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Balancing Risk and Return in a Customer Portfolio

Crina O. Tarasi, Ruth N. Bolton, Michael Hutt, and Beth Walker

Companies can efficiently reduce the risk associated with their customer portfolios without compromising revenue levels. Using a large B2B customer database, the authors show that in the long run, an efficient portfolio outperforms the current portfolio and a profit-maximizing portfolio.

Report Summary

In the late 1990s, IBM and Sun Microsystems had very different approaches to their customer base. Sun Microsystems' customer base was dominated by newly established dot-com companies, despite the potentially volatile demand for its products. Meanwhile, IBM focused on large, established companies that had historically been lucrative sources of revenue. Sun experienced fast-growing sales, but when the dot-com bubble burst, the impact crippled Sun. In contrast, IBM was less severely affected, as outsourcing contracts from *Fortune* 500 companies provided a steady stream of cash flow.

This study explores how the financial principles of diversification can be applied effectively to manage a firm's customer portfolio. First, the authors aim to identify risk that should be divested because firms do not reap higher returns for assuming it and suffer losses when market conditions change. Second, they seek to construct efficient customer portfolios. Third, they build on these components to develop an actionable approach that exploits the synergies of a diverse customer base characterized by heterogeneous risk-return profiles.

The authors apply risk-return concepts and methods to a large customer database from a business-to-business services company. First they investigate whether there are significant differences in variability among customer classes. Then, they establish clusters of customers with similar variability and identify efficient customer portfolios (e.g., portfolios that have either maximum return for a certain level of risk or minimum risk for a desired level of return). Using forward- and back-testing, the authors show that companies can efficiently reduce the risk associated with their customer portfolio without compromising revenue levels. In the long run, an efficient portfolio outperforms the current portfolio and a profit-maximizing portfolio.

Managers must assess the similarities and differences among customers' cash flows to determine the ultimate impact on a company's business performance. The key to business success is managers' ability to dynamically adjust the customer portfolio as market conditions change. ■

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Introduction

The advantage of knowing about risks is that we can change our behavior to avoid them. . . . Optimal behavior takes risks that are worthwhile.

—Robert F. Engle III,
Nobel Prize Acceptance Lecture,
December 8, 2003

Customers are the primary source of all future positive cash flows. A firm typically manages its customer portfolio by segmenting the market and targeting the most profitable market segments. In general, firms attempt to acquire and retain individual customers who offer the highest financial returns, without considering the risk associated with these customers' cash flows or their impact on the composition of the entire customer base and (thus) the firm's aggregate cash flow. This practice is at odds with financial theory that posits that, even though assets are selected individually, performance is measured on the entire portfolio, where there is a tradeoff between risk and return. Specifically, Markowitz's (1952) portfolio theory proposed that return and risk are related, and to optimize performance, returns must be maximized for a certain level of risk. Since managing returns is suboptimal without considering risk, there is a significant gap between theoretical principles and managerial practice with respect to customer portfolio management. This gap is rather surprising because marketing scientists have recognized that different customers have different risk/return profiles (Dhar and Glazer 2003; Gupta and Lehmann 2005; Srivastava, Shervani, and Fahey 1998), and that the customer asset is critical to assessing the true value of a firm (Wiesel, Skiera, and Villanueva 2008).

We believe that rather than simply investing in programs that target customers and increase revenue streams, firms can improve business performance by developing a more nuanced approach to customer portfolio management that balances risk and return. Specifically, we believe that it is important to build a portfolio of customers that complement each other, so that the return and risk of the overall portfolio can be maintained at targeted levels regardless of changes in the performance of sectors in the marketplace or in the overall marketplace. The information technology (IT) sector provides a vivid illustration of the benefits of considering risk as well as return in constructing a customer portfolio.

In the late 1990s, IBM and Sun Microsystems adopted very different strategies. Sun Microsystems targeted newly established dot-com companies—despite potentially volatile demand for its products—and built a customer portfolio dominated by them. Meanwhile, IBM focused on large, established companies that had historically been lucrative sources of revenue. Sun experienced fast-growing sales from the booming dot-com market, whereas IBM attracted extensive criticism from Wall Street for failing to capture a share of it. When the dot-com bubble burst, the impact on Sun was crippling; millions of dollars worth of Sun systems were still unpacked when bankruptcy hit many of the Internet start-ups (Kerstetter et al. 2003). In contrast, IBM was less severely affected, as outsourcing contracts from *Fortune* 500 companies provided a steady stream of cash flow. When growth in the IT sector resumed, IT spending by small and medium-size businesses (SMBs) grew eight times faster than spending by large customers. Companies such as Microsoft and Dell had established strategies for SMB customers and consequently grew accordingly. IBM, which in the aftermath of the bubble developed a dedicated strategy for SMBs, grew as well. Hewlett-Packard, Cisco, and Apple made a late start in serving SMB customers and missed the window of opportunity (Veverka 2003).

This anecdote illustrates two key principles: (1) the structure of the customer base affects the stability of the firm (i.e., risk as well as return), so managers must assess similarities and differences among customers' cash flows to determine the ultimate impact on the firm's business performance; and (2) the key to business success is managers' ability to dynamically adjust the customer portfolio as market conditions change. IBM learned the lesson, and by developing a dedicated strategy to SMBs, it secured a piece of the new, growing pie.

The purpose of our research is to explore how financial principles of diversification can be applied effectively to manage a firm's customer portfolio. We do so in the following way. First, we aim to identify risk that can (and should) be divested away because firms do not reap higher returns for assuming it and (instead) suffer losses when market conditions change. Second, we seek to identify ways to construct efficient customer portfolios. Third, we build on these components to develop an actionable approach that, looking beyond the returns from individual customers, exploits the synergies of a diverse customer base characterized by heterogeneous risk-return profiles.

This paper makes four major contributions to marketing science and practice. First, it shows—theoretically and empirically—how to make a nuanced assessment of customer value by calculating the beta and the Sharpe ratio for each customer. Beta can be used to measure the impact an individual customer has on the value of the entire portfolio, and, by adjusting for variability, the Sharpe ratio takes into account the risk/reward tradeoff associated with the customer. Second, it evaluates the extent to which classic market segmentation variables (e.g., demographics or firmographics) can be used to predict cash flow characteristics (i.e., risk-return profiles) of customers, so that managers can assess how potential customers (as well as existing customers) might contribute to the customer portfolio. By linking classic market segmentation variables to the risk-return profiles of customers, firms may be able to identify new strategies for new and existing markets. 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, our paper shows—conceptually and empirically—how to identify synergies among customers and how to identify the optimal mix of customers by constructing an efficient frontier for customer portfolios. The efficient frontier is the set of optimal customer portfolios characterized by minimum risk for a certain level of return, or maximum return for a certain level of risk, so it describes alternative customer portfolios for the firm. Fourth, our paper applies these concepts and methods using customer data from a business-to-business services company and shows that diversification strategies are actionable. In summary, we conceptually explore whether efficient customer portfolios can be built and then empirically show how to build them.

In the next section, we review the customer relationship management literature and discuss how financial portfolio theory can be applied to the customer portfolio. Next, we test the feasibility of applying key financial concepts to customer portfolios by implementing them using 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 the classification of financial assets. 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 importantly, we demonstrate that the firm's efficient portfolio has constantly lower variability than the current customer mix or the profit-maximization portfolio, while the profit performance is superior in the long run.

Literature Review and Theory

State-of-the-art customer relationship management

Recent research has focused on the impact of marketing's strategic actions on a firm's value (Gupta and Lehmann 2003; Moorman and Lehmann 2004; Srinivasan and Hanssens 2009). Marketers have long recognized that the "customer is a financial asset that companies and organizations should measure, manage and maximize, just like any other asset" (Blattberg, Getz, and Thomas 2001, p. 3). Therefore, companies try to acquire and retain customers with high levels of spending (Kumar and Shah 2004) or profitability (Kumar, Shah, and Venkatesan 2006).

