Customer Analytics Part I

V. Kumar, W. Reinartz, *Customer Relationship Management*, Springer Texts in Business and Economics, https://doi.org/10.1007/978-3-662-55381-7_5

5

Overview

Customer value management rests on the idea of allocating resources differently to different customers. The basis of this differential resource allocation is the economic value of the customer to the firm. Thus, before one can start to manage customers, one must have a thorough understanding of how to compute the value contribution each customer makes to a firm. Various economic concepts and procedures have been developed that help us to achieve this. Some are based on simple notions, whereas others require the application of mathematical techniques. But as a precursor to understanding and applying these concepts, it is necessary to define measures or metrics of marketing activities and their outcomes. This chapter reviews traditional marketing metrics and introduces various primary customer-based metrics for acquisition and customer activity measurement, before it explains some popular customer-based metrics. The following chapter will then introduce surrogate metrics of customer value used in the industry.

It is important at this stage to note the difference between traditional marketing metrics and customer-based metrics. *Market share* and *sales growth* are popular traditional marketing metrics normally computed for the geographical area covered by a particular market. These metrics were developed when individual customer data were hard or impossible to obtain and therefore do not provide customer-level insight into the market. However, over the years, the increased availability of customer-level data has resulted in the development of a new set of metrics that reflect the need to evaluate managerial performance based on the value each individual buyer brings to the customer base of the firm. In order to arrive at some measure of customer value, various activities and their costs and returns need to be recorded and assessed. We denote such metrics primary customer based metrics which can be further subdivided into customer acquisition metrics and customer activity metrics. *Acquisition rate* and *acquisition cost* are two primary metrics measuring the customer-level success of marketing efforts aimed at acquiring new customers. Specific metrics have also been developed to track customer activities from the point of their acquisition until they cease to be customers. The customer activity measures comprise *average inter-purchase time*, *retention rate, survival rate, probability of a customer being* active—P(Active)—and *customer lifetime duration*. A third block of customer metrics are popular customer-based metrics: *Size of wallet* and *share of wallet* are popular metrics firms frequently apply to evaluate a customer's worth. In FMCG categories the *share of category requirement* is a commonly used popular customer-based metric to track consumer loyalty.

Thus, the various marketing metrics which will be discussed in the course of this chapter can be classified as follows (Table 5.1):

Table 5.1 Metrics used in customer analytics part 1

Metrics	
5.1 Traditional marketing metrics	**5.2 Customer acquisition metrics**
5.1.1 Market share	5.2.1 Acquisition rate
5.1.2 Sales growth	5.2.2 Acquisition cost
5.3 Customer activity metrics	**5.4 Popular customer-based value metrics**
5.3.1 Average inter-purchase time	5.4.1 Size of wallet
5.3.2 Retention & defection rate	5.4.2 Share of category requirement
5.3.3 Survival rate	5.4.3 Share of wallet
5.3.4 Lifetime duration	(5.4.4 Transition matrix)
5.3.5 P(Active)	

5.1 Traditional Marketing Metrics

Traditional marketing metrics have been used by marketing professionals for years and are helpful in measuring performance of brands, products, and firms in a given geographical region. These metrics were developed when individual customer data were hard or impossible to obtain. Traditional marketing metrics provide information about how products or brands perform in a market neglecting the individual customer-level. Historically, managerial rewards and incentives have been based on how well a manager is able to deliver on these metrics.

5.1.1 Market Share

Market Share (MS) is one of the most common metrics for measuring marketing performance. It is defined as the share of a firm's sales relative to the sales of all firms—across all customers in the given market. MS is an aggregate measure across customers. It can be calculated either on a monetary or a volumetric basis.

$$MS\ \ of firm\, j(\%) = 100 \times \left[\frac{S_j}{\sum_{i=1}^{I} S_i} \right] \quad (5.1)$$

Where
j = focal firm
S_i = sales of firm i
I = all firms in the market

Where Does the Information Come from?

- **Numerator:** Sales of the focal firm are readily available from internal records.
- **Denominator:** Category sales are available from market research reports or from competitive intelligence.

Evaluation

MS is one of the most common measures of marketing performance because it conveys an important piece of information and is readily computed. It is a typical measure of a product-focused marketing approach. However, it does not provide any information about how the sales are distributed across customers—it only gives an aggregate notion of category performance. For example, a given MS can be caused by selling large amounts to a small percentage of the customer base or by making small sales to a large proportion of the market.

5.1.2 Sales Growth

Sales growth of a brand, product, or a firm is a simple measure that compares the increase or decrease in sales volume or sales value in a given period to sales volume or value in the previous period. Hence, it is measured in percent. It indicates the degree of improvement in the sales performance between two or more time periods and acts as a flag for the management. A negative sales growth or sales growth lower than the rest of the market is normally a cause for concern.

$$Sales\ growth\ in\ period\ t(\%) = 100 \times \left[\frac{\Delta S_{jt}}{S_{jt-1}} \right] \quad (5.2)$$

Where
j = focal firm,
t = time period
ΔS_{jt} = change in sales in period t from period t − 1
S_{jt-1} = sales of firm j in period t − 1

Where Does the Information Come from?

- Both the numerator and denominator are available from internal records.

Evaluation

Sales growth is a quick indicator of the current health of a firm. If compared with the sales growth of the other players in the market, it also provides a relative measure of performance. However, it does not tell us which customers have grown and which ones have not. This information is necessary if we are to take customer-level marketing initiatives.

5.2 Customer Acquisition Metrics

One group of primary customer based metrics is customer acquisition metrics. The second are customer activity metrics which are discussed in ► Sect. 5.3. Customer acquisition metrics have been receiving increased attention recently. Managers have become more sensitive toward balancing customer acquisition and customer retention activities. In order to evaluate customer acquisition activities, we use two simple concepts—acquisition rate and acquisition cost.

5.2.1 Acquisition Rate

When firms attempt to acquire customers, they are typically targeting a specific group of prospects. For example, a European credit card issuer might target the student market in Italy. In order to describe the success of the acquisition campaign, a key performance indicator is the acquisition rate, i.e., the proportion of prospects converted to customers. It is calculated by dividing the fraction of prospects acquired by the total number of prospects targeted.

$$Acquisition\ rate\,(\%) = 100 \times \frac{\#\ of\ \ prospects\ \ acquired}{\#\ of\ \ prospects\ \ targeted} \quad (5.3)$$

For example, the target market of the credit card issuer might have been two million students in Italy. Acquisition was measured in terms of new credit cards issued. The bank issued a total of 60,000 new credit cards. Thus, the acquisition rate was 100 * (60,000/2,000,000) = 3%.

The acquisition rate denotes an *average probability* of acquiring a customer from a population. Thus, the acquisition rate is always calculated for a *group* of customers (e.g., a segment), not for an individual customer. The equivalent measure for an individual is the acquisition probability. An acquisition rate for an individual customer does not exist.

Defining What Acquisition Is

Firms have different definitions for the term *acquisition.* In the credit card example, an acquisition was recorded when a new credit card was issued to the prospect. However, it is possible that the prospect signed up for the card only because she was interested in the promotional incentive and that she will never use the card. As a solution, the bank could define two different levels of acquisition—for issuing the credit card and issuing a statement (which depends on credit card activity). For example, although 60,000 credit cards have been issued to new customers, only 55,000 of them have received a statement, indicating activity on the card account. Thus, the level 1 acquisition rate is 3% and the level 2 acquisition rate is 2.75%.

In noncontractual contexts, acquisition is typically defined as the first purchase or purchasing in the first predefined period. For example, an outdoor direct-mail merchant received 110 first-time orders from a campaign based on a new mailing list of 5,000 prospects. Thus, the firm's acquisition rate is 2.2%.

It is important to note that acquisition rates are typically computed on a campaign-by-campaign basis. Since acquisition rates can vary tremendously within the same firm, an average (firm-wide) acquisition rate is mostly of limited value.

Where Does the Information Come from?

- **Numerator:** Number of prospects acquired is determined from internal records.
- **Denominator:** Number of prospects targeted can be available from internal records or has to be estimated from market research data (e.g., for television campaigns).

