other Industries</td>
<td>30</td>
</tr>
<tr>
<td>30</td>
<td>Rubber, and Miscellaneous Plastic Products</td>
<td>23</td>
</tr>
<tr>
<td>35</td>
<td>Industrial, Commercial Machinery, Computer Equipment</td>
<td>47</td>
</tr>
<tr>
<td>36</td>
<td>Electrical, Other Electrical Equipment, Excluding Computers</td>
<td>40</td>
</tr>
<tr>
<td>37</td>
<td>Transportation Equipment</td>
<td>72</td>
</tr>
<tr>
<td>42</td>
<td>Motor Freight Transportation, Warehouse</td>
<td>6</td>
</tr>
<tr>
<td>45</td>
<td>Transportation by Air</td>
<td>75</td>
</tr>
<tr>
<td>47</td>
<td>Transportation Services</td>
<td>7</td>
</tr>
<tr>
<td>48</td>
<td>Communications</td>
<td>57</td>
</tr>
<tr>
<td>49</td>
<td>Electric, Gas, Sanitary Services</td>
<td>255</td>
</tr>
<tr>
<td>52</td>
<td>Building Material, Hardware, Garden Retail</td>
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</tr>
<tr>
<td>53</td>
<td>General Merchandise Stores</td>
<td>98</td>
</tr>
<tr>
<td>54</td>
<td>Food Stores</td>
<td>66</td>
</tr>
<tr>
<td>56</td>
<td>Apparel and Accessory Stores</td>
<td>8</td>
</tr>
<tr>
<td>57</td>
<td>Home Furniture and Equipment Stores</td>
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</tr>
<tr>
<td>58</td>
<td>Eating and Drinking Places</td>
<td>36</td>
</tr>
<tr>
<td>59</td>
<td>Miscellaneous Retail</td>
<td>19</td>
</tr>
<tr>
<td>60</td>
<td>Depository Institutions</td>
<td>46</td>
</tr>
<tr>
<td>63</td>
<td>Insurance Carriers</td>
<td>36</td>
</tr>
<tr>
<td>70</td>
<td>Hotels, Other Lodging Places</td>
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</tr>
<tr>
<td>73</td>
<td>Business Services</td>
<td>33</td>
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<tr>
<td>99</td>
<td>Conglomerates</td>
<td>16</td>
</tr>
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</table>
### Table 2

**Descriptive Statistics and Correlation Matrix**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Obs</th>
<th>Mean</th>
<th>S.D.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
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<tr>
<td><strong>Levels of Variables</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Systematic Risk</td>
<td>1318</td>
<td>0.91</td>
<td>0.45</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Down Side Systematic Risk</td>
<td>1318</td>
<td>0.91</td>
<td>0.55</td>
<td>0.77</td>
<td>1.00</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Idiosyncratic Risk</td>
<td>1318</td>
<td>1.80</td>
<td>1.07</td>
<td>0.28</td>
<td>0.24</td>
<td>1.00</td>
<td></td>
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<td></td>
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<td></td>
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<td></td>
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<tr>
<td>4 Down Side Idiosyncratic Risk</td>
<td>1318</td>
<td>1.24</td>
<td>0.81</td>
<td>0.29</td>
<td>0.29</td>
<td>0.93</td>
<td>1.00</td>
<td></td>
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<td></td>
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<tr>
<td>5 Customer Satisfaction</td>
<td>1318</td>
<td>4.32</td>
<td>0.09</td>
<td>-0.27</td>
<td>-0.23</td>
<td>-0.22</td>
<td>-0.21</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>6 Leverage</td>
<td>1297</td>
<td>0.28</td>
<td>0.23</td>
<td>0.20</td>
<td>0.17</td>
<td>0.18</td>
<td>-0.36</td>
<td>1.00</td>
<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>7 R&amp;D-Total Assets</td>
<td>1162</td>
<td>9.65</td>
<td>1.45</td>
<td>0.05</td>
<td>-0.31</td>
<td>-0.25</td>
<td>-0.16</td>
<td>0.27</td>
<td>-0.09</td>
<td>-0.21</td>
<td>1.00</td>
<td></td>
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<tr>
<td>8 Return on Assets</td>
<td>1269</td>
<td>0.13</td>
<td>0.08</td>
<td>-0.22</td>
<td>-0.17</td>
<td>-0.30</td>
<td>-0.29</td>
<td>0.24</td>
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<tr>
<td>9 Total Assets</td>
<td>1288</td>
<td>6.15</td>
<td>1.45</td>
<td>0.05</td>
<td>-0.31</td>
<td>-0.25</td>
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<td>10 Dividends</td>
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<td>0.04</td>
<td>-0.05</td>
<td>-0.03</td>
<td>-0.03</td>
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<td>0.16</td>
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<tr>
<td>11 Liquidity</td>
<td>1179</td>
<td>1.25</td>
<td>0.69</td>
<td>0.14</td>
<td>0.16</td>
<td>0.14</td>
<td>0.11</td>
<td>-0.22</td>
<td>0.07</td>
<td>-0.03</td>
<td>-0.32</td>
<td>-0.08</td>
<td>1.00</td>
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<tr>
<td>12 Herfindahl Index</td>
<td>1318</td>
<td>0.19</td>
<td>0.19</td>
<td>-0.06</td>
<td>-0.05</td>
<td>-0.06</td>
<td>-0.12</td>
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<td>0.07</td>
<td>-0.02</td>
<td>0.00</td>
<td>1.00</td>
<td></td>
</tr>
</tbody>
</table>