Two studies have demonstrated that even though evaluating the customers individually is insightful, the firm must evaluate the overall customer portfolio to optimize its business performance. First, Johnson and Selnes (2004, 2005) pointed out that the firm's decision about which customers to acquire and retain will be different when it considers the entire customer portfolio versus when it analyzes individual customers. For example, newly acquired customers may become more profitable over time, and customers who are highly profitable today may not maintain that status tomorrow (Kumar, Shah, Venkatesan 2006). Second, Dhar and Glazer (2003) noted that when discounting the profitability of a customer portfolio to present day value, it is evident that the strategy of acquiring the most profitable customers does not necessarily create the most valuable customer portfolio. Indeed, adding some "less profitable" customers, who demonstrate a different purchasing pattern, lowers the variability for the entire portfolio, thereby creating a higher level of expected return.

We wish to emphasize that the conceptual distinction between an approach that evaluates the entire customer portfolio and an approach that analyzes individual customers is meaningful regardless of the financial metric that the firm uses to evaluate individual customers, such as current profitability, customer lifetime value, or an index that reflects recency, frequency, and monetary value (RFM). All metrics based on individual customers ignore some aspects of risk and the synergy (or lack of it) among the individual elements. We know from the segmentation literature that large businesses behave differently than SMBs, that customers from different cultures differ in their response to satisfaction levels, or upgrading behavior differs based on the length of the relationship with the firm (Bolton, Lemon, and Verhoef 2008; Bolton and Myers 2003; Kim and Burnie 2002). The question that arises is how to build a portfolio that combines these differences in a way that is advantageous for the firm.

Risk in the marketing literature

Consistent with an emphasis on financial accountability for marketing actions, recent research has often focused on the association between marketing actions and business performance or shareholder value. (See Srinivasan and Hanssens 2009 for a review.) Many studies have focused on the effect of market-based assets (customer equity, customer satisfaction, brand quality) and marketing actions (product innovation and advertising) on company risk. Investments in R&D and advertising result in lower systematic risk, i.e., the risk associated with the market (McAlister, Srinivasan, and Kim 2007). However, radical innovation, even though it increases normal and abnormal profits, increases overall company risk due to its higher variability (Sorescu and Spanjol 2008). Customer satisfaction reduces not only cash flow variability (Gruca and Rego 2005), but also the systematic and idiosyncratic[1] risk, and also insulates firms in downturns (Tuli and Bharadwaj 2009).

This aforementioned stream of research focuses on firm-level measures of risk, whereas managers require an understanding of the underlying mechanisms that link the risk-return profiles of individual customers (or market segments) to the risk-return profile of the firm. Recently, Tuli, Bharadwaj, and Kohli (2009) have shown that, at a customer level, the number of ties a company builds with its best customers ensures not only higher revenue, but also reduces the variability of their purchases. Their study suggests that it may be possible to manage risk through firm actions, but as yet there is little or no evidence that managers consider such risk-return tradeoffs in their marketing decisions. We extend their work by showing that the firm can manage its portfolio of customer relationships to control the overall variability of the firm's cash flow. We show that the risk associated with an individual customer doesn't arise solely from the probability of defection (which is accounted for in the calculation of customer lifetime value); it also arises from variability in their purchases. Moreover, we show that individual customer risk influences the risk of the entire customer base and (consequently) the company's risk.

Conceptual Framework

This section reviews modern financial portfolio theory and conceptualizes how key financial constructs can be applied to customer portfolios. Then, it describes how these financial constructs can be calculated from customer purchase history data. Next, it discusses how firms can identify the most desirable customers by assessing the rate of reward on risk for each customer. Finally, we address how firms can use these constructs and measures to segment the firm's customer base in ways that are comparable with the classification of financial assets.

Modern portfolio theory

An investor who combines assets with different variability (risk) can obtain a portfolio with lower variability than any of the individual assets by diversifying to incorporate assets that yield countercyclical returns. In a stock portfolio, the lower the total correlation of a stock with the total return, the more desirable it is that the particular stock be integrated into the portfolio. For example, stocks drawn from different industries, different countries, and different-size companies are affected by the environmental and economic changes in specific ways (Niemira and Klein 1994). Since many market changes cannot be anticipated, diversification ensures that the portfolio includes positive cash flow opportunities and smoothes out potentially negative cash flows. Based on the variability and return of each of the assets, the optimal (efficient) portfolio is considered to be 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).

Key Constructs. Risk represents the subjective expectation of loss; the greater the perceived probability of encountering a loss, the greater the risk perceived (Stone and Gronhaug 1993). Business risk represents the degree of uncertainty associated with the future performance of the business and is defined as "the dispersion of unexpected outcomes" (Jorion 1997, p. 63). Markowitz (1987) measured risk using the variability of the price of the asset, which represents a good proxy for the probability of encountering a failure.

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 very difficult to forecast. However, we will 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).

Individual Customer Risk and Overall Customer Portfolio Risk. Risk is defined 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:

$$V_A = \frac{\sum_{i=1}^{N_A} (x_{Ai} - x_A)^2}{N_A - 1},$$

and standard deviation is $\sigma_A = V_A^{1/2}$, where x_{Ai} is the cash flow for customer A in the i^{th} 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.

In order 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,

$$C_V = \sigma_A / x_A .$$

The risk of the entire portfolio V_P will be computed using a similar formula, just that the cash flow used will be the average of all customer cash flows (Markowitz 1987).

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

where x_j is the cash flow from all customers active in period j, $x_j = \sum_1^{M_j} x_{jk}$ (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,

$$x_P = \frac{\sum_{j=1}^{N} x_j}{N - 1}.$$

In order to be able to compare the performance of portfolios with different levels of performance (e.g., different means), we will standardize the values by dividing the monthly values by the mean of the portfolio before computing variability.

Components of Risk. Risk is considered to have two components, the systematic or market risk as measured by beta (a reflection of how sensitive an asset is relative to changes in the market) and the unsystematic (idiosyncratic) or residual risk:

$$R_i = \alpha_i + \beta_i \times R_M + \varepsilon_i,$$

where R_i represents the return on asset i, β represents the systematic or market risk, RM represents the market return, and ε_i represents the unsystematic or unexplained risk. If we use the overall customer base as the reference instead of the market portfolio, the formula will provide the historic β for the customer, as compared to the current composition of the customer portfolio.

The residual risk (ε, $\varepsilon_i = R_i - \beta_i \times R_M - \alpha_i$) has two components: the specific risk and the extra-market covariance (Rudd and Clasing 1988). Specific risk is unique to the firm and independent of all other sources and may, for example, be represented by a lawsuit, the discovery of unexpected mineral resources, or managerial particularities. The extra-market covariance accounts for the tendency of similar assets to move together, such as stock of companies in the same industry, companies with high degree of dependence on oil, or high-growth stock. In this research, the focus is on the overall risk—the total variability—while paying attention to the sources of risk, especially market-related and common risk. We assume that, just as individual investments influence the risk and return of a stock portfolio, customers' *purchases* influence the risk-return characteristics of a firm's cash flows.

Identifying the most desirable customers: The rate of return on risk

Beta. For managers, business success is the result of decisions about which customers to acquire and retain. To identify the most desirable customers, we need a reliable measure of the consistency of returns for an individual customer vis-à-vis 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. Beta is normally defined as the "slope in a security's market model [which] measures the sensitivity of the security's return to the market index's return" (Sharpe, Alexander, and Bailey 1999 p. 183).

$$\beta_A = \frac{\mathrm{cov}(x_A, x_R)}{V_R}$$

The overall market portfolio is used as reference because it is considered efficient (Sharpe, Alexander, and Bailey 1999).

In a customer (as opposed to financial security) context, the overall customer portfolio is *not* efficient. In the financial context, the market portfolio is considered the result of investors acting using the full information available, and therefore it is assumed to be efficient (Fama 1970). Within a company, variations in the customer portfolio might reflect the overall economy or the performance of certain industries or sectors of the economy. Hence, we cannot use beta (relative to the overall customer portfolio) as an indicator of customer risk, but as a measure of the correlation of the individual customer with the overall customer portfolio; it reflects the degree to which the individual customer contributes to the risk of the entire portfolio.

Sharpe Ratio. Another method of assessing the desirability of an asset is the Sharpe ratio, which measures the rate of return on risk, or in other words, the reward for assuming variability (Sharpe 1994). The reward is measured as the return above the risk-free rate.

$$S_i = \frac{R_i - R_f}{\sigma_i},$$

where R_i is the return on the asset to be evaluated, R_f is the return of the risk free asset, and σ_i is the standard deviation of the return.

