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Marketing Models for the Customer-Centric Firm

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Abstract

A customer-centric firm takes the view that there are three key drivers of (organic) growth and overall profitability: Customer acquisition, customer retention, and customer development (i.e., increasing the value of each existing customer (per unit of time) while they remain a customer). In this chapter we review the key data-based tools and methods that have been developed by marketing scientists (and researchers and practitioners in related fields such as operations research, statistics, and computer science) to assist firms in their understanding and implementing these activities more effectively.

1 Introduction

The past two decades have seen marketing academics and practitioners move from a product-centric, transaction-focused view of marketing towards one that is more customer-centric and relationship-oriented in nature (e.g., Fader 2012, Galbraith 2005, Hoekstra et al. 1999, Lamberti 2013, Ravi and Sun 2016, Seybold et al. 2001). With such a mindset, a firm's customers are viewed as (intangible) assets that generate cash flow not just this period but in future periods as well (Blattberg et al. 2001, Gupta and Lehmann 2005).

While all firms care about their customers, there are several factors that clearly distinguish those that are truly "customer-centric" from those that are merely "customer-oriented." A genuinely customer-centric firm (i) has the ability to track individual customers over time (and across channels) and seeks to calculate forward-looking metrics (e.g., customer lifetime value, hereafter CLV) at a granular level, (ii) seeks to identify the high CLV customers and sees them as a "growth engine" for the enterprise (in the same way that a product-centric firm views its best products in such a manner), and (iii) sees its product development efforts as a "means to an end," i.e., to elevate the value of its customers (and attract valuable new ones), instead of seeing it as "an end unto itself."

With this characterization in mind, a customer-centric firm takes the view that there are three key drivers of (organic) growth and overall profitability: Customer acquisition, customer retention, and customer development (i.e., increasing the value of each existing customer (per unit of time) while they remain a customer).[1] In order to make informed decisions in these three key areas, the firm must have access to rich customer-level data from both internal and external sources,[2] along with the capabilities to analyze these data. At the heart of this is a database (or collection of databases) that tracks customers' purchases and their interactions with the firm (Imhoff et al. 2001).

By the very nature of their operations, mail-order catalog companies, along with firms that have a contractual/subscription-based business model (such as many magazine publishers and financial services firms), have been in a position to build customer-level databases from the beginning of their operations. Historically, the challenge faced by all such firms was the cost of collecting, storing, and processing this customer data. (See, for example, Howard's (1978) description of operations at Sears, Roebuck and Company in the late 1950s.) Starting in the 1960s, the ever-increasing power and ever-decreasing cost of computing resources meant that more and more firms could collect customer data, with the more innovative firms developing analytical tools that would help them improve the performance of their marketing activities. (See Petrison et al. (1997) for an historical review of direct and database marketing.)

In this chapter we review the key data-based tools and methods that have been developed by marketing scientists (and researchers and practitioners in related fields such as operations research, statistics, and computer science) to assist firms in their customer acquisition, retention, and development activities. We start by reviewing the work on customer acquisition (Section 2).

[1]There are other ways of expressing this basic idea. For example, instead of talking about retention and development, Bolton et al. (2004) talk of the length, depth, and breadth of the relationship between a customer and a service provider, where "the depth of a relationship is reflected in the frequency of service usage over time [... and ...] in customers' decisions to upgrade and purchase premium (higher margin) products instead of low-cost variants [, ... and ...] the breadth of a relationship is reflected in cross-buying or 'add-on' buying; that is, the number of additional (different) products or services purchased" (p. 273).

[2]See Deighton and Johnson (2013) for an examination of the complex network of firms that collect and use data about individuals for marketing purposes.