| Changes in Variables             |     |       |      |     |     |     |     |     |     |     |     |     |     |     |     |
| 1 Systematic Risk                | 1162| -0.01 | 0.44 | 1.00|     |     |     |     |     |     |     |     |     |     |     |     |
| 2 Down Side Systematic Risk      | 1162| 0.00  | 0.66 | 0.68| 1.00|     |     |     |     |     |     |     |     |     |     |     |
| 3 Idiosyncratic Risk             | 1162| -0.01 | 0.81 | 0.27| 0.20| 1.00|     |     |     |     |     |     |     |     |     |     |
| 4 Down Side Idiosyncratic Risk   | 1162| 0.00  | 0.74 | 0.27| 0.26| 0.86| 1.00|     |     |     |     |     |     |     |     |     |
| 5 Customer Satisfaction         | 1162| 0.00  | 0.04 | -0.06| -0.07| -0.06| -0.05| 1.00|     |     |     |     |     |     |     |     |
| 6 Leverage                       | 978  | 0.00  | 0.01 | -0.01| -0.11| 0.05| 0.06| -0.02| 1.00|     |     |     |     |     |     |     |
| 7 R&D-Total Assets               | 1116| 0.00  | 0.04 | -0.07| -0.03| -0.18| -0.20| 0.05| -0.08| 1.00|     |     |     |     |     |     |
| 8 Return on Assets               | 1133| 0.07  | 0.20 | -0.02| 0.04| -0.05| -0.03| 0.00| -0.06| -0.25| 1.00|     |     |     |     |
| 9 Total Assets                   | 1130| 0.00  | 0.02 | 0.00| 0.03| 0.03| 0.09| 0.07| -0.01| -0.06| -0.09| 1.00|     |     |     |
| 10 Dividends                     | 1034| -0.01 | 0.34 | -0.02| 0.02| 0.01| -0.02| -0.01| -0.05| 0.03| -0.04| -0.04| 1.00|     |     |
| 11 Liquidity                     | 1143| 0.00  | 0.09 | 0.14| 0.10| 0.30| 0.33| -0.03| 0.04| -0.23| 0.18| 0.18| 0.08| 1.00|     |
| 12 Herfindahl Index              | 1162| 0.00  | 0.07 | -0.04| -0.03| 0.01| 0.00| -0.07| -0.01| 0.05| -0.05| -0.01| 0.02| -0.04| 1.00|

