14. Risk considerations in the management of customer equity

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INTRODUCTION

Customers are intangible assets of the firm. Customer equity represents the total value of the current and potential customers to the firm. When firms measure or manage customer equity, they typically focus on expected cash flow streams but not the risk associated with them. Hence, customer risk complements the concept of customer equity – it allows managers to assess whether the firm's returns from customers are commensurate with their risk. The notion of balancing customer equity and customer risk is rather new, so many scholars and managers have an incomplete understanding of how to manage the customer portfolio and optimize customer equity. The marketing literature has typically approached customer risk by considering the probability of customer defection and all other risks are assumed to be accounted for in the cost of capital. However, in the finance literature, risk is considered to arise from unanticipated variability in future cash flows. This chapter discusses the implications of this conceptualization of risk for managing customer equity. We argue that it is important to consider the variability or unpredictability of cash flows – arising from underlying customer interactions, consumption patterns, and purchase behavior, plus from organizational processes that support them. An understanding of customer variability is critical for firms to effectively forecast, allocate expenditures, manage customer equity, and prepare for the future via strategic investments.

Risk can be managed both at the individual customer level and the level of the overall customer portfolio. Although a customer portfolio and a financial portfolio seem similar, the underlying assumptions concerning risk are very different. Nevertheless, we can build upon the financial approach to measuring and managing risk to generate important insights for managing customer portfolios. A firm should identify customer risk that can (and should) be divested away because it does not reap higher returns for assuming this risk and (instead) suffers losses when conditions change (Gupta et al., 2006). Trade-offs between customer risk and return have become increasingly important due to the critical role of the

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marketing–finance interface in firms' strategic decisions and pressures to make marketing accountable.

A richer conceptualization of customer risk complements managers' and researchers' understanding of the drivers of individual customer value and customer equity. It adds many nuances to our understanding of customer cash flow levels and their variability and allows managers (and investors) to assess the true value of a customer in context. This chapter offers some practical guidance on how to incorporate risk into the measurement and management of customer equity and the customer portfolio.[1] In this way, firms can improve how they allocate expenditures and make investment decisions.

CUSTOMER EQUITY, FUTURE CASH FLOWS AND SOURCES OF RISK

The Customer Asset and Customer Equity

The concept of market-based assets, introduced in Srivastava, Shervani, and Fahey's (1998) landmark article, drew attention to customers as intangible assets of the firm. Their article sparked an important set of questions regarding the correct way to measure the value of customers as assets – that is, their value to the firm. These questions are important because the firm must select which customers or market segments to allocate resources to. Traditionally, the value of the customer asset, termed customer equity, was calculated by summing customers' net contribution margins over time, discounted to reflect the time value of money (Berger and Nasr, 1998). This calculation can be performed for an individual customer, a market segment or the entire customer base. For example, summing the discounted net contribution margins of a customer over his or her expected lifetime yields lifetime value.

This chapter uses the term 'customer equity' (CE) to refer to the long-term value of the firm's potential and existing customers (in aggregate), and the term 'customer lifetime value' (CLV) to refer to the long-term value of individual customers or customer segments. The availability of customer data has usually determined whether customer equity was calculated at the aggregate level (e.g., Gupta et al., 2004) – or whether CLV was calculated at the individual or segment level and then aggregated across customers to yield CE (e.g., Blattberg, Getz, and Thomas, 2001). Different methods of aggregation are possible. The simplest method of aggregation – which is not necessarily correct – simply sums across existing customers. However, distributional assumptions about purchasing patterns within and across (potential and existing) customers over time are required to develop a robust model that maximizes the value of the customer base (Ryals and Knox, 2005; Drèze and Bonfrer, 2009).[2] For a detailed classification of existing studies on customer portfolio management, see Table 14.1.

Early Emphasis on the Risk of Customer Defection

Blattberg and Deighton (1996) investigated the following question: what is the optimal level of spending on customer acquisition versus retention that maximizes CE? They explicitly recognized the importance of the risk associated with customer defection (or its inverse, customer retention). Hence, the treatment of defection risk became important to subsequent approaches to the calculation of CE – either at the individual, market segment or aggregate level. Approaches to CE calculations have made different assumptions about the probability of customer retention, margins, and the time horizon (Gupta et al., 2004; Kumar and George, 2007; Wiesel, Skiera, and Villanueva, 2008). For example, are customer retention rates and margins constant or changing? How are they distributed across customers? Short-run measures of profitability or CLV can be quite different than long-run measures. This observation raises another question: is the time horizon finite or infinite? Gupta and Lehmann (2003, 2005) showed that using an expected customer lifetime generally overestimates CLV.

Most approaches use the firm's weighted average cost of capital to calculate discounted cash flows. They usually do not recognize that defection risk – typically reflected in the firm's cost of capital – has been isolated and given explicit treatment in CLV or CE calculations. Hogan, Lehmann et al. (2002) note that cash flows from a customer segment should be discounted using a risk-adjusted rate that reflects customer-specific capital costs. Marketers (unlike their counterparts in finance) have been somewhat inattentive to how the firm's cost of capital is obtained because they focus on spending across customers or marketing activities. For example, Tirenni et al. (2007) describe a decision support system to optimize marketing planning for Finnair's frequent flyer program, accounting for customers' probability of responding to marketers' actions and generating profits.