While the literature focusing on customer acquisition is, understandably, quite distinct from that which focuses on creating/extracting value from existing customers (i.e., retention and development), it is much harder to cleanly separate papers that focus on retention from those primarily centered on development issues. The overlap (or, perhaps, lack of clarity) in our literature reflects a similar pattern in practice: while some businesses clearly distinguish between their customer retention and customer development-related marketing activities, these efforts are deeply (and inextricably) intertwined for most others. As a result, we do not offer separate coverage of retention and development issues. Rather, we discuss the various models that have been developed to guide decisions concerning the overall management of acquired customers, encompassing the length, depth, and breadth of their relationship with the firm (Section 3).

We then briefly consider work on the coordination of acquisition and retention activities (Section 4), and conclude with a brief discussion of key areas that warrant the attention of researchers interested in developing marketing models for the customer-centric firm (Section 5).

2 Customer Acquisition

Despite its obvious importance, and with the obvious exception of work in the traditional direct mail and database marketing literature, "there is very little research on acquisition marketing. The traditional marketing literature does not separate the issue of acquiring customers from retaining customers. Positioning, segmentation, targeting is a generic concept. Research in advertising studies the general impact of communications but does not separate newly acquired customers from retained customers" (Blattberg et al. 2008, p. 514). Many papers that at first glance appear to have a customer acquisition focus are actually "acquiring" customers for the *product*, which is not the same as acquiring customers for the *firm*.[3] For example, in Schwartz et al.'s (2016) work on optimizing the design of an online display advertising campaign using multi-armed bandit experiments, a customer is "acquired" if they open an account having clicked on the display advertisement; no distinction is made between those account openers who are first-time customers of the bank versus those who already have an account with the bank. The work on generating new product trial and the vast majority of the work on the adoption/diffusion of innovations is similarly product-centric. (This is not to say that these models are of no value to the customer-centric firm wanting to model customer acquisition (e.g., McCarthy et al. 2016b); it is simply the case that their application has been product-centric in nature.)

Our review of the literature first considers the methods and models developed by those working with traditional direct marketers, and then explores

[3] A notable exception is the work of Natter et al. (2015).

the broader acquisition-related literature. In what follows, we take the view that a customer is "acquired" when they make their first purchase of the company's products or services (or make their first donation in a charity setting, etc.). The notion of "acquisition" is not so clear in a freemium business setting, where some parts of the organization may view someone as being acquired when they sign-up for the free service, while other parts may focus on the receipt of the first payment (thereby viewing the free service as an acquisition channel).

2.1 Direct Approaches to Customer Acquisition

While firms do make use of direct response advertising (be it via print, radio, TV, or online), inserts, and other such media (Tapp et al. 2014), the classic direct marketing acquisition campaign sees the firm contacting a list of prospects, be it via mail, outbound telemarketing, or email.[4] "A prospect is someone you hope to be able to attract to become a customer, but he is not a customer until he has made a purchase" (Rosenwald 2004, p. 22).

In its simplest form, the firm sends the same message/offer to everyone on the list, and each prospect either responds or does not. This is effectively mass marketing by mail (Petrison et al. 1997) and email. There is a long tradition of experimenting with the message and offer before deciding on the *single* message to roll out to the whole list. This ranges from simple A/B tests to more complex methods such fractional factorial designs (Almquist and Wyner 2001) and Plackett-Burman designs (Bell et al. 2006). When the firm has the option of buying lists from different sources, it is standard practice to undertake a test in which mailings are sent to a sample of prospects from each list, and the choice of list(s) is made on the basis of the observed response rate(s).

When any experiment or test is undertaken, the test mailing response rate is used as a prediction of the response to the rollout mailing. It is not uncommon to find that the rollout response rate is actually lower than that observed in the test. Allenby and Blattberg (1987), Ehrman (1990), Ehrman and Miescke (1989), and Morwitz and Schmittlein (1998), amongst others, have proposed methods that adjust the test results to arrive at a more accurate prediction of rollout response.