Evaluation

Acquisition rate gives a first indication of the success of a marketing campaign by setting the number of new customers in relation to the number of targeted customers. However, it cannot be regarded in isolation. For example, it does not account for the costs of acquiring the customers. Other important factors that have an impact on the acquisition rate are the marketing strategy and the selection of target customers.

5.2.2 Acquisition Cost

The second key metric in customer acquisition is the acquisition cost (AC). The acquisition rate measures responsiveness to a campaign, but it does not say anything about the cost efficiency of a campaign. AC is defined as the acquisition campaign spending divided by the number of acquired prospects. AC is measured in monetary terms.

$$\frac{Acquisition\ cost\,(\$)\ per}{prospect\ acquired} = \frac{Acquisition\ \ spending\,(\$)}{Number\ of\ \ prospects\ \ acquired} \quad (5.4)$$

For example, the cost of the acquisition campaign of the Italian credit card issuer was $3 million. Thus, the average cost of acquiring a single new customer for this campaign was $3,000,000/60,000 = $50. Depending on the exact definition of what constitutes acquisition, the cost can be calculated for different acquisition levels.

Delineating Acquisition Spending

It is not difficult to identify acquisition spending in an organization that (1) acquires prospects in distinct campaigns and (2) is able to pinpoint its acquisition efforts quite precisely to the prospect group. In this situation AC can be calculated with the highest accuracy. Any company targeting prospects through direct mail would fall into this category—it knows the precise target group and the acquisition spending directed toward that group. As soon as firms rely on broadcasted communication (e.g., advertising through television, social media, or print media) measurement of AC becomes less precise. For example, prospects can be persuaded by advertising that was originally not targeted at them but toward existing customers. Clearly, AC will seem lower if those customers enter the AC calculation—making the numbers look more attractive than they really are. Also, firms might not necessarily differentiate between acquisition advertising and retention advertising. Calculating the precise AC in such a case can become quite difficult.

Where Does the Information Come from?

- Both the numerator and denominator are available from internal records.

Evaluation

AC is a very important metric that firms should strive to continuously monitor as it indicates how effective a customer acquisition investment is.

5.3 Customer Activity Metrics

Once a prospect has been converted into a customer, the main phase of the customer-firm relationship begins. The concept of measuring the activity status of this relationship deals with a very fundamental issue—whether a customer is a customer. On first sight, this might appear to be obvious. If a customer buys, then the customer is, in fact a customer—otherwise, they are not. However, digging a little bit deeper, it seems that we are uncovering a quite complicated matter. It is not at all clear what constitutes a living relationship. What is more, the meaning of an active relationship differs across industries. Clearly, one has to look at more than just purchasing acts executed by a customer. Customers interact with the firm in multiple ways (pre-purchase inquiry, post-purchase service, complaints, etc.), all of which contribute to the entirety of the customer-firm relationship. Even in a simple case such as grocery shopping where the purchase per se is of highest importance to both parties involved, a multitude of other nonpurchase interactions adds or detracts from the relationship quality (e.g., the interaction with service employees, the communication of the store toward the customer, and the shopping experience).

Thus, it becomes clear that the customer-firm interaction comprises many more elements that may contribute to the essence of the relationship. In most cases, however, the sequence of purchase is used to define whether a relationship exists. However, even if one uses this simplification, there still is the issue of customer dormancy. Dormancy occurs when an ongoing relationship is disrupted temporarily during a period without any observable purchase activity. To state an example, this might occur naturally when someone loses her job and therefore is forced to scale down consumption. Once the person finds a new position, they are likely to return to the old consumption pattern. Consequently, the person is not starting a new relationship but is continuing an existing relationship. (We admit this discussion becomes complex when the period of dormancy has been very long.)

The challenge from a managerial point of view is to establish whether a seemingly dormant relationship has ended or the customer will return. In practice, this is a very tough call to make. Dormancy will or will not be considered, depending on the specific measure used to estimate customer activity.

5.3.1 Objective of Customer Activity Measurement

The reason we want to shed light on customer activity measurement is twofold. First, knowing the status of a customer's (or a segment's) activity is important for managing marketing interventions. A customer-oriented organization tries to align resource allocation with actual customer behavior. Instead of mass advertising or mass marketing, managerial action can gain tremendous efficiency by adjusting its interventions to the actual customer needs or activity status. The second reason for measuring customer activity is because it is a key input in customer valuation models such as net-present value (NPV) models like the lifetime value. The marketing function has come under increasing pressure to demonstrate how it adds to shareholder value. This demonstration typically involves the estimation of the evolving customer value over time. Thus, measuring customer activity is a critical intermediary step in this valuation process.

This section covers the following types of customer activity measures:

1. Average inter-purchase time (AIT)
2. Retention rate and defection rate
3. Survival rate
4. Lifetime duration
5. P(Active)

Each metric has a purpose with its own set of strengths and weaknesses. Thus, the task of the manager will be to find the most suitable metric for a given situation.

5.3.2 Average Inter-Purchase Time

Average Inter-Purchase Time (AIT) is the average time elapsing between purchases. It is measured in terms of specific time periods (days, weeks, months, etc.). It is computed by taking the inverse of the number of purchase incidences per time period.

$$AIT\ of\ a\ customer = \frac{1}{\begin{array}{c}Number\ of\\ purchases\ during\\ a\ prespecified\\ period\end{array}} \tag{5.5}$$

Example

If a Publix supermarket customer buys, on average, six times at Publix during a month, then the AIT for that customer will be 1/6 = 0.1667 months, or approximately 5 days (0.1667 × 30).

Where Does the Information Come from?

- **Denominator:** Sales records are used, assuming individual customer records are maintained and individual customers are identified.

Evaluation

AIT is an easy-to-calculate indicator which can be an important statistic of the customer's activity status, especially for those industries where customers buy on a frequent basis.

5.3.3 Retention and Defection Rate

Retention and defection are like two sides of the same coin. One can be inferred from the other, and, depending on the context, it is better to use one or the other metric. *Retention rate* in period t (Rr_t) is defined as the average likelihood that a customer purchases from the focal firm in a period (t), given that this customer has also purchased in the period before (t − 1). The *defection rate* is defined as the average likelihood that a customer defects from the focal firm in a period (t), given that the customer was purchasing up to period (t − 1).

$$Rr_t(\%) = 100 \times \left(\frac{\begin{array}{l}\#\,of\ customers\ in\\ cohort\ buying\ in\ (t) \mid \\ customer\ in\ (t-1)\end{array}}{\begin{array}{l}Total\ \#\,of\ customers\ in\\ cohort\ buying\ in\ (t-1)\end{array}} \right) \tag{5.6}$$

The resulting retention rate refers to the average retention rate of a cohort or segment of customers. Theoretically, the retention rate differs for each individual customer but is approximated by the average retention rate of a (homogeneous) customer group or segment. Most of the time, no distinction is made between the (individual level) retention rate and the average retention rate.

Average retention rate and average defection rate are directly related:

$$Rr_t(\%) = 100 - Avg.defection\ rate\ (\%) \tag{5.7}$$

Table 5.2 Example for customer lifetime calculation

Customers starting at the beginning of year 1:	100.00	
Customers remaining at the end of year 1:	75.00	(0.75 × 100)
Customers remaining at the end of year 2:	56.25	(0.75 × 75)
Customers remaining at the end of year 3:	42.18	(0.75 × 56.25)
Customers remaining at the end of year 4:	31.64	(0.75 × 42.18)

Although we use the case of an average retention rate, one has to be aware that retention rates are typically not equal across different periods. For example, if one deals with a single cohort (wherein a cohort refers to a batch of customers acquired within a specified period of time), proportionally fewer customers leave over time, thus forcing the average retention rate (for this cohort) to increase over time. One has to keep this in mind when extrapolating retention rates for one period to an entire time horizon for a cohort of customers.

