Balancing Risk and Return in a Customer Portfolio

Author(s): Crina O. Tarasi, Ruth N. Bolton, Michael D. Hutt and Beth A. Walker

Source: *Journal of Marketing*, May 2011, Vol. 75, No. 3 (May 2011), pp. 1-17

Published by: Sage Publications, Inc. on behalf of American Marketing Association

Stable URL: https://www.jstor.org/stable/41228591

Crina O. Tarasi, Ruth N. Bolton, Michael D. Hutt, & Beth A. Walker

Balancing Risk and Return in a Customer Portfolio

Marketing managers can increase shareholder value by structuring a customer portfolio to reduce the vulnerability and volatility of cash flows. This article demonstrates how financial portfolio theory provides an organizing framework for (1) diagnosing the variability in a customer portfolio, (2) assessing the complementarity/similarity of market segments, (3) exploring market segment weights in an optimized portfolio, and (4) isolating the reward on variability that individual customers or segments provide. Using a seven-year series of customer data from a large business-to-business firm, the authors demonstrate how market segments can be characterized in terms of risk and return. Next, they identify the firm's efficient portfolio and test it against (1) its current portfolio and (2) a hypothetical profit maximization portfolio. Then, using forward- and back-testing, the authors show that the efficient portfolio has consistently lower variability than the existing customer mix and the profit maximization portfolio. The authors provide guidelines for incorporating a risk overlay into established customer management frameworks. The approach is especially well suited for business-to-business firms that serve market segments drawn from diverse sectors of the economy.

Keywords: customer portfolio management, market-based assets, financial portfolio theory, return on marketing, market segmentation

> The advantage of knowing about risks is that we can change our behavior to avoid them.... Optimal behavior takes risks that are worthwhile. (Engle 2004, p. 405)

Although risk management is central to financial portfolio theory and occupies much of chief financial officers' time, researchers have given sparse attention to risk in the theory and practice of market segmentation and customer portfolio management. The existing portfolio of most firms reflects incremental and uncoordinated decisions from the past, when they gave little attention to how newly acquired customers contributed to the profitability and risk of the entire portfolio. For example, Homburg, Steiner, and Totzek (2009) find that firms tend to overestimate the value of top-tier customers and underestimate that of bottom-tier customers. In a similar vein, Dhar and Glazer (2003, p. 88) observe that few companies consider "whether all of their individually desirable customers are, from the standpoint of risk, desirable collectively." This practice is at odds with financial portfolio theory, which posits that although assets are selected individually, performance is measured on the entire portfolio, in which there is a tradeoff between risk and return (Markowitz 1952). We theorize that, like a financial portfolio, a customer portfolio is formed by making choices among market-based assets (i.e., customers) that present different risk–reward characteristics and allocating resources to optimize performance (Gupta and Lehmann 2005; Srivastava, Shervani, and Fahey 1998).

The purpose of our research is to explore how financial principles of diversification and the tenets of financial portfolio theory can be effectively applied to manage a firm's customer portfolio. We demonstrate how fundamental tools of analysis that professional investors use in constructing and managing a stock portfolio can be adapted and used to enrich a firm's market segmentation and customer portfolio decisions. First, we aim to identify risk that can (and should) be divested away because firms do not reap greater returns from assuming it and (instead) suffer losses when market conditions change. Second, we attempt to identify ways to construct efficient customer portfolios. Third, we build on these components to develop an actionable approach that, by looking beyond the returns from individual customers, exploits the synergies of a diverse customer base characterized by heterogeneous risk–return profiles and provides a new approach for managing a firm's market-based assets.

Cardozo and Smith's (1983) initial application of financial portfolio theory to product portfolio decisions spawned criticism from Devinney, Stewart, and Shocker (1985), who identify key differences between financial and product investment decisions, arguing that crucial assumptions of the theory were violated (see Cardozo and Smith's [1985] reply). However, recent research has demonstrated the potential insights that financial portfolio theory can contribute to customer portfolio management. Dhar and Glazer

Crina O. Tarasi is Assistant Professor of Marketing, Central Michigan University (e-mail: crina.tarasi@cmich.edu). Ruth N. Bolton is 2009–2011 Executive Director, Marketing Science Institute (e-mail: rbolton@msi.org). Michael D. Hutt is Ford Motor Company Distinguished Professor of Marketing (e-mail: michael.hutt@asu.edu), and Beth A. Walker is State Farm Professor of Marketing (e-mail: beth.walker@asu.edu), W.P. Carey School of Business, Arizona State University. The authors acknowledge the support of the Marketing Science Institute and are grateful to the managers at the sponsor firm for their responsive support and high level of cooperation. The authors thank Don Lehmann, Kay Lemon, and Michael Mokwa for their valuable comments. In addition, the authors thank the three anonymous *JM* reviewers for their incisive comments and useful suggestions.

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

(2003) describe the importance of measuring the riskiness of customers (i.e., customer beta) and illustrate how a firm can maximize returns by acquiring or retaining particular customers or market segments on the basis of how their spending patterns contribute to the diversification of the cash flow of the overall customer portfolio.

Ryals (2002, 2003) also adopts a financial theory perspective to examine the risk and return characteristics of a customer portfolio and describe how a customer relationship scorecard can be used to assess customer risk. Likewise, Buhl and Heinrich (2008) offer a quantitative model based on financial portfolio theory that (1) considers the customer lifetime value (CLV) in addition to the associated risks of customer segments and (2) provides a method for adding and subtracting market segments. Using a case study from the financial services industry, they test the model by using the average annual incomes of key customer segments (e.g., lawyers, physicians) as an indicator of cash flows and demonstrate how the optimal portfolio provides both higher utility and better risk diversification than the existing portfolio.

This study makes the following contributions to customer portfolio theory and practice: First, we build on past research to show theoretically and empirically how to make a nuanced assessment of customer value by calculating the customer beta (Buhl and Heinrich 2008; Dhar and Glazer 2003) and contribute a new metric for customer portfolio management: the customer reward ratio. Customer beta provides a relative measure of the sensitivity of an individual customer's cash flow return to that of the firm's current customer portfolio. By adjusting for variability, the customer reward ratio, drawn from Sharpe's (1994) work, takes into account the risk–reward trade-off associated with the customer.

Second, the study evaluates the extent to which classic market segmentation variables (e.g., demographics, firmographics) can be used to predict cash flow characteristics (i.e., risk–return profiles) of customers so that managers can assess how potential (and existing) customers might contribute to the customer portfolio. Note that unlike some prior research that controls for customer heterogeneity (Niraj, Gupta, and Narasimhan 2001; Venkatesan and Kumar 2004), our approach evaluates and exploits customer heterogeneity to improve business performance.

Third, the current study is responsive to calls for research that examines the financial impact of customer portfolio management decisions (e.g., Rust et al. 2004). We show conceptually and empirically how a firm can identify synergies among customers and assemble the optimal mix of customers by constructing an efficient frontier for customer portfolios. The efficient frontier describes alternative optimal customer portfolios—those characterized by minimum risk for a certain level of return or maximum return for a certain level of risk. Finally, Tuli, Bharadwaj, and Kohli (2010) provide evidence that the number and types of ties a company builds with its best customers not only ensures higher revenue but also reduces the variability of their purchases. We extend their work by demonstrating that the firm can manage its portfolio of customer relationships to control the overall variability of its cash flow.

We test the feasibility of applying key financial concepts to customer portfolios by implementing them using a seven-year series of customer data from a large business-to-business company. We begin by exploring whether we can segment the firm's customer base in ways that are comparable with financial asset classification. Then, we identify the firm's efficient customer portfolio and test it against (1) its current portfolio and (2) a hypothetical profit-optimization portfolio. Our results show that customers exhibit substantial differences in their risk–return profiles and that clustering techniques can be used to identify market segments for building efficient portfolios. Most important, we demonstrate that the firm's efficient portfolio has constantly lower variability than the existing customer mix and the profit maximization portfolio and that its profit performance is superior in the long run.

Conceptual Framework

This section reviews financial portfolio theory and conceptualizes how key financial constructs can be applied to customer portfolios. Then, we describe how these financial constructs can be calculated from customer purchase history data. Next, we turn to how firms can identify the most desirable customers by assessing the rate of reward on risk for each customer. Last, we address how firms can use these constructs and measures to segment their customer bases in ways that are comparable with financial asset classification.

Financial Portfolio Theory

Financial portfolio theory describes how investors can construct portfolios to maximize return according to a given level of market risk, emphasizing that risk is an inherent part of greater reward (Markowitz 1952). In a stock portfolio, the lower the total correlation of a stock with the total return, the more desirable the particular stock is to the portfolio. For example, stocks drawn from different industries, different countries, and different-sized companies are affected by environmental and economic changes in specific ways (Niemira and Klein 1994). Because many market changes cannot be anticipated, diversification ensures that the portfolio includes positive cash flow opportunities and smoothes out potentially negative cash flows. In terms of the variability and return of each asset, the optimal (efficient) portfolio is considered the one that has the least risk for a desired level of return or the highest level of return for a certain level of risk. Any other portfolio would be suboptimal. The set of efficient portfolios form the efficient frontier, which borders the set of all possible portfolios (Markowitz 1987).

Among the criticisms of financial portfolio theory is the assumption that asset returns are normally distributed, although large swings in the market occur far more frequently than the normal distribution would predict. For example, the S&P 500 stock index has experienced a three-standard-deviation negative monthly return event ten times since 1926, though a normal distribution would predict such extreme returns perhaps one or two times (Kaplan 2009). Another criticism centers on the assumption that correlations between assets are stable. However, during periods of market stress, assets that were previously found to be uncorrelated can suddenly move in lockstep (e.g., Hubbard 2009).

Criticism has also been leveled against the efficient portfolio concept. For example, DeMiguel, Garlappi, and Uppal (2007) evaluate 14 optimal portfolio models advanced in the finance literature, which are based largely on the capital asset pricing model (Sharpe, Alexander, and Bailey 1999), and find that none is better than a naïve approach, in which an investor allocates a fraction of wealth to each of the assets available for investment. However, by drawing on financial portfolio theory and defining the market portfolio as the existing customer base of a firm, our focus differs from the capital asset pricing model (for a critique in the context of customer portfolios, see Buhl and Heinrich 2008).

Despite these criticisms, financial portfolio theory "plays a role in almost every area of financial practice and can be a useful tool for many important managerial decisions" (Grinblatt and Titman 2002, p. 97). In turn, the theory has been used to inform economic development strategies at multiple levels of analysis. By applying financial portfolio theory to regional economics, Conroy (1974) introduces a method for measuring economic diversification that has spawned a rich research tradition in the regional science literature (for a review, see Dissart 2003). In this context, a region represents a portfolio of assets (industry sectors) that make up the local economy, and each industry yields a return (employment) but also entails a risk (employment volatility).