Sources of Customer Risk

From a market-based asset perspective, each customer or market segment is associated with a stream of (unpredictable) future cash flows for the firm. Hence, the customer is a risky asset, with risk originating from

Table 14.1 Classification of existing studies of customer portfolio management

General Approach	Managerial Problem	Study Objective and Treatment of Risk	Exemplar Studies
Reach, frequency, monetary value models	Allocation of direct marketing effort	Maximize predicted purchases, profitability or CLV over the next T period(s) as a function of direct marketing activities. Emphasis on size and frequency of purchases	Dwyer (1997); Fader, Hardie, and Lee (2005); Borle, Singh, and Jain (2008)
Balancing spending allocated to acquisition versus retention	Allocating marketing spending between acquisition and retention and allocating across communication channels	Deterministic model (e.g., decision calculus model) that maximizes cumulative profits where customer profitability is measured as total revenue less direct costs (including acquisition and retention costs) over a fixed time period	Blattberg and Deighton (1996); Reinartz, Thomas, and Kumar (2005)
Relationship marketing or CRM models	Maximize CE, with an emphasis on customer retention and relationship bonds	Maximize duration of individual customer–firm relationships and/or revenues from existing customers using service strategies, loyalty programs etc.	Bolton (1998); Thomas (2001); Blattberg et al. (2001); Lemon, White, and Winer (2002); Bolton, Lemon, and Verhoef (2004); Reinartz et al. (2005); Bolton, Lemon, and Bramlett (2006); Tirenni et al. (2007)

Maximize CE by assessing return on marketing	Maximize CE through allocation of investments to all activities, recognizing controllable and non-controllable effects	Maximize CE with explicit consideration of defection to competitors through a brand-switching matrix	Rust, Lemon, and Zeithaml (2004)
Adding or subtracting segments[a]	Improve CE by reducing risk for a given level of return or increasing return for a given level of risk	Consider return and risk profilesof customers or segments, then add or subtract customers so that cash flow patterns complement each other	Dhar and Glazer (2003); Buhl and Heinrich (2008); Ryals (2002, 2003)
Re-weight portfolio of potential and/or existing segments[a]	Optimize CE by moving towards the efficient frontier of potential customer portfolios	Optimally re-weight the customer portfolio or incrementally adjust the customer mix to improve risk-return characteristics	Tarasi et al. (2011)
Strategies that modify consumption and cash flow patterns[a]	Decrease customer risk without adversely affecting CE	Adjust strategies for managing customers, service and marketing activities to reduce cash flow variability over time for a customer or market segment	Tarasi et al. (2013)

Note: a. These research streams account for how customer cash flows covary with each other.

different sources of variability inherent in cash inflows and outflows. Sources of variability include individual customer behavior dynamics: defection, product usage, and cross-buying. They are influenced by customer characteristics (Nitzan and Libai, 2011), competitive effects (Du, Kamakura, and Mela, 2007) and firm actions (Hogan, Lehmann et al., 2002, p. 27). Studies attempt to produce accurate CLV predictions by recognizing some sources of risk – but they do not quantify risk or assess risk–return trade-offs. In aggregate models of CE, customer behavior dynamics are often captured by an (expected) growth factor that influences margins – thereby recognizing uncertainty without quantifying it (Gupta et al., 2006). Approaches for capturing different sources of risk are displayed in the top half of Table 14.2 and approaches that recognize factors that influence these sources are displayed in the bottom half.

Sources of risk

Customer purchase behavior (trial, loyalty, usage, and cross-buying) generates cash flows and there is uncertainty about whether and when each of these potential behaviors will occur. Researchers have accounted for customer behavior dynamics in their CLV calculations in different ways. Measures of the recency, frequency, and monetary value (RFM) of purchases have been used to score customers for (short-run) targeting, calculate customer profitability and forecast CLV (Fader et al., 2005; Borle et al., 2008). Behavioral models can be used to predict the duration of customer–firm relationships, usage levels, and cross-buying based on customer characteristics and firm actions (Bolton, 1998; Bolton and Lemon, 1999; Lemon et al., 2002; Verhoef, 2003; Bolton et al., 2004), yielding CLV estimates. They can take into account customer expectations, experiences, and learning (e.g., Lewis, 2005). In general, CLV models out-perform RFM models. Researchers' goal has been to improve predictions of cash flows from individual customers or market segments, thereby yielding a measure of CE. They recognize sources of risk (via probabilities of outcomes), but they do not explicitly measure or manage customer risk.

Factors influencing sources of risk

Customer characteristics influence all sources of customer risk. To date, the most interesting work has studied how social effects – that is, organic word-of-mouth – influence customer behavior dynamics. Nitzan and Libai (2011) model how customers' social networks influence their defection from a service provider. Models of the factors driving win-back offer effectiveness – that is, re-acquiring lost customers – can take into account marketing and social effects (Thomas et al., 2004; Tokman et al., 2007).

