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Toward an Individual Customer Profitability Model

A Segment-Based Approach

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Although most published customer lifetime value models focus on strategic-level marketing decisions, managers also need models that enable them to make resource allocation decisions for individual customers. A common misperception among scholars and managers is that it is necessary to use individual-level customer profitability models to make such decisions. This article argues that a segment-based approach to customer profitability analysis can be a reasonable alternative to an individual model. The proposed stochastic segment-based approach retains the actionable information associated with individual-level analysis while also maintaining the simplicity of the more aggregate-level models. In this article, the authors develop such a segment-based assessment of customer profitability and then briefly describe an example of a major European retailer that successfully uses the approach to manage its customer base. Directions for future research in the area of stochastic customer equity modeling are also discussed.

Considerable anecdotal evidence suggests that firms increasingly rely on long-term customer profitability models to guide marketing strategy decisions (e.g., Brady 2000; Helf 1998; Peppers and Rogers 1997). By linking these customer lifetime value (CLV) models to marketing actions, the firm can attempt to optimize its marketing mix across its customer base (Blattberg, Getz, and Thomas 2001; Mulhern 1999; Rust, Zeithaml, and Lemon 2000; Zeithaml 2000).

An important challenge facing marketers in this regard is how to assess and manage *individual* customer profitability over time. One of the great promises of customer relationship management (CRM) is that it would help companies leverage the continuous stream of customer-related data acquired through various touch points to make individual-level marketing decisions. Ideally, firms would be able to make a real-time assessment of an individual customer's profitability to offer him or her the right product, at the right time, at the right price. On the basis of this promise, firms continue to make substantial investments in

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CRM information systems (Rigby, Reichheld, and Schefter 2002).

It is notable, therefore, that extant customer profitability models have a limited capability to guide individual customer-level marketing decisions. Although marketing scholars have made considerable progress in developing customer profitability models that identify the relationship between marketing variables and customer equity, these models are generally strategic in nature because the analysis is performed at the aggregate or large segment level. Such models are of great use to managers attempting to allocate scarce resources to obtain the maximum return on investment (ROI). However, there is a pressing need for tactical models that account for individual customer heterogeneity and that can be updated based on customer-specific data. Such models would enable firms to improve marketing efficiency by reducing instances in which too much money was invested in unprofitable customers and too little invested in profitable customers. This is a challenging goal that will likely take several years to accomplish. As a first step toward that goal, we propose the use of a segment-level model that can provide important management insights for firms attempting to make individual-level customer decisions.

The purpose of this article is to explore the inherent challenges of developing and implementing stochastic segment-level profitability models. The article is organized as follows. First, we discuss basic profitability models and the issues that limit their applicability to individual customer-level decisions. We then present an example of how a segment-based approach can be used to assess customer profitability. We describe the use of a segment-based approach by a major European retailer. The proposed approach is then compared with existing market and customer-level approaches. We conclude by offering suggestions for future research.

MEASURING CUSTOMER PROFITABILITY

Marketing scholars and managers alike have recognized the importance of developing individual-level profitability models. However, using customer profitability models as an individual-level decision tool that is integrated into the CRM system requires two elements. First, it is necessary to have a model of customer profitability based on individual customer data. Second, the model must be able to be updated based on observed changes in customer behavior. In an effort to explore these issues in more detail, we first review the literature on customer profitability.

CLV Modeling

Customer profitability models are frequently referred to as CLV models to signal the long-term view of a customer's profitability. Typically, CLV models calculate the net present value of a customer's profit stream accounting for the firm or segment-level retention rate. The basic model suggests that if a firm's average retention rate is r, the average profit from a customer per period is p, and the discount rate is d, then CLV over n years is:

$$CLV = \sum_{t=0}^{n} \frac{p \cdot r^t}{(1+d)^t} \qquad (1)$$

If the cash flows are modeled as a perpetuity (i.e., t approaches in infinity), the CLV in (1) becomes:

$$CLV = \frac{p}{1+d-r} \qquad (2)$$

Equations 1 and 2 are the basis for most CLV assessments in the published literature (Berger and Nasr 1998; Blattberg and Deighton 1996; Berger and Nasr 1998) and are also frequently used in trade publications (e.g., Peppers and Rogers 1997). In a well-known example, Reichheld and Sasser (1990) showed that a firm's long-range profitability is very sensitive to small changes in the customer retention rate. Blattberg and Deighton (1996) used this approach to suggest a way to optimally decide on customer acquisition and retention investments. Blattberg, Getz, and Thomas (2001) suggested how this modeling approach can be the basis for planning customer acquisition, relationship development, and customer retention strategies. Berger and Nasr (1998) demonstrated how the basic CLV model could be relaxed, for example, to allow incorporation of different promotion expenditures.