Researchers have used this portfolio management framework to study the growth–instability trade-offs of metropolitan areas (e.g., Conroy 1974), individual states' and countries' economies (e.g., Lande 1994), and international regions, including Western Europe (Chandra 2003). For example, Lande (1994) examines the economic structure of selected states, identifying industry sectors that contribute to employment growth and stability in an optimal portfolio. Collectively, studies from this research tradition lend strong support to our view that financial portfolio theory can provide a valuable framework for evaluating and managing a customer portfolio, particularly for business-to-business firms that serve customers drawn from diverse industry sectors.

Cash Flow Stability and Firm Value

Extending the work of Srivastava, Shervani, and Fahey (1998), we theorize that the market-based assets of a firm include distinct customer asset classes, which are characterized by differing degrees of cash flow variability and vulnerability. Customer asset classes represent the market segments that constitute the existing customer base and embody the outcomes of relationships between the firm and its customers. Investment portfolio decisions involve choices within and among various asset classes of stocks and bonds; in contrast, customer portfolio decisions involve choices within and among distinct customer asset classes (e.g., governance type, size, industry) that encompass both new and existing customers in the served market and present different risk–return profiles for the firm. In support, Gupta and Lehman (2005, p. 8) assert that customers are indeed assets, and therefore customer-related expenditures "should be treated as investments rather than expenses." They demonstrate that the value of the customer base provides a strong guideline for firm value.

In choosing among customers to add to a portfolio, the less a customer's purchasing behavior promises to be like that of the current portfolio, the stronger is its contribution to the stability and predictability of the portfolio; conversely, the more the behavior is like that of the existing portfolio, the weaker is its contribution. Therefore, the attractiveness of a customer hinges not only on the size and frequency of purchases but also on the degree to which the customer's pattern of purchases covaries with those of other customers in the portfolio. The declining cash flow from one customer may be offset by increased returns from another. For example, during a recession, a transportation company might experience a decline in revenue from discretionary retailers that is offset by an increase from discount retailers or declining revenue from auto producers that is partially offset by a growing revenue stream from after-market auto parts retailers.

By developing a risk-adjusted customer portfolio to achieve profit targets, marketing managers can contribute to firm value. Because investors favor stable over volatile earnings (Ang, Chen, and Xing 2006; Srinivasan and Hanssens 2009) and cash flows that are more stable and predictable reduce working capital needs (Rao and Bharadwaj 2008; Srivastava, Shervani, and Fahey 1998), firms can enhance shareholder value by reducing the vulnerability and volatility of cash flows from the customer portfolio.

Customer Portfolios Versus Financial Portfolios

As the preceding section indicates, customers, like stocks, represent risky assets, and the cost of acquiring them should reflect the cash flow they are expected to generate over time. However, we acknowledge that key differences exist between financial and customer portfolios with respect to the nature of the assets, returns, and uncertainty.[1]

Assets. Because customer portfolio decisions represent only one of many levels of marketing investment a firm makes, they are embedded in a far more complex investment management framework than financial portfolio decisions. Marketing investments are made to enhance the value of brand assets through, for example, product research and development, channel support, and advertising. To enhance the value of customer assets, the firm gives special emphasis to investments in customer relationship building by using elements of the marketing promotion mix (e.g., communications, sales force, customer–firm interactions; Ambler et al. 2002).

Financial assets can be identified and readily purchased; in contrast, particular customers can be targeted, but there is no assurance that the firm will be successful in attracting them to the portfolio. Likewise, individual customer relationships take time to develop and usually require continuing investments (Johnson and Selnes 2004; Kumar 2008). Therefore, an existing customer asset's price is the retention costs represented by these continuing expenditures, and the

[1]We thank an anonymous reviewer for suggesting this organizational scheme and focus.

a new customer asset's price is the associated acquisition costs. Compared with a customer portfolio, investors can also readily make portfolio adjustments by selling assets at a market price and changing the proportion (weight) assigned to particular asset classes. In contrast, there is no liquid market for customer assets (Kundisch, Sackmann, and Ruch 2008), and customer divestment can be costly and represents a strategic option that must be exercised sparingly (Mittal, Sarkees, and Murshed 2008).

Financial assets can be purchased in parcels of any size; in contrast, customer assets are not infinitely divisible, and major portfolio adjustments can be costly and difficult to implement in a timely manner. An investor who wants to increase the portfolio weighting of a particular industry sector can readily implement this change by selling stocks from one sector (e.g., energy) and buying stocks in another (e.g., technology). To make corresponding changes in the weighting of market segments within the customer portfolio, a manager faces a longer time horizon, new strategy priorities, and a host of rigidities that the current strategy imposes. To illustrate, reorganizing the customer portfolio might require a realignment of sales and marketing communication strategies, highlighting the higher transaction costs associated with customer versus financial portfolios.

Return. For an investor, return is the change in value of the investment, which includes capital appreciation (or loss) plus the cash yield. Unlike financial assets, customers can be interconnected and contribute to the return of a market segment through social processes, such as positive word of mouth (Ryals 2003). Return for the customer portfolio is the cash flow and profit (revenue minus cost to serve) that accrue to the firm from investments made in individual customers and market segments. The firm makes a host of other marketing investments that enrich the customer relationship strategy but are not directly captured in the cost-to-serve calculation. To illustrate, the decision to increase the weighting of particular market segments in a customer portfolio might require corresponding investments in new product development or service support that go beyond the direct customer costs that we consider.

In a financial portfolio, the rate of return is independent of the amount invested. In contrast, a distinct difference between customer and financial portfolios is that the returns from investing in customers are likely to be nonlinear. Specifically, the amount of investment has a nonlinear relationship with the "return on customer," which means, for example, that small investments might be insufficient to attract or retain an individual customer or market segment.

Managerial control is among the unique characteristics that distinguish customer investments from financial investments (Devinney and Stewart 1988). For example, a firm can increase sales and reduce sales variability by forging multiple types of relationship ties with a customer organization (Tuli, Bharadwaj, and Kohli 2010) or enhance returns by identifying elements of its customer management effort that provide the greatest marginal return on additional investments (Bowman and Narayandas 2004). When an investor chooses an optimal weight for a particular asset class and purchases the associated securities, there is no impact on the risk and return for that asset class. In contrast, managers can exercise a significant degree of control over the risk and return characteristics of the customer portfolio. For example, the weight assigned to a market segment can affect the performance of that segment because of increasing or decreasing returns to scale. Some market segments complement the economies of the seller's business better than others, and some customers within these segments are less costly to serve than others.

Uncertainty. The difference between the expected and actual realized returns of an asset constitutes uncertainty in financial portfolio theory. Investment uncertainty is characterized by the variability, or risk, in the return of a security—namely, the deviation of the return from expected value during the holding period. Then firms use the variations in the returns of securities to estimate the covariance among the array of assets that constitute a portfolio. In the customer portfolio context, the deviation of customer cash flow and profit from their expected values provides a measure of risk. However, there are other sources of uncertainty that are unique to a customer portfolio. Unlike financial assets, which can be retained as long as the investor desires, customers can take independent actions and defect or shift a share of their total purchases to a competitor. Therefore, customer cash flow stability provides a narrow measure of the strength of a customer relationship.

Customer portfolio applications. To capitalize on the strength of financial portfolio analysis while managing the associated constraints and limitations, a firm can examine the risk–return characteristics and structure of its current customer portfolio. Specifically, we demonstrate how portfolio theory provides an organizing framework and supporting methodology for (1) diagnosing the variability in the overall customer portfolio, (2) assessing the complementarity/similarity of market segments, (3) exploring the weights of market segments in an optimized portfolio, and (4) gauging the reward on variability that individual customers or segments provide.

In applying financial theory to customer portfolio management, some key limitations must be understood and managed. First, during periods of severe economic stress, market segments that were previously uncorrelated can suddenly move in tandem, limiting the benefits of diversification. Second, our approach determines how the current customer base might be reconfigured into an optimal portfolio, but some of these adjustments are costly and raise a host of strategic issues beyond the scope of our analysis. The optimal portfolio can best be viewed as an ideal customer base that managers can evaluate, revise, and assemble over time. Therefore, the optimization process should include a qualitative overlay based on managerial judgment to arrive at recommended resource allocations by segment. In Markowitz's (1952, p. 91) seminal work, he emphasizes that the statistical results that issue from his approach should be viewed as tentative and then enriched by judgment "on the basis of factors or nuances not taken into account by the formal computations."

Third, our analysis examines the cash flow and profit of individual customers but does not assess other important customer metrics, including customer satisfaction, loyalty, or share of wallet. Likewise, we do not consider the host of factors that influence individual customer profitability, such as demand stimulating the firm's efforts or competitive behavior (Bowman and Narayandas 2004). To that end, our conceptualization of customer portfolio risk complements, rather than replaces, other approaches from the customer management research tradition that examine other types of risk, such as the risk of defection and the probability of achieving CLV outcomes (e.g., Blattberg, Getz, and Thomas 2001; Bolton, Lemon, and Verhoef 2008; Rust, Lemon, and Zeithaml 2004).

Appropriate market contexts. Our approach specifically applies to situations in which there are meaningful differences in variability across the market segments that constitute a firm's customer portfolio. Therefore, we believe the approach is best suited for the business market, in which these conditions are often present. Compared with consumer packaged goods contexts, business marketers tend to allocate greater proportions of their sales and marketing resources at the individual customer level. Likewise, many business-to-business firms serve market segments drawn from diverse sectors of the economy, each of which demonstrate a distinct demand function (Dickson and Ginter 1987). The approach might also be appropriate for business-to-consumer firms that have direct contact with the customer, such as telecommunications and financial services companies. However, the approach will be less suitable in these or other situations if market segments tend to be highly correlated.

Customer Portfolio: Risk and Reward

Markowitz (1987) measures risk using the variability of the price of the asset, which represents a good proxy for the probability of encountering an unexpected outcome. The risk and return associated with the cash flow of each customer can be computed using purchase history data. Historic analyses are based on the assumption that the future will be like the past (Sharpe, Alexander, and Bailey 1999), and variance is difficult to forecast. However, we assume that the relationships and correlations of the past are sufficiently stable and that past variability is a good proxy for future variability (Balagopal and Gilliland 2005; Chan, Karceski, and Lakonishok 1999).

Cash flow variability and overall customer portfolio risk. We define "risk" as volatility or variability associated with cash flow, and it is traditionally estimated using standard deviation or variance. The formula for computing the variance of customer A, V_A, is $V_A = [\Sigma_{i=1}^{N_A}(x_{Ai} - x_A)^2]/(N_A - 1)$, and standard deviation is $\sigma_A = V_A^{1/2}$, where x_{Ai} is the cash flow for customer A in the ith period in which a cash flow occurred, x_A is the average value of cash flow from customer A for the N_A periods, and N_A is the number of periods in which a cash flow from customer A occurred.