Table 14.2 Sources of risk and their antecedents

	Approach	Metrics	Exemplar Studies
Source of risk			
Risk arising from customer behavior dynamics: acquisition, retention or gross margin (via cross-buying etc.)	Maximize CLV by maximizing the duration of individual customer–firm relationships or retention	Models of customer retention or length of customer–firm relationship as a function of marketing, service or channel strategies, with predictions (usually) linked to CLV calculations	Bolton (1998); Thomas (2001); Lemon et al. (2002); Reinartz et al. (2005); Bolton et al. (2006)
	Maximize revenues from existing customers by increasing sales or contributions per customer	Models of the amount purchased over time, including current product usage levels, upgrading and cross-buying.	Kamakura, Ramaswami, and Srivastava (1991); Bolton and Lemon (1999); Blattberg et al. (2001); Verhoef (2003); Bolton, Lemon, and Verhoef (2008)
Factors influencing sources of risk			
Customer characteristics (that are not controllable by the firm)[a]	Models that focus on maximizing retention or CLV	Customer behavior component emphasizes accounting for social effects, specifically positive and negative word-of-mouth or network effects	Ryals(2003); Tokman, Davis, and Lemon (2007); Nitzan and Libai (2011)

Table 14.2 (continued)

	Approach	Metrics	Exemplar Studies
Factors influencing sources of risk			
	Balance cash flows from groups of customers with different risk return profiles by adding or subtracting customers	The firm's goal is to forge multiple types of relationship marketing ties with customers. This approach entails assigning a risk metric to customers that reflect how their cash flows covary with cash flows of other customers. Proxy variables for customer risk in B2B markets include firm size and other firmographics; they include lifecycle, relationship, and other consumer characteristics in consumer markets	Dhar and Glazer (2003); Johnson and Selnes (2004); Buhl and Heinrich (2008); Tuli, Bharadwaj, and Kohli (2010)
Competitive factors	Models maximize CE or CLV, with specific focus on competitive effects	Customer behavior component includes brand switching to/ from competitors or 'second lifetime value' obtained through win-back strategies that re-acquire and retain lapsed customers	Thomas, Blattberg, and Fox (2004); Rust et al. (2004); Nitzan and Libai (2011)

Firm factors Especially product management decisions	Maximize CE through allocation of marketing investments that enhance the value of brand assets	Models emphasize the role of product R&D, channel support, promotion strategies, service strategies and loyalty programs	Bolton, Kannan, and Bramlett (2000); Bolton et al. (2004); Dong, Swain, and Berger (2007). Tarasi et al. (2013)
All forms of unanticipated cash flow variability or customer risk[a]	Optimal customer using financial portfolio risk metrics	Risk measured by deviations of actual cash flows from anticipated cash flows	Tarasi et al. (2011)
Environmental and market changes[a]	No current approach or metric in the customer portfolio literature because correlations between customers' cash flow patterns may not remain stable during periods of substantial environmental change		

Note: a. Non-routine risk.

Competitive factors Competitive factors influence customer acquisition, retention or switching, win-back and brand-switching probabilities – and each increase variability in cash flows or risk. An award-winning article by Rust et al. (2004) develops a comprehensive model of how marketing actions influence CE that incorporates competitive effects through a switching matrix. Choice models are especially useful for modeling competitive effects on CE when modelers have access to transactional data in direct marketing contexts (Kamakura et al., 2005). These studies do not consider customer risk (yet).

Firm factors A firm's decisions influence the product life cycle, new product development, and extension into other categories, as well as influencing customer behavior. For example, researchers have noted that channel quality has an important influence on customer acquisition and retention, so that resource allocation across communication channels influences individual customer profitability (Reinartz et al., 2005). This research typically focuses on maximizing individual customer profitability over a fixed time period, rather than CE. In a notable exception, Dong et al. (2007) present a model of CE that uses decision calculus methods to allocate resources across channels; they explicitly acknowledge that their model is deterministic, abstracting from risk.

Environmental and market changes Customers' cash flow patterns will not remain stable during periods of substantial environmental or market or economic changes. All three sources of customer risk (acquisition, retention, and margin) are likely to be altered in unanticipated ways. Moreover, the covariation among customers' cash flows is likely to change in ways that can't be predicted. Since our understanding of customer risk is based on historical cash flow patterns, there is no way to anticipate or manage this situation.

Risk and the Cost of Capital

Gupta et al. (2004) note that the cost of capital or discount rate is a critical variable in the evaluation of the net present value of a cash flow stream (p. 17); they suggest that it is useful to consider the sensitivity of any CE calculations to different rates of discount (p. 12). Sensitivity analyses are especially important if the cost of capital may change in the future. The value of the firm measures the true returns of shareholders after all costs – including all costs of capital (both cost of debt and equity) have been deducted. Since it is created only when returns exceed the cost of capital, the cost of capital should include risk inherent in uncertain future cash flow streams. Thus, cash flows in future periods should be adjusted for any customer-specific capital costs, such as marketing and customized services, as well as a discount rate.

Ryals and Knox (2005, p. 459) argue that managers should quantify the risk of targeting customer segments for investments intended to realize forecasted growth. Discount rates can vary substantially across firms utilizing different strategies. For example, Amazon's cost of capital is typically considered closer to the cost of capital of other Internet-based firms, rather than other book retailers. In business-to-business (B2B) markets, customer-associated risks can include risk of fraud, default risk, and risks due to competitive intensity or industry situation – as well as defection risk. There are standard financial methods for estimating the risk-adjusted cost of capital for a particular firm (Modigliani and Miller, 1958).

Synthesis

Many studies recognize sources of risk in predictions of customer profitability, CLV and CE. However, they typically recognize routine risk (Berger et al., 2006, p. 161) – that is, outcomes for which researchers or managers can assign a probability. Most studies cannot quantify unanticipated variability in cash flows from individual customers or groups of customers that arise from outcomes such as unanticipated firm actions or market changes that are not routine. Until recently, most research has not considered risk–return trade-offs in models of customer acquisition, retention, marketing spending, customer equity or customer portfolio optimization.