* All correlations in italics are significant at 90% level
Table 3  
Customer Satisfaction Lowers Systematic and Idiosyncratic Risk*  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Systematic Risk</th>
<th>Down Side Systematic Risk</th>
<th>Idiosyncratic Risk</th>
<th>Down Side Idiosyncratic Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ (Dependent Variable)_{i(t-1)}</td>
<td>-.01</td>
<td>-.05</td>
<td>-.07*</td>
<td>-.16***</td>
</tr>
<tr>
<td>Δ (log(Customer Satisfaction))_{it}</td>
<td>-1.88**</td>
<td>-3.76***</td>
<td>-3.42**</td>
<td>-2.31**</td>
</tr>
<tr>
<td>Δ (Leverage)_{it}</td>
<td>.76**</td>
<td>.89*</td>
<td>4.06***</td>
<td>3.64***</td>
</tr>
<tr>
<td>Δ (R&amp;D Ratio)_{it}</td>
<td>-3.10**</td>
<td>-7.80***</td>
<td>-.26</td>
<td>1.24</td>
</tr>
<tr>
<td>Δ (ROA)_{it}</td>
<td>-1.21**</td>
<td>1.14</td>
<td>-5.36***</td>
<td>-3.02***</td>
</tr>
<tr>
<td>Δ (Total Assets)_{it}</td>
<td>.16*</td>
<td>.37**</td>
<td>.10</td>
<td>.01</td>
</tr>
<tr>
<td>Δ (Dividends Paid)_{it}</td>
<td>-1.36</td>
<td>4.75**</td>
<td>.51</td>
<td>.13</td>
</tr>
<tr>
<td>Δ (Liquidity)_{it}</td>
<td>.11</td>
<td>-.12</td>
<td>.19</td>
<td>-.10</td>
</tr>
<tr>
<td>Δ (Industry Concentration)_{it}</td>
<td>-1.30***</td>
<td>-1.26**</td>
<td>1.80**</td>
<td>1.18**</td>
</tr>
<tr>
<td>Δ (Coverage)_{it}</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ (Stock Return Volatility)_{it}</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>806</td>
<td>806</td>
<td>806</td>
<td>806</td>
</tr>
</tbody>
</table>

Wald's Chi-Square  
- 100.23 (20)***  
- 92.32 (20)***  
- 601.28 (20)***  
- 412.16 (20)***

Hansen Test  
- 107.37 (110)  
- 107.65 (127)  
- 106.67 (110)  
- 107.45 (127)

* * (p < 0.10), ** (p < 0.05), *** (p < 0.01)
Table 4
Assessing the Robustness of Results∗

<table>
<thead>
<tr>
<th></th>
<th>Removing + / - 5% tile Residuals</th>
<th>Removing Observations where Stock Price is Less than $2</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Systematic Risk</td>
<td>Down Side Systematic Risk</td>
</tr>
<tr>
<td>Δ (Log (CUSAT))it</td>
<td>-5.13***</td>
<td>-3.63***</td>
</tr>
<tr>
<td>Δ (Leverage)it</td>
<td>.93***</td>
<td>1.24***</td>
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<tr>
<td>N</td>
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<td>725</td>
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<tr>
<td>Wald's Chi-Square</td>
<td>159.64 (20)***</td>
<td>143.22 (20)***</td>
</tr>
<tr>
<td>Hansen Test</td>
<td>97.63 (110)</td>
<td>102.75 (127)</td>
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</table>

Estimating Levels Model

<table>
<thead>
<tr>
<th></th>
<th>Systematic Risk</th>
<th>Down Side Systematic Risk</th>
<th>Idiosyncratic Risk</th>
<th>Down Side Idiosyncratic Risk</th>
<th>Systematic Risk</th>
<th>Down Side Systematic Risk</th>
<th>Idiosyncratic Risk</th>
<th>Down Side Idiosyncratic Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log (CUSAT)it</td>
<td>-.82***</td>
<td>-.84***</td>
<td>-2.33***</td>
<td>-1.88***</td>
<td>-.86***</td>
<td>-1.06***</td>
<td>-1.35***</td>
<td>-.87***</td>
</tr>
<tr>
<td>(Leverage)it</td>
<td>.00</td>
<td>.18*</td>
<td>.29***</td>
<td>.27***</td>
<td>.57***</td>
<td>.72***</td>
<td>2.96***</td>
<td>2.47***</td>
</tr>
<tr>
<td>N</td>
<td>869</td>
<td>869</td>
<td>869</td>
<td>869</td>
<td>869</td>
<td>869</td>
<td>869</td>
<td>869</td>
</tr>
<tr>
<td>R²</td>
<td>.32</td>
<td>.16</td>
<td>.63</td>
<td>.51</td>
<td>.29</td>
<td>.14</td>
<td>.65</td>
<td>.53</td>
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</tbody>
</table>

Using Unanticipated Changes Calculated From Residuals

<table>
<thead>
<tr>
<th></th>
<th>Systematic Risk</th>
<th>Down Side Systematic Risk</th>
<th>Idiosyncratic Risk</th>
<th>Down Side Idiosyncratic Risk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log (CUSAT)it</td>
<td>-.86***</td>
<td>-1.06***</td>
<td>-1.35***</td>
<td>-.87**</td>
</tr>
<tr>
<td>(Leverage)it</td>
<td>.57***</td>
<td>.72***</td>
<td>2.96***</td>
<td>2.47***</td>
</tr>
<tr>
<td>N</td>
<td>869</td>
<td>869</td>
<td>869</td>
<td>869</td>
</tr>
<tr>
<td>R²</td>
<td>.29</td>
<td>.14</td>
<td>.65</td>
<td>.53</td>
</tr>
</tbody>
</table>