To obtain a standardized measure of variance that corrects for differences in the average levels of cash flows across customers, we compute the coefficient of variation as follows:

$$Cv = \sigma_A/x_A.$$

We compute the risk of the entire portfolio V_p using a similar formula, except that the cash flow used is the average of all customer cash flows (Markowitz 1987):

$$V_P = \frac{\sum_{j=1}^{N}(x_j - x_P)^2}{N-1}, \quad (1)$$

where x_j is the cash flow from all customers active in period j, $x_j = \Sigma_1^{M_j}x_{jk}$ (where M_j is the number of customers active in period j and x_{jk} is the cash flow from firm k in period j); N is the number of periods considered; and x_p is the average value of cash flow from the customer portfolio for the N periods and M firms, $x_P = (\Sigma_{j=1}^{N}x_j)/(N - 1)$. To compare the performance of portfolios with different levels of performance (e.g., different means), we standardize the values by dividing the monthly values by the mean of the portfolio before computing variability.

Customer Beta and Customer Reward Ratio

Customer beta. To identify the most desirable customers, we need a reliable measure of the consistency of returns for an individual customer compared with a reference customer or portfolio. In finance applications, beta—a measure of the volatility of an investment—is computed relative to an appropriate asset class, usually the market portfolio. The market portfolio consists of all assets, with the weight of each held in proportion to the total market value. Because the determination of a comparable portfolio that includes all customer assets across all firms represents a daunting, if not impossible, task, we define the market portfolio as the firm's current customer base, in line with Buhl and Heinrich (2008), Dhar and Glazer (2003), and Ryals (2002).

In the financial context, the market is assumed to be efficient, implying that information is fully and immediately reflected in market prices (Fama 1970; Sharpe, Alexander, and Bailey 1999). In contrast, the customer portfolio is not efficient. For a company, variations in the customer portfolio might reflect the overall performance of certain industries or sectors of the economy. Therefore, rather than using beta to describe the risk of the overall portfolio, customer beta captures the degree to which an individual customer contributes to the risk of the entire portfolio:

$$\beta_i = \frac{\text{cov}(x_i, x_P)}{V_P}, \quad (2)$$

where $\text{cov}(x_i, x_P)$ is the covariance between the individual customer cash flow and the cash flow of the overall customer portfolio and V_p is the variance of the cash flow for the overall customer portfolio.

Customer reward ratio. In measuring the rate of return on risk of a customer—in other words, the reward for assuming variability—Sharpe's pioneering work (1994; see also 1966) provides the foundation for the customer reward ratio. The reward is measured as the return above the risk-free rate:

$$(3) \qquad RR_i = \frac{R_i - R_f}{\sigma_i},$$

where RR_i represents the customer reward ratio, R_i represents the return for customer i and R_f represents the return for the risk-free customer proxy, and σ_i represents the standard deviation of the return. When there is no risk-free asset available, $R_f = 0$, and the equation is simplified to

$$(4) \qquad RR_i = \frac{R_i}{\sigma_i}.$$

Finding a risk-free proxy for the customer portfolio (the equivalent of treasury bills, the benchmark for risk-free investments) is often possible. For example, some companies have a set of low-return customers that they might prefer not to serve, but they choose to do so to fill spare capacity and achieve a modest return. Although not directly targeted, these customers provide a benchmark return.

If one of the goals in designing a customer portfolio is to minimize the risk for a certain level of return, a key question becomes, What is the level of return that a customer or segment with a certain level of variability provides? The customer reward ratio provides the means for evaluating the risk–reward trade-offs of customers in the portfolio. We provide a measure for evaluating the relative attractiveness of customers with different levels of return and variability. When customers possess similar return or variability characteristics, distinguishing the most desirable customer is straightforward. (For the same level of risk, the customer with the highest return is preferred, and for the same level of return, the customer with the lowest variability is preferred, all else being equal.) However, when both risk and return are different, the customer reward ratio provides the means to identify the most attractive customer.

Segmenting or Classifying Customers According to Risk

In financial markets, assets are grouped into categories that share certain risk–return and variability characteristics (e.g., blue chip stocks, bonds, treasury bills). We can group customers into segments using cluster analysis according to the monthly variability in their cash flows and then observe whether the resultant segments share other characteristics that are meaningful and actionable in the marketplace, such as demographics and firmographics. In other words, two key questions in determining the feasibility for building an efficient customer portfolio include the following: (1) Are there significant differences in variability and rate of return across market segments? and (2) Can we identify the differences in variability associated with specific customer characteristics (e.g., size of the company, industry)? If the answer to both questions is yes, we can build efficient portfolios according to the risk–return profiles of clusters rather than individual customers (for which cash flows can be somewhat unpredictable). Therefore, we first test whether there are significant differences in cash flow variability among different segments that can be characterized in ways that are normally used for segmentation. Then we attempt to construct an efficient customer portfolio and evaluate its performance.

Research Design

Study Context

We test the applicability of our approach to customer portfolios using purchase history data from a business-to-business company with a diverse customer base.[2] The client company provided monthly sales and profit data (earnings before interest and taxes; hereinafter, EBIT) for all customers for a seven-year period. The company's records also contained information for each customer regarding number of product lines purchased, size of business, geographic locations, and industry sector. The company had served more than 10,000 customers in the seven years. However, we focused on the top 250 customers from each of the years 2001–2007, which amounts to 516 unique customers and 98% of all sales. We supplemented the cooperating company's purchase records with information from public databases. Specifically, 456 of the 516 business customers were uniquely identified using Dun & Bradstreet codes, so that we could record the number of employees and sales revenues for specific sites and the entire company/customer.

Analysis Plan

In Stage 1, before developing the efficient portfolio, we want to assess whether meaningful differences in variability exist among customer segments. Stage 2 centers on segmenting (i.e., clustering) customers according to purchasing patterns (using standardized monthly purchases over six years) rather than using an a priori segmentation scheme. Next, we identify the segments by examining their financial and nonfinancial characteristics. For the segmentation to be actionable for managers, customers in the same segments must share common characteristics, which can be used to identify similar (potential) customers.

Stage 3 centers on identifying the efficient frontier and building an efficient customer portfolio using the variability-based segmentation scheme identified in Stage 2 to develop a diversified portfolio of customers, which should outperform value maximization portfolios in the long run. Stage 4 involves an evaluation of the diversified portfolio's performance. The firm's business performance should be enhanced in two ways: higher returns or reduced risk (or both). Thus, we evaluate the success of our approach by comparing the scenario reflecting the outcomes of the efficient frontier with the "actual" risk–return profile for the following year and a profit maximization scenario—all calculated using the holdout sample data.

Stage 5 makes necessary adjustments in the composition of the customer portfolio by reexamining the performance (purchases) of current customers, individually and by segment. Using customer reward ratios and customer beta indicators, we can asses the riskiness of individual cus-

[2]To respect confidentiality agreements, we scaled the numbers.

tomers and gauge their impact on the overall portfolio. Using this information—and maintaining a perspective of company goals and the external environment—marketing managers can decide on a case-by-case basis whether it is desirable to attract more business from the specific customer or to identify segments with similar characteristics to pursue in the future.

Stage 1: Assessing Differences in Variability Among Customer Segments

Our assessment is based on an examination of the sales over time from different market segments defined on an a priori basis. Specifically, we use the first six years of purchase history data to investigate whether there are significant differences in coefficients of variation across market segments defined by relationship type (contractual vs. noncontractual), size of business, and industry type. Appendix A provides a full discussion of this analysis.

Compared with noncontractual relationships, the analysis indicates that contractual customer relationships have lower variability and their introduction into a customer portfolio reduces the overall variability. Likewise, customers from small and medium-sized businesses (SMBs) have lower variability than large business customers. For the industry analysis, we classified customers using the NAICS (North American Industrial Classification System) combined with Standard & Poor's (S&P) sector classification.[3] Appendix B provides customer reward ratios, betas, and coefficients of variation of customer purchases over time in different industry sectors. The industry analysis was inconclusive because many of the industries were represented by only a few large customers; however, the trends were visibly distinctive.

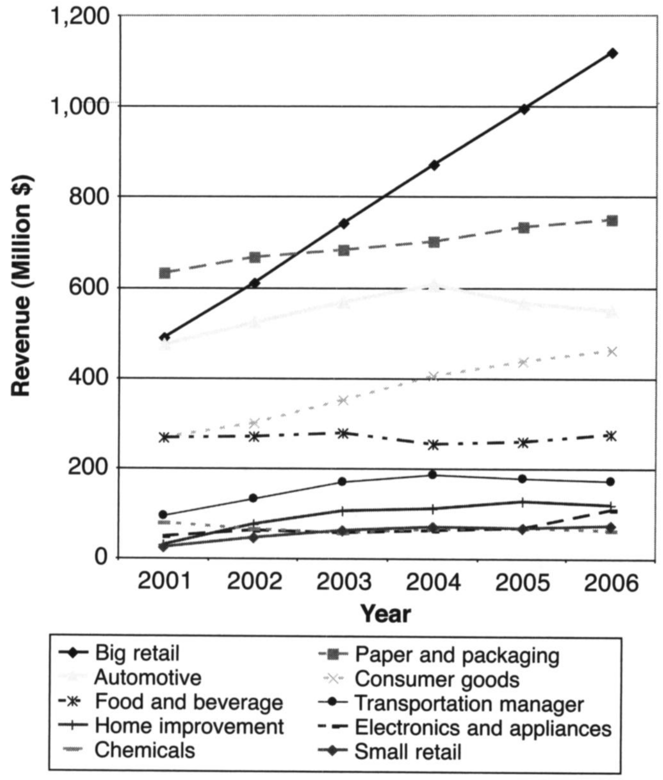
Figure 1 provides a graph of sales revenue over time for the ten industry categories of customers that generated the highest average sales. For example, observe that the retail sector exhibits a pronounced growth pattern over six years, while all others exhibit more modest growth, with the auto sector and transportation manager customers registering a noticeable decline after 2004.

On the basis of this analysis, we conclude that there are statistically significant differences in sales variability for customers with contractual versus noncontractual relationships and between customers of different sizes. There are also meaningful differences in sales trends for customers from different industries. Therefore, we believe the foundation is in place to identify market segments characterized by different risk levels (e.g., betas, customer reward ratios) and to build an efficient customer portfolio for the cooperating company.

Stage 2: Transactional Segmentation

Market segments should be characterized by different demand functions and purchase patterns (e.g., Dickson and Ginter 1987). Market segmentation based on similarities or differences in purchasing patterns is called transactional segmentation, which has been used in financial services firms to determine patterns that signal defections (Pearson and Gessner 1999).