CUSTOMER EQUITY AND THE EVOLVING UNDERSTANDING OF RISK

Marketers have long known that the conceptualization of risk in financial portfolio theory is applicable to marketing decisions (Cardozo and Smith, 1983). However, they have been equally aware of the differences between financial and marketing investments (Devinney and Stewart, 1988). Dhar and Glazer (2003) highlighted the importance of measuring the riskiness of customers, termed customer beta. They demonstrated how a firm can maximize returns by acquiring or retaining particular customers or segments on the basis of how their spending patterns contribute to the diversification of the customer portfolio. Ryals (2002, 2003) examined the risk and return characteristics of a customer portfolio and described how a customer relationship scorecard could be used to assess customer risk.

Researchers have worked to integrate customer portfolio ideas within the well-developed stream of research focused on measuring CLV and CE (e.g., Von Wangenheim and Lentz, 2005). Buhl and Heinrich (2008) proposed a quantitative model based on financial portfolio theory that (1) considers CLV as well as the associated risks of customer segments and (2) provides a method for adding or subtracting market segments. They tested the model in a financial services context by using the average annual incomes of key customer segments (e.g., lawyers, physicians) as an indicator of future cash flows and demonstrated how they could create a customer portfolio with higher utility and better risk diversification than the existing portfolio.

From a conceptual standpoint, there are many ways for a firm to build more valuable customer portfolios: customer relationships in different stages can balance each other (Johnson and Selnes, 2004) and the number and types of ties a firm builds with its best customers can reduce their purchase variability (Tuli et al., 2010). By extension, the basic principle that underlies the creation of an optimal customer portfolio is fairly straightforward. By combining customers or market segments with different (i.e., offsetting) cash flow patterns, firms can reduce aggregate cash flow variability – so that risk is minimized for a given level of return.

Tarasi et al. (2011) extended these ideas by describing how the stream of future cash flows associated with a customer or group of customers is variable or risky because it is influenced by customer, competitive, and market conditions that are beyond the firm's control. The firm can (mathematically) optimize the portfolio or mix of customers by effectively allocating its resources across potential and existing customers – thus anticipating and managing future cash flow levels and their variability across the entire customer base. An optimal customer portfolio balances customer risk and return so that risk is minimized for the targeted level of return (or cash flow levels). Managing resources and customers to optimize (rather than maximize) customer equity enables managers to make decisions that are aligned with the long-term goals of the firm. It empowers managers to make the best decisions in a specific context – and evaluate the consequences for the customer portfolio and for (long-run) shareholder value.

This approach is a significant departure from early CLV and CE studies. Resource allocation decisions (such as acquiring versus retaining customers) were made by predicting the future cash flow streams of individual customers or groups of customers and making independent decisions about how to maximize the cash flow stream from a customer or group of customers. Managers and researchers didn't consider how individual customers' cash flows covary and potentially offset each other at the aggregate level. Hence, maximizing the CLV of individual customers or market segments can be sub-optimal from the firm or shareholder perspective (Drèze and Bonfrer, 2009). The magnitude and variability of aggregate future cash flows over the long run matter for the firm and they are influenced by the composition of the customer base. Shareholders require returns that are commensurate with risk.

Tarasi et al. (2011) pointed out that, in choosing what customers to add to a portfolio, a customer with purchasing behavior that is less similar to that of current customers will make a strong contribution to the stability of the customer portfolio (i.e., lowering customer risk); the more similar his or her behavior to existing customers, the weaker its contribution to lowering risk. 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. A declining cash flow from one customer may be offset by increased returns from another. In other words, by re-weighting the customer portfolio it is possible to reduce the variability (risk) of the firm's future cash flows without decreasing its returns. They describe an approach for applying financial principles of diversification to a customer portfolio and show, in an empirical application, that a firm can substantially lower customer risk without decreasing CE. Through forward and backward testing, they demonstrated that an efficient customer portfolio built at one point in time consistently outperforms portfolios designed to (only) maximize profits, as well as outperforming current portfolios.

CONCEPTUALIZATION AND MEASUREMENT OF CUSTOMER RISK

We have introduced our key theoretical ideas without any mathematical exposition. However, at this point, it is useful to deepen our conceptualization of customer risk by describing how it can be measured and used. Each of the following measures goes beyond classical criteria such as average customer profitability, revenue or CLV to incorporate some measure of variability.

Variability or Standard Deviation

In the preceding discussion, we have been equating risk with variability in future cash flows over time.[3] However, it is important to note that we are specifically interested in unexpected variability in cash flows – that is, deviations from expected future cash flows. From this perspective, the standard deviation in cash flows over time – calculated relative to expected or predicted future cash flow levels – is a suitable measure of variability. Predictions might be generated from time series data using the average cash flow level, a trend line, or a more complex model. The standard deviation is also useful because it can be calculated at the level of the individual customer, the market segment or in aggregate. (Of course, we must assume that the variability in historical data will continue into the future.) Unfortunately, the standard deviation can be a misleading metric because higher average values are typically accompanied by higher standard deviations (Tarasi et al., 2013). This can be a significant drawback because managers are interested in determining whether returns (average cash flow levels) are commensurate with risk (the standard deviation of cash flows). Hence, we prefer that returns and variability are considered simultaneously – within a single metric – when making decisions to optimize CE. Hence, it is useful to consider alternative measures of variability.

Coefficient of Variation

The coefficient of variation (CoV) is calculated by dividing the standard deviation of cash flows (relative to an expected value) by the average or mean. It corrects for the relationship between average cash flow levels and corresponding variability, and provides a way to compare customers with different levels of risk and return. CoV has been used as dependent variable by Tarasi et al. (2013). They showed that CoV could be predicted reasonably well using simple descriptor variables such as satisfaction and relationship characteristics embedded in a model based on a semi-log function. A drawback is that CoV doesn't distinguish between large and small customers, whereas, in most real-world applications, managers prefer large customers – even if they are not particularly profitable – because they contribute to covering fixed costs. When using the CoV to evaluate the relative attractiveness of customers, managers can separately consider large and small customers, as shown by Tarasi et al. (2013).