The practices described above see all the prospects on the list receiving the offer, even though we expect them to vary in their propensity to respond. When the list contains data on each prospect (e.g., demographic,

[4] While a sale may be the "direct response" to the advertisement, it is frequently a referral (i.e., the individual revealing that they are a prospect very interested in the product or service being advertised), which may or may not result in a sale. Calli et al. (2012) and Tellis et al. (2000) are examples of work that model the response to direct response advertising on radio and/or TV, both focusing on referrals and making no distinction between new referrals (i.e., prospects) and repeat customers.

socioeconomic, geographic, psychographic variables) we can start to be selective. The simplest approach is to create *a priori* segments on the basis of some of the variables and conduct an experiment in which the offer is mailed to a sample from each segment. The offer is then rolled out to those segments whose test response rate (ideally adjusted, as noted above) is above a threshold.

A more sophisticated approach involves making the offer to a random sample of the list and recording each contacted prospect's response. Using logistic regression, discriminant analysis, CHAID, CART, or some more advanced method, the analyst builds a model that identifies those prospect characteristics that are predictive of response to the offer (e.g., Bult 1993).[5] This model is then used to score the rest of the prospects, with those above a threshold being contacted and the rest ignored. Such an approach can be extended to test different offers, with the goal of identifying which offer to send to which types of customers (Hansotia and Wang 1997).

The test response rate or probability of response rollout threshold is based on a breakeven calculation (i.e., roll out if expected profit > 0). While this could be the expected profit associated with the new customer's first transaction with the firm, it has long been recommended that it should be based on the expected lifetime value of a new customer — see Simon (1967) and Petrison et al.'s (1997) discussion of industry practices in the 1940s–1960s. Simon (1993) suggests doing so using data from a sample of 300 customers — active and inactive — who first bought over 3 years ago. (More sophisticated approaches for calculating lifetime value are discussed in Section 3.1.)

Just as prospects are expected to vary in their propensity to respond, they can also differ in their value to the firm assuming they respond. As such, it may make sense to target those prospects with lower response probabilities but higher value given acquisition than ones with higher response probabilities but lower value given acquisition. In order to take such an approach, we must model expected customer value (given acquisition) as a function of the prospect covariates (Hansotia and Wang 1997). Ainslie and Pitt (1998) go one step further, modeling response to the mailing, profitability given acquisition, and riskiness; also see Liu et al. (2015) for a consideration of risk in the form of bad debt. When developing such models, it is important to control for sample selection bias (e.g., Vaidya and Cassidy 1999).

The work discussed above considers the questions of who to contact and (to a lesser extent) with what message. Another question is what to do with those prospects who do not respond to the mailing. Should the marketer

[5]Note that the vast majority of the response/predictive/classification models presented in the direct marketing related literature are not acquisition focused. Rather, they consider the response to mailings to existing customers (as opposed to prospects). Any model that includes past purchasing behavior as a covariate obviously falls in this category. We review this work in Section 3.3.

send a second solicitation? A third? Buchanan and Morrison (1988) develop a model of consumer response to direct mail solicitations that can be used to determine the number of profitable solicitations for a customer acquisition campaign. Rao and Steckel (1995) extend Buchanan and Morrison's model to accommodate descriptor variables that characterize the individuals on the list of prospects. In turn, their model is extended by Ehrman and Funk (1997) and Pfeifer (1998) to account for non-readers of direct mail.

2.2 Beyond Classic Direct Marketing

While the classic direct marketing approach discussed above still holds for some firms, the reality is more complex for most. We only have to reflect on how we were "acquired" by the numerous companies of which we are customers to realize that, regardless of whether the path to acquisition was long and winding or short and direct, our purchase decisions have been influenced by both actions of the firm (be they explicitly focusing on customer acquisition or not) and our interactions with its customer base. (Within the diffusion literature (e.g., Peres et al. 2010), these are labeled as external and internal influence.)