When there is no risk-free asset available, the equation is simplified to

$$S_i = \frac{R_i}{\sigma_i}.$$

Applied to a customer portfolio, the Sharpe ratio is the return divided by the standard deviation, without considering the "risk-free" class of customers. Finding a risk-free analogy in the customer portfolio is not as challenging as it seems. Most companies have some group of customers that they might prefer not to serve due to their low rate of return, but they choose to serve them with spare resources because their rate of return is still higher than keeping resources idle. These customers are most often outside marketers' radar, but they represent a good reference point. Hence, in our context, the Sharpe ratio provides an absolute measure of the return from including an individual customer (with his or her concomitant risk) in the customer portfolio.

In summary, besides the coefficient of variation, which measures the variability adjusted by mean, we have two methods to assess the worth of a customer: beta and the Sharpe ratio. Using beta, we can assess the potential contribution of the customer to the portfolio risk. Using the Sharpe ratio, we can assess the true rate of return on risk.

Segmenting or classifying customers based on risk

In financial markets, assets are grouped into categories that share certain risk-return and variability characteristics (blue chips, bonds, treasury bills). We can group customers into segments using cluster analysis based on 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 or firmographics. In other words, two key questions in determining the feasibility of an efficient portfolio approach to the customer base are: (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, division they purchase from, industry)? If the answer to both questions is yes, then we can build efficient portfolios based on the risk-return profiles of clusters, rather than individual customers (for which cash flows can be somewhat unpredictable). Therefore, in the remainder of this paper, we will test whether there are significant differences in cash flow variability among different segments that can be characterized in ways that are visible and traditionally used for segmentation. Then, we will attempt to construct an efficient customer portfolio.

Research Design and Study Context

The empirical portion of our paper uses the conceptual framework, constructs, and measures discussed in the preceding section to develop and apply a method for classifying customers into market segments, anchored in traditional investment theory, that: (1) minimizes the risk for a desired level of return, (2) can be applied to existing customers and potential customers (that do not yet have a relationship with the firm), and (3) relies on customer characteristics that are actionable for marketing managers.

The five steps for building an efficient customer portfolio are: (1) determine strategic objectives and assess current risk-return profile for the existing customer base; (2) segment customers and potential customers based on calculating individual betas; (3) determine the efficient frontier customer portfolios and identify an optimal portfolio of customers for targeted return (or risk) preferences; (4) evaluate portfolio performance; and (5) determine necessary adjustments. The details of each step are presented in Table 1, in parallel with equivalent steps for the building of an efficient financial portfolio. The remainder of this section provides an overview of the empirical portion of our work, which will implement these steps.

Study context

We test the applicability of diversification principles and efficient portfolio theory to customer portfolios using purchase history data from a business-to-business company with a diverse customer base.[2] We selected a business-to-business context for our empirical work because market segmentation information for all customers and potential customers is readily available and specific customers can be directly targeted. The client company provided monthly sales and profit data for all customers for the past seven years. The company's records also contained information for each customer concerning number of product lines purchased, size of business, geographic locations, and industry sector. The company had served more than 10,000 customers in the past seven years. However, we focused on the top 250 customers from each of the years from 2001 through 2007, which amounts to 516 unique customers (where 89 have been in the top 250 every year). These 516 business customers account for 98% of all sales. During the seven-year time period, the minimum dollar volume of purchases by a customer was $680,000, and the maximum was more than $2 billion. We supplemented the cooperating company's purchase records with information from public databases. Specifically, 456 of the 516 business customers were uniquely identified based on Dun & Bradstreet (D&B) codes so that we could record the number of employees and sales revenues for specific sites and for the entire company/customer.

Analysis plan

Since we are testing the applicability of diversification principles and efficient portfolio theory to the customer portfolio context using data from a single firm, it is important to use a "strong" test; that is, we do not wish to evaluate our approach on the same data that we used to develop it. Hence, we use a holdout

Table 1

Steps in Developing a Customer Portfolio Compared with Steps in Developing an Investment Portfolio

	Investment Portfolio	Customer Portfolio
1	**Set investment policy** Identify client's investment objectives, including those relating to the tradeoff between risk and return.	**Set customer acquisition and retention policy** Determine objectives for the customer portfolio function of firm's strategy. Determine the current structure and risk level of current customers and current customer portfolio.
2	**Perform financial securities analysis** Scrutinize individual securities and groups of securities to identify mispriced situations and fast growing segments. Based on beta and the amount invested, determine the impact of the proposed securities on the overall portfolio.	**Perform customer segment analysis** Scrutinize market segments, individual customers, and groups of customers in order to identify underserviced needs or markets. Estimate the beta of the identified segments relative to the current portfolio. Estimate the costs to acquire the identified segments. Based on the size of the target segments, estimate the potential impact on the portfolio.
3	**Construct a portfolio of financial securities** Identify specific financial securities in which to invest, along with the proportion of investable wealth to be put in each security.	**Construct a portfolio of customers** Based on the analysis of current and potential customers, determine the efficient frontier portfolios and estimate attainability. Identify the most desirable segment(s) to retain and acquire based on return and risk impact, and determine the amount to be invested in each segment. Design appropriate acquisition/retention strategies.
4	**Evaluate portfolio performance** Determine the actual performance of a portfolio in terms of risk and return, and compare with an appropriate "benchmark" portfolio.	**Evaluate portfolio performance** Evaluate cash flow performance in terms of risk and return and compare to previous years or target revenue/risk or other benchmarks. Identify events that have an impact on future performance and desirable segments that might alleviate the impact.
5	**Revise the portfolio** Assess the current risk and return of the assets in the portfolio and of the portfolio overall. Determine which financial securities in the current portfolio are to be sold and which securities should be purchased to replace them.	**Revise the portfolio** Determine the current structure and risk level of current customers and current portfolio. Reassess objectives for the customer portfolio function of firm's strategy and objectives. Decide allocation of investments in existing customers based on contribution to risk and return. Decide whether to pursue new segments (see step 2).

Source for investment management: Sharpe, Alexander, and Bailey (1999); Berk (2005); Gulko (2005).

sample approach whereby our methods are applied using the first six years of data and evaluated based on the seventh year's data.

The five-step process can be broken down into two stages. In Stage 1, we implement the first two steps of the process—evaluating the existing customer portfolio and clustering individual customers into segments based on the variability in their sales data. At the end of Stage 1, we assess whether the notions of risk discussed in the preceding section can be meaningfully applied in this study context. 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 number of product lines purchased, size of business, geographic areas served, and industry.

In Stage 2, we implement the remaining steps of the process. The third step, the construction of the efficient customer portfolio, is the most complex. We segment (i.e., cluster) the customers based on 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. Note that since the firm has now identified the segments based on nonfinancial characteristics, the segments are actionable because managers can identify and assess potential customers as well as current customers. Then, we build the efficient frontier using the actionable segments. Finally, using our risk-based segmentation scheme, we develop a diversified portfolio of customers, which should outperform value maximization portfolios in the long run. Step four is the 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). Hence, 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. Step five, revising the composition of the portfolio, requires revisiting current customers' performance (purchases), individually and by segment. Using Sharpe ratios and beta indicators, we can assess the riskiness of individual customers and the impact on the overall portfolio. Using this information—and keeping in perspective of the company's goals and the external environment—marketing managers can decide case by case whether it is desirable to attract more business from the specific customer, or identify segments with similar characteristics to pursue in the future.

Stage One: Testing the Feasibility of Implementation

In this section, we will focus on identifying whether there are significant differences among classes of customers segmented along actionable dimensions such as contractual relationships, size of the business, and industry. For these analyses, we use the 2001 through 2006 data. We begin by considering financial asset classes and how we might identify market segments that reflect these similar risk-return characteristics (see Table 2). A given firm will not necessarily have a market segment that corresponds to each asset class. However, if a firm wants to alter the composition of its customer base, managers can design strategies or products to attract other market segments. As shown in Table 2, market segments corresponding to asset classes can be identified based on well-understood customer characteristics: contractual or noncontractual relationships, size of business, and so forth.