Customer Beta as a Measure of Risk

In the finance literature, a common measure of risk is beta, or the correlation between an asset (e.g., a stock) and the market portfolio. The market portfolio consists of all assets, with the weight of each held in proportion to the total market value. In finance theory, it is assumed that the market portfolio is efficient because it accounts for all information in the market.

However, there is no (easily observed) equivalent to the efficient market portfolio in a customer portfolio context. Instead, we observe that a firm has a customer portfolio with specific risk and return characteristics; it is not efficient. Hence, for the purpose of calculating a customer beta (β), researchers replace the market portfolio with the firm's current customer portfolio (Ryals, 2002; Dhar and Glazer, 2003; Buhl and Heinrich, 2008; Tarasi et al., 2011).

We can calculate a customer β as the covariance between an individual customer's cash flow and the cash flows of all customers, divided by the variance of the cash flow for the overall customer cash flow. It represents the correlation between the cash flows of an individual customer and the cash flows of the focal firm's entire (existing) customer base.[4] A customer's β reflects how the customer responds to firm's actions compared to the existing customer base. A customer with a negative β is likely to reduce the overall variability of the portfolio, whereas a positive β means that the customer added to the portfolio may increase variability. Unlike beta in financial portfolio theory, customer β has no information regarding optimal risk.

Another assumption from financial portfolio theory that does not apply to customer portfolios is that the risk and return are independent from investors' actions. However, returns from customers are not independent of firm's actions. Expected variability due to firms' anticipated actions should not be considered risk. Risk is only the deviation from expected return (Buhl and Heinrich, 2008). We discuss this notion further in the next section.

Customer Reward Ratio

The customer reward ratio (RR) measures the reward for assuming customer risk, where a higher value can be interpreted as a greater reward. It was inspired by the Sharpe ratio (Sharpe, 1994), which measures the investor's reward for assuming risk above the risk-free rate. The RR is calculated as the expected return for a given customer less the return for a risk-free customer, divided by the variability in the customer's returns over time. In a customer portfolio context, a proxy for a risk-free customer asset may not exist. In this situation, the customer RR is calculated as the expected return for a given customer divided by the variability in the customer's returns over time, where variability is measured by the standard deviation (σ) of the returns (Tarasi et al., 2011, p. 6). The intuition about how to interpret the RR is fairly straightforward: for the same level of variability, the customer with the highest return will be preferred and, for the same level of return, the customer with the lowest variability will be preferred, all else being equal. However, when both risk and return are different, the customer with the highest RR is the most attractive customer. The customer RR has an advantage over the customer β in that managers can compare customers with various levels of returns and variability. For both customer β and RR, if measures of customer profitability are not available or reliable, using customer revenue is often acceptable (Wiesel et al., 2008).

Standard Deviation, CoV, Customer β or Customer RR: Which Measure is Best?

A comparison among the various measures for variability is presented in Hutt, Tarasi, and Walker (2012). Each of the four measures captures different aspects of variability and the optimal measure depends on the goals of the analysis. If the composition of the customer portfolio is a given, then adding customers with negative β and high RR is optimal. However, if the firm is in the process of building an optimal customer portfolio, identifying the customer segments first based on customer needs, behavior, and characteristics represents the logical first step. Then, an optimal customer portfolio can be identified using the efficient frontier. The efficient frontier identifies the portfolios for which variability is minimized for the desired level of return, or return is maximized for the desired level of risk. Next, steps are taken either to reduce risk or to increase return (or both) depending on the firm's strategic goals. The last step is to assess current and potential customers, identify their risk/return characteristics, and allocate resources accordingly to reach the desired levels of risk and return (Tarasi et al., 2011).

FOUR APPROACHES TO MANAGING CUSTOMER EQUITY

There are four approaches to managing CE. They differ in their treatment of customer risk, so they are suitable for different purposes. They are: (1) approaches to maximize CE by balancing resource allocations between acquisition and retention, (2) strategies to maximize CE that emphasize the management of customer relationships by allocating spending to different marketing activities, (3) optimization of CE by managing the composition of the customer portfolio (weighing customer groups), or (4) improving CE by managing underlying consumption, purchase, and organizational processes that yield cash flows. Only the last two approaches consider the trade-off between CE and customer risk.

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Approach 1 Maximize CE by Balancing Spending on Acquisition versus Retention

Marketers have been keenly interested in how to allocate spending between acquisition and retention efforts. Blattberg and Deighton (1996) used a (deterministic) decision calculus model to allocate expenditures to customer acquisition versus retention. They assume that acquisition and retention are independent. Thomas (2001) developed a methodology for linking customer acquisition to retention, arguing that they are not independent processes. For example, customers acquired through a retail channel might have higher retention rates than those acquired through the Internet. (Ideally, we would like to model the mechanism that links acquisition and retention.) Blattberg et al. (2001) argue that firms should manage customer acquisition, retention, and cross-selling as interdependent activities. They provide an in-depth discussion of each of these activities, including statistical tools, models, and key performance indicators – as well as a CE balance sheet and cash flow statement. However, the quantification and management of risk in building CE is not explicitly addressed.