Since the early work of Katz and Lazarsfeld (1955) and Whyte (1954), both academics and practitioners have been interested in the impact of word-of-mouth (WOM) on buyer behavior. Developments in electronic communications technologies over the past 15 years have further stimulated this interest. Rather than simply rely on organic WOM, firms are interested in actions that can stimulate WOM, such as seeding campaigns (e.g., Hinz et al. 2011, Libai et al. 2013) and the development of viral marketing campaigns (e.g., Van der Lans et al. 2010). One form of WOM marketing activity that has a particular customer acquisition focus is the referral program, in which existing customers are rewarded when they bring in new customers. See Kumar et al. (2010), Schmitt et al. (2011), and Van den Bulte et al. (2015) for analyses of the effectiveness of such programs.

More generally, several researchers have examined the relative value of customers acquired through different acquisition channels. For example, Steffes et al. (2011) compare internet, direct mail, direct sales, and telesales, Trusov et al. (2009) compare WOM referrals, traditional media, and promotional event activity, Verhoef and Donkers (2005) compare direct-response advertising in mass media, direct marketing, website, and WOM, and Chan et al. (2011) compare Google search advertising and other search engines. Less attention has been paid to the issue of the impact of various acquisition-related promotions on the value of acquired customers. Datta et al. (2015) consider the impact of offering a free trial, while Lewis (2006) considers the impact of introductory discounts.[6]

[6]It is also important to consider the impact of acquisition campaigns on the behavior of existing customers. For example, offering new customers better deals than existing

Reflecting on this body of work on customer acquisition, it is clear that Blattberg et al. (2008) are correct when they comment on the limited amount of research on customer acquisition. We are now in a multichannel world in which firms must decide how to allocate their marketing efforts across paid and owned media, as well as on attempts to influence "earned" media and WOM. Technology increasingly allows us to track an individual's online journey to their first purchase, yet the influence of offline activities is still hard to track. The relative importance of different media changes as prospects are developed (e.g., Carroll 2006) and it can be argued that the nature of the message in a given media channel should change as the prospect is developed (e.g., Lambrecht and Tucker 2013). Furthermore, it must be recognized that many non-acquisition-specific activities (e.g., brand advertising, PR) have a positive impact on customer acquisition, even if partialling out their effect is difficult. There is a lot of scope for researchers to develop models that help the manager answer acquisition-related questions such as "How much should we spend on our acquisition activities?"[7] "Who do we target?" "Which messages do we use in which channels?" and so on.

3 Managing Acquired Customers

The notion of customer acquisition, retention, and development being the three key drivers of (organic) growth is widely accepted, and has even made its way into core marketing teaching materials (e.g., Gupta 2014). The logic of these three drivers is clear, and the notion of organizing a firm's activities around these drivers is attractive. However, in many business settings, the distinction between "retention" and "development" activities is not at all clear. For example, is getting the next transaction "retention" or "development"? This blurring of retention and development is also present in a lot of the modeling work by academic researchers. We therefore structure our review of the literature around the idea of managing acquired customers. We start by reviewing the literature on computing customer lifetime value and follow this with an examination of the literature that relates to the topic of churn management. We then review the literature on modeling the response to contacts by the firm, and conclude with a review of work on contact customization.

customers can potentially result in customer dissatisfaction — "I've been a loyal customer for many years and I'm getting a worse deal than new customers!" See Lhoest-Snoeck et al. (2014) for a discussion and examination of these issues.

[7]This question is partially addressed by research on allocating marketing expenditures between acquisition and retention activities, which we consider in Section 4.

3.1 Computing Customer Lifetime Value[8]

A fundamental marketing metric for any customer-centric firm is customer lifetime value (CLV), which can be defined as "the present value of the future cash flows attributed to the customer relationship" (Pfeifer et al. 2005, p. 17). (The term "customer equity" (CE) denotes the sum of the lifetime values of a firm's customers, both current and future; see Kumar and Shah (2015) for a comprehensive guide to the literature on customer equity.)