The business press provides some evidence that firms recognize the importance of such customer characteristics, although they may not explicitly recognize the risk-return tradeoffs that they represent. For example, IBM has a policy of attracting large customers (*Forbes* 500) with whom it has relatively rigid contracts, so that this segment is comparable to blue-chip and AAA bonds (depending on the rigidity of the contract). It also has a strategy dedicated to small and medium-size companies, characterized by higher volatility and growth (i.e., with smaller market capitalizations), as well as numerous international customers.

The question that arises—beyond the comparison presented in the table—is whether there are significant differences in variability across customers segmented on an a priori basis

Table 2
Comparison Between Investment Classes and Customer Segments

Market Portfolio	Customer Portfolio
Blue-chip stocks • Stock of companies with long operating history, steady earnings, and good reputation • No return is guaranteed, but among stocks, they have the lowest risk • Little overall growth	**Large enterprise customers, long-term relationships** • No return is guaranteed, but trust and commitment have developed • Predictable • May not be associated with high growth or high profitability
Medium-size and small company stocks • High growth potential • High risk • Countercyclical with large company stock	**Medium-size and small business customers** • High growth potential • High risk • Often countercyclical with large customers
International stocks • High growth potential • High risk (political, exchange rate) • Report with different accounting systems • Often countercyclical with other regions/countries	**International customers** • Higher growth potential • Higher risk (political, exchange rate) • Often countercyclical with other regions/countries
High-quality bonds (AAA) • High degree of certainty since both the timing and the size of cash flow is known • Low risk of defaulting • Presence in the portfolio reduces overall risk	**Long-term contracts/close relationships** • Contracts by definition reduce risk and uncertainty in exchange relationships • The long-term collaboration allows for trust and commitment to develop
Medium-quality bonds (AA to BBB) • Relatively secure • Lower return • Constant rate of return	**New contracts** • The short term of the collaboration makes the outcome relatively unsure • Trust and commitment have not yet developed
Treasury securities • Highly predictable • Lowest risk (and return)	**Rigid contracts** • Highly predictable • Lowest return

using actionable customer characteristics. We investigate this question by comparing the coefficient of variation in customer purchases over time between: (1) contractual and non-contractual relationships, (2) different sizes of businesses, and (3) different industries with different economic trends. We provide the theoretical justification for examining these variables below.

Contractual Relationships. Customer–firm relationships range from formal contractual relationships to transactional relationships[3] (Gundlach and Murphy 1993). 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 relative to firm expectations. Hence, 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. This type of diversification is based on

Table 3
Coefficient of Variation by Product Line

	Product Line 1 (contractual relationships)	Product Line 2	Product Line 3	Product Line 4	Overall
Coefficient of variation	.525	.870 (p = .000)*	1.216 (p = .000)*	1.740 (p = .000)*	.708 (p = .000)*
Number of customers	105	436	394	419	467

*Note: The comparison was made to the product line 1 (*t*-test).

averaging risk, which means that the resulting risk falls between the lowest risk and the highest risk (Alexander and Sharpe [1989] describe this phenomenon for market securities). Hence, the synergies from combining (i.e., averaging) individual customers with different risk levels will diminish the overall customer portfolio risk. Note that we are not implying that the introduction of contracts at a firm that previously did not have them will reduce overall customer portfolio risk.

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, with somewhat different characteristics regarding delivery characteristics), and most customers buy more than one. The main distinction across the product lines is the flexibility available to the firm. Product line #1 relies on contractual relationships, whereby assets are allocated to a specific customer, thus restricting the firm's flexibility to deploy these assets elsewhere. Product line #2 allows for high flexibility and accounts for the most firm revenue (42%). The company offers two other product lines: product line #3 (medium flexibility) and product line #4 (high flexibility).

The average coefficient of variation for each product line is displayed in Table 3. The coefficient of variation for product line #1 is significantly lower (p = .000) than the coefficient of variation for any other product line. In other words, the contractual product line (#1) has the smoothest, most predictable cash flows. Hence, it provides insulation from troughs (downtimes) and peaks (busy times). By serving customers who prefer this product, the firm reduces the coefficient of variation for its overall customer portfolio.

Size of Business. Research regarding financial portfolios has shown that small firms tend to periodically outperform and underperform large firms, exhibiting a negative correlation in returns (Reinganum 1992). Small firms outperform large firms in returns 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 with a long operating history, steady earnings, and a good reputation, but slower growth. In contrast, small and medium-size businesses (SMBs) have high growth potential (Acs and Audretsch 1990; Veverka 2003). If large businesses dominate a financial portfolio, variations in their business cycles will have a substantial impact on their suppliers (LaBahn 1999). SMBs usually have less influence on the overall financial portfolio individually, but they can be combined to achieve diversification and lower overall variability, provided that their revenue streams are not positively correlated (Markowitz 1987).

There are good reasons to believe that these findings regarding financial portfolios will extend to customer portfolios. There is extensive evidence that small and medium-size customers behave differently than large customers, so that size is the most common market segmentation variable for B2B firms. There is evidence that the smaller companies respond differently than larger companies to changes in economic policies. For example, smaller companies usually account for a disproportional share of the manufacturing decline following tightening monetary measures (Gertler and Gilchrist 1994), but are also more nimble during favorable economic conditions. Since SMB customers may exhibit countercyclicality in reaction to business cycles and are (relatively) less predictable, we believe that they can be combined to create a diverse portfolio of customer sizes with smaller overall business risk.

We compare the coefficients of variation for customer purchases over time between different sizes of business customers in the following way. The business customers for the client company are diverse in size. They have average annual sales of seven billion dollars, with a maximum of $350 billion. The average number of employees for these business customers is 1,900 per location and 28,800 across locations. The maximum number of employees across locations is 383,000. We conducted a median split of the customer base, based on the number of employees. The coefficient of variation for the small companies was .67, statistically different ($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 house construction and an increase in home improvement projects. A price increase for a commodity, such as silicone, might result in a substantial price increase for automobile tires, whereas the price of personal grooming products (such as shampoos and liquid soaps) might increase very little because silicone is not a major component. Dhar and Glazer (2003) show that targeting customers in different segments reduces the risk of decreasing revenue when economic conditions are changing.

We compare the Sharpe ratios, betas, and coefficients of variation for customer purchases over time among business customers in different industry sectors in the following way. The cooperating company's business customers belong to 27 industries, with substantially different average sales and variability in sales. We classified the customers using NAICS (North American Industry Classification System) combined with the Standard & Poor's (S&P) sector classification. First, customers were classified into the following NAICS categories: transportation (86), paper and packaging (82), food and beverages (66), and automotive (42). The industry that accounts for the largest percentage of the company's sales revenue is retail (26%), followed by paper and packaging (21%), automotive (12%), and consumer goods (11%). It is evident that different sectors within the same industry exhibit different trends; for example, staple products are less affected by downturns in the economy than discretionary products. Second, we added the S&P global industry classification standard, which is designed to capture sector differences.[4] Hence, by combining classification schemes, we obtain a finer granularity that allows for more uniformity within the identified categories.

As shown in Table 4, classification by industry and sector enables us to distinguish between retailers in the staples category (e.g., Wal-Mart) and those in the discretionary category (e.g., Kohl's). There are only a small number of companies in each category (e.g., the 26% in revenue from big retail companies is provided by seven customers), so there is insufficient statistical power for t-tests of the differences in the average coefficients of variation across categories. However, when we compare, for example, the office supplies segment (line 9 in table 4), with the food and beverage segment (line 14), we notice important differences. Office