FIGURE 1
Industry Trends

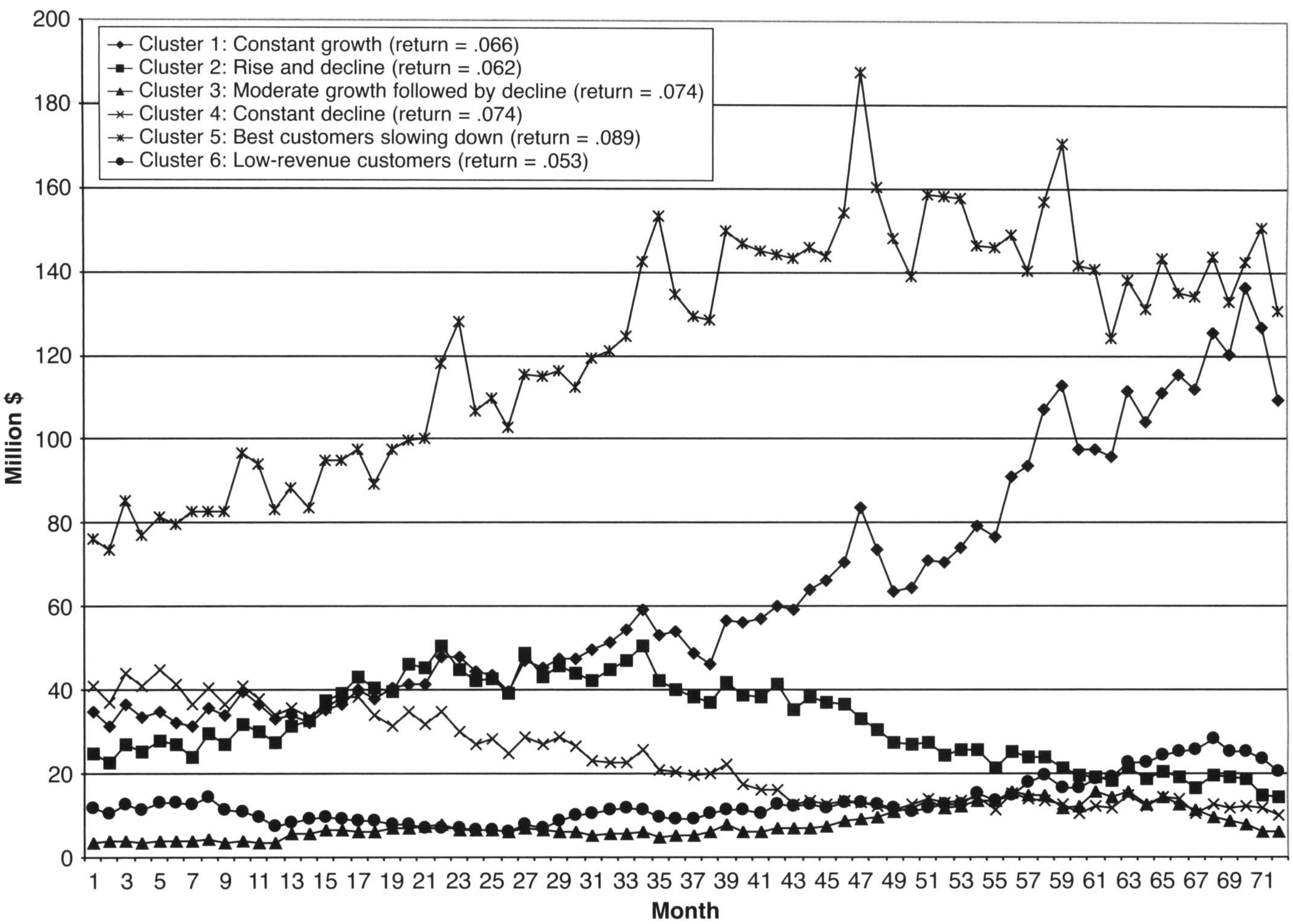


Each customer has unique and common characteristics, so we utilized a hierarchical clustering analysis of the monthly purchase data for each customer to observe the common characteristics. The procedure (PROC CLUSTER, in SAS, using the average linkage method) grouped customers according to squared distances, in which distance was measured by the monthly cash flow levels (standardized revenue).[4] Because there are 72 months of observation in the data, each customer is characterized by 72 variables. A six-cluster solution was robust to method changes, providing support for a solution that is useful for managerial action. The six-cluster solution grouped together customers with similar trend characteristics. Comparisons among clusters revealed that even though the statistical techniques were based on cash flow patterns exclusively, the resulting clusters differed in terms of company size, dominant industries, overall variability, customer reward ratios, and betas. Appendix C presents the results of these comparisons, and Figure 2 illustrates the patterns of the clusters.

[3]Standard & Poor's identifies ten industry sectors: energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services, and utilities (Source: "S&P Industry Classification Standard," [accessed June 5, 2009], [available at www2.standardandpoors.com/spf/pdf/index/GICSIndexDocument.PDF]).

[4]We standardized each customer's revenue by dividing the monthly value by the mean revenue for the 72 months. Standardization enables us to cluster by using variability patterns alone, without interference from the size of the customer purchases.

FIGURE 2
Revenue by Cluster



Stage 3: Identifying the Efficient Frontier and Building an Efficient Customer Portfolio

Each cluster has a certain level of return, as Figure 2 shows. We computed the return per cluster using profitability data by customer as provided by the sponsoring firm (return = total EBIT per cluster divided by the total revenue per cluster). Using the six clusters, we can now build an efficient portfolio by minimizing the cash flow variability for 2006 given a certain level of return. Although we use the data for 2001–2006 to build the clusters, we use 2006 as the reference year—because it is closest to the holdout period (2007)—to compute the efficient frontier. We need to identify a set of optimal weights for each of the clusters $X' = [x_1\ x_2\ x_3\ x_4\ x_5\ x_6]$ that minimizes the portfolio variance and that, multiplied by the return per cluster, adds up to the targeted return. By varying the expected return, we can draw the entire efficient frontier (Markowitz 1991).

To develop the efficient frontier, we used the quadprog function in MATLAB to minimize variance–covariance matrix for various levels of return (in increments of .2%). The quadprog function is designed to solve quadratic programming problems, in which a covariance matrix is minimized by varying the weights of the parameters, while satisfying certain linear conditions:

$$\min {}^1/_2 X^T H X, \text{ such that } AX \leq B \text{ and } Aeq\ X = Beq,$$

where X is the vector of weights (X^T is X transposed) and H is the return covariance matrix or the covariance matrix computed using the monthly return for all clusters. The inequality $AX \leq B$, where $A = -[I_6]$ (I being the identity matrix) and $B' = [0, 0, 0, 0, 0, 0]$, ensures that all cluster weights are positive. The equations $Aeq\ X = Beq$, where $Aeq = [1, 1, 1, 1, 1, 1; r_1, r_2, r_3, r_4, r_5, r_6]$ (with r_1–r_6 being the actual returns for clusters 1 to 6) and $Beq' = [1, R]$ (with R being the target return), ensure that the sum of weights for all clusters is 1 and the sum of the returns for the efficient portfolio matches the desired return. Quadratic programming is classically used for mean-variance portfolio selection (Feldstein 1969). The quadprog function uses the medium scale algorithm for this type of problem and involves a two-stage approach: It first estimates a feasible point and then generates a sequence of feasible points until convergence occurs.[5]

[5]MathWorks (http://www.mathworks.com/help/toolbox/optim/ug/brnox7l.html).

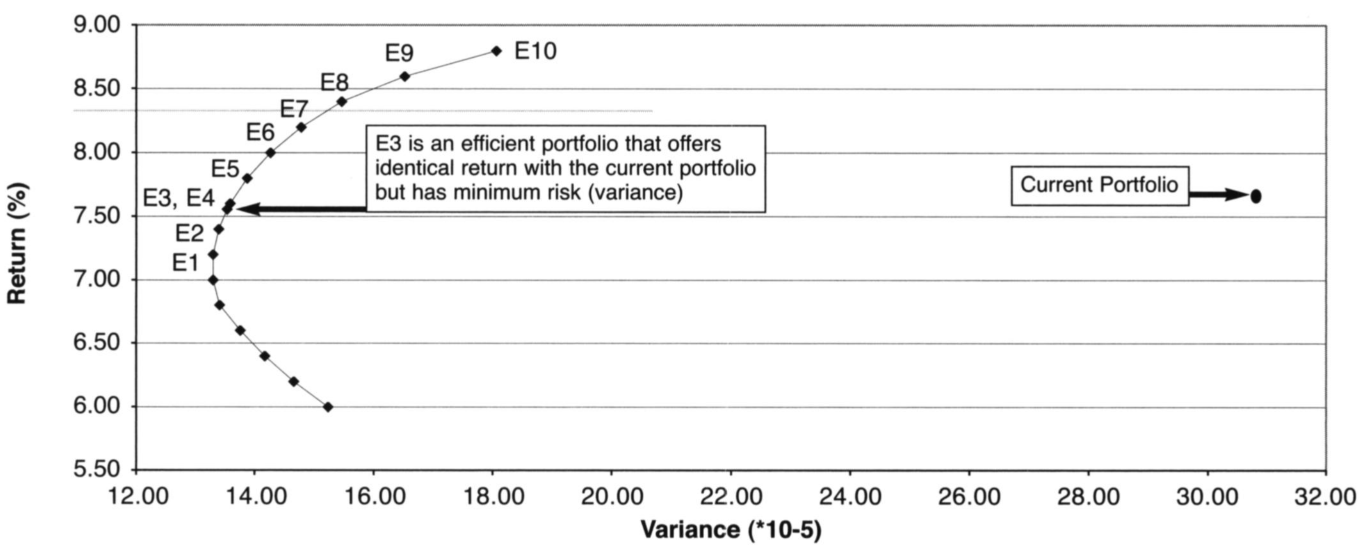
As expected, the efficient portfolios bordered the set of possible portfolios (Markowitz 1959). The efficient portfolio with the lowest risk is Portfolio E1 (see Figure 3 and Table 1), which has a relatively equal representation of all clusters, except Cluster 6.[6] Observe that Cluster 3, which is composed predominantly of small business customers, has the highest representation in this portfolio (26%). The efficient portfolio with the highest return is Portfolio E10, which is dominated by Cluster 5 (92%; see Table 1), the cluster with the highest return.

The weights of Cluster 3 (small business customers) in the efficient frontier portfolios vary from 6% in Portfolio E9 to 26% in Portfolio E1. As the percentage of Cluster 3 decreases, the level of risk increases. This pattern shows how diversity increases the stability of a portfolio because introducing smaller business customers into a portfolio overweighted with large business customers reduces the risk of the portfolio. To have a balanced portfolio, the cooperating company requires a certain percentage of small business customers, but no more than 26%. Above 26%, the variability of small business customers outweighs the benefits of diversification. From the standpoint of an individual investor buying securities, the stocks of the companies that constitute a firm's efficient customer portfolio would not represent an efficient stock portfolio for that investor because a host of factors influence stock values, including company strategy, new product announcements, operating efficiency, among many others (e.g., Srinivasan and Hanssens 2009).