Managers frequently use short-term customer profitability measures as proxies when it is difficult to forecast CLV for an individual or segment. Reinartz et al. (2005) develop a 'bottom-up' model that is intended to be highly actionable for direct marketing firms. They investigate how to allocate spending across communication channels to acquisition and retention using the criterion of maximizing customer profitability over the projected duration of the customer–firm relationship. In their predictive model, individual customer profitability depends on customer, competitor, firm, and 'control variables' (such as relationship duration and cross-buying). Their approach to CE does not rely on financial analyses or behavioral models that quantify risk or consider risk–return trade-offs. They use predictive models and simulations of cumulative profitability to identify the best allocation of spending to modes of contact (including number of contacts). Interestingly, the profit-maximizing contact strategy doesn't maximize acquisition likelihood or relationship duration. Their results indicate that overspending is more profitable than underspending and, if there is a choice between spending a dollar on acquisition versus retention, firms are better off choosing retention. However, from a risk–reward standpoint, we must view these results with caution. In two consumer contexts, Tarasi et al. (2013) find that contact-intensive retention strategies (such as loyalty programs that rely on economic rewards) increase variability in cash flows without a commensurate increase in returns.

Approach 2: Customer Relationship Management Models that Maximize CE

Optimizing CE requires an understanding of how to create, build, and sustain relationships – thereby influencing customer behaviors that generate cash flows. Individual customers' CLV depends on the duration of the customer–firm relationship (i.e., retention), its depth as reflected in the amount/frequency of product usage over time, and its breadth as reflected in cross-buying or 'add-on' buying. These forecasts, combined with information about prices and costs, enable calculation of CLV and CE. CLV is also influenced by non-purchase behaviors, especially customer engagement dimensions, which are less well understood by marketers (e.g., Ittner and Larcker, 1998). For example, Hogan, Lemon, and Libai (2003) argue that when a firm loses a customer it also loses revenues attributable to the word-of-mouth influence of that customer.

Bolton et al. (2004) offer a comprehensive conceptual framework for understanding how these behavioral components – and their antecedents (price, service quality, communications etc.) – jointly influence CLV and CE. However, their primary focus is a theoretical specification of the behavioral components so that individual customers' future purchase behavior and cash flow streams can be predicted. They suggest that calculations of CLV and CE should be embedded in financial spreadsheets so that managers can conduct sensitivity analyses to evaluate alternative actions (p. 286). Their model does not explicitly quantify risk, but they emphasize that an improved understanding of dynamic and competitive effects (which influence the variability of cash flows) will be important to understanding CE.

In their article 'Return on Marketing', Rust et al. (2004) develop a model for allocating marketing expenditures to maximize projected financial return and (consequently) increase in CE. Individual CLV measures are calculated from the frequency of category purchases, average quantity of purchase, and brand-switching patterns (measured from survey data), combined with the firm's contribution margin and an appropriate discount rate. These measures are summed across all customers in the industry, explicitly accounting for switching to a competitor and/or defection, to produce an estimate of return on investment for a particular firm action. This model addresses a major challenge in customer relationship management and CE: assessing the impact of the firm and competitors' actions (using cross-sectional data). By doing so, they recognize many aspects of 'routine' risk. The authors recognize that there will be variability in purchases over time – due to market expansion, cross-buying, changes in usage rates, and other non-routine events. However, a discussion of how to measure or manage the customer risk associated with CE is beyond the scope of their article.

Approach 3: Optimizing CE by Re-weighting the Portfolio of Potential and Existing Customers

The optimization of the customer portfolio is a relatively recent innovation. It is quite different from the profit-, CLV- or CE-maximizing objectives discussed above. The intuition behind customer portfolio methods is that combining customers or market segments with different (i.e., offsetting) cash flow patterns reduces aggregate cash flow variability or customer risk without eroding CE (Ryals, 2002, 2003; Dhar and Glazer, 2003; Ryals, Dias, and Berger, 2007; Buhl and Heinrich, 2008). Note that the concept of measuring the CLV of market segments is not new (e.g., Libai, Narayandas, and Humby, 2002); it is the way they are combined that is novel.

Tarasi et al. (2011) demonstrated their approach to optimizing the customer portfolio as follows. First, they segmented B2B customers (using cluster analysis) based upon monthly cash flow patterns over six years. Then, they observed that customers with similar cash flow patterns shared common characteristics, including purchase cycles, industry, and size of company. Their analyses confirmed that measures of cash flow variability complement traditional segmentation variables. Next, they identified the efficient frontier of customer portfolios by varying the weights of the market segments to reflect how much they are represented in the customer portfolio – where risk was minimized for each level of return. The firm's current customer portfolio was far below the efficient frontier. Last, they showed how managers could identify in which customers to invest and how much to invest, with the goal of moving closer to a portfolio with less risk, a higher return, or both. In this way, firms can move toward a better risk–return profile without 'firing' or 'stealing' customers or other actions with negative consequences.

Their findings are encouraging because simulation results (based on forward and backward testing on an extensive customer data base) showed that their optimal portfolio outperformed the current portfolio – that is, lower risk without lower revenue. However, re-weighting the customer portfolio implies that the firm acquires or divests certain customers and makes strategic changes in how it allocates resources across customer groups. Selnes (2011) argues that the customer portfolio perspective should take into account strategic considerations such as changes in the market place, industries, and relationship building.