A notable limitation to this basic approach is that it uses the "lost for good" assumption under which a customer who leaves the firm does not come back in the short run (Berger and Nasr 1998). This assumption is commonly made but may not be robust in markets in which consumers tend to switch between brands because it would underestimate the true CLV. Another limitation is that it does not offer a comprehensive means for incorporating marketing mix variables and customer perceptions into the customer profitability calculation. Recently, Rust, Lemon, and Zeithaml (2001) offered a decision support system that takes into account future brand switching (i.e., the customer can leave and come back) and ties marketing actions and perceptions (based on a sampling technique) into the CLV calculations.

An important feature of these approaches to customer profitability modeling is that they are essentially strategic models that are best suited to guiding resource allocation decisions for the entire customer base or very large segments. Typically, these modeling approaches use average retention rates or sample-based switching probabilities and customers' perceptions to calculate the CLV of an average customer or the expected value of all customers (i.e., customer equity). These calculations are an important input to the firm's strategic marketing decisions dealing with issues such as the effects of changes in retention rate on expected CLV (Reichheld 1996) or understanding how different marketing mix actions affect firm profitability (Rust, Lemon, and Zeithaml 2001). Clearly, they represent a significant step toward incorporating long-term customer profitability effects into firm-level managerial decision making.

However, these models provide less insight into decisions about how to manage individual customers in a way that accounts for the heterogeneity and provides a mechanism for dynamic updating of the profitability assessment. This problem has become increasingly important as marketers gain access to growing volumes of detailed customer data. Using sophisticated CRM information systems and data from sources such as loyalty programs, the questions many marketers face is not how to get data but how to use them effectively. Specifically, after a decade in which the importance of customer profitability analysis has been effectively disseminated and accepted, marketers now struggle to understand how CLV modeling can be an aid for individual customer profitability analysis.

There are numerous examples in the trade press to illustrate the many ways in which firms are adapting their marketing programs in an attempt to move toward more individualized marketing strategies. For example, Comstock Bank of Reno assigns letter grades to its individual customers based on their profitability to let tellers and customer service staff know instantly how to treat customers when they walk into a branch office (Stoneman 1997). Thomas Cook Travel of Boston also divides its customers to letter grades. In this case, when a C-level client requests travel planning services without a guaranteed reservation, they are charged a $25 fee, whereas A-level clients receive the same services for free (Rasmusson 1999). More broadly, the multimillion dollar investments that firms make in CRM systems are frequently justified based on the ability to discriminate between profitable and unprofitable customers (Rigby, Reichheld, and Schefter 2002). Insights into the inherent challenges posed by developing an individual customer profitability model can be gained from recent work in database marketing, which uses predictive response modeling.

Predictive Response Modeling and CLV

As the lead article in this special issue points out, one literature stream dealing with individual-level customer analysis is direct marketing (Hogan, Lemon, and Rust 2002). There is a rich tradition in the database marketing literature of methods to rate customers by their expected response to marketing actions that includes logistic regression; neural networks; and recency, frequency, and monetary value (RFM) analysis (e.g., see Blattberg, Getz, and Thomas 2001; Levin and Zahavi 2001). Typically, the objective is to predict some kind of a response measure for each customer as a function of customer-related explanatory variables. One advantage of these models is that they use individual-level data to provide predictions of specific customer behavior. However, as Levin and Zahavi (1998) noted, in most practical applications, the response is measured by a discrete, dichotomous measure such as buy/no buy, respond/did not respond, and the like. Yet, in many cases, the customer response that companies are interested in is a richer measure, capturing monetary value over time.

Efforts to predict response over time are beginning to emerge in the literature. However, the continuous cases described to date have been relatively simple (Levin and Zahavi 1998). This is problematic because the assessment of CLV is a complicated task, often involving the reaction of a customer to multiple offers through time and subsequent changes in customer attitudes. It is reasonable to expect that continued research into data-mining techniques might eventually improve the ability to handle relatively complex analysis such as CLV prediction. However, there is a need to pursue additional approaches as well.