Not only is it computationally more efficient to build the efficient frontier using clusters of customers rather than individual customers, but it is also more actionable for managers. An efficient customer portfolio constructed from individual customers might suggest seeking incremental sales from a given customer that far exceed the customer's requirements. By selecting customers from clusters, the role

[6]Although we introduced Cluster 6 in the analysis, it had zero weight in all the efficient portfolios. This cluster was characterized by low return and high variability.

FIGURE 3
The Efficient Frontier Portfolios and Current Portfolio Risk and Return



Notes: Portfolio 3 offers identical return to the current portfolio for less then half the variance (43%).

TABLE 1
Evolution of Cluster Weights for the Portfolios on the Efficient Frontier

		Cluster Weights						
Portfolio	Return Rate	X_1	X_2	X_3	X_4	X_5	X_6	Variance (10^{-5})
E1	7.20%	.20	.22	.26	.16	.16	—	13.30
E2	7.40%	.14	.20	.24	.18	.24	—	13.39
E3	7.56%	.10	.18	.23	.19	.31	—	13.53
E4	7.60%	.09	.17	.22	.19	.32	—	13.58
E5	7.80%	.04	.14	.20	.21	.41	—	13.87
E6	8.00%	—	.11	.18	.22	.49	—	14.26
E7	8.20%	—	.05	.16	.22	.57	—	14.78
E8	8.40%	—	—	.13	.20	.67	—	15.46
E9	8.60%	—	—	.06	.15	.79	—	16.52
E10	8.80%	—	—	—	.08	.92	—	18.06
Current	7.56%	.36	.06	.04	.04	.43	.07	31.47

of similar characteristics is emphasized, making the identification of potential new customers easier and implementation more straightforward. This approach offers managers the choice of either increasing the level of business conducted with current customers in the cluster (if the opportunity exists) or serving new customers with similar characteristics that define the cluster. Moreover, from a practical standpoint, managers can even apply this approach at the group (cluster) level if they find it difficult to determine the specific return per customer. The risk could be estimated according to the variability of the customer revenue and used in combination with the return per cluster to estimate the efficient portfolio.

Stage 4: Testing the Efficient Portfolio

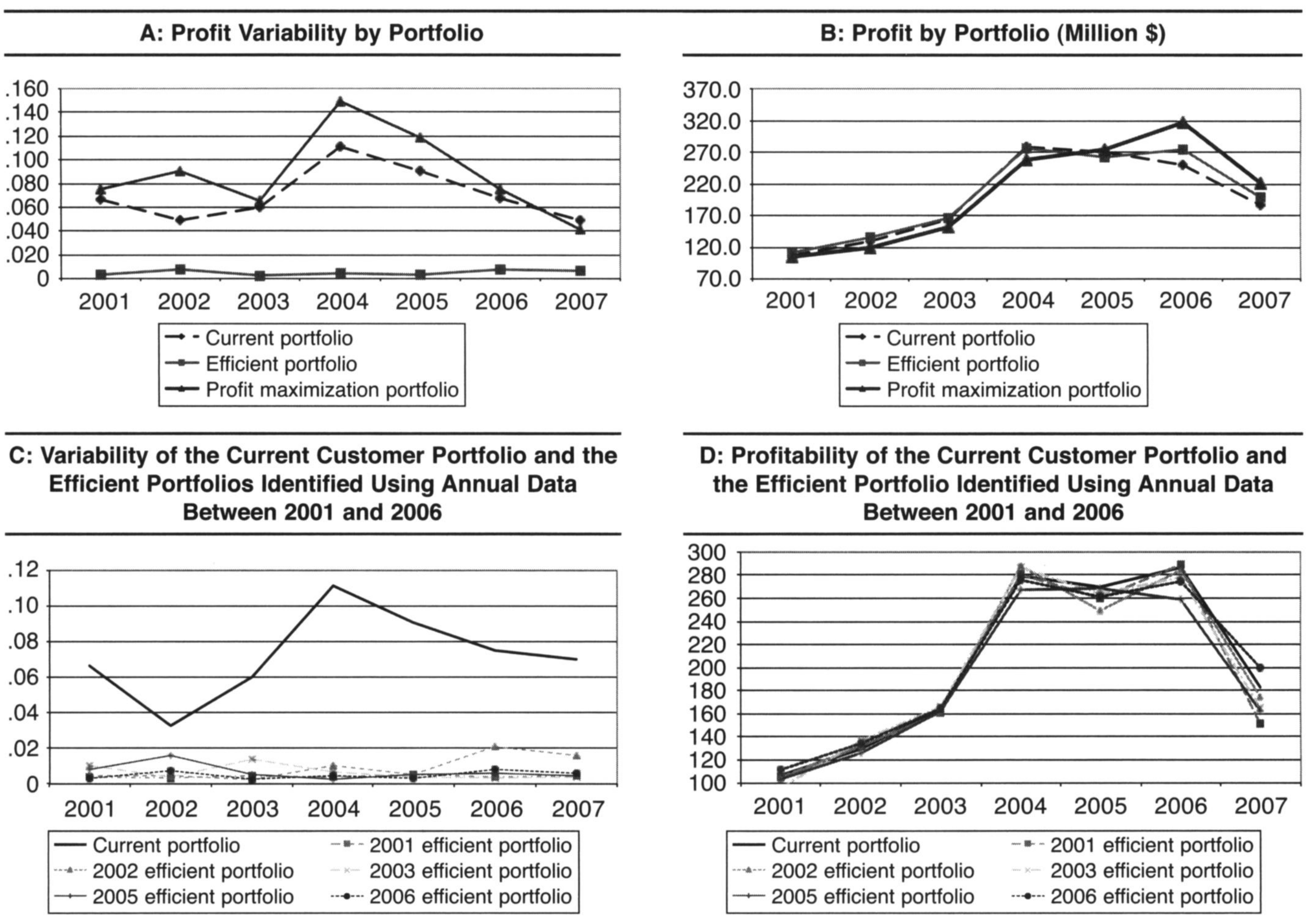
We have constructed an efficient customer portfolio that minimizes variance for the study period. We compare the performance of this portfolio with that of a profit maximization portfolio, built using the best customers for 2006 and assuming that the company is able to acquire 25% more customers with the same level of profit as its best customers (which the client company would do if it could).

First, we compare the performance of an efficient portfolio (E5), the actual portfolio and the profit maximization portfolio and "back-test" them for 2001 through 2005.[7] A customary practice in finance is to test strategies under historical market conditions to evaluate their viability and effectiveness. This method is especially useful to test a portfolio under different economic conditions, given that testing with future data is not an option. In Figure 4, Panels A and B, we compare the results for the three portfolios; that is, we compare variability (risk) and actual profits (return).

Using back-testing, we notice that the efficient portfolio constantly has much lower variability than either of the other two portfolios for all six years examined (Figure 4, Panel A). In terms of profit performance, the efficient portfolio outperforms the actual portfolio each year except 2004 and 2005, which were extremely profitable for the company (Figure 4, Panel B). The profit maximization portfolio outperforms the actual and efficient portfolios for just one of the years, 2005. In years of high growth, riskier portfolios are more likely to outperform low-risk portfolios. However, for the other years, further out on the horizon from the benchmark year for which the portfolio has been optimized, the efficient portfolio outperforms both the actual and profit

[7]We used the data for 2001–2005 to identify the clusters but not for the efficient frontier.

FIGURE 4
Back- and Forward-Testing the Efficient Portfolio (Simulation Results)



maximization portfolios, providing evidence for the stability of our method.

Second, we compare the three portfolios using forward-testing; that is, we use the data for 2007 that have not been used in any other previous analysis. (To do so, we matched the customers that entered the top 250 for the first time in 2007 to clusters using the size of the business, industry profile, and previous purchase history.) When comparing 2007 performance, the efficient portfolio outperforms the actual portfolio: higher profit and lower variability. The efficient portfolio has lower overall profitability than the profit maximization portfolio, but it has a much lower variability. In stable economic conditions, we expect that in the first year (short run), the efficient portfolio might not outperform a profit maximization portfolio.

To further test the robustness of the efficient portfolio concept as applied to a customer portfolio, we also built efficient portfolios using the data for each of the years in the 2001–2005 interval and then using data from the remaining years as the holdout sample. For example, we built the efficient frontier for 2001 and used 2002–2007 data as the holdout sample. Except for 2004, when the company implemented midyear accounting changes related to the measurement of customer profitability, we could fully identify the efficient frontier. According to the simulation results, each efficient portfolio had similar benefits: The variability was constantly much smaller for all the years examined while controlling for the mean (Figure 4, Panel C) and in absolute value (Figure 5), though the profitability was comparable with that of the current portfolio (Figure 4, Panel D). These results show the stability of the solutions computed for different years; in simulations, they all manifested a similar level of profitability and substantially lower variability.

Stage 5: Revising the Current Customer Portfolio Toward an Efficient Portfolio

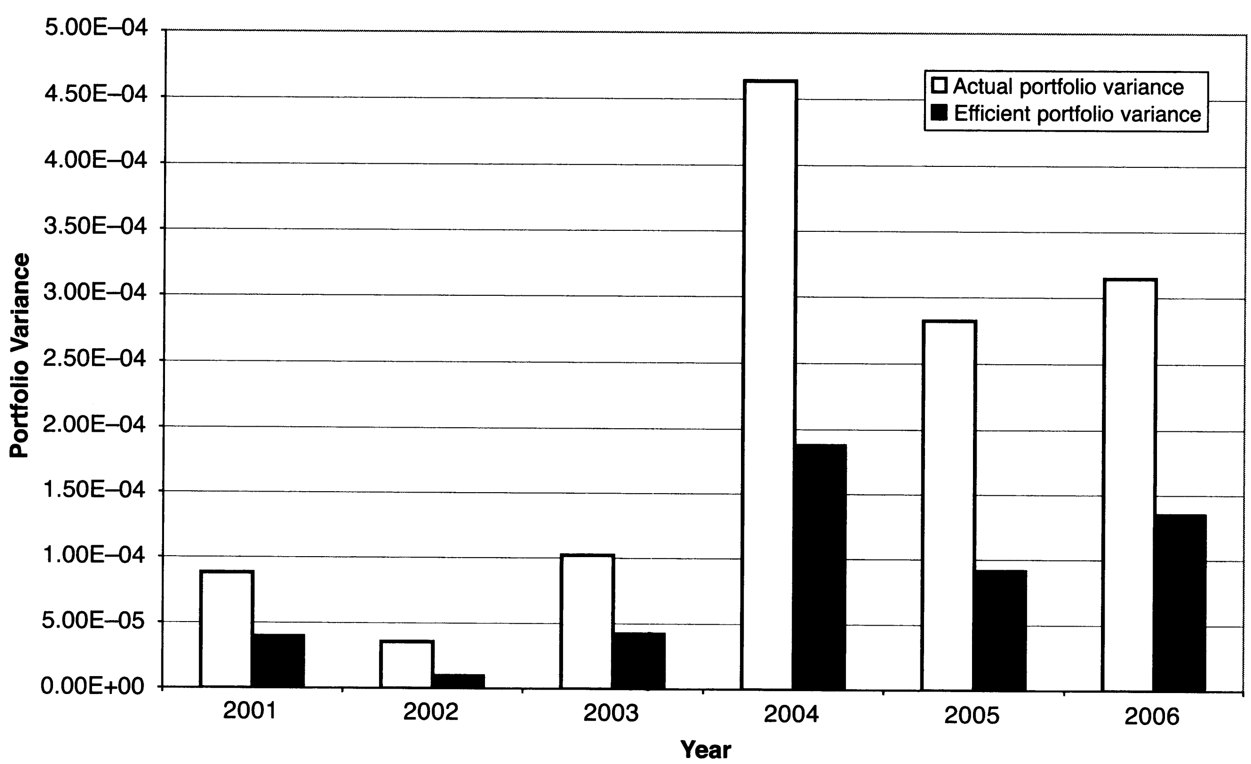
Thus far, our analysis has centered on groups of customers that share certain characteristics. However, inside clusters, some customers might be more desirable than others, and given limited resources, the firm should prioritize its customer retention/acquisition efforts. This issue should be considered when the firm reweights its customer portfolio to move toward an optimal composition.