Approach 4: Strategies that Modify Cash Flows by Changing Underlying Firm Processes

Most approaches to optimizing CE assume future cash flows are fixed characteristics of customers or segments. This assumption was carried over from financial portfolio analysis, where bonds and stocks have fixed cash flow characteristics. However, most firms use classic market segmentation, target marketing, and customer management methods that shape cash flow patterns and ultimately influence their efficient frontier of customer portfolios. Hence, it is useful for managers to ask whether cash flow patterns, the building blocks of the customer portfolio, can be changed through firms' strategies, tactics, and processes.

Since firm actions influence customer behavior and ultimately CE, it should not be surprising that they also influence the variability of cash flows. However, Tarasi et al. (2013) took this notion one step further: is there a way for firms to reduce aggregate variability in future cash flows of an existing customer portfolio without adversely affecting cash flow levels? They identified several possible ways to reduce the cash flow variability of customers or groups of customers while maintaining their cash flow levels and aggregate CE. They focused on simple approaches to managing the service consumption process through firm actions that influence customers. First, customer satisfaction and cross-buying affect the level and variability of future cash flows (e.g., Fornell, Rust, and Dekimpe, 2009). Hence, managers can design programs to improve customer satisfaction and cross-sell products so that they obtain more desirable cash flow patterns (i.e., lowering risk for a targeted level of return). Second, their study also suggests that loyalty programs should be changed from economic incentives to social incentives (e.g., Drèze and Nunes, 2009) because economic rewards are more likely to be associated with higher variability, but not necessarily with higher cash flow levels (ibid.)

Although the relationship characteristics identified by Tarasi et al. (2013) might not apply to all firms or industries, their general approach can be widely applied. For example, studies have investigated how customers engage in consecutive buying of financial products according to their 'financial maturity' (Li, Sun, and Wilcox, 2005). With this information, financial services firms are able to better manage the uncertainty related to customers' future purchases and (consequently) manage customer risk. This approach requires a significant change in managerial viewpoint. We must view risk as variability that we cannot foresee and for which we cannot prepare. Whereas, when we can foresee and prepare for variability, it is an operations management problem, as opposed to a risk management problem.

DIRECTIONS FOR FUTURE RESEARCH ON CUSTOMER RISK

Over the past decade, advances in marketing science and practice have substantially improved our ability to calculate CE and to consider how alternative resource allocation strategies might affect it. However, much more work is needed on the quantification and management of customer risk – to ensure it is commensurate with returns/CE.

Marketing communications and loyalty programs

The direct marketing literature has made important contributions to our understanding of CE. However, it has typically focused on the effects of tactical (marketing communications) decisions on short-run customer profitability or CLV – leading to firm decisions that are sub-optimal in the long run (Godfrey, Seiders, and Voss, 2011). Hence, despite the adoption of the CLV concept, these approaches do not optimize CE. For example, marketing decisions related to loyalty programs – and especially the reward point system that is prevalent in the marketplace – may not be effective or efficient in the long term. Kivetz, Urminsky, and Zheng (2006) found that customers accelerate purchases in the short term to reach a target, but that behavior results in simple acceleration, without increased benefits for the firm (Tarasi et al., 2013). Loyalty programs that focus on social or status rewards and other similar customer targeting tactics are more likely to decrease variability in customers' cash flows. Marketers do not know, as yet, what specific features of loyalty programs are most likely to result in higher cash flow levels without unduly increasing risk in the long term.

Social and network effects

In a socially connected world, a customer's opinions and behavior influence other customers, thereby influencing their cash flows. In this way, the CLV of a customer partially depends on his or her connections in a social system (Goldenberg et al., 2009) – and these effects have become more powerful with the advent of social and digital media. We must recognize that social and network effects are likely to influence cash flow variability, as well as cash flow levels. Moreover, social influences can interact with customer satisfaction, such that they amplify variability in cash flows. Satisfied (dissatisfied) customers can attract (repel) other customers, where these effects are magnified by review sites, blogs, brand or user communities, and so on. Research suggests that investments in satisfaction reduce customer risk, but we have limited understanding of how social networks ultimately influence CE and customer risk (Gupta et al., 2006). Since social networks can be broad (e.g., extending across market segments), it is critical that we understand how they influence risk.

Firms' strategic decisions

Predictions of customers' cash flow streams are conditional on assumptions about a fixed set of firm decisions. (This feature often becomes apparent when marketers must reconcile predictions from two different models built to describe the same customer base.) However, this approach raises three important challenges. First, firms may change the timing of decisions (e.g., a new product launch) or there may be unanticipated changes in strategy or market conditions – which will alter cash flow levels (returns) and their variability (risk). We have been calling the former routine risk or uncertainty because it can be represented by a probability distribution. In contrast, uncertainty due to unanticipated changes in firm or market activities is not usually considered in current risk metrics. Second, researchers have a limited understanding of how managerial actions may reduce customer risk without adversely affecting CE (or increase CE without increasing customer risk). For example, how should managers think about (and quantify) the effects of a brand extension into a new market on customer risk? Several authors have argued that marketers should use real option theory to address these phenomena (Hogan, Lehmann et al., 2002; Berger et al., 2006). Third, we can reverse the way we think about this issue. How would considering customer risk change managers' decisions to introduce or eliminate channels or products from the product line? How does considering customer risk influence pricing and branding decisions?