Table 4

Coefficient of Variation Classified Using Both NAICS and S&P

	S&P	Industry	N	Beta	Sharpe Ratio	Sharpe Ratio**	Coef. of Var. (CoV)	Average Monthly Revenue (thou.)	Six Year Revenue*** (mill.)
1	Beverage*	Food & Beverage	14	1.199	1.344	2.133	.710	369	328
2	Discretionary	Apparel	9	1.261	2.467	3.512	.802	245	128
3	Discretionary	Automotive	35	1.616	1.400	2.207	.604	1,000	2,381
4	Discretionary	Consumer Goods	4	.883	.609	1.694	.720	599	170
5	Discretionary	Durables	10	1.874	.181	1.116	.656	182	110
6	Discretionary	Electronics & Appl.	18	1.533	2.398	3.366	.786	368	361
7	Discretionary	Home Improvement	27	.067	1.169	1.953	.705	313	559
8	Discretionary	Lawn and Garden	4	.336	8.521	10.580	1.145	167	48
9	Discretionary	Office Supply	3	–3.668	2.948	4.633	.461	798	162
10	Discretionary	Paper & Packaging	11	1.584	1.976	2.596	.592	659	311
11	Discretionary	Retail	7	1.125	1.673	2.511	.675	5,042	2,476
12	Discretionary	Sporting Goods	7	–.233	.289	1.027	.751	123	46
13	Energy	Oil	5	1.067	2.050	2.726	.680	355	64
14	Food	Food & Beverage	42	8.568	.774	1.518	.794	352	973
15	Health	Medical Supplies	6	.773	.111	0.937	.644	138	55
16	Industrials	Automotive	8	.909	1.001	1.542	.598	237	98
17	Industrials	Electronics & Appl.	5	1.856	.878	1.674	.774	152	47
18	Industrials	Machinery	4	.107	3.120	4.207	.567	656	181
19	Industrials	Paper & Packaging	9	3.871	.315	0.855	.693	347	223
20	Industrials	Transportation	10	–18.483	.557	1.127	1.212	243	129
21	Materials	Chemicals	18	.834	1.213	2.134	.668	274	308
22	Materials	Metal Manufact.	12	1.569	1.266	2.084	.773	87	62
23	Materials	Paper & Packaging	30	1.516	.850	1.664	.622	770	1,576
24	Materials	Wood Manufact.	4	.948	.854	1.683	.474	142	33
25	Staples	Consumer Goods	18	–3.780	1.058	1.888	.792	1,763	2,048
26	Staples	Paper & Packaging	17	.742	.891	1.691	.714	1,687	2,036
27	Staples	Pet Supplies	5	16.118	1.789	2.241	.631	440	88
28	Staples	Retail	5	.366	.674	1.539	.629	7,544	2,683
29	Transportation	Transportation	55	.035	2.498	3.565	.702	244	743

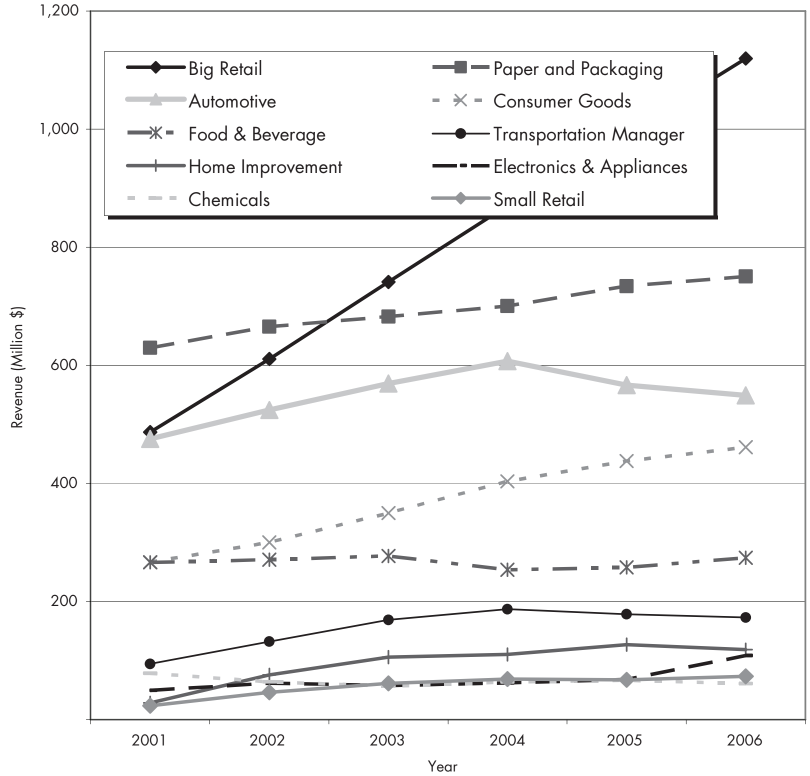
*The distinction between food and beverage, though not in the S&P standards, is useful for distinguishing the different patterns that are likely to characterize foods (e.g., cereals) from beverages (e.g., beer, soda).

**Computed without reference to the "risk-free" segment.

***Cumulative revenue for the years 2001–2006.

supplies customers are more attractive (less risky) compared with the food segment. Beta is negative (negative correlation with the overall portfolio means that it contributes to reducing risk), Sharpe ratios are much higher (i.e., higher reward for the risk assumed), and the coefficients of variation are much smaller (i.e., lower risk). However, the company has many

Figure 1
Industry Trends



more customers in the food sector (42), compared to office supply (3). To illustrate the differences among industries, we graphed sales revenue over time for the 10 categories of customers that generated the highest average sales revenue. Figure 1 shows that there are markedly different trends and variability in sales revenue derived from customers in different industries. For example, the retail sector exhibits a pronounced growth over six years, and there is a similar evolution, though less dramatic, for the consumer goods, paper and packaging, and home improvement sectors. In contrast, the chemical, food, and beverage industries have extremely low fluctuations in average sales over the years, and the auto sector and transportation manager businesses registered a noticeable decline in the past two years. These trends reflect both economic conditions and company policy effects (i.e., the company may choose to focus on certain customers based on their expectations regarding sales).

Stage 1 Summary. After controlling for average sales levels, there are differences in sales variability for customers with contractual versus noncontractual relationships and between customers of different sizes. Also, there are meaningful differences in sales trends for customers from different industries. Hence, it may be possible for us to identify market segments characterized by different risk levels (e.g., betas, Sharpe ratios) and to build an efficient customer portfolio for the cooperating company.

Stage Two: Constructing an Efficient Customer Portfolio

Customer segmentation using cluster analysis

Market segments should be characterized by different demand functions and purchase patterns (e.g., Dickson and Ginter 1987; Elrod

Table 5
Comparisons among Clusters

Cluster Characteristics	Industry Dominance
Cluster 1 (Constant Growth): 84 customers and 24% of the 6-year revenue	
Higher beta (more rapid growth) than all other clusters Higher variability (risk measured using coefficient of variation) than clusters 2, 3, 5, 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 6-year revenue	
Lower beta than clusters 1, 3, 5, and 6, but higher than cluster 4 Lower variability (covariance) than clusters 1, 4 Smaller size customers (by number of employees) than cluster 1, but larger than cluster 3 Customers in cluster 2 buy overall and in 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 6-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 business size customers (by number of employees) than clusters 2, 4, 5, 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)
Cluster 4 (Constant decline): 71 customers and 9% of the 6-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 6-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 business size 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%)

Continued

Table 5
Continued

Cluster Characteristics	Industry Dominance
Cluster 6 (Low Revenue Customers): 125 customers and 5% of the 6-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 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 6-year revenue), and do not have the absolute majority for any of the categories	This cluster has (statistically) as large a percentage of the transportation industry as cluster 5 (about 23%), and second most highest revenue from the lawn and garden industry (32%, while 45% is in cluster 5).

*The difference is significant at 90% confidence level. All other comparisons are statistically significant at 95% confidence level or higher.

and Winer 1982). Market segmentation based on similarities or differences in purchasing patterns is called transactional segmentation. Transactional segmentation has been previously used in financial services firms to determine patterns that signal defections (Pearson and Gessner 1999).