Assuming that the retention rate is constant over time (i.e., $Rr_t = Rr$ for all t) allows a simple calculation of the average lifetime duration.[1]

$$Avg.life\ time\ duration = \frac{1}{(1 - Rr)} \quad (5.8)$$

How to assess lifetime duration in a more general setting will be discussed in ▶ Sect. 5.3.5.

Example

If the average customer lifetime duration of a group of customers is 4 years, then the average retention rate is 1 – (1/4) = 0.75, or 75% per year. This means that on average, 75% of the customers remain customers in the next period. If we look at the effect for a cohort of customers over time (see Table 5.2) we find that from 100 customers who are acquired in year 1, about 32 remain at the end of year 4.

1 The terms lifetime duration, customer lifetime, and customer tenure are often used interchangeably.

Assuming constant retention rates, the number of retained customers in any arbitrary period $(t + n)$ can simply be calculated using (5.9):

$$\begin{aligned} &\#\ of\ retained\ customers\ in\ period\ (t+n) \\ &= \#\ of\ acquired\ customers\ in \\ &\quad cohort\ at\ time\ (t) \times Rr \end{aligned} \quad (5.9)$$

Where

n = Number of periods elapsed

For the previous example, the number of retained customers at the end of year 4 is $100 \times 0.75^4 = 31.64$. If we plot the entire series of customers who defect each period, we see the variation (or heterogeneity) around the average lifetime duration of 4 years (see Fig. 5.1).

Given an average retention rate of 75% (constant over time), many customers leave in the early years. However, a small number of customers continue to stay for a long duration. This pattern results in average lifetime duration of 4 years.

As already mentioned, the concepts of defection and retention are closely related. Defection rate is calculated as follows:

$$Avg.defection\ rate\ in\ t(\%) = 100 - \mathrm{Rr}_t(\%) \quad (5.10)$$

Example

The average retention rate in the previous example is 75%. Thus, the average defection rate is:

$$100 - 75\% = 25\%.$$

Where Does the Information Come from?

- Internal records and customer tracking (e.g., loyalty card programs or contractual information).

Evaluation

A key assumption of the retention rate concept is that once customers leave the relationship, they are gone forever. The concept of retention rate does not allow for temporary dormancies. Managers have to make a judgment whether the dormancy phenomenon plays a major or a minor role in their business. Using the retention rate is fine if it plays a minor role. If dormancy plays a major role, other concepts have to be used to assess customer activity. These concepts will be dealt with in ▶ Sect. 5.4 and Summary.

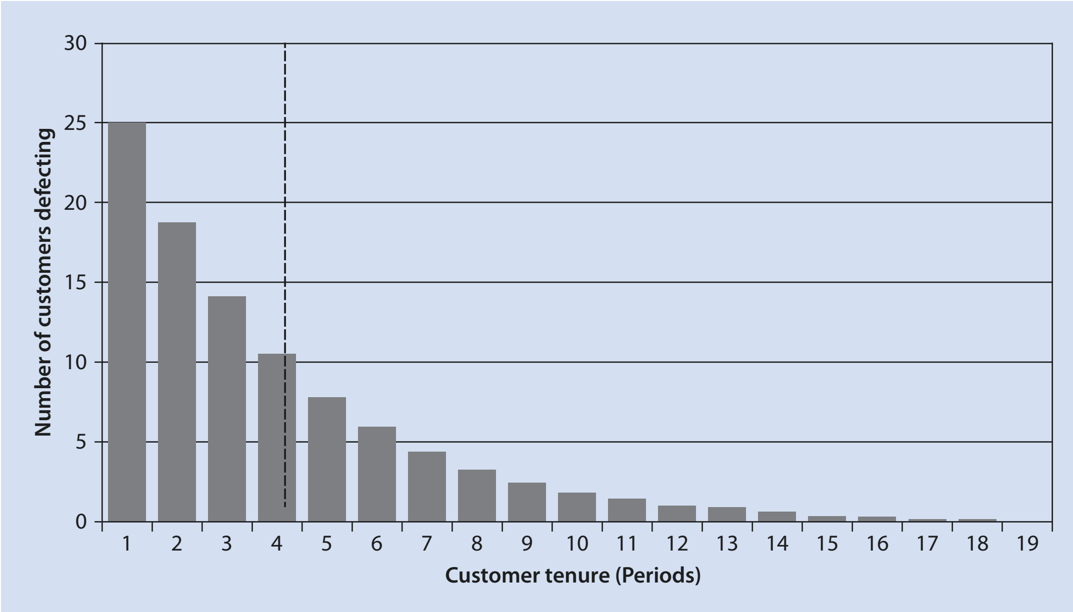


Fig. 5.1 Variation in defection with respect to customer tenure

Is Retention Only about Buying?

Typically, retention refers to the fact that a customer continues to purchase goods or services from the company. This is not always the case.

Take, for example, Google.com. Most of Google's services, such as basic email and Google calendar, or Google docs, are free. Although most of Google's customers do not have any transactions in the traditional sense, one would consider site visits as the critical activity, which then would be used to measure retention for Google. Thus, in the case that the customer-firm relationship is not primarily about monetary transactions, it is important to define an appropriate basis in order to measure retention.

How Is Retention Different from Loyalty?

Retention is *not* the same as customer loyalty. Although retention is measured on a period-by-period basis and indicates whether customers are coming back, the loyalty construct has a much stronger theoretical meaning. If somebody is loyal toward a store or a brand, such as the Apple iPhone, for example, this person has a positive emotional or psychological disposition toward this brand. People might continue to purchase a particular brand or might patronize a particular store, but this may be purely out of convenience or inertia. In this case, someone might be retained, but the person is not loyal (see ▶ Chap. 10).

Projecting Retention Rates

Very often, we find ourselves in a situation where we would like to get an idea about future retention rates of a particular cohort of customers. To do so, we use information on past retention rates to make a prediction of future retention rates. We have already discussed that retention rates tend to increase over time. As short-term customers drop out, the retention rate of the remaining (loyal) customers increases necessarily. This increase, however, is not linear. Almost always, retention rates tend to increase at a decreasing rate.

There is a simple method which allows us to forecast nonlinear retention rates—a simple exponential form. This approach models the retention rate as a function of time.

$$Rr_t = Rc \times \left(1 - e^{-rt}\right) \tag{5.11}$$

Where

Rr_t = predicted retention rate for a given period t in the future

Rc = retention (rate) ceiling

r = coefficient of retention

Rc is defined as the maximum attainable retention rate if unlimited resources were

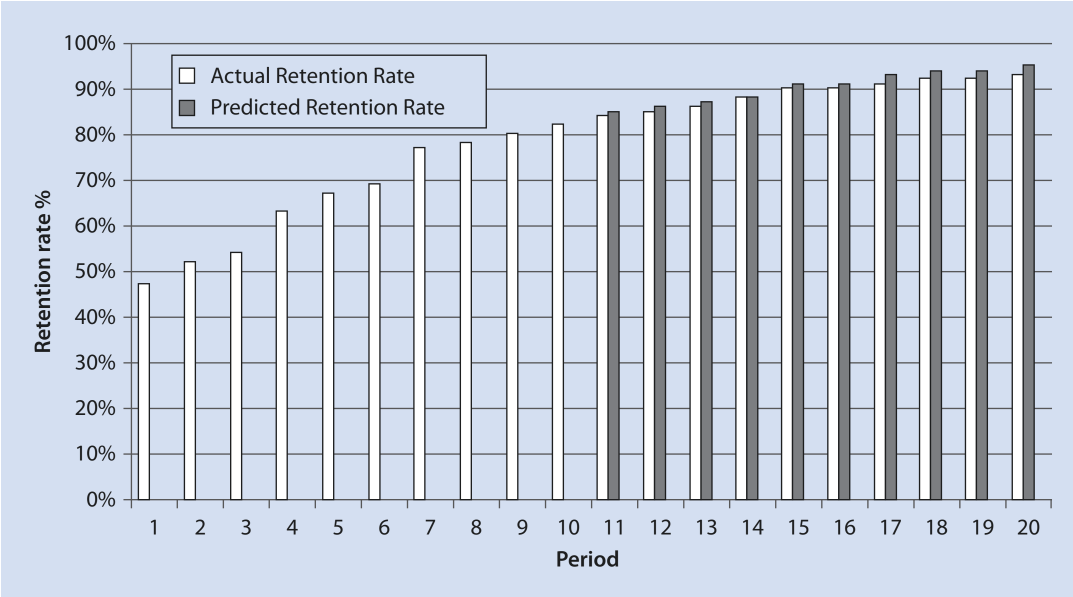


Fig. 5.2 Actual and predicted retention rate for a credit card company

available. Clearly, a firm will not be able to retain all customers even if they spent unlimited advertising on them. Rc is typically estimated through managerial judgment. The parameter r is the coefficient of retention. This parameter determines how quickly retention rates converge over time to the retention ceiling. It can easily be estimated through spreadsheet analysis based on past retention data.