Capturing CLV Dynamics

As firms seek to accurately measure and predict CLV, understanding the dynamic nature of customer-firm relationships is critical. The firm's relationship with a customer is a dynamic entity whose value will change over time due to the evolution of the relationship or due to external factors such as a change in the customer's family circumstances. In an aggregate CLV model, these changes in individual status are less relevant because they wash out when determining the average value of the customer base. Such is not the case with an individual model, where the financial impact of a change in relationship status can be substantial. We broadly categorize these types of changes as either endogenous or exogenous.

Endogenous customer life-cycle factors. We define endogenous customer life-cycle effects are those related to the duration of the relationship between the customer and

the firm. Prior research suggests that the duration of the customer relationship has a substantial effect on customer profitability but that this relationship is complex and dependent on several factors (Reinartz and Kumar 2000). It has been argued that longtime customers tend to buy more (because they are better acquainted with the firm's offerings), cost less to serve (because the firm knows them better), and are less price sensitive (because they have higher switching costs) (Reichheld 1996; Heskett, Sasser, and Schlesinger 1997).

One example of such an endogenous factor relates to the inherently dynamic nature of the retention rate. A positive correlation (especially in the early stages of a customer's relationship with the firm) exists between a customer's tenure with the firm and his or her retention rate (Blattberg, Getz, and Thomas 2001; Bolton 1998; Riechheld 1996; Wheaton 2000). One explanation for this correlation is that customers are constantly evaluating the firm's performance as they decide between staying and leaving. Initially, customers may know little about the firm's product offering, but that uncertainty is gradually resolved and unsatisfied customers eventually leave. For a given cohort, then, each additional year will reduce the number of unsatisfied customers, leading to an increase in retention rate. Another factor relates to the tendency of companies to draw deal-prone consumer through promotions (Reichheld 1996). Such consumers are less loyal and will stay with the company for a relatively short time, increasing the defection rate in the early years of a cohort.

Exogenous lifecycle factors. We define exogenous life-cycle factors as those in which the source of change in customer profitability is not directly related to the customer-firm interaction. One such factor that has been noted for consumer goods and services is the family life cycle, sometimes labeled the "customer life cycle" (Javalgi and Dion 1999; Thomas 1998; Wells and Gubar 1966). There is a general consensus among researchers that each family passes through a number of distinct stages from its point of formulation to its ultimate demise (Javalgi and Dion 1999). Wells and Gubar (1966) identified nine stages through which a family passes in some of the earliest work on the family life cycle. Their framework has been updated to include nontraditional forms of families (Javalgi and Dion 1999; Murphy and Staples 1979).

The family life cycle can be broadened to incorporate other activities that can be expected to change the individual customer profitability. For example, one can expect that a medical student will go through several life cycle stages that will affect his or her consumption patterns: from premed college studies, to medical school, to specializing in a hospital, to opening private practice, and so forth. Similarly, children go through several growth stages that affect their consumption patterns.

The importance of exogenous life-cycle considerations lies in their potential effect on consumption and, hence, on customer profitability. It has been demonstrated that the changing needs of the family at various life-cycle stages affect its potential profitability (Javalgi and Dion 1999). The advantage to the firm of using a life-cycle approach is that the demographic and personal data that enable a life-cycle assessment is often available through sources such as customer loyalty programs. Therefore, firms may be able to assess stages of the current customer life cycle with relative ease, which can, in turn, help predict future customer profitability.

However, as we have noted, capturing the dynamic nature of customer relationships in an individual CLV metric remains a substantial challenge for marketers. Customer profitability will change over time due to the evolution of the customer's relationship with the firm and the evolution of the customer's personal relationships. Although a truly individual-level model probably remains some years away from development, we suggest that many of the benefits of an individual approach can be obtained by using a detailed segment-level analysis.

A STOCHASTIC SEGMENT-BASED APPROACH TO CLV MODELING

Consider a retailer that wants to assess the lifetime value of an individual customer to tailor its marketing operations. Using data from its customer membership programs, the retailer has information about the demographic and possibly the lifestyle profile of an individual customer. In addition, the retailer has a constant flow of data on the purchases of this individual and his or her response to the retailer's marketing initiatives. The retailer now wants to assess the profitability of this customer to guide marketing mix decisions.