As we look to the future, we do not know the customer's lifetime or the timing and nature of their purchasing while they are "alive" as a customer. These quantities must be considered as random variables and we therefore need to think of *expected* customer lifetime value, $E(CLV)$. Following Rosset et al. (2003), we can express this mathematically as

$$E(CLV) = \int_0^\infty E[V(t)]S(t)d(t)dt\,, \tag{1}$$

where, for $t > 0$ (with $t = 0$ representing the "birth" of the customer), $E[V(t)]$ is the expected net cash flow of the customer at time t (assuming they are alive at that time), $S(t)$ is the probability that the customer has remained alive to at least time t, and $d(t)$ is a discount factor that reflects the present value of money received at time t.

It is important to distinguish between the lifetime value of an as-yet-to-be-acquired customer, the lifetime value of a just-acquired customer, and the *residual* lifetime value (RLV) of an existing customer. (The difference between the first two quantities is simply the value of the first transaction that signals the start of the relationship.[9]) We can express the notion of RLV mathematically as

$$E(RLV) = \int_{t'}^\infty E[V(t)]S(t|t > t')d(t - t')dt\,, \tag{2}$$

where t' is the "age" of the customer at the point in time where their residual lifetime value is computed.

Reflecting on these definitional formulas, it is important to note that any calculation of CLV or RLV cannot terminate the calculation at, say, three years and call the resulting quantity *lifetime* value. Furthermore, we should not assume that the customer is "alive" (i.e., actively contemplating transactions) throughout the whole of this finite period (cf. Kumar et al. 2008, Rust et al. 2004, Venkatesan and Kumar 2004, Venkatesan et al. 2007). It also raises the fundamental problem of trying to incorporate the effects of

[8]This section draws on material presented in Fader and Hardie (2009, 2015). Readers are referred to these references for a deeper review of this literature.

[9]We may also wish to include the acquisition cost in the calculation of the second quantity.

time-varying covariates (e.g., marketing activities) in any true calculation of CLV or RLV. Any analyst wishing to do so will need to forecast the values of these covariates far into the future, which clearly introduces a lot of additional noise into the exercise. As a result, the stream of literature that has developed models for computing lifetime value has tended to ignore the effects of time-varying covariates and drawn on the well-established traditions of stochastic models of buyer behavior, which have been part of the marketing science literature from its very beginning (Fader et al. 2014).[10][11]

As we think about operationalizing (1) and (2), we must ask ourselves whether we are in a business setting where the loss (or "death") of an individual customer is actually observed by the firm (e.g., the customer terminates their contract or fails to renew their fixed-term subscription) or one where it is unobserved (Schmittlein et al. 1987). It is now standard to use the term contractual to characterize a relationship when the death of a customer is observed by the firm, and the term noncontractual to characterize a relationship where the death of a customer is unobserved by the firm.[12][13] The vast majority of businesses fit into this categorization. As we shall see, this categorization underpins most of the tools developed by marketing scientists to support businesses in the management of acquired customers, and we structure our review of literature on computing customer lifetime value around it.

Note that we are starting to see the emergence of some business settings in which the firm has a "hybrid" contractual/noncontractual relationship with its customers (i.e., we can expect observed and unobserved attrition in the same pool of customers). See Ascarza, Netzer, and Hardie (2016) for an examination of such settings.

[10]A related stream of work uses homogeneous Markov chains to characterize customer behavior (e.g., Deming and Glasser 1968, Pfeifer and Carraway 2000, Soukup 1983). Such work does not account for heterogeneity in the underlying behavioral characteristics, which can lead to misleading interferences about the nature of buying behavior (e.g., Frank 1962). See Ching et al. (2004) for an example of how these simple Markov models of customer behavior can be embedded in broader marketing optimization models.

[11]Of course, if it is possible to characterize these time-varying covariates by a separate stochastic process, we could take the expectation of the covariate-dependent process over the distribution of covariate paths. How the resulting estimates of $E(CLV)$ and $E(RLV)$ would differ from those based on models of customer behavior that do no consider time-varying covariates is an open question.

[12]David Shepard Associates (1999) use the labels contractual and implied; "an implied relationship is one in which there is no obligation on either party's part to do anything in the future" (p. 416).