Figure 5.2 shows actual retention rates for a credit card company (white bars). The time horizon is 20 quarters. Equation 5.10 was applied with Rc = 0.95, which means that managers believe that the maximum attainable retention rate is 95%. The parameter r = 0.2 is based on estimates that come from previous observations. Applying (5.10), the retention rates for periods 11–20 were estimated (grey bars). It can be seen that the method to approximate the actual retention rates was very close.

If past estimates of the parameter r are not available, one can use another method. The retention rate Rr_t is observed for a number of past periods. Equation 5.10 can be regrouped to form (5.11):

$$r = \left(\frac{1}{t}\right) \times \left(\ln\left(Rc - Rr_t\right)\right) \tag{5.12}$$

For example, the known retention rate in period 9 is 80%, while the one in period 10 is 82%. Thus, the parameter r for period 9 is (1/9) × (ln(0.95) – ln(0.95–0.8)) = 0.205. The parameter r for period 10 is (1/10) × (ln(0.95) – ln(0.95–0.82)) 0.198. One can see that for both periods the parameter r is fairly close to the value 0.2.

5.3.4 Survival Rate

Another concept closely linked with retention and defection is survival. The survival rate (SR) indicates the proportion of customers who have *survived* (or, in other words, continued to remain as a customer) until a period *t* from the beginning of observing these customers. SR is measured for cohorts of customers, wherein a cohort refers to a group of customers acquired within a specified period of time.

Although retention rate and defection rate provide information for a given period, the SR gives a summary measure of how many customers survived between the start of the formation of a cohort and any point in time afterward. SR at time *t* is equal to the product of the retention rate at time *t* and the SR during the immediately preceding period (*t* – *1*).

$$SR_t\left(\%\right) = 100 \times Rr_t \times SR_{t-1} \tag{5.13}$$

In the initial period, SR_1 is, set to equal the retention rate_1.

5

CRM at Work 5.1

Amazon: Acquisition and Retention

Amazon.com is one of the leaders in implementing customer relationship management programs on the Web and operates with the vision of being the most customer-centric company offering everyone the possibility of discovering anything they might want to buy online. Because of its unique and sophisticated CRM program, the company has constantly been able to drive both customer acquisition and retention. In 1999, 5 years after the company was founded, Amazon acquired 11 million new customers nearly tripling its number of customers from 1998. Amazon has been able to acquire and retain customers at such a high rate by striving to learn about its customers and their needs, then using this information to offer them value-added features. This is done via numerous technological tools enabling the company to learn. But its greatest success in 1998 was not adding customers, but keeping those that it already had. Repeat customers during the year accounted for 71% of all sales. Amazon has since grown its membership numbers every year, especially its Prime members, which topped 63 million in 2016, an increase of 43% from the previous year. Prime members now exceed the number of non-Prime members with 52, and 70% of wealthy American households subscribe to Prime. Amazon also saw notable increases of customer usage with the launch of Prime Day, which boasts deals similar to Black Friday that are only available to Prime members, providing another incentive for customers to sign up for Prime. Prime memberships have been linked to dramatic increases of spending on Amazon, which comes with additional benefits such as music, movie and television streaming, two-day free shipping and easy use mobile purchasing apps.
Source: Blattberg, Getz, and Thomas (2001), Tuttle (2016).

Where Does the Information Come from?

- Similarly to retention rate, information comes from internal records and customer tracking (e.g., loyalty card programs or contractual information).

Evaluation

The SR is of great interest, because one can conveniently calculate the absolute number of survivors in a given period t. One simply multiplies the SR, by the cohort size in the beginning.

Example

Number of customers starting at the beginning of year 1 is 1,000.

Computing the number of survivors:

Number of survivors for period 1 = Survival rate for period$_1$

* Number of customers at the beginning

Therefore,

Number of survivors for period 1 = 0.55 × 1000 = 550

Computing survival rate:

$\text{Survival rate}_t\ (\%) = \text{Retention rate}_t \times \text{Survival rate}_{t-1}$

In Table 5.3:

Table 5.3 Survival rate example

	Retention rate	Survival rate	Survivors
Period 1	0.55	0.55	550
Period 2	0.62	0.341	341
Period 3	0.68	0.231	231
Period 4	0.73	0.169	169

$\text{Survival rate}_2 = \text{Retention rate}_2 \times \text{Survival rate}_1$
$\text{Survival rate}_2 = 0.62 \times 0.55 = 0.341$, or 34.1%

5.3.5 Lifetime Duration

It is sometimes unclear how long a customer has been associated with a firm in a noncontractual setting, since there is no expiration date explicitly stated by the customer. In such situations, it is important to be able to predict the lifetime duration of a customer by observing buying patterns and other explanatory factors. Knowing for how long a customer remains a customer is a key ingredient in the calculation of the *customer lifetime value*—a key strategic metric. Furthermore, it has implications for churn management, customer replacement, and management of lifetime duration drivers.

The calculation of average lifetime duration for the case that the retention rate remains constant over time has already been presented (see ▶ Sect. 5.3.3). But since the retention rate usually changes over time (e.g., through customer self-selection) such a calculation would be misleading. We need to weigh in the number of survived periods. For one cohort of customer the avg. lifetime duration is defines as:

$$\begin{matrix} Avg.lifetime \\ duration \end{matrix} = \frac{\sum_{t=1}^{T} \begin{pmatrix} t \times Number\ of\ retained \\ customers\ in\ t \end{pmatrix}}{N} \tag{5.14}$$

Where

N = cohort size

t = time period

T = time horizon

(t × Number of retained customers in t) represents the number of active customer periods for the cohort at time t

▶ Section 5.3.7 provides a comprehensive example of the calculation.

Limitations

If information is not complete, i.e., either the time of first purchase or the time of last purchase or both are unknown, the calculation of lifetime duration becomes more challenging. The case where either the time of first purchase, or the time of last purchase or both are unknown is illustrated in ◘ Fig. 5.3. The information for buyer 1 is complete. The data for buyer 2 is left-censored, i.e., the start of the relationship is not recorded. Buyer 3's information is right-censored. His relationship continued beyond the end of the observation window. Thus, it is not known to the firm at t_1 how much longer the customer will in fact be a customer. Finally Buyer 4's relationship started before the observation window and ends after the observation window. This observation is called left- and right-censored. Data that consists of right-censored observations require the use of survival analysis techniques (e.g., retention rate, P(Alive)).

Where Does the Information Come from?