There is little research to guide marketers attempting to build an efficient mechanism of updating individual customer profitability. However, a possible approach is to use a stochastic segment-based model. Under a segment-based approach, the retailer would use customer-level profitability or other data (e.g., demographic and lifestyle, family life cycle, purchase patterns) to divide the population into segments whose CLV can be assessed based on the knowledge of their past behaviors. The retailer can then use a stochastic switching model to move customers between segments over time. Using this approach, the vector equation for the number of customers in each segment is:

$$\mathbf{C}_t = \mathbf{MM}_t \times \mathbf{C}_{t-1}, \qquad (1)$$

where $\mathbf{C}_t$ is the vector of the number of customers in each segment in year t, $\mathbf{MM}_t$ is the movement matrix containing the probability of switching to the segment from other segments in a given year. When combined with a profit vector, $\mathbf{P}_t$, defined as the profit from each segment in year t, then the customer equity calculation generalizes to:

$$\text{Customer Equity}^1 = \sum_{t=0}^{T} MM_i \cdot C_i \cdot P_i,$$

where customer equity is equal to the sum of the customer lifetime values of all the firm's customers.

This is a Markov probability series where customers can either stay in their current segment or move to another segment. Markov models have frequently been used to model brand-switching behavior (Bass et al. 1984; Vilcassim and Jain 1991). In the context of valuing customer relationships, Rust, Lemon, and Zeithaml (2001) suggested the use of a Markov process to develop a customer equity model that takes into account brand switching. Note that the approach suggested here moves a customer between segments within the brand. In a manner that is somewhat similar to the segment-based approach presented here, Pfeifer and Carraway (2000) used Markov chains to model the switching of customers between different levels of recency of buying with the firm. In this case, each recency level can be seen as a "segment" and is a specific application of the general model that we propose.

There are a number of advantages associated with the use of Markov chains to model customer relationships (see Pfeifer and Carraway 2000 or Puterman 1994 for details). Because they are probabilistic in nature, they explicitly account for the uncertainty that characterizes customer relationships. Markov chain modeling has been used extensively in many disciplines and is grounded in a well-developed theory base.

An Example of How This Approach Could Be Applied

A leading European retailer that is a world leader in the use and analysis of customer data is using the segment-based approach of the kind we have described. The retailer has 10 million card-carrying shoppers (i.e., who can be identified). The shoppers' population can be segmented by 7 different segmentation variables such as RFM, family status, promotion behavior, or shopping basket behavior. The variables themselves are built on multiple criteria reflecting the firm's experience with the market. For example, the shopping basket behavior describes the consumer across 20 key shopping drivers.

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1. Assuming appropriate discounting of per period cash flows.

Given the number of levels on each segmentation variable, the total number of possible cells can be more than 20 million. However, depending on the objective, typically two to three segmentation variables are used, yielding 10,000 to 20,000 cells. In some cases, the company has used as many as 4 million cells.

Segment membership is updated every few weeks or months, depending on the objective. Updating is typically based on the behavior and status of the customer that the company learns from its extensive use of the database. However, when aiming to undertake long-term loyalty (and thus profitability) customer-level analysis, a probability-based method is used. In such a case, the probabilities of the customer migrating between segments as well as the probability of customer lapsing (dropping out) are considered.

The membership card data have become a major input source for any marketing action the firm takes in its marketing communication, pricing, promotion, and customer acquisition and retention strategies. Using the card data, the company has gained notable success in several areas of marketing, including doubling the coupon redemption rate.

The retailer believes that its ability to use the membership card data to tailor marketing actions toward the right set of customers has had a major impact on its profits in the past several years. So much so that this process has become a key input to its strategic thinking. The segment-based approach enables the retailer to tailor marketing actions such as promotions and rewards to the right customers and still keep it simple enough to perform and to execute across its customer base. This approach has given the firm considerable control, because it has provided the retailer with a common point from which the retailer can integrate marketing expenditures and measure their impact from changes in key measures for each segment.