Growth

The treatment of growth poses three challenges to customer portfolio methods. First, measures of variability in cash flows do not distinguish between variability due to growing versus declining sales or cash flows. Tarasi et al. (2013) provide some analyses of this issue in two industry contexts and identify some strategies that will reduce risk while maintaining CE. However, more work is needed. Second, growth (or lack of) may be due to product management strategies. Hogan, Lehmann et al. (2002, p. 28) describe how firm expansion into a related product category or market has different consequences for anticipated growth (returns or CE) and uncertainty (customer risk). Expansion into an unrelated category or market may offer an opportunity for higher returns, but it will usually be associated with higher risk. Moreover, the firm's expansion beyond current categories and markets (and its concomitant uncertainty) is likely to influence the firm's cost of capital – the extent of the effect will depend on the firm's capabilities (Hogan, Lemon, and Rust, 2002, p. 7). Third, risk metrics (customer β or RR) are calculated on the basis of historical data – assuming that past volatility is a good predictor of future volatility. This assumption will be unsuitable when firms expand into new categories or markets.

Risk adjustment and risk optimization

Recall that current approaches to calculating CE typically apply a single discount rate to all cash flows, usually the weighted average cost of capital. However, as we have discussed, the anticipated cash flows from a customer or market segment are at risk from customer behavior dynamics, social, competitive, and product management effects, and so on. When predicted cash flows are adjusted to reflect any of these sources of routine risk (e.g., by incorporating the probability of defection, competitors' actions or the outcomes of product management decisions), the weighted average cost of capital is no longer appropriate. Ideally, the discount rate should be adjusted to reflect the true risk of the particular customer segment that is being valued – by measuring the unanticipated variability in cash flows at a given point in time. Hogan, Lehmann et al. (2002) have suggested that the finance literature on stochastic valuation models could be helpful in this respect.

Another facet of this issue, termed 'risk optimization', arises when managers within firms make resource allocation decisions. What level of risk is recommended for which types or categories of customers? If segments have different responses to the firm's activities intended to alleviate risk, how can we take them into account before we build the customer portfolio? What is the optimal way to arrive at optimal customer portfolios, given that the response of the customer asset is not independent of the actions of the firm? Hutt et al. (2012) provide the steps for building a customer portfolio, but further research is needed to identify the ideal customer-targeted actions to match each of the steps.

Implementation challenges

The effectiveness of strategies for managing customers depends on how well these strategies are implemented and integrated with firms' existing processes and capabilities, as well as coordinated across channels, technologies, customers, employees, and other stakeholders. Clearly, there is a need to reward managers from different functional areas and levels for behaving in ways that are optimal for the firm. However, the cross-functional and future-oriented nature of these tasks is emphasized insufficiently. To optimize CE, the firm must target and manage segments of the customer portfolio using an adaptive foresight process (Berger et al., 2006; Zeithaml et al., 2006). This process entails understanding how each segment will respond to firm actions (e.g., offering characteristics, value proposition, relationship and service management) and thereby influence future cash flows. Thus, the firm can manage the risk associated with the customer portfolio with greater effectiveness and efficiency, attracting and retaining customers that offer the highest promised return and profitability in the context of potential and existing customers. Selnes (2011, p. 20) proposes that 'customer portfolio theory would be advanced to a greater degree by incorporating customer purchase behaviors and marketing managers' multifaceted objectives'.

Big data and computer science models

In general, marketers have favored a decompositional approach to customer portfolio management. That is, they utilize cross-sectional or longitudinal data to predict the buying behavior of individual customers or market segments as a function of marketing activities. Then, they calculate CLV, customer risk, and CE – as well as identify the optimal customer portfolio – using financial identities (based on revenue and cost allocations to activities) and simulations of future outcomes (e.g., Villanueva, Yoo, and Hanssens, 2008; Rust, Kumar, and Venkatesan, 2011). With these methods, different modeling approaches (e.g., probability models versus econometric models) are appropriate depending on the buying context – for example, consumer package goods, services, catalog sales, and so forth. However, Gupta et al. (2006, p. 148) point out that there are also many computer science approaches to predictive modeling that could work well, especially for 'big data'. In the future, marketers should pay more attention to these models. They may be especially useful for forecasting future volatility in cash flows when market conditions are evolving. Firms that are successful in exploiting big data (by adopting technology, as well as investing in their employees and organizational learning) to better manage CE and risk will have a sustainable competitive advantage in the marketplace. In this way, non-relational assets leverage relational assets (Hogan, Lemon, and Rust, 2002).

Managing risk in the customer portfolio is a challenging task – both strategically and tactically. Some tools exist and there is the potential – through research – to identify additional tools to quantify and manage variability in cash flows from individual customers and in aggregate. Strategic goals prevail, but within the context of the greater purpose, balancing customer risk and return ensures long-term shareholder value. The CE framework enhances our understanding of the role of marketing in maximizing shareholder value.

NOTES

1. This chapter does not discuss models that link customer lifetime value or customer equity (CE) to shareholder value or the firm's stock price. However, there is substantial research on this topic. Gupta, Lehmann, and Stuart (2004) show that customer lifetime value calculations can be used to approximate shareholder value. Firms' strategic decisions (brand equity, satisfaction levels etc.) are linked to shareholder value through its future cash flow patterns. Kumar and Shah (2009) show that the relationship between CE and market capitalization is moderated by risk factors in the form of volatility and vulnerability of cash flows from customers.
2. The Pareto/NBD (negative binomial distribution) model, first developed by Schmittlein, Morrison, and Columbo (1987) has been a very popular way of specifying purchase patterns, but there are many other alternatives.
3. We refer to cash flows throughout this chapter. Firms may use revenues or profits depending on their ability to correctly allocate costs.
4. We estimate the customer β for short-lived or potential customers by extrapolating from existing customers who are similar in terms of demographics, psychographics or responsiveness to marketing variables.

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