- Similarly to retention and SR, information comes from internal records and customer tracking (e.g., loyalty card programs or contractual information)

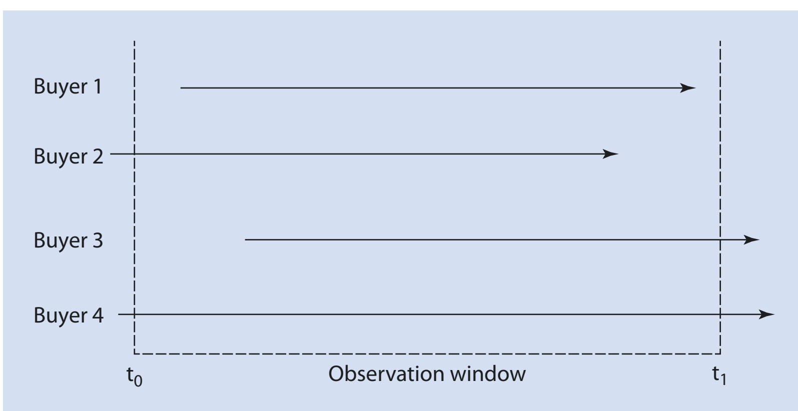
Evaluation

The average lifetime duration of a cohort of customers gives an indication of how fast the company needs to replace its customer base. When talking about the concept of a customer's lifetime duration, not all relationships are equal. We must take the type of product, which is subject to exchange into account. Here, we are specifying the following three cases:

1. Contractual
2. Noncontractual (or always-a-share)
3. One-off purchases

Contractual Relationships

Contractual relationships are those where buyers engage in a specific commitment. This commitment may foresee duration and/or level of usage. A contractual relationship that defines length and level of usage is, for example, an apartment rental lease or a magazine subscription. A contractual relationship, which defines only length, is, for example, a mobile phone contract. Finally, a contractual relationship



◘ **Fig. 5.3** Customer lifetime duration when the information is incomplete

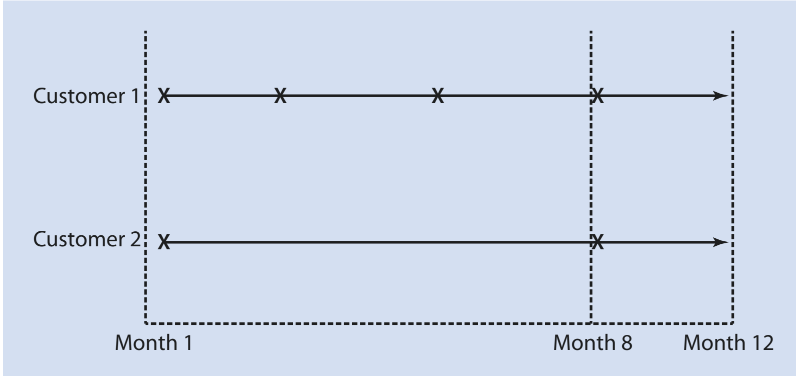


Fig. 5.4 Sample purchase patterns of two customers for the estimation of P(Active)

5

which defines neither length nor usage level is a credit card. This category has also been labeled *lost-for-good* because a company loses the entire customer relationship once a client terminates the contract.

Noncontractual Relationships

Noncontractual relationships are those where buyers do not commit in any way, either in duration or level of usage. Purchasing an item at a department store, or with an airline, are examples. Since customers may use several suppliers at any given time (e.g., go to several different supermarkets), this category has been labeled *always-a-share*.

One-Off Purchases

In case of One-off purchases there is no need to talk about a relationship between the exchange partners since it involves a once in a lifetime buy, such as a yacht or a vacation house.

5.3.6 P(Active)

In a noncontractual case, given a particular customer, it may be useful to know whether the customer is likely to transact in a particular time period. In other words we would like to know the probability of that customer being active in time *t*, P(Active). A simple approach for computing the probability of being active, P(Active), is via the following formula (Schmittlein & Morrison, 1985):

$$P(Active) = \tau^{n} \quad (5.15)$$

Where

n = the number of purchases in a given period

τ = the time of the last purchase (expressed as a fraction of the observation period)

Example

To compute the P(Active) of each of the two customers in the twelfth month of activity, where customer A bought four times within the first 8 out of the observed 12 months and customer B bought only two times within the first 8 out of the last 12 months (see Fig. 5.4).

Thus for Customer A: $\tau_A = (8/12) = 0.6667$ and $n_A = 4$

$P(Active)_A = (0.6667)^4 = 0.197$

And for Customer B: $\tau_B = (8/12) = 0.6667$ and $n_B = 2$

$P(Active)_B = (0.6667)^2 = 0.444$

It is interesting to observe that a customer who has bought four times in the first 8 months but has not bought in the last 4 months has a lower probability of buying in the 12 month over a customer who has bought only twice in the same window of 8 months. This is due to the assumption that customers do not change the frequency of buying. For an advanced application of further methods of calculating P(Active) see Reinartz and Kumar (2000, 2002).

Where Does the Information Come from?

- Information comes from customer tracking, e.g., loyalty card programs.

Evaluation

The probability of a customer being active in time t is a function of the duration since the last purchase and applicable in non-contractual cases. When calculating P(Active) it is assumed that customers pertain to their usual purchase patterns with respect to the frequency of buying.

Table 5.4 Actual retention pattern of a direct marketing firm

1	2	3	4	5	6	7
Period since acquisition	Actual retention rate (%)	Predicted retention rate (%)	Defection rate (%)	Survival rate (%)	Expected number of active customers	Number of active customer periods
1	32.0		68.0	32.0	2,400	2,400
2	49.1		50.9	15.7	1,178	2,357
3	63.2		36.8	9.9	745	2,234
4	69.0		31.0	6.9	514	2,056
5	72.6		27.4	5.0	373	1,865
6	76.7		23.3	3.8	286	1,717
7	77.9		22.1	3.0	223	1,560
8	78.5		21.5	2.3	175	1,400
9	79.0		21.0	1.8	138	1,244
10	80.0		20.0	1.5	111	1,106
11		79.7	20.3	1.2	88	969
12		79.8	20.2	0.9	70	844
13		79.9	20.1	0.7	56	730
14		79.9	20.1	0.6	45	628
15		80.0	20.0	0.5	36	538

5.3.7 Comprehensive Example of Customer Activity Measures

Looking at an actual retention pattern of a direct marketing firm, we want to illustrate the concepts of retention rate, defection rate, SR, and lifetime duration. A cohort of 7500 customers was acquired at the outset of the analysis. Table 5.4 shows the actual retention pattern for ten periods in column 2. For example, after period 1, only 32% of the customers are retained into the second period. Thus, this company has a rather high defection rate. If we are at the end of period 10 and want to make an assessment of future retention rates, we need to make a customer activity forecast.

Column 3 shows the predicted retention pattern, based on (5.11) (p. 13). The underlying retention rate ceiling (Rc) for the example is 0.80, and the coefficient of retention (r) is 0.5 (estimated from past company data). Thus, retention rates approximate the maximum rate already at period 10. This means that after period 10, the company retains approximately 80% of its customer base from period to period. The defection rate in column 4 is simply calculated as (1 − retention rate). Finally, the SR, calculated with (5.12), indicates the proportion of the original cohort that survives until period *t*. For example, only 1.2% of the original cohort survives until period 11. If the SR is multiplied by the original cohort size—in this case, 7,500—we obtain the number of customers surviving up to period *t* (column 6).

Another important measure which can be derived from the information is that of lifetime duration. A simple approach (as illustrated in (5.8), p. 11) would be to calculate the mean lifetime duration from the average retention rate. The average retention rate across the 15 periods (column 2 and 3) is 71.8%, which results in an average lifetime duration of 3.54 periods. Since the retention rates change over time, we would have to compute an appropriate measure of average retention in order to compute average lifetime duration. More specifically, since many more customers are subject to a lower retention rate in the early periods as compared to higher retention rates in later periods, using a simple average of retention rates 1–15 would be misleading. In the computation of an average retention rate, the number of survived periods needs to be weighed accordingly (see (5.14), p. 17). The result of the weighing process is shown in column 7. Intuitively, it is the number of active customer periods for every period. For example, at the end of period 1 we have 2,400 (2,400 customers × 1 period) active periods, at the end of period 2 we have 2,357 (1,178 customers × 2 periods) active periods, and so on. If we add all active periods 1–15 and divide by the initial cohort size of 7,500, the average lifetime duration is 2.89 periods (=21,648/7,500). Thus, the company needs to replace its customer base every 3 periods, and not every 3.5 periods, as indicated before.

5.4 Popular Customer-Based Value Metrics

Firms have adopted some popular surrogate measures of customer value which they anticipate to be reasonable indicators of the actual customer value. These metrics assist firms in prioritizing their customers in a manner that helps them assign a higher proportion of resources to the customers who they expect will generate greater profits in the future. We suggest managers attempt to correlate these surrogate measures on a selective basis with more rigorous customer value metrics. Only if these correlations yield satisfactory results (i.e., correlations are substantial) can and should the surrogate measures be used for decision making.