Discussion and Research Implications: A Segment-Based Approach to Customer Equity Management

The stochastic segment-based approach we have proposed has significant implications for marketing managers. In particular, it provides the firm with a useful resource allocation mechanism for marketing expenditures. For example, the approach can guide retention-related expenditures such as customer service, delivery logistics, and complaint handling. Similarly, the approach can inform migration expenditures intended to change the probability of a customer migrating from one segment to another. Such expenditures would encourage light users to increase usage or, at the very least, prevent them from migrating further down the usage ladder. Migration expenditures

might include development of new service offerings, trial offers, and so forth. Finally, the approach can guide acquisition expenditures that can be viewed as a special form of migration where customers switch from prospects to active customers.

Altering the switching probabilities. One way in which firms can improve the value of customer equity is to increase the probability that a customer will move to a more profitable segment or reduce the probability of a move to a less profitable segment. For example, a retailer can examine the different customer segments and how their growth and decline affect different members of the segment. For some segments, the issue might be about retention, whereas for others, it might be more closely related to the growth of the customer base.

By identifying the key differences between the segments, the firm can adjust the marketing and customer service mix for each group of customers. This might be through making the offer more relevant to key customer segments, or it might involve identifying new customer practices for key groups of customers or the need for a more suitable product portfolio for another segment. In this way, it focuses customer expenditure on actions that increase the lifetime value of customers.

Increasing segment profitability. Profitability can also be improved for a particular segment by understanding the key driver of each segment's profitability. If one can influence those drivers that play the most significant role for each segment, the firm can increase CLV. For example, using automatic call answering may reduce the cost to serve of a significant number of customer segments. Using a machine interface could also potentially increase customer dissatisfaction and lead to customer churn among the firm's most profitable customers who expect high service levels. In this situation, a dual policy is more desirable, that is, a dedicated high-profitability customer service line staffed by people rather than a maze of automated choices.

Optimizing segment size. The question of the optimal segment size relates to what the firm wants to do with the profitability calculations. One approach is to use a small number of segments, which makes the handling and updating relatively simple. For example, a possible segmentation approach commonly known as a customer pyramid divides the customer base into tiers, based on the customers' profitability (Curry and Curry 2000; Zeithaml, Rust, and Lemon 2001).

Using a few large segments, our proposed approach can serve as a way to improve strategic-level analysis. For example, Zeithaml, Rust, and Lemon (2001) qualitatively discussed what they label *customer alchemy*: ways to move customers between segments (e.g., platinum, gold, iron, and lead). The segment-based approach can help firms quantify the effect of customer alchemy and consider the resulting customer equity as a by-product of different marketing actions directed toward customer switching.

A more interesting view is to use the segment-based approach as a move toward individual-level CLV modeling. It is possible to use customer pyramid/tier membership for individual assessments. For example, each customer's profitability is estimated to be the profitability average of the tier he or she is in. However, although relatively easy to perform, this approach will not use the full spectrum of data held by the firm. For example, different family life-cycle and past consumption data may enable a firm to predict profitability much better than the average of a large tier. Hence, when a firm has a large number of customers in its database, it can use a many-segment approach. Some segments may be very small and thus help the firm get closer to individual-level calculations. Yet, the firm can still stay away from the need to build individual-level functions.

In a more general sense, the segment-based approach leads marketers to a more probabilistic view of customer relationships. Indeed, as marketing analysis moves toward the individual level, there is a need to talk about the probability of retention rather than retention rates and expected customer profit instead of average profits of a customer group (Pfeifer and Carraway 2000). The marketing literature provides a number of examples on customer-related stochastic processes (see Lilien, Kotler, and Moorthy 1992 for a good review of some of these approaches). Although most of this effort has been geared toward understanding brand switching, some of these approaches may be adapted to a customer-centered segment-based approach. This is a potentially fruitful avenue for future research regarding the segment-based approach.

To summarize, the segment-based approach to customer profitability measurement has a number of advantages. First, it enables companies to estimate long-run customer equity profitability using switching probabilities between segments with relative ease. Switching probabilities can be evaluated based on the company's history with the segments. In contrast, building a function that will explicitly describe the change in individual customer profitability through time appears to be much more complex. This stochastic segment-based approach can also allow a relatively simple *what-if* analysis. The effects of different marketing actions can be estimated both by a possible change in segment profitability and in switching probabilities. Finally, the segment-based approach allows the firm to update individual customer profitability. As more data come in, the firm can use previous knowledge to estimate segment profitability.