[13]This is not the same as Jackson's (1985) lost-for-good versus alway-a-share classification. Following Fader and Hardie (2014a), we feel that the contractual versus noncontractual classification is a better way of thinking about the nature of a firm's relationship with its customers, as the notion of latent attrition is missing from the basic always-a-share "model."

3.1.1 Contractual Settings

Since we observe the loss of a customer in contractual settings, it is a straightforward exercise to fit a survival model (also called a duration-time model or hazard-rate model) to the data (thereby giving us $S(t)$). This analysis strategy has been used by a number of researchers examining the correlates of the duration of a customer's relationship with the firm (e.g., Bolton 1998, Jamal and Bucklin 2006, Schweidel et al. 2008a). However, as noted above, including time-varying covariates in a model for $S(t)$ creates problems when we want to use it as the basis for computing CLV or RLV, as the analyst will need to forecast the values of these covariates far into the future.

Standard marketing textbook discussions of CLV use a discrete-time version of (1) and express the survivor function in terms of a constant retention rate (i.e., $S(t) = r^t$). While such "CLV formulas" have pedagogical value as a means of introducing the concept of lifetime value to students, they are of limited value in the "real world" (Fader and Hardie (2012, 2014c). If we consider a cohort of customers acquired at the same time, we typically observe that the cohort-level retention rates increase over time (e.g., Kumar and Reinartz, 2012, Figure 5.2), which challenges the textbook assumption of constant retention rates. (It also has implications for work that explores the linkage between the value of a firm's customer base and its stock market valuation, such as Gupta et al. (2004), Schulze et al. (2012); see McCarthy et al. (2016b).) While it is tempting to tell a story of individual-level time dynamics (e.g., increasing loyalty as the customer gains more experience with the firm, and/or increasing switching costs with the passage of time), a far simpler story — and one consistent with the fundamental marketing concept of segmentation — is that of a sorting effect in a heterogeneous population.

A simple stochastic model for the duration of a customer's relationship with the firm that captures the phenomenon of increasing retention rates is the beta-geometric (BG) distribution (Potter and Parker 1964). Despite what may seem to be overly simplistic assumptions, the analyses presented in Fader and Hardie (2007a, 2014b) demonstrate that this two-parameter model generates very accurate forecasts of retention. This model for $S(t)$ can be substituted into (1) and (2) and used to compute CLV and RLV in contractual settings, something explored in Fader and Hardie (2010). Note that this work simply focuses on *when* customers choose to terminate their relationship with the firm. Braun and Schweidel (2011) extend this to account for "competition" among the different reasons that ultimately lead to termination.

3.1.2 Noncontractual Settings

The challenge of noncontractual settings is that the loss of a customer is not observed and so we cannot estimate any model of S(t) directly from the data. What we do observe are realizations of the product of $V(t)$ and $S(t)$, and the challenge facing the analyst to identify these two components of behavior from the observed behavior. In other words, how do we differentiate those customers with low purchase propensities who have ended their relationship with the firm (without informing it) from those who are simply in the midst of a long hiatus between transactions. While we can never know for sure which of these two states a customer is in, we can use statistical models to make probabilistic statements.

The seminal work in this area is Schmittlein et al. (1987), which introduced a latent-attrition framework in which a customer's relationship with a firm has two phases: they are "alive" for an unobserved period of time, then "dead." Ignoring the effect of random purchasing around their means, individual customers purchase the product at steady but different underlying rates. At different unobservable points in time they "die."[14] In their operationalization of this framework, Schmittlein et al. (1987) assume that (i) while "alive" the customer's purchasing is characterized by the NBD (negative binomial distribution) model (i.e., a gamma mixture of Poissons), and (ii) the unobserved customer lifetimes are treated as-if random and are characterized by the Pareto Type II distribution (i.e., a gamma mixture of exponentials); the resulting model of buyer behavior in noncontractual settings is called the Pareto/NBD.