5.4.1 Size of Wallet

Size of wallet is the amount of a buyer's total spending in a given category—or, stated differently, the category sales of all firms to that customer. The size of wallet is measured in monetary terms.

$$Size\ of\ wallet\ (\$)\ of\ customer\ i\ in\ a\ category = \sum_{j=1}^{J} S_{ij} \tag{5.16}$$

Where

i = a particular customer

j = firm

J = all firms offering products in the considered category

S_{ij} = sales value (in category) to customer i by firm j, j = 1, …, J

Example

A consumer might spend an average of $400 every month on groceries, across several supermarkets. Thus, her size of wallet is $400.

Where Does the Information Come from?

Information about the size of wallet can be gathered in many ways. For existing customers, the information can be collected through primary market research (e.g., surveys). A typical question a firm might ask is, «On average, how much do you spend every month on category A?» For prospects, it is quite difficult to obtain the size-of-wallet information on an individual level. Instead, segment-level information is often used.

Evaluation

Size of wallet is a critical measure of the customer-centric organization. When firms attempt to establish and maintain profitable relationships, the customer's buying potential (i.e., size of wallet) is a critical piece of information. Firms are particularly interested in acquiring and retaining customers with large wallet sizes. The assumption firms make here is that large wallet customers will bring in more revenues and profits.

5.4.2 Share of Category Requirement

Share of Category Requirement (SCR) is defined as the proportion of category *volume* accounted for by a brand or focal firm within its base of buyers. This metric is often computed as an aggregate level metric, when individual purchase data are unavailable.

On an aggregate level the SCR is calculated as follows:

$$aSCR\ (\%)\ of\ firm\ (or\ brand)\ j_0\ in\ a\ category = \frac{\sum_{i=1}^{I} V_{ij_0}}{\sum_{i=1}^{I}\sum_{j=1}^{J} V_{ij}} \times 100 \tag{5.17}$$

Where
j_0 = focal firm or brand
i = customer
I = all customers buying in focal category
J = all firms or brands available in focal category
V_{ij} = purchase volume of customer i from firm (or brand) j

Example

In this example, there are three customers in the category. The category consists of three brands—SAMA, SOMO, and SUMU. Table 5.5 shows the number of purchases during a 3-month period.

The category volume in the 3-month period is 24 units. Brand SAMA has a MS of 33% (i.e., 8 purchases out of a total of 24) and an aSCR of 42.1% (i.e., 8 purchases out of 19, made by its two buyers). This example shows that even though SAMA's MS is already substantial, its aSCR is even higher. The high aSCR for SAMA indicates that once consumers have purchased this brand, they tend to prefer it disproportionately more than its two competitors.

Table 5.5 Calculation of aSCR—purchases during a 3-month period

	Brand SAMA	Brand SOMO	Brand SUMU	Total
Customer 1	2	8	0	10
Customer 2	6	0	3	9
Customer 3	0	4	1	5
Total	8	12	4	24

The aSCR ratio is sometimes calculated simply by using purchase occasions or product units as the unit of analysis. The computation discussed here is for the aggregated case. aSCR can also be calculated for individual customers.

Individual Share of Category Requirement (iSCR)

At the individual level, when such data are available, iSCR is computed by dividing the volume of sales (V) of the focal firm to a particular customer by the total category volume she buys. The metric thus indicates how much of the category requirements the focal firm satisfies of an individual customer.

$$iSCR\ (\%)\ of\ customer\ i_0\ that\ firm\ \times$$
$$(or\ brand)\ j_0\ satisfies = \frac{V_{i_0 j_0}}{\sum_{j=1}^{J} V_{i_0 j}} \times 100 \quad (5.18)$$

Where
j_0 = focal firm or brand
i_0 = focal customer
J = all firms or brands available in focal category
V_{ij} = purchase volume of customer i from firm (or brand) j

Example

Suppose a computer manufacturer, say PEAR Computers, has collected the following data about its annual customer purchases on Notebook Computers for the year 2010. Using Table 5.6, it can compute the iSCR ratio for each of its customers and identify those customers who have a higher iSCR ratio from those with a lower iSCR ratio. From Table 5.6, we can see that customer 3 has the highest iSCR. PEAR Computers should

Table 5.6 Individual SCR-ratios

	A	B	B/A
	Total requirement of notebook computers per customer in 2010	Total number of notebook computers purchased from PEAR computers per customer in 2010	iSCR for PEAR computers per customer in 2010 (%)
Customer 1	100	20	0.20
Customer 2	1,000	200	0.20
Customer 3	2,000	500	0.25

5

identify high iSCR customers such as customer 3, and target more of its marketing efforts (mailers, advertisements, etc.) toward such customers and their respective requirements. In addition, customer 3's size of wallet (column A) is the largest, making her even more attractive.

Where Does the Information Come from?

- **Numerator:** Volumetric sales of the focal firm are readily available from internal records.
- **Denominator:** The total volumetric purchases of the focal firm's buyer base are typically obtained through market and distribution panels, which are quite common for certain industries (e.g., fast-moving consumer goods [FMCG]). Other industries use mainly primary market research (surveys). Since this information is costly to gather, it is typically collected for a representative sample and then extrapolated to the entire buyer base. Qualitative managerial judgment is another potential low-cost alternative.

Evaluation

The aggregate level SCR (aSCR) is a general indicator of loyalty for a specific firm (or brand), whereas the individual level SCR (iSCR) is a measure of the importance of a particular firm (or brand) for a single customer. SCR is one of the most commonly accepted measures of customer loyalty, at least for FMCG categories. It separates the question, «whether anyone buys the brand» from the question, «how much they buy.» An important characteristic of this measure is that it controls for the total volume of the segments/individuals category requirements. In other words, regardless of the total value of purchases per period, in terms of percentage of allocated purchases (loyalty), it puts all customers on the same metric. However, this metric does not necessarily indicate whether a high iSCR customer will generate substantial revenues or profits—this is only achieved by knowing something about the size of wallet of this customer.

5.4.3 Share of Wallet

Share of Wallet (SW) is defined as the proportion of category value accounted for by a focal brand or a focal firm within its base of buyers. It can be measured at the individual customer level or at an aggregate level (e.g., segment level or entire customer base).

Individual Share of Wallet (iSW)

Individual Share of Wallet (iSW) is defined as the proportion of category value accounted for by a focal brand or a focal firm for a buyer from all brands she purchases in that category. It indicates the degree to which a customer satisfies her needs in the category with a focal brand or firm. It is computed by dividing the value of sales (S) of the focal firm ($j0$) to a buyer i in a category by the size of wallet of the same customer in a predefined time period.

$$iSW\ (\%)\ of\ \ firm\ \ j_0\ \ to\ \ customer\ \ i = \frac{S_{ij_0}}{\sum_{j=1}^{J} S_{ij}} \times 100 \qquad \textbf{(5.19)}$$

Where
j = firm
i = customer
S_{ij} = sales of firm j to customer i
J = see below

Example

If a consumer spends \$400 monthly on groceries, and \$300 of her purchases are with the supermarket Publix, then Publix's iSW for that consumer is 75% in that month.

Aggregate Share of Wallet (aSW) (Brand or Firm Level)

Aggregate share of wallet (aSW) is defined as the proportion of category *value* accounted for by a focal brand or a focal firm *within its entire base of buyers*. It indicates the degree to which the customers of a focal firm satisfy their needs on average, in a category with a focal firm.

$$aSW\,(\%)\ of\ \ firm\ \ j_0 = \frac{\sum_{i=1}^{I} S_{ij_0}}{\sum_{j=1}^{J}\sum_{i=1}^{I} S_{ij}} \times 100 \qquad \textbf{(5.20)}$$

Where
i = customer
j = firm
I = all customers
J = all firms who offer the category under consideration
S_{ij} = sales (value) of firm j to customer i

Example (Continued)

Publix may calculate its aSW, using (5.20). The aSW is Publix's sales (value) in period t ($750,000) divided by the total grocery expenditures of Publix's customers in the same period ($1,250,000); thus, 750,000/1,250,000 = 60%.