Recall that the customer reward ratio can be measured as a function of a risk-free asset (in our case, a risk-free customer proxy) or in absolute terms. By incorporating the risk-free asset into the calculation, the customer reward ratio provides a more meaningful measure of the relative attractiveness of alternative customer investments.[8] The manager can consider the return provided by investing in the risk-free asset and take into account how a diversified allocation of resources might be more attractive than investing in a single asset.

Consider the risk-free asset that a logistics service company might use. Transportation managers act as brokers for

[8]For example, for a return of 15 and a standard deviation of 10, the customer reward ratio without the risk-free asset is 1.5 (15/10); with a risk-free asset with a return of 3, it is 1.2 (12/10). For an asset with return of 28 and standard deviation of 20, the customer reward ratio without the risk-free asset is 1.4 (28/20, less attractive than the first asset), but taking into account the risk-free rate, the customer reward ratio is 1.25 (25/20, compared with 1.2 for the first example), which is more attractive than the first asset considered.

FIGURE 5
Absolute Variance Reduction in Efficient Portfolios Versus the Current Portfolio Results



SMBs. They are often used by logistics service companies to find customer shipments to fill at least some capacity for return routes from one-way transports. For performing this helpful service, they are charged less than most other customers, and their purchases are highly variable. Considering them the "risk-free proxy" in computing the reward ratio provides a useful benchmark for a logistics company. For firms that produce maintenance and operating supplies, a risk-free proxy might be a segment of large distributors that desire private label products that a firm could produce to fill excess capacity. Identifying the risk-free customer proxy for a business requires deep insight into the strategic and daily operations of the business because, ideally, the risk-free customers should be strategically irrelevant and always available for the right price. For businesses in which the "strategically irrelevant" customers cannot be identified, the return of the risk-free proxy is 0.

For the client company, we identified a segment as a risk-free proxy that initially seemed rather unappealing: a lower return (EBIT) than other customers (2.4% compared with 6.2%, $p < .05$), without loyalty, and strategically irrelevant. Importantly, observe that the customer reward ratio does not determine the absolute desirability of a customer. Firms should also consider the impact of the customer on the overall portfolio (i.e., customer beta) in addition to other strategic aspects, like growth potential. However, for customers with similar impact on the portfolio and no specific strategic consideration, the customer reward ratio provides a clear criterion for choosing the most desirable customer. Appendix B provides a summary of the customer reward ratios for key industry sectors.

Appendix B shows that most of the industries in the top ten (if ranked using the customer reward ratio) belong to the discretionary category. It is noteworthy that customers in lawn and garden, machinery, and office supply categories have the highest levels of reward on risk. When the client company executives saw the analysis, they realized that many of the customers that provided the highest reward on risk were not receiving adequate attention. Represented here are customers that provide attractive margins but also are characterized by high variability. These clients request services when they need them, and to receive the speed and quality of the services that they demand, they are willing to pay a premium price.

Data Analysis Conclusion

Using the efficient frontier applied to customer segments, we identify an optimal composition of the customer portfolio that outperformed, in terms of variability, both the client company's current strategy and a profit maximization portfolio, as demonstrated by back- and forward-testing (see Figure 4). By using a diversified, efficient portfolio, companies could reduce the vulnerability and volatility of cash flow from the customer portfolio, better insulating the firm during downturns in the economy without sacrificing performance in the long run. We demonstrate how managers can use customer beta and the customer reward ratio to evaluate specific individual customers and to make corresponding adjustments in the customer portfolio.

Discussion and Managerial Implications

Marketing managers face increased pressure to demonstrate the financial impact of marketing resource allocation decisions (Rust et al. 2004). By demonstrating how financial portfolio theory can be applied to customer portfolio management, our research contributes to marketing theory and practice on several counts. First, we extend Srivastava, Shervani, and Fahey's (1998) work by demonstrating conceptually and empirically how the market-based assets of a firm include distinct customer asset classes that are characterized by differing degrees of cash flow variability and vulnerability. We test whether customers can be categorized into segments that share similarities with asset classes used in traditional financial investments and find support for our belief that financial portfolio theory is relevant in a customer portfolio context. In particular, we show that market segments—defined a priori according to classic market segmentation variables—could be characterized in terms of their risk, in addition to their return, thereby contributing to traditional market segmentation theory.

Second, we contribute to research on customer portfolio management (e.g., Dhar and Glazer 2003; Johnson and Selnes 2004) by introducing two methods to assess the value of a customer: customer beta and the customer reward ratio. Responding to the call of Rust et al. (2004), our approach embraces (rather than controls for) customer heterogeneity as a path to improved business performance. For example, we demonstrate how the customer reward ratio can be used to examine a customer portfolio through a new lens that allows managers to isolate desirable customers that receive high scores on the reward-on-variability measure. As we illustrate, the attractive customers that rise to the top on this measure often present a profile that may not be detected when using classical criteria such as average level of purchases.

Third, we present an actionable plan to guide marketing managers in creating and managing a diversified portfolio among existing and new customers. To this end, we constructed segments according to the variability of standardized revenue. We obtained clusters with a high degree of uniformity in terms of level of revenue, size of the business, and industry. We combined the clusters to form an efficient frontier that describes the portfolio with the lowest variability of returns for a desired level of return. Both back- and forward-testing showed that it is possible to build an efficient customer portfolio. We conclude that if companies want to increase the stability of the customer cash flow, risk management techniques can be implemented to ensure diversity among existing and potential customers/segments. This study demonstrates that companies can diversify their customer portfolios by developing a thorough understanding of customers' purchase patterns and the drivers of these purchasing patterns (e.g., size, preferences for product lines, industry sector).

The Efficient Versus the Profit-Maximizing Customer Portfolio

The goal of building an efficient customer portfolio is different from the profit-maximizing objectives first identified in Blattberg and Deighton's (1996) path-breaking article and extended in subsequent studies (Blattberg, Getz, and Thomas 2001; Reinartz and Kumar 2003; Reinartz, Thomas, and Kumar 2005), which focus on profit maximization in the short and long run. There will be some similarities between the efficient and profit-maximizing customer portfolios, but there will also be differences. For example, observe in Table 1 that Cluster 5, which dominates the current portfolio and contains some of the most profitable customers, has similar weight in the optimized portfolio (E5).

In contrast, in the efficient portfolio, weights for the other clusters are increased dramatically, especially for Cluster 3, which is dominated by SMBs. In other words, SMBs—often not a priority for some businesses—provide a balancing element when it comes to portfolio optimization. Cluster 1, which has relatively low profitability and high variability, is the one in which weight has been decreased most drastically for the efficient portfolio compared with the company's current portfolio, from 41% to 4%. Considering that Cluster 1 is one in which customers have exhibited the most growth, decisions regarding the customers in this group should be made on a case-by-case basis.

Implementing the Portfolio Approach

Compared with corresponding adjustments in a financial portfolio, changes in the composition of a customer portfolio involve higher transaction costs, require a longer time horizon to implement, and can introduce a host of strategic alignment issues to consider. Managerial judgment and the strategic goals of the firm ultimately guide the selection of the target portfolio. Therefore, the cluster weights that define the efficient customer portfolio provide a tentative portfolio structure that managers can then adjust after examining the full range of customer metrics that CLV-based methods employ. Observe from Table 1 that the portfolios along the efficient frontier vary widely in cluster weights. For example, the portfolio with the lowest risk (E1) has a balanced composition, whereas the portfolio with the highest return (E10) gives dominant weight (92%) to Cluster 5. Represented in Cluster 5 are large customers, drawn from several industries, which provide higher average revenue and lower variability than other clusters. By isolating the risk–return characteristics of these customers, managers can make more informed judgments for targeting customers and estimating future returns.

The key difference between customer and financial portfolios is that managers can directly influence outcomes. Past studies in the CLV research tradition provide valuable insights into how profitability can be enhanced by selecting the right customers for targeting and determining the level of resources to be allocated to specific customers (e.g., Kumar 2008; Bowman and Narayandas 2004). Also, a wealth of other metrics, such as customer loyalty, share of wallet, and strength of the exchange relationship, guides customer management. Our approach can be readily incorporated in established customer management frameworks to aid managers in balancing risk and return in a customer portfolio.

Limitations and Further Research

Although our approach allows managers to examine the risk–return characteristics of a customer portfolio through a new lens, this study presents some limitations that could spawn further research. First, because the current study is confined to a single firm and industry, further research is needed to test the viability of our approach in different industry contexts. The data and methods used in this research are available to most companies: purchase transactions over time, limited demographics or firmographics, and profitability by cluster. Second, the current study centers squarely on the structure of the existing portfolio and therefore does not consider the addition of new market segments. Buhl and Heinrich (2008) offer a heuristic method for adding new segments to the customer portfolio, which provides a promising start for further research.

Third, the customer portfolio measures used in this study center on the variability of cash flow and profitability but are insensitive to the direction of movement. Therefore, managerial judgment, informed by established customer management approaches, is needed to discern the root cause of the variability (i.e., growth or decline of cash flow). Further research could explore customer resource allocation from a downside-risk perspective (Harlow 1991). Fourth, we assessed the desirability of customers by analyzing the past volatility of purchases. However, for estimating future customer worth, the most appropriate measure would be future volatility. To determine the future volatility, Engle (1982) proposes a weighted moving average model that takes into account the long-term behavior of a financial asset. By analyzing customer purchase information, a similar model of weighted moving averages could be explored to predict future customer cash flow variability more accurately.