Directions for Future Research

We believe that the proposed segment-based approach to customer lifetime value and customer equity estimation represents a solid step forward in customer relationship modeling. However, there is much yet to be done. One feature of Markov process modeling that should be taken into account in future research is the importance of the path the consumer takes to any specific probabilistic state. In a typical Markov process model, the switching of a customer between states depends only on the state he or she is in, not on the path to this state. In the segment-based model discussed above, the probability of switching from Segment A to Segment B will be independent of the segments the customers belonged to before becoming a member of Segment A. This assumption makes the customer equity calculation easier but fails to use all data associated with a certain customer (i.e., it might be that the manner in which the customer reached Segment A may actually affect its probability to move to Segment B). Future models should investigate the importance of relaxing this assumption.

In addition, incorporating firm-controllable variables when examining customer movement between the segments could extend the segment-switching model we have proposed. One approach would be to use a semi-Markov process in which the timing of the stay in a certain state is a state-dependent random variable (see Hauser and Wisniewski 1982). Such an approach might enable the firm to better determine the effect of different marketing mix variables on segment switching and consequently on customer equity. It should be noted that adding complexities to the basic Markov process could make the analysis very complex. Given the trade-off between simplicity and completeness, it seems that a first-order segment-based approach, the former, is a good starting place.

CONCLUSIONS

In this article, we have recommended a stochastic segment-based approach to customer profitability. The idea behind any profitability model is that evaluations of both the anticipated return on the investments (ROI) and the associated risks of those investments typically underlie the choice between investment opportunities. The same is true with customer profitability models. Managers are interested in customer profitability models for a variety of reasons. They can use such information to (a) make organization-level changes on how they manage their customers, (b) decide on which customers to serve and which relationships to terminate, or (c) fine-tune their effort at an individual customer level.

Depending on the end use, the type of profitability model would be different. To view the segment-based profitability model presented in this article in the right perspective, it would be useful to go back and contrast it with systems that are at higher and lower levels of aggregation, that is, market-level and customer-level profitability models.

The benefits of market or firm-level profitability models are clear; they are easier to calculate and more robust to changes. These models also have enormous value as benchmarks to evaluate a firm's performance vis-à-vis its competitors and firms in other industries. In the research stream based on the American Customer Satisfaction Index (ACSI), firm- and industry-level indexes are used by firms as useful competitive benchmarks to calibrate their overall organization-level customer management effort. The ACSI is a cross-industry national indicator that links customer satisfaction to financial returns that reports indexes on a 0 to 100 scale at the national level, for seven economic sectors, 34 industries, and nearly 200 individual companies or agencies. In addition to the company-level satisfaction scores, the ACSI produces indexes for the drivers of customer satisfaction, its outcomes, and the interrelationship between these variables. With such information, firms can calibrate the returns to their own efforts and change their market-level strategies accordingly. However, these models do not offer the manager much support when it comes to prescriptions on how to manage individual customers or in evaluating the effects of attributes other than satisfaction on customer/firm profitability.

As discussed earlier in this article, moving from segment to customer-level profitability models brings with it complications of data collection, measurement, and analysis. Depending on how the firm plans to use these models, customer-level profitability models can be of several types. In the most extreme case, firms can measure the short- and long-run impact on revenues derived from individual elements of the marketing effort for each customer. Coupled with information on the costs of undertaking any marketing action in a customer relationship, firms can now calculate the profitability of a single marketing action for each individual customer. In a way, we can call these "customer-level marketing effort profitability models." With this information, firms can literally decide between several courses of action during each encounter with an individual customer. In our opinion, with the explosion of customer-initiated contacts resulting from interactive technologies (Bowman and Narayandas 2001), such models are not outside the realm of reality in the world of direct marketers or in business-to-business contexts. Nonetheless, these models might be unrealistic in most situations for two reasons. First, in our field investigations, we have

found that firms usually lack the precision to link their efforts with customer response at such a fine granular level. Second, the gains in individual profitability and response gained from individual customer-level models, relative to the segment-level models as suggested in this article, will often not be worth the significant effort and costs required to achieve them.

In each of the cases discussed above, there are trade-offs to be made in addition to constraints and limitations that need to be considered. Given the complexities involved in moving to either individual-level or firm-level models, we believe that the segment-level approach that we recommend is the optimal mix between the cost savings achieved from collecting and analyzing data at a higher aggregate level and the benefits derived.

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