Where Does the Information Come from?

- **Numerator:** Typically, sales information comes from internal records. In case of the iSW that information has to be available on the individual customer level.
- **Denominator:** Sales value across all firms comes from primary market research (surveys), administered to individual customers. Since this information is costly to gather, it is often collected for a representative sample and then extrapolated to the entire buyer base. Sometimes, firms can infer the size, of wallet for a certain product, especially in certain business-to-business (B-to-B) contexts. For example, BASF, one of the few manufacturers of car paint, supplies its product to Mercedes-Benz. Based on its knowledge of how much paint it takes to paint an average sized car, it can infer Mercedes-Benz's size of wallet for car paint based on its worldwide production output—a figure easily derived from secondary sources.

Evaluation

Just like SCR, SW is a measure of customer loyalty and can be an important metric. The main difference is the focus on sales volume (SCR) and the focus on sales value (SW). The iSW sheds light on how important the firm is for an individual customer in terms of his expenditures in the category. The aSW indicates how important (value wise) a specific firm is for its customer base in terms of their expenditures in the category. However, SW is unable to provide a clear indication of future revenues and profits that can be expected from a customer.

When to Use SCR and When to Use SW

Information on SW is slightly more difficult to obtain than for SCR. SCR is, in most cases, the preferred measure. This is particularly true for categories where the variance of customer expenditures is relatively small (groceries, for example). If purchases are similar in volume, a customer's lifetime value is primarily driven by his frequency of purchases. Thus, SCR is a fairly appropriate measure of loyalty. However, if the variance of consumer expenditures is relatively high (furniture, cars, or other infrequent purchases), then SW is a better measure of loyalty than SCR. In the former case, the frequency is more easily remembered. In the latter case, the customer more easily remembers the expenditures.

Table 5.7 Share of wallet and size of wallet

	Individual share of wallet (%)	Individual size of wallet ($)	Absolute expenses with firm ($)
Buyer 1	50	400	200
Buyer 2	50	50	25

Share of Wallet and Size of Wallet Hold Important Pieces of Information

Even though two buyers might have the same SW, firms might find their attractiveness as customers to be different as illustrated in Table 5.7.

Depending on the size of wallet, the absolute attractiveness of buyer 1 is eight times higher, even though the SW is the same as for buyer 2. The example shows it is always important to consider SW and size of wallet simultaneously.

The matrix presented in Fig. 5.5 illustrates this and shows the recommended strategies for the various segments. The firm makes optimal resource allocation decisions only by segmenting the customers along both dimensions simultaneously.

Difference of Share of Wallet to Market Share

It is important to recognize the difference between market share (MS) and share of wallet (SW). MS is calculated across buyers and non-buyers, whereas SW is calculated *only among actual buyers.* The MS of a firm is the SW across all its customers in the category divided by the sales across all firms in the category in period *t.*

$$MS\ of firm\ j_0(\%) = \frac{\sum_{i=1}^{I}(iSW\ of\ customer\ i\ to\ firm\ j_0 \times Size\ of\ Wallet\ of\ customer\ i)}{\sum_{i=1}^{I}\sum_{j=1}^{J} S_{ij}} \times 100 \quad (5.21)$$

5

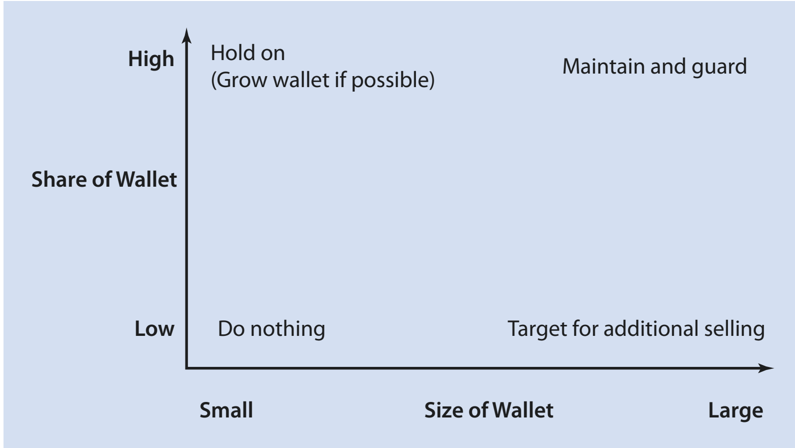


Fig. 5.5 Segmenting customers along share of wallet and size of wallet

Where
- i = customer
- j = firm
- I = all buyers of the category
- J = all firms offering the category
- S_{ij} = sales of company j to customer i

Example (Continued)
If Publix has 5,000 customers with an average expense at Publix of $150 per month (SW times size of wallet), and the total grocery sales in Publix's trade area are $5,000,000 per month, then Publix's MS is (5,000 × $150)/$5,000,000 = 0.15, or 15%. The implication here is that although Publix has an overall low MS, it has a high SW for those consumers buying at Publix. This indicates that Publix is a niche player with a very loyal clientele.

5.4.4 Transition Matrix

All of the previously discussed metrics describe only the current state and make no prediction about the future development. A simple idea to forecast SCR or SW is to use a transition matrix. A transition matrix is a convenient way to characterize a customer's likelihood to buy over time or a brand's likelihood to be bought. The assumption is that a customer moves over her lifetime through various stages of activity. Table 5.8 shows such a transition matrix.

In Table 5.8, the top row indicates the movements for customers who are currently brand A buyers; 70% of them will buy brand A next time, 20% will buy brand B, and 10% will buy brand C. The diagonals (in bold) are customer-retention probabilities computed by the company. However, we see that consumers can switch back and forth from brands. For example, the probability that a consumer of brand A will transition to brand B and then come back to brand A in the next two purchase occasions is 20 * 10% = 2%. If, on average, a customer purchases twice per period, the two purchases could be AA, AB, AC, BA, BB, BC, CA, CB, or CC. We can compute the probability of each of these outcomes. This process can be continued for as many purchase occasions as desired. Information for the matrix may come from routine surveys, with questions such as, «Which hotel did you stay in last time?» or «The next time you stay in a hotel, what is the probability that you will stay at each of the hotels that you consider as options?»

Table 5.8 Transition matrix

		Brand purchased next time		
		A (%)	B (%)	C (%)
Brand currently purchased	A	**70**	20	10
	B	10	**80**	10
	C	25	15	**60**

Source: Rust, Zeithaml, and Lemon (2000)
Note: Customer retention probabilities are in bold

Minicase 5.1

Catalina is Changing Supermarket Shopper Measure ment

Catalina Inc. is a Florida-based company specializing in supermarket shopper tracking and coupon issuing. The company has about 1,200 employees and operates in the United States, as well as in major European countries. The company built its business model on issuing coupons to grocery shoppers online when they check out. The basis for this business model is that traditional print media has long production lead times, and the response to these media is not measurable on the individual customer level. Thus, supermarkets and manufacturers cannot run and track individualized campaigns with traditional media. Catalina's system consists of a printer connected to the cashier's scanner and a database. The information on each shopping basket that checks out via the scanner is then stored in the database. Using the person's credit card number or check number, the database links individual shopping baskets over time. If the person pays cash, the system cannot link the basket. The system then allows both manufacturers and retailers to run individualized campaigns based on the information in the database. For example, Catalina could partner with the retailer to improve its cross-selling. A typical issue for any given retailer is that certain customers use the store as their primary shopping location, whereas others use it as their secondary store. To improve the SW with the latter group of customers, Catalina first investigates basket composition of the various buyers. It then finds that certain buyers buy, for example baby or children products (thus, there is apparently a family behind this shopping bask), yet the number of calories in that basket does not match that of an average family. One explanation for this might be that this shopper uses this outlet as a secondary store. Given this interpretation, the decision then is to allocate to this customer a gift of say $10, for shopping for 4 weeks in a row spending at least $40 per week in the store. The goal is to selectively target those shoppers of whom the store captures only a low SW, and to entice them to change their behavior.