∗ (p < 0.10), ** (p < 0.05), *** (p < 0.01)
Table 4 (Cntd.)
Assessing the Robustness of Results

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Systematic Risk</td>
<td>Down Side</td>
<td>Idiosyncratic Risk</td>
<td>Down Side</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Systematic Risk</td>
<td></td>
<td>Idiosyncratic Risk</td>
</tr>
<tr>
<td>Δ (Log (CUSAT)ₙ)ᵢ</td>
<td>-1.41*</td>
<td>-3.57***</td>
<td>-3.37**</td>
<td>-2.24**</td>
</tr>
<tr>
<td>Δ (Leverage)ᵢ</td>
<td>.95**</td>
<td>1.54***</td>
<td>4.09***</td>
<td>3.67***</td>
</tr>
<tr>
<td>N</td>
<td>806</td>
<td>806</td>
<td>806</td>
<td>806</td>
</tr>
<tr>
<td>Wald's Chi-Square</td>
<td>74.81 (20)***</td>
<td>94.86 (20)***</td>
<td>588.73 (20)***</td>
<td>401.44 (20)***</td>
</tr>
<tr>
<td>Hansen Test</td>
<td>108.50 (110)</td>
<td>106.11 (127)</td>
<td>107.11 (110)</td>
<td>104.79 (127)</td>
</tr>
</tbody>
</table>

|                      | Systematic Risk      | Down Side     | Idiosyncratic Risk      | Down Side     |
|                      |                      | Systematic Risk |                  | Idiosyncratic Risk |
| Δρ (Log (CUSAT)ₙ)ᵢ   | -1.91***             | -4.27***      | -.89*                   | -1.33**       |
| Δρ (Leverage)ᵢ       | .56**                | .76**         | 1.51***                 | 2.08***       |
| N                    | 660                  | 660           | 660                     | 660           |
| Wald's Chi-Square    | 69.71 (17)           | 56.54 (17)    | 284.33 (17)             | 283.19 (17)   |
| Hansen Test          | 110.22 (110)         | 103.70 (127)  | 89.13 (88)              |               |

|                      | Using Non-CAPM Risk Measures |               |                      |
|                      | Standard Deviation of Stock Returns | Downside Standard Deviation of Stock Returns | Dispersion in Analyst Earnings Forecast |
| Δ (Log (CUSAT)ₙ)ᵢ   | -4.62*** | -3.26*** | -5.75** |
| Δ (Leverage)ᵢ       | 4.24***  | 3.63***  | 3.68*** |
| N                    | 806      | 806      | 733      |
| Wald's Chi-Square    | 643.49 (20)*** | 432.97 (20)*** | 95.72 (22)*** |
| Hansen Test          | 110.22 (110) | 103.70 (127) | 89.13 (88) |

* (p < 0.10), ** (p < 0.05), *** (p < 0.01)
### Appendix Table A1
Definitions, Measures, and Literature Sources for Control Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Quarterly COMPUSTAT Data Items</th>
<th>Prior Literature Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return on Assets</td>
<td>The ratio of operating income to total assets</td>
<td>[DATA21/DATA44]</td>
<td>Hong and Sarkar (2007)</td>
</tr>
<tr>
<td>Total Assets</td>
<td>The logged value of total assets of a firm.</td>
<td>Log [DATA44]</td>
<td>Beaver, Kettler, and Scholes (1970)</td>
</tr>
<tr>
<td>Leverage Ratio</td>
<td>The ratio of total long-term debt to the sum of long-term debt and the market value of equity of a firm.</td>
<td>[DATA51] / [DATA51+(DATA14*DATA61)]</td>
<td>Hong and Sarkar (2007)</td>
</tr>
<tr>
<td>Liquidity</td>
<td>The current ratio of a firm.</td>
<td>[DATA40]/[DATA49]</td>
<td>Beaver, Kettler, and Scholes (1970)</td>
</tr>
<tr>
<td>Competitive Intensity</td>
<td>The SIC 4 digit concentration index of firm revenues</td>
<td>Herfindahl Concentration Index Using DATA 2</td>
<td>Hou and Robinson (2006)</td>
</tr>
</tbody>
</table>
References


Rooney, Jennifer (2008), “As if you didn’t know by now, it’s about the bottomline for CMOs”, *Advertising Age*, May 5.