Conclusion

In his Nobel Prize acceptance speech, Markowitz (1991, p. 496) mentions that "an investor who knows the future returns with certainty will invest in only one security, namely the one with the highest future return." However, as Bernstein (1999, p. 1) notes, "Even the most brilliant of mathematical geniuses will never be able to tell us what the future holds. In the end what matters is the quality of our decisions in conditions of uncertainty." We propose an approach that customer portfolio managers can follow to cope with uncertain market conditions and to improve the quality of their resource allocation decisions. This research offers a new perspective on customer portfolio management, acknowledging an aspect that has been virtually ignored: the risk of the customer. Paraphrasing Engle's (2003) Nobel Prize acceptance speech, we infer that acknowledging risks should provide insight into which customers are truly worthwhile.

Appendix A
Cash Flow Variability by Customer Type

Contractual Relationships

Customer–firm relationships range from formal contractual to transactional relationships. Transactional relationships are low involvement, occurring on an as-needed basis. Contractual relationships are governed by rules that are mutually agreed on by the contracting parties (Gundlach and Murphy 1993). Due to their explicit nature, contractual relationships are more predictable than transactional ones and typically yield cash flows with less variability. Thus, when a high proportion of customers have entered into contractual agreements with the firm, especially long-term contracts, the overall risk of the firm's customer portfolio will be low.

We compare the coefficients of variation for customer purchases over time between contractual and noncontractual relationships for the cooperating company in the following way: The client company offers four different product lines (similar services, but with different delivery characteristics). Product Line 1 relies on contractual relationships, in which assets are allocated to a specific customer, thus restricting the firm's flexibility to deploy these assets elsewhere. All other product lines have greater flexibility and no contracts attached.

The coefficient of variation (CoV) for Product Line 1, $CoV_{Line\ 1} = .525$, is significantly lower ($p = .000$) than the coefficient of variation for any other product line ($CoV_{Line2} = .879$, $CoV_{Line3} = 1.216$, $CoV_{Line4} = 1.740$, $CoV_{All\ Lines} = .708$). In other words, the contractual product line (1) has the smoothest, most predictable cash flows, thereby insulating the firm from troughs (downtimes) and peaks (busy times). By serving customers that prefer a contractual relationship, the firm reduces the coefficient of variation for its overall customer portfolio.

Size of Business

Research regarding financial portfolios has shown that small firms periodically tend to outperform and underperform large firms, exhibiting a negative correlation in returns (Reinganum 1992). Small firms outperform large firms during economic booms, but the effect disappears during recessions (Kim and Burnie 2002). Large business customers, characterized by financial soundness and greater volume, represent the equivalent of the blue-chip stocks in a financial portfolio (i.e., stocks of companies with steady earnings and a solid reputation but slower growth). In contrast, SMBs have high growth potential (Acs and Audretsch 1990). If large firms dominate a financial portfolio, variations in their business cycles will have a substantial impact on their suppliers (LaBahn 1999). Although SMBs usually have less influence on the overall financial portfolio individually, they can be combined to achieve diversification and lower overall variability, provided their revenue streams are not positively correlated (Markowitz 1987).

We compare the coefficients of variation for customer purchases over time between companies of different sizes using a median split based on the number of employees. The coefficient of variation for the small companies was .67, statistically different ($p = .023$) from the value of .77 for large companies.

Industry Classification

Industries are affected differently by external economic events. For example, a downturn in the economy is often accompanied by a decrease in home construction and an increase in home improvement projects. A price increase for a commodity (e.g., silicone) might result in a substantial price increase for automobile tires, whereas the price of personal grooming products (e.g., shampoos, liquid soaps) might increase very little because silicone is not a relevant component. Dhar and Glazer (2003) show that targeting customers in different segments reduces the risk of a revenue decline when economic conditions are changing.

We classified customers into major NAICS categories (e.g., transportation, paper and packaging, automotive) combined with the S&P global industry classification categories, which are designed to capture sector differences. By combining classification schemes, we obtain a finer granularity that allows for more uniformity within the identified categories. For example, NAICS identifies retailers, whereas the S&P standard makes the distinction between discretionary (e.g. Kohl's) and staples (Wal-Mart) retailers, which are likely to respond differently to peaks and troughs in the economy. Appendix B presents customer reward ratios, betas, and coefficients of variation for customer purchases over time in different industry sectors.

Because there are only a small number of companies in each category (e.g., seven customers provide revenue from large discretionary retail companies [line 11 in Appendix B]), there is insufficient statistical power for t-tests of the differences in the average coefficients of variation across categories. However, for example, when we compare the office supply segment (line 9), with the food and beverage segment (line 14), we notice important differences. Office supply customers are more attractive than the food segment: Negative beta signals negative correlation with the overall portfolio, the customer reward ratio is much higher, and the coefficient of variation is much smaller (i.e., lower risk). However, the cooperating company has many more customers in the food sector (42) than in the office supply sector (3), and therefore the t-tests were inconclusive.

APPENDIX B
Coefficient of Variation Classified Using Both NAICS and S&P

	S&P Categorization	Industry	N	Beta	Reward Ratio	CoV[b]	Average Monthly Revenue (in Thousands of Dollars)	Six-Year Revenue[c] (in Millions of Dollars)
1	Beverage[a]	Food and beverage	14	1.199	1.344	.710	369	32
2	Discretionary	Apparel	9	1.261	2.467	.802	245	128
3	Discretionary	Automotive	35	1.616	1.400	.604	1000	2381
4	Discretionary	Consumer goods	4	.883	.609	.720	599	170
5	Discretionary	Durables	10	1.874	.181	.656	182	110

APPENDIX B
Continued

	S&P Categorization	Industry	N	Beta	Reward Ratio	CoV[b]	Average Monthly Revenue (in Thousands of Dollars)	Six-Year Revenue[c] (in Millions of Dollars)
6	Discretionary	Electronics and appliances	18	1.533	2.398	.786	368	361
7	Discretionary	Home improvement	27	.067	1.169	.705	313	559
8	Discretionary	Lawn and garden	4	.336	8.521	1.145	167	48
9	Discretionary	Office supply	3	–3.668	2.948	.461	798	162
10	Discretionary	Paper and packaging	11	1.584	1.976	.592	659	311
11	Discretionary	Retail	7	1.125	1.673	.675	5042	2476
12	Discretionary	Sporting goods	7	–.233	.289	.751	123	46
13	Energy	Oil	5	1.067	2.050	.680	355	64
14	Food	Food and beverage	42	8.568	.774	.794	352	973
15	Health	Medical supplies	6	.773	.111	.644	138	55
16	Industrials	Automotive	8	.909	1.001	.598	237	98
17	Industrials	Electronics and appliances	5	1.856	.878	.774	152	47
18	Industrials	Machinery	4	.107	3.120	.567	656	181
19	Industrials	Paper and packaging	9	3.871	.315	.693	347	223
20	Industrials	Transportation	10	–18.483	.557	1.212	243	129
21	Materials	Chemicals	18	.834	1.213	.668	274	308
22	Materials	Metal manufacturing	12	1.569	1.266	.773	87	62
23	Materials	Paper and packaging	30	1.516	.850	.622	770	1576
24	Materials	Wood manufacturing	4	.948	.854	.474	142	33
25	Staples	Consumer goods	18	–3.780	1.058	.792	1763	2048
26	Staples	Paper and packaging	17	.742	.891	.714	1687	2036
27	Staples	Pet supplies	5	16.118	1.789	.631	440	88
28	Staples	Retail	5	.366	.674	.629	7544	2683
29	Transportation	Transportation	55	.035	2.498	.702	244	743

[a]The distinction between food and beverage, though not in the S&P standards, is useful for distinguishing the patterns that are likely to characterize foods (e.g., cereals) from those of beverages (e.g., beer, soda).
[b]CoV = coefficient of variation.
[c]Cumulative revenue for the years 2001–2006.

APPENDIX C
Comparisons Between Clusters

Cluster Characteristics	Industry Dominance
Cluster 1 (Constant Growth): *84 customers and 24% of the six-year revenue*	
•Higher beta (more rapid growth) than all other clusters •Higher variability (risk measured using coefficient of variation) than Clusters 2, 3, 5, and 6 •Higher absolute and average revenue per customer than Clusters 3 and 6* •Larger business customers (higher number of employees) than Cluster 2	•89% of the discretionary retailers (and 53% of all discretionary products) •56% of material paper and packaging (and 48% of all materials) •55% of all health products •39% of home improvement
Cluster 2 (Rise and Decline): *74 customers, 12% of the six-year revenue*	
•Lower beta than Clusters 1, 3, 5, and 6 but higher than Cluster 4 •Lower variability (covariance) than Clusters 1 and 4 •Smaller-sized customers (by number of employees) than Cluster 1 but larger than Cluster 3 •Cluster 2 customers buy overall and on average more than the customers in Clusters 3 and 6 but relatively less than the customers in Cluster 5*	•Discretionary electronics and appliances (61%) and discretionary consumer goods (42%) •Manufacturers of metal (47%) and wood (39%) •Food and beverages (35%)
Cluster 3 (Consistency Followed by Decline): *52 customers and 3% of six-year revenue*	
•Lower revenue per customer than Clusters 1, 2, 4,* and 5 but higher than Cluster 6 •Lower variability (CoV) than Clusters 1 and 4 •Smaller-sized customers (by number of employees) than Clusters 2, 4, 5, and 6 •Average level of beta (more explicitly, lower beta than Clusters 1 and 5 but higher beta than Clusters 2 and 4)	•Health (35%, while 55% is in Cluster 1) •Energy (30%, while 66% is in Cluster 5) •Machinery (15%, while 80% is in Cluster 5)

APPENDIX C
Continued

Cluster Characteristics	Industry Dominance
Cluster 4 (Constant Decline): *71 customers and 9% of the six-year revenue* •Lower average revenue and overall revenue than Cluster 5 but higher overall revenue than Clusters 3* and 6 •Higher variability (CoV) than Clusters 2 and 3 but lower than Clusters 5 and 6 •The lowest beta among all clusters in terms of revenue but highest beta among all clusters in terms of return	•Industrial electronics (60%) •Discretionary automotives (51%) •Durables (45%) •Beverages (47%)
Cluster 5 (Best Customers Slowing Down): *61 customers and 47% of six-year revenue* •Higher average revenue and overall revenue than Clusters 2,* 3, 4, and 6 •Lower variability (CoV) than Clusters 1, 4, and 6* •Lower beta than Cluster 1 but higher beta than Clusters 2, 3, 4, and 6 •Larger-sized customers than Cluster 3 (by number of employees) and Cluster 6* (by annual sales)	•Staples in general (77%) •Automotive—staples (74%) •Paper and packaging—staples (92%) •Consumer goods—staples (86%) •Energy (66%) •Industrials (43%) •Chemicals (industrial and materials: 36%) •Machinery (80%) •Lawn and garden (45%)
Cluster 6 (Low-Revenue Customers): *125 customers and 5% of the six-year revenue* •Lower revenue per customer than any other cluster •Lower variability (CoV) than Clusters 1 and 4 but higher than Cluster 5* •Lower beta than Clusters 1 and 5 but higher beta than Clusters 2 and 4 in terms of revenue, but lowest beta among all clusters in terms of return •Larger company sizes (based on the number of employees) than Cluster 3 but smaller customer business size (based on annual sales) than Cluster 5* •Customers in this cluster buy significantly less than the average customer (more than 25% of customers account for 5% of the six-year revenue) and do not have the absolute majority for any of the categories	•This cluster has (statistically) as large of a percentage of the transportation industry as Cluster 5 (about 23%), and the second-highest revenue from the lawn and garden industry (32%, while 45% is in Cluster 5)

*The difference is significant at the 90% confidence level. All other comparisons are statistically significant at the 95% confidence level or higher.
Notes: CoV = coefficient of variation.