Questions on Minicase 5.1

1. Explain whether Catalina's approach to storing customer buyer information and using it to target shoppers who visit the store as a secondary location is a good business practice. Do you think this helps the store build customer retention?
2. Discuss the role of traditional metrics (such as market share) in this new CRM environment. Should they be discarded?
3. Do you think Catalina's legal practice of targeting shoppers based on past buying behaviors is ethically acceptable? Discuss from the perspective of both, the customer and the store owner.

Summary

Since customer value management involves allocating resources differently for individual customers based on their economic value, understanding value contribution from each of the customers to the firm is very important. In the absence of individual customer data, companies have relied on traditional marketing metrics such as market share and sales growth. Market share (MS) is defined as the share of a firm's sales relative to the sales of all firms—across all customers in the given market. It only gives an aggregate notion of category performance, but does not give any information about how the sales are distributed among customers. Sales growth provides a relative measure of performance but fails to indicate which customers contributed more and which contributed less.

The availability of customer-level data helps firms utilize a new set of metrics which enables the assignment of value to each individual customer. These so-called primary customer-based metrics can be subdivided into customer acquisition metrics and customer activity metrics. Customer acquisition metrics measure the customer level success of marketing efforts to acquire new customers. Two important metrics are the acquisition rate and acquisition cost (AC). Acquisition rate is the proportion of prospects converted to customers, and acquisition cost is the campaign spending per acquired customer. Customer activity metrics, by contrast, serve to track customer activities after

5

the acquisition stage. Some critical customer activity metrics are average inter-purchase time (AIT), retention rate, survival rate (SR), customer lifetime duration, and probability of a customer being active, P(Active). These are important inputs for the calculation of customer value and for aligning resource allocation with customers' behavior. AIT is defined as the average time elapsed between purchases. The retention rate is the average likelihood a customer purchases from the focal firm in a period (t), given this customer has purchased in the last period (t – 1). The defection rate expresses the average likelihood a customer defects from the focal firm in a period (t), given the customer was purchasing up to period (t – 1). The survival rate (SR) is another preliminary customer metric, and indicates the proportion of customers that have «survived» (or, in other words, continued to remain as a customer) until a period t from the beginning of the relationship with these customers. SR is closely linked with retention rate. SR is a summary measure of how many customers survived between the start of the formation of a cohort and any point in time afterward, while retention rate reflects retention in a given period only. The SR can be measured as the product of the retention rate at time t and the SR during the immediately preceding period (t – 1). Lifetime duration is a key strategic metric in the calculation of the customer lifetime value. The calculation of lifetime duration is different in contractual and noncontractual situations. In a contractual case, this is the time from the start of the relationship until the end of the relationship. However, in a noncontractual situation, firms are interested in the likelihood the customer is active at a given point in time. If the likelihood is below a threshold value, the customer is considered inactive. An estimation of whether a customer is active is given by P(Active). A simple formula for P(Active) is P(Active) = T^n, where n is the number of purchases in a given period and T is the time of the last purchase expressed as a fraction of the observation period.

Firms use different surrogate measures of customer value to prioritize their customers and to differentially invest in them. Popular customer-based metrics comprise size of wallet, share of category requirement, and share of wallet. Size of wallet is the buyer's total spending in a category and usually firms are interested in acquiring and retaining customers with large wallet sizes. (Aggregate) Share of category requirement (aSCR) is an aggregate level measure of the proportion of the category volume accounted for by a brand or a focal firm. SCR is one of the most commonly accepted measures of customer loyalty for FMCG categories. On an individual level the iSCR indicates how much of the category requirement of an individual a firm satisfies. Although this is an overall indicator of customer loyalty, it does not necessarily indicate whether a high iSCR customer will generate substantial revenues or profits, for which the knowledge about the customer's size of wallet is necessary. Share of wallet (SW) is the proportion of category value accounted for by a focal brand or firm within its base of buyers. At an individual level, iSW is defined as the proportion of category value accounted for by a focal brand or firm for a buyer. It indicates the degree to which a customer satisfies her needs in the category with a focal brand or firm. Firms can use the information about size of wallet and share of wallet together for optimal allocation of resources. To forecast the SCR or SW a transition matrix can be used. The transition matrix provides us with the probability a customer will purchase a particular brand if we know which brand she purchased previously.

? International Perspectives: Did You Know?

1. Idea Cellular, a leading mobile phone operator in India, measures the quality of their subscribers against three key metrics – how active are the subscribers (as reflected by the Visitor Location Register (VLR) database maintained by the Telecom Regulatory Authority of India), how many users prefer Idea Cellular over competition, and the average revenue per user (ARPU) from its subscriber base (Idea Cellular, 2015).

2. Daisy Group, a B2B IT and telecommunications service provider in the UK, uses predictive analytics that has gone past the traditional loyalty card to manage customer experiences. By integrating text analytics and other customer information, the company is able to manage customer experiences and loyalty on a «virtual» space, rather than at the loyalty card level. Further, by observing the behavioral patterns of customers, the company is able to identify potential churn behavior and actively manage save the valuable customers from leaving (Fisher, 2016).

Exercise Questions

1. How would you calculate the retention rate of your company's customer base? What assumptions do you need to make?
2. How will you calculate the acquisition cost per customer? Consider a retail store. What are the underlying assumptions? How precise are your calculations?
3. Try to predict retention rates using (5.13).
4. Explain the difference between contractual, noncontractual and one-off purchases and why the distinctions are important for companies.
5. How will you determine if a customer is still your customer in noncontractual settings? What specifically would you need to know?
6. How would you implement the recommended strategies in Fig. 5.5? What are some specific marketing actions you would take in the four quadrants?

Appendix I Notation Key

Notation	Explanation
a	Coefficient of acquisition
AC	Acquisition costs
ACS	Acquisition costs savings
Ar	Acquisition rate
c	Category
CE	Customer equity
Dr	Defection rate
GC	Gross contribution
i	Individual customer
I	Total number of buyers with a focal firm
j	Firm
J	Total number of firms in a market
LTV	Lifetime value
MC	Marketing costs
n	Customer in cohort
N	Cohort size
r	Coefficient of retention
Rr	Retention rate
Rr_c	Retention rate ceiling
S	Sales (value)
Sr	Survival rate
t	Time period
T	Length of time horizon
V	Sales (volume)
δ	Applicable discount rate

References

Blattberg, R. C., Getz, G., & Thomas, J. S. (2001). *Customer equity: Building and managing relationships as valuable assets*. Cambridge, MA: Harvard Business School Press.

Fisher, L. (2016, May 6). The future of customer loyalty is card free. *Marketing Week*. 2016. https://www.marketingweek.com/2016/05/04/the-future-of-customer-loyalty-is-card-free/. Accessed March 24, 2017.

Idea Cellular. (2015). Quarterly Report – Fourth Quarter Ended March 31, 2015. *Idea Cellular Limited*. https://www.ideacellular.com/wps/wcm/connect/7e8ce8c2-4dce-4417-b41b-099911c87fbc/QR_Q4FY15.pdf?MOD=AJPERES&CACHEID=7e8ce8c2-4dce-4417-b41b-099911c87fbc. Accessed March 24, 2017.

Reinartz, W., & Kumar, V. (2000). On the profitability of long-life customers in a noncontractual setting: An empirical investigation and implications for marketing. *Journal of Marketing, 64*(4), 17–35.

Reinartz, W., & Kumar, V. (2002). The mismanagement of customer loyalty. *Harvard Business Review, 80*(7), 4–12.

Rust, R. T., Zeithaml, V. A., & Lemon, K. N. (2000). *Driving customer equity*. New York: The Free Press.

Schmittlein, D. C., & Morrison, D. G. (1985). Is the customer still active? *The American Statistician, 39*(4), 291–295.

Tuttle, B. (2016, July 12). Why Amazon Prime is Pretty Much Already Unstoppable. *Time*. http://time.com/money/4402876/amazon-prime-powerful-retail-force/. Accessed April 4, 2017.