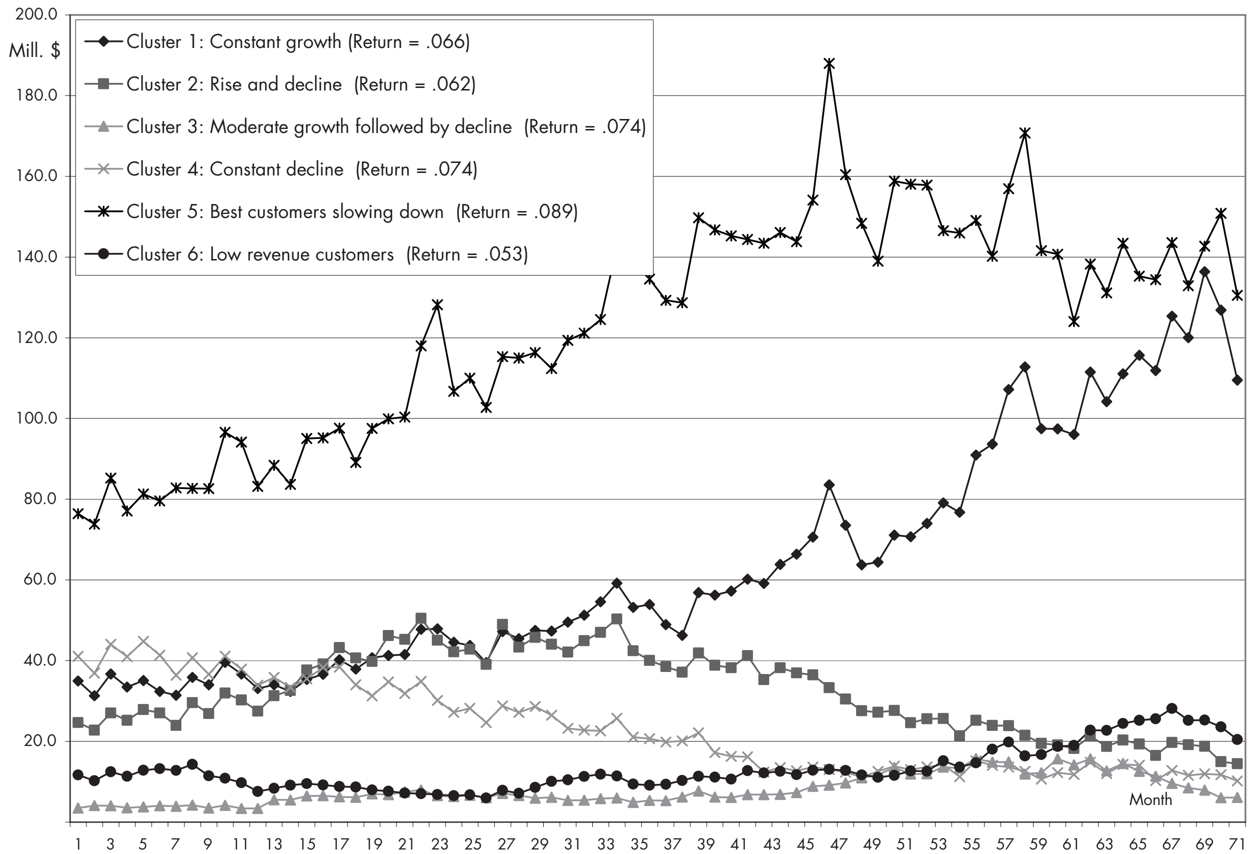
Each customer has unique and common characteristics, so we utilized a hierarchical clustering analysis of the monthly purchase data for each customer to observe the common characteristics. The procedure selected (PROC CLUSTER, in SAS, using the average linkage method) grouped customers based on squared distances, where distance was measured by the monthly cash flow levels[5] (standardized). Since 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, and betas. The results of these comparisons are presented in Table 5. The patterns of the clusters are presented in Figure 2.

Identifying the efficient frontier, and building an efficient customer portfolio

Each cluster has a certain average return by customer, as presented in Figure 2. Based on the six clusters, we can now build an efficient portfolio by minimizing the cash flow variability for 2006 given a certain level of income. Even though we use the data for 2001 through 2006 to build the clusters, we use 2006 as the reference year—being the closest to the hold-out 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. The constraints used in developing the efficient frontier are $\sum_{i=1}^{6} x_i = 1$, and $x_i \geq 0$ (e.g., the sum of percentage weights will add up to 100%, and all the weights will be positive).

To develop the efficient frontier, the function quadprog was used in Matlab to minimize variance–covariance matrix for various levels of return (in increments of .2%). As expected, the

Figure 2
Revenue by Cluster

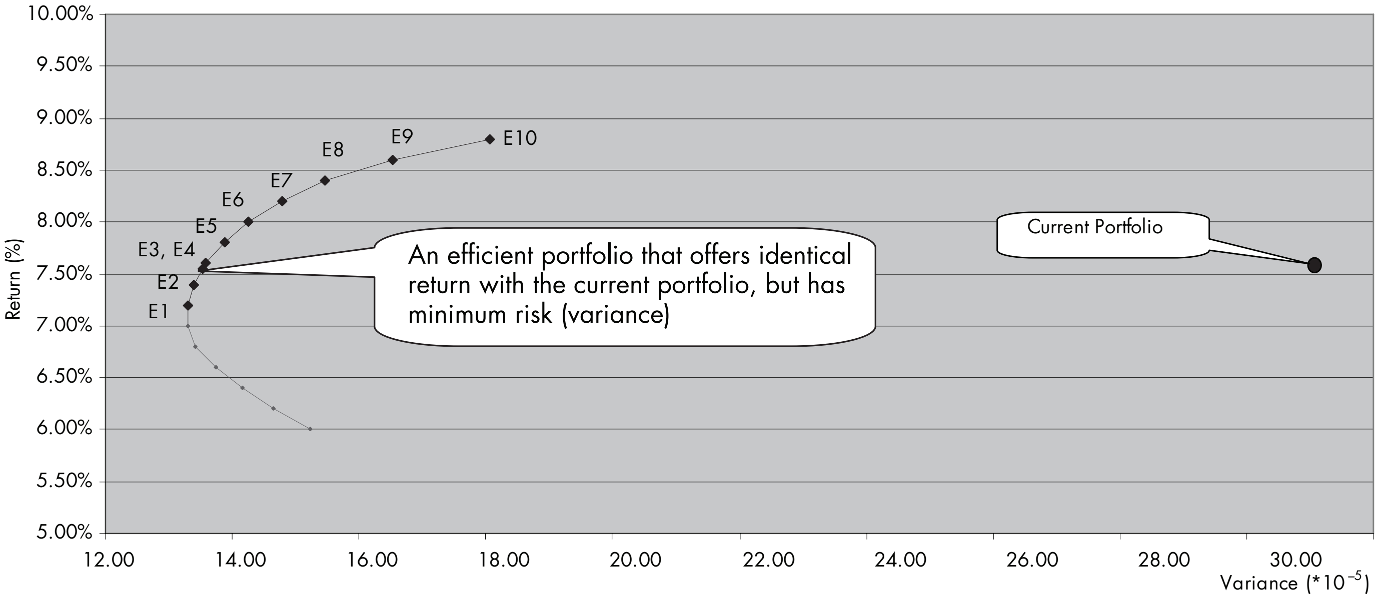


efficient portfolios bordered the set of possible portfolios. The efficient portfolio with the lowest risk is portfolio E1 (see Figure 3 and Table 6), which has a relatively equal representation of all clusters, except cluster 6. It is interesting to note that cluster 3, which is formed predominantly of small business customers, has the highest representation in this portfolio (26%). The efficient portfolio with the highest return is portfolio E10, and is dominated by cluster 5 (92%, see Table 6), which is the cluster with the highest return.[6]

The weights of cluster 3 (small business customers) in the efficient frontier portfolios varies 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 overweighed with large business customers reduces the risk of the portfolio. In order to have a balanced portfolio, the cooperating company requires a certain percentage of small business customers, but no more than 26%. Above 26%, it no longer benefits from adding small business customers to the portfolio, because their variability outweighs the benefits of diversification.

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

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



Note: Portfolio 3 offers identical return with the current portfolio, for less than half the variance (43%).

characteristics is emphasized, making the identification of potential new customers easier and implementation more straightforward. Moreover, it 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. Further details on selecting individually desirable customers are provided in the section regarding managerial implications.

Testing the efficient portfolio

We have constructed an efficient customer portfolio that minimizes variance for the study period. However, we can also construct a "traditional" customer portfolio that maximizes return for the next period, which is what companies do when they try to target and retain the most profitable customers. This traditional profit-optimization portfolio is built using the best customers for 2006 and assuming that the company is able to acquire 25% more customers with the same levels of profit as its best customers (which the client company would choose to do if it could) in 2007.

Now we compare the efficient customer portfolios with this traditional profit-optimization portfolio as well as the company's current customer portfolio. First, we use a comparison method that starts with the portfolios identified and applied to 2007 and "back-tests" them for 2001 through 2005.[7] It is customary in finance to "test strategies under historical market conditions to determine whether certain scenarios would have worked well in the past. The rationale is that, if a trading strategy would have performed well previously, it may be worth considering today."[8] 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, we compare the results for the three different portfolios, that is, we compare variability (risk) and actual profits (return).