REFERENCES

Acs, Zoltan J. and David B. Audretsch (1990), "The Determinants of Small-Firm Growth in U.S. Manufacturing," *Applied Economics*, 22 (February), 143–53.

Ambler, Tim, C.B. Bhattacharya, Julie Edell, Kevin Lane Keller, Katherine N. Lemon, and Vikas Mittal (2002), "Relating Brand and Customer Perspectives on Marketing Management," *Journal of Service Research*, 5 (August), 13–25.

Ang, Andrew, Joseph Chen, and Yuhang Xing (2006), "Downside Risk," *Review of Financial Studies*, 19 (4), 1191–1239.

Balagopal, Balu and Guy Gilliland (2005), "Integrating Value and Risk in Portfolio Strategy," report, Boston Consulting Group.

Bernstein, Peter L. (1999), "Wimps and Consequences," *Journal of Portfolio Management*, 26 (Fall), 1.

Blattberg, Robert C. and John Deighton (1996), "Manage Marketing by the Customer Equity Test," *Harvard Business Review*, 74 (July/August), 136–44.

———, Gary Getz, and Jacquelyn Thomas (2001), *Customer Equity: Building and Managing Relationships as Valuable Assets*. Boston: Harvard Business School Press.

Bolton, Ruth N., Katherine N. Lemon, and Peter C. Verhoef (2008), "Expanding Business-to-Business Customer Relationships: Modeling the Customer's Upgrade Decision," *Journal of Marketing*, 72 (January), 46–64.

Bowman, Douglas and Das Narayandas (2004), "Linking Customer Management Efforts to Customer Profitability in Business Markets," *Journal of Marketing Research*, 41 (November), 433–47.

Buhl, Hans Ulrich and Bernd Heinrich (2008), "Valuing Customer Portfolios Under Risk–Return Aspects: A Model-Based Approach and Its Application in the Financial Services Industry," *Academy of Marketing Science Review*, 12 (5), 1–32.

Cardozo, Richard N. and David K. Smith Jr. (1983), "Applying Financial Portfolio Theory to Product Portfolio Decisions: An Empirical Study," *Journal of Marketing*, 47 (Spring), 110–19.

——— and ——— (1985), "On the Use of Financial Portfolio Theory in Marketing Decisions: A Reply to Devinney, Stewart and Shocker," *Journal of Marketing*, 49 (Fall), 113–15.

Chan, Louis K.C., Jason Karceski, and Josef Lakonishok (1999), "On Portfolio Optimization: Forecasting Covariances and Choosing the Risk Model," *The Review of Financial Studies*, 12 (January), 937–74.

Chandra, Siddharth (2003), "Regional Economy Size and the Growth-Instability Frontier: Evidence from Europe," *Journal of Regional Science*, 43 (1), 95–122.

Conroy, Michael E. (1974), "Alternative Strategies for Regional Industrial Diversification," *Journal of Regional Science*, 14 (1), 31–46.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal (2007), "Optimal Versus Naïve Diversification: How Inefficient Is the

1/N Portfolio Strategy?" *The Review of Financial Studies*, 22 (5), 1916–53.

Devinney, Timothy M. and David W. Stewart (1988), "Rethinking the Product Portfolio: A Generalized Investment Model," *Management Science*, 34 (September), 1080–1095.

———, ———, and Allan D. Shocker (1985), "A Note on the Application of Portfolio Theory: A Comment on Cardozo and Smith," *Journal of Marketing*, 49 (Fall), 107–112.

Dhar, Ravi and Rashi Glazer (2003), "Hedging Customers," *Harvard Business Review*, 81 (May), 86–92.

Dickson, Peter R. and James L. Ginter (1987), "Market Segmentation, Product Differentiation, and Marketing Strategy," *Journal of Marketing*, 51 (April), 1–10.

Dissart, J.C. (2003), "Regional Economic Diversity and Regional Economic Stability: Research Results and Agenda," *International Regional Science Review*, 26 (October), 423–46.

Engle, Robert F., III (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation," *Econometrica*, 50 (July), 987–1008.

——— (2004), "Risk and Volatility: Econometric Models and Financial Practice," *American Economic Review*, 94 (3), 405–420.

Fama, Eugene F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, 25 (May), 383–417.

Feldstein, Martin S. (1969), "Mean-Variance Analysis in the Theory of Liquidity Preference and Portfolio Selection," *Review of Economic Studies*, 36 (January), 5–12.

Grinblatt, Mark and Sheridan Titman (2002), *Financial Markets and Corporate Strategy*, 2d ed. Boston: McGraw-Hill/Richard D. Irwin.

Gundlach, Gregory T. and Patrick E. Murphy (1993), "Ethical and Legal Foundations of Relational Marketing Exchanges," *Journal of Marketing*, 57 (October), 35–46.

Gupta, Sunil and Donald R. Lehmann (2005), *Managing Customers as Investments: The Strategic Value of Customers in the Long Run*. Upper Saddle River, NJ: Wharton School Publishing.

———, ———, and Jennifer A. Stuart (2004), "Valuing Customers," *Journal of Marketing Research*, 41 (February), 7–18.

Harlow, W.V. (1991), "Asset Allocation in a Downside-Risk Framework," *Financial Analysis Journal* (September/October), 28–40.

Homburg, Christian, Viviana V. Steiner, and Dirk Totzek (2009), "Managing Dynamics in a Customer Portfolio," *Journal of Marketing*, 73 (September), 70–89.

Hubbard, Douglas W. (2009), *The Failure of Risk Management*. Hoboken, NJ: John Wiley & Sons.

Johnson, Michael D. and Fred Selnes (2004), "Customer Portfolio Management: Toward a Dynamic Theory of Exchange Relationships," *Journal of Marketing*, 68 (April), 1–17.

Kaplan, Paul D. (2009), "Déjà Vu All Over Again," *Morningstar Advisor*, (February/March), 28–33.

Kim, Moon K. and David A. Burnie (2002), "The Firm Size Effect and the Economic Cycle," *Journal of Financial Research*, 25 (Spring), 111–24.

Kumar, V. (2008), *Managing Customers for Profit: Strategies to Increase Profits and Build Loyalty*. Philadelphia: Wharton School Publishing.

Kundisch, Dennis, Stefan Sackmann, and Markus Ruch (2008), "Transferring Portfolio Selection Theory to Customer Portfolio Management—The Case of an e-Tailer," in *Enterprise Applications and Services in the Finance Industry*, D.J. Veit Dennis Kundisch, Tim Weitzel, Christof Weinhardt, Fefhi A. Rabhi, and Federico Rajda, eds. Berlin: Springer, 32–49.

Labahn, Douglas W. (1999), "Avoiding Over-Reliance on a Single Large Customer: The Impact of Technical Capability, Product Development and Alternative Key Customers," *Journal of Business to Business Marketing*, 5 (4), 5–37.

Lande, Paul S. (1994), "Regional Industrial Structure and Economic Growth and Instability," *Journal of Regional Science*, 34 (3), 343–60.

Markowitz, Harry (1952), "Portfolio Selection," *Journal of Finance*, 7 (March), 77–91.

——— (1959), *Portfolio Selection: Efficient Diversification of Investments*. New York: John Wiley & Sons.

——— (1987), *Mean-Variance Analysis in Portfolio Choice and Capital Markets*. New York: Blackwell.

——— (1991), *Portfolio Selection: Efficient Diversification of Investments*. Malden, MA: Blackwell.

Mittal, Vikes, Matthew Sarkees, and Feisal Murshed (2008), "The Right Way to Manage Unprofitable Customers," *Harvard Business Review*, 86 (April), 95–102.

Niemira, Michael P. and Philip A. Klein (1994), *Forecasting Financial and Economic Cycles*. New York: John Wiley & Sons.

Niraj, Rakesh, Mahendra Gupta, and Chakravarthi Narasimhan (2001), "Customer Profitability in a Supply Chain," *Journal of Marketing*, 65 (July), 1–16.

Pearson, Michael M. and Guy Gessner (1999), "Transactional Segmentation to Slow Customer Defections," *Marketing Management*, 8 (Summer), 16–23.

Rao, Ramesh K.S. and Neeraj Bharadwaj (2008), "Marketing Initiatives, Expected Cash Flows, and Shareholders' Wealth," *Journal of Marketing*, 72 (January), 16–26.

Reinartz, Werner J. and V. Kumar (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration," *Journal of Marketing*, 67 (January), 77–99.

———, Jacquelyn S. Thomas, and V. Kumar (2005), "Balancing Acquisition and Retention Resources to Maximize Customer Profitability," *Journal of Marketing*, 69 (January), 63–79.

Reinganum, Mark R. (1992), "A Revival of the Small-Firm Effect," *Journal of Portfolio Management*, 18 (Spring), 55–62.

Rust, Roland T., Tim Ambler, Gregory S. Carpenter, V. Kumar, and Rajendra K. Srivastava (2004), "Measuring Marketing Productivity: Current Knowledge and Future Directions," *Journal of Marketing*, 68 (October), 76–89.

———, Katherine N. Lemon, and Valarie A. Zeithaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy," *Journal of Marketing*, 68 (January), 109–127.

Ryals, Lynette (2002), "Measuring Risk and Returns in the Customer Portfolio," *Journal of Database Marketing*, 9 (March), 219–27.

——— (2003), "Making Customers Pay: Measuring and Managing Risk and Returns," *Journal of Strategic Marketing*, 11 (September), 165–75.

Sharpe, William F. (1966), "Mutual Fund Performance," *Journal of Business*, 39 (January), 119–38.

——— (1994), "The Sharpe Ratio," *Journal of Portfolio Management*, 21 (1), 49–58.

———, Gordon J. Alexander, and Jeffery V. Bailey (1999), *Investments*, 6th ed. Upper Saddle River, NJ: Prentice Hall.

Srinivasan, Shuba and Dominique Hanssens (2009), "Marketing and Firm Value: Metrics, Methods, Findings, and Future Directions," *Journal of Marketing Research*, 46 (June), 293–312.

Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-Based Assets and Shareholder Value: A Framework for Analysis," *Journal of Marketing*, 62 (January), 2–18.

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

Venkatesan, Rajkumar and V. Kumar (2004), "A Customer Lifetime Value Framework for Customer Selection and Resource Allocation Strategy," *Journal of Marketing*, 68 (October), 106–125.