Table 6

Evolution of Cluster Weights for the Portfolios on the Efficient Frontier

Portfolio	Return Rate	Cluster Weights 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	

Using back-testing, we notice that the efficient portfolio constantly has much lower variability than any of the other two portfolios for all six years compared. In terms of profitability performance, the efficient portfolio outperforms the actual portfolio in each of the years except for 2004 and 2005, which were extremely profitable for the company. The profit-maximization portfolio outperforms the actual portfolio and the efficient portfolio for just one of the years, 2005. Importantly, note that the further the horizon from the benchmark for which the portfolio has been optimized, the more likely it is that the efficient portfolio outperforms both the actual portfolio and the profit-maximization portfolio, providing supporting evidence for the stability of our method.

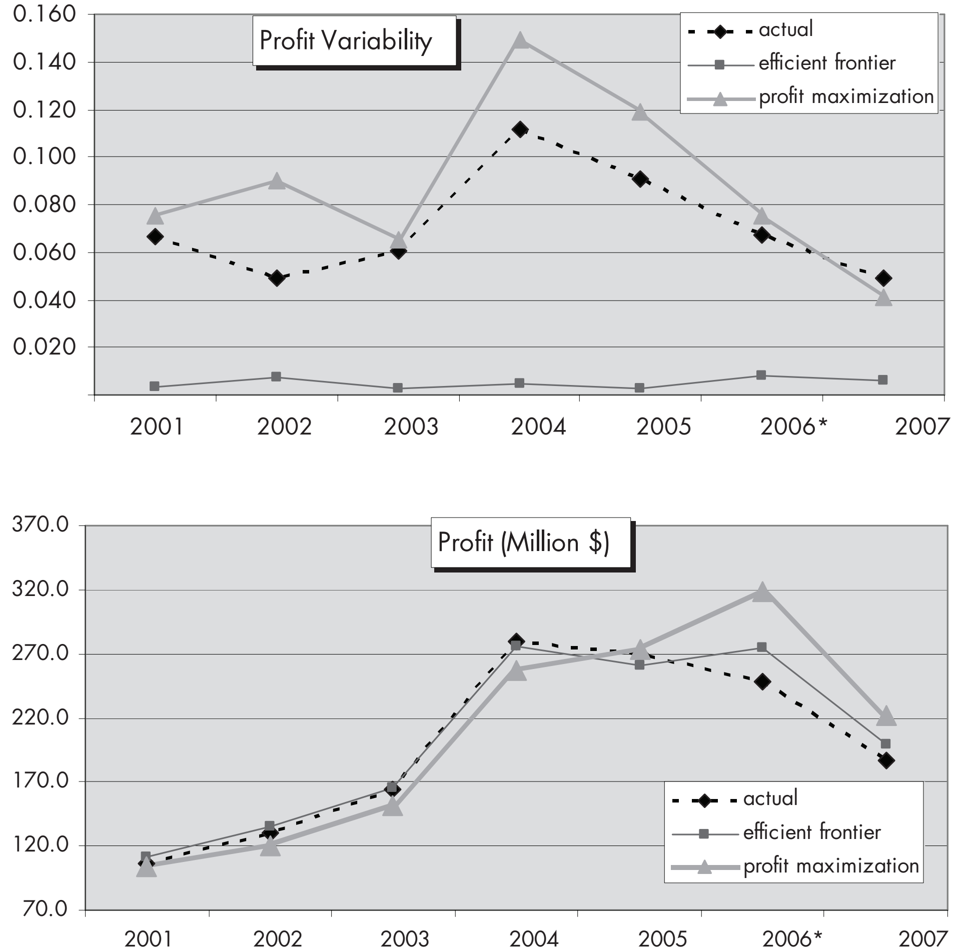
Second, we compare the three portfolios using forward-testing, that is, we use the data for 2007 that have not been used in any other previous analysis. (To do so, the customers who have entered the top 250 for the first time in 2007 have been matched to clusters using the size of the business, industry 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. Of course, it is to be expected that in the first year (short run), the efficient portfolio would not outperform a profit-maximization portfolio.

Revising the current customer portfolio toward an efficient portfolio

Until this point in our analysis, we have focused 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 acquisition efforts. This issue should be considered when the firm reweights its customer portfolio to move toward an optimal composition. In our process for developing an efficient customer portfolio (Table 1), our last step (step 5) calls for evaluation and updating of the customer portfolio. We will discuss this process and illustrate it by showing how a firm might use financial measures to identify a desirable customer.

The firm can use the equivalent of the Sharpe (1994) ratio to measure the desirability of cur-

Figure 4
Back-testing and Forward-testing the Efficient Portfolio



*Represents the year for which the portfolio has been built.

rent and future customers. As previously discussed, a Sharpe ratio can be a measured function of a risk-free asset (in our case, a risk-free customer) or in absolute terms. The mechanics of the equations are more interesting when the risk-free asset is present because the decision can change concerning which investment is the most attractive. By investing a portion of the resources in the risk-free asset, the investor can obtain a higher expected return than by investing just in risky assets. For example, for a return of 15 and a standard deviation of 10, the Sharpe ratio without the risk-free asset is 1.5 (15/10), while with a risk-free asset with a return of 3, it is 1.2 (12/10). For an asset with a return of 28 and standard deviation of 20, the Sharpe 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 Sharpe ratio is 1.25 (25/20, compared to 1.2 for the first example), which is more attractive than the first asset considered. Thus, by introducing the risk-free asset into the ratio, a manager can take into account the nonzero return of investing in the risk-free asset.

Think about a logistics services company that is considering adding transportation managers to its customer portfolio. Transportation managers act as brokers for small and medium-size companies. They are often used as sources for finding loads for return routes from one-way transports. Relationships are rarely built with this customer category, but the segment can be relied on to fill excess capacity. They pay less than most other customers and their purchases are highly variable. Considering them as the "risk-free asset" in computing the reward-to-variability ratio for the customer provides a useful benchmark for a logistic company. In a banking industry setting, the risk-free customers may be a segment of customers who use the free checking only, readily switch providers, and provide limited revenue for the servicing institution. Easy to acquire, but hard to serve (e.g., college students with their first checking account), these customers provide a good benchmark for a financial services firm. Identifying the risk-free customers 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 where the "strategically irrelevant" customers cannot be identified, the Sharpe ratio can be used without the reference rate, as Sharpe initially conceived it (Sharpe 1966).

For the client company, we identified a segment that initially seemed rather unappealing: a lower return (EBIT) than other customers (2.4% compared to 6.2%, $p < .05$), without loyalty, and strategically irrelevant. Just 58 of the customers from other industries have a lower return than this segment. Interestingly, about half of these customers belong to cluster 1, characterized by high growth. It is important to note that the reward-to-variability (Sharpe ratio) does not provide the absolute desirability of a customer. One should consider also the impact of the customer on the overall portfolio (which is given by the correlation of the customer with the overall portfolio, beta) or other strategic aspects, like growth expectations. However, for customers with similar impact on the portfolio and no specific strategic consideration, the ratio provides a clear criterion for choosing the most desirable customer. A summary of the results for the Sharpe ratio, computed with and without the benchmark, is provided in Table 4.

Stage 2 Summary. Using the efficient frontier applied to customer segments, we were able to identify an optimal composition of the customer portfolio that outperformed in terms of variability the client company's current strategy and a profit-maximization portfolio in back-testing and forward-testing (see Figure 4). Using a diversified, efficient portfolio, companies could insulate against downturns in the economy without sacrificing performance in the long run. Using the full set of information on customers (adding variability and correlation to the overall portfolio to the traditional segmentation variables), companies can properly manage the expected value of the customer portfolio. We also showed how by using beta and the Sharpe ratio, companies can gain insight for incremental retention and acquisition of specific individual customers.

Discussion and Managerial Implications

Diversification principles for efficient customer portfolios

In Stage 1, we tested whether customers can be categorized into segments that share similarities with asset classes used in traditional financial investments. We found support for our belief that modern financial portfolio theory is relevant in a customer portfolio context. In particular, we showed that market segments—defined a priori based on classic market segmentation variables—could be characterized in terms of their risk, as well as their return.

In Stage 2, we constructed segments based on the variability observed for a certain level of revenue (i.e., we normalized by dividing by monthly sales by their mean).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-testing 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, it is possible to implement risk management techniques by ensuring diversity among existing and potential new customers. Moreover, due to recent advances in computing and data storage, 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. Consequently, this paper has shown 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, and industry sector).

Strategic differences between the efficient customer portfolio and the profit-maximizing customer portfolio

The creation of an efficient customer portfolio requires firms to reallocate their efforts for acquisition and retention across segments. In other words, it identifies strategic objectives for managers that guide them toward "optimizing" the value of the firm's customer base or customer equity. However, these "efficient" strategic objectives will be different from the profit-maximizing objectives first identified in Blattberg and Deighton's (1996) path-breaking article and extended in subsequent research (Blattberg, Getz, and Thomas 2001; Reinartz and Kumar 2003; Reinartz, Thomas, and Kumar 2005). There will be some similarities between the efficient customer portfolio and the profit-maximizing customer portfolio, but there will also be differences. For example, it is interesting to note that cluster 5, which dominates the original portfolio and contains some of the most profitable customers, has similar weight in the optimized portfolio. In contrast, cluster weights for the other clusters are increased dramatically, especially for cluster 3, which is dominated by SMBs. Cluster 1, which has relatively low profitability and high variability, is the one in which weight has been decreased most drastically, from 41% to 4%. Considering that cluster 1 is one of the clusters in which customers have exhibited the most growth, decisions regarding the customers in this cluster should be made on a case-by-case basis.

Short-run versus long-run considerations

Substantial changes in the composition of a customer portfolio take time, so a long-term perspective should be employed. At the same time, the construction of an efficient customer portfolio is not a one-time exercise. Rather, the customer portfolio should be evaluated and revised on a regular basis, for example, using a rolling five-year perspective similar to other strategic planning exercises. Recall that Table 1 describes how to implement and revise a customer portfolio, where step 5 describes the revision process. In this way, the firm's strategy can be fine-tuned as the economic environment changes. However, the costs of actively managing a customer portfolio can be higher than the potential profits if strategic objectives are changed too frequently. The primary reason is that the costs of acquiring customers are nontrivial (indeed, they are frequently much higher than retaining customers), and consequently the cost of frequent changes in the composition of the customer portfolio could more than offset the benefits derived from the same changes. However, once an efficient (low variability), balanced portfolio has been reached, the firm will achieve benefits in the long run. Note that beyond the benefits we have already described, we can expect substantial operating efficiencies and productivity enhancements from a more stable customer base.

Considerations in updating the customer portfolio

Earlier, we demonstrated how the firm might use the Sharpe ratio to identify desirable customers. There are two ways to score high on the reward-on-variability or Sharpe ratio. Either there is equilibrium between risk and return, or in spite of the high variability, the customer provides above-average returns. The customers who ranked highest according to a ranking using the reward-on-variability ratio are companies that provide outstanding margins but also are characterized by very high variability. These clients request services when they need them, and in order to receive the speed and quality they demand, they are willing to pay a premium price. Our analysis provides sustained evidence that the true "ideal" customers might have a different profile than those previously identified as ideal based on classical criteria such as average level of purchases.

Limitations and Future Research

Potentially diminishing or negative returns

Generally, we predict that diversifying across customer types or industry sectors or internationally reduces the overall risk of the customer portfolio. However, there is an important caveat. Research in management has shown that diversification into unrelated businesses increases risk because there is little opportunity for synergies, and efficiently managing businesses active in different markets is extremely difficult (Balagopal and Gilliland 2005; Lubatkin and Chatterjee 1994; Wind, Mahajan, and Swire 1983). The complexity of governance may outweigh the benefits of diversification in terms of risk reduction. In the same way, it is well recognized that conventional market segmentation practices—which group customers into homogeneous segments—allow firms to serve targeted customers more effectively and efficiently. Hence, as the firm diversifies its customer portfolio, it may not be able to serve customers as effectively and efficiently. This reasoning suggests that there may be a curvilinear relationship between the above segmentation variables and risk levels. In other words, when customers are somewhat dissimilar, risk is reduced; as customers become very dissimilar (and consequently difficult to serve), risk increases.

Nonlinearity of customer investment

In the investment markets, the rate of return is not likely to be affected by the amount invested. In contrast, a distinct difference between a customer portfolio and a financial portfolio 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 that small investments might be insufficient to attract or retain an individual customer or market segment. Similarly, after a certain level of investment in an individual customer or market segment, additional incremental expenditures might not improve returns. Hence, future research might investigate how to identify the optimal investment in an individual customer or market segment in order to optimize the customer portfolio.

Network externalities

The value of a customer to a company springs from multiple sources. Besides the pure economic value, customers often provide the company with prestige, referrals, learning opportunities, and innovative ideas (see Ryals 2007). According to the net promoter score stream of literature, customers who have high promoter scores (e.g., are highly likely to recommend the company) account for 80% of referrals and the most positive word of mouth (Reichheld 2006). These claims are controversial, and recent research suggests that classic measures, such as customer satisfaction, are better at predicting economic outcomes (Keiningham, Cooil, Andreassen, and Aksoy 2007). However, there is no question that an economic benefit of customers is positive word-of-mouth recommendations that lead to new customer acquisitions. Though the true economic effect of word of mouth is notoriously hard to measure (Rust, Lemon, and Zeithaml 2004), firing customers can easily backfire (Hogan, Lemon, and Libai 2003).

Network externalities that are business specific—e.g., considering the mix of customers asking for return routes from a hub where most customers want to deliver, in a logistic context or in a banking context having a mix of borrowers and customers who maintain deposits with the bank—should also be considered when making customer portfolio decisions. These functional externalities can provide a wealth of efficiencies, given that the existence of one customer affects the desirability of another.

Prediction of cash flow variability

We based our decision regarding the desirability of customers on the analysis of the past volatility of purchases. However, for assessing future customer worth, the most appropriate measure would be future volatility. In order 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 in order to increase the accuracy of predicting future customer cash flow variability.

Conclusion

This research provides insight for companies on how to work smarter: for higher profits (in the long run) with lower risks. Markowitz, in his Nobel Prize acceptance speech, mentioned that "an investor who knows the future returns with certainty will invest in only one security, namely the one with the highest future return" (1991). However, as Bernstein (1999) says, "[E]ven 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." Under these conditions, given that predicting which will be the most profitable customers in the future is a task that we cannot undertake, we propose an approach that marketing managers can follow to cope with uncertain market conditions and improve the quality of their customer portfolio decisions. This research offers a different 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 about which customers are truly worthwhile.[9]

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Notes

1. Idiosyncratic risk is the variability in the value of an asset that cannot be explained by variations in the market.

2. In order to respect confidentiality agreements, all numbers regarding dollar figures have been scaled.

3. We do not focus here on non-normative aspects of relationships, such as quality or extent of relationships. The focus of this paper is on simple ways to manage risk. Analyzing the link between customer risk and relationship characteristics is beyond the scope of this paper.

4. S&P identifies 10 different industry sectors: Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Telecommunication Services, and Utilities (Source: S&P Industry Classification Standard http://www2.standardandpoors.com/spf/pdf/index/GICSIndexDocument.PDF, accessed June 5, 2009).

5. The variables used for segmentation were the monthly cash flows, standardized by dividing each value by the average level of cash flows (over all years that customer

was active with the firm) for each customer. Since there are 72 months of observation in the data, each customer is characterized by 72 variables.

6. Even though cluster 6 was introduced in the analysis, it had zero weight in all the efficient portfolios. This cluster was characterized by low return and high variability.

7. The data for 2001–2005 have been used to identify the clusters, but not to identify the efficient frontier. The data for 2007 have not been used for any other analysis.

8. http://eresearch.fidelity.com/backtesting/landing, accessed June 12, 2009.

9. "The advantage of knowing about risks is that we can change our behavior to avoid them. [. . .]Optimal behavior takes risks that are worthwhile." See Robert F. Engle III (2003), "Risk and Volatility: Econometric Models and Financial Practice." Nobel Lecture (Ed.). New York., p. 326.

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