Empirical validations of the model are presented in Schmittlein and Peterson (1994) and Fader, Hardie, and Lee (2005b), amongst others; its predictive performance is impressive. Applications of this model include the work of Reinartz and Kumar (2000, 2003) on customer profitability, Hopmann and Thede (2005) on "churn" prediction, and Huang (2012) and Wübben and v. Wangenheim (2008) on managerial heuristics for customer-base analysis.

The basic Pareto/NBD model has been modified and extended by a number of researchers. An important stream of work has focused on variants that are easy to implement, resulting in the BG/NBD (Fader et al. 2005a) and BG/BB (Fader et al. 2010) models, both of which can be implemented in a standard spreadsheet environment. Other work has relaxed the assumption of Poisson counts, exponential lifetimes and/or gamma heterogeneity (e.g., Abe 2009, Bemmaor and Glady 2012, Jerath et al. 2011, Platzer 2008, Singh

[14]What lies behind this death? It could be a change in customer tastes, financial circumstances, and/or geographical location, the outcome of bad customer service experiences, or even physical death, to name but a few possible causes. But given the modeling objectives, why this death occurs is of little interest to the analyst; the primary goal is to ensure that the phenomenon is captured by the model.

et al. 2009), explored estimation issues (e.g., Jerath et al. 2016, Ma and Liu 2007), allowed for multi-category purchasing (Park et al. 2014), or relaxed the "buy"/"die" nature of customer behavior (e.g., Ma and Büschken 2011, Romero et al. 2013, Schwartz et al. 2014).

Several researchers have sought to incorporate the effects of covariates. While this is easy for the case of time-invariant covariates (e.g., Abe 2009, Fader and Hardie 2007b), the inclusion of time-varying covariates is less straightforward. Schweidel and Knox (2013) and Schweidel et al. (2014) build on the foundations of the BG/BB model, allowing covariates to influence the customer's behavior while alive and/or their likelihood of dying: Schweidel and Knox (2013) incorporate the effects of direct marketing activity, while Schweidel et al. (2014) incorporate the effects of past customer activity. Braun et al. (2015) and Knox and Van Oest (2014) both build on the foundation of the BG/NBD, allowing covariates to impact the latent attrition process: Braun et al. (2015) incorporate the effects of the customer's service experience, while Knox and Van Oest (2014) incorporate the effects of customer complaints.

The Pareto/NBD (and the variants discussed above) is a model for the flow of transactions. Models for spend per transaction were proposed by Colombo and Jiang (1999) and Schmittlein and Peterson (1994). Despite all the components being in place, Fader et al. (2005b) were the first to bring them together via (1) and (2) to come up with explicit formulas for CLV and RLV (conditional on the customer's observed behavior) in noncontractual settings. Drawing on the work of Colombo and Jiang (1999) and Schmittlein et al. (1987), their key result is that we only need to know three things about a customer's buying behavior in a given time period in order to compute their residual lifetime value: recency, frequency, and monetary value (i.e., RFM). Fader et al. (2005b) model spend per transaction and assume a constant margin. McCarthy et al. (2016a) extend this by allowing for heterogeneity in margin per transaction.

3.2 Churn Management

The defining characteristic of contractual settings is that attrition is observed. For most firms operating in such settings, churn rate is an important KPI, and the management of churn is of great interest to decision makers. For many firms, the efforts to retain a customer are *reactive*; for example, a mobile phone operator offers some incentive to a customer who indicates that they wish to cancel their contract, etc. Increasingly, firms are becoming *proactive*, undertaking their retention marketing activities before the customer has the opportunity to churn. (See Passant (1995) for an early critique of retention marketing practices.) Both logic and limited budgets mean that a firm's retention efforts should be focused on a subset of those customers whose contracts are coming up for renewal. (Why, for example, spend money trying to retain a customer who has no intention of churning?) As a result, a key component of any proactive churn management exercise is a churn model that predicts a customer's likelihood of churning (voluntarily).[15]

When developing a standard churn model, the dependent variable of interest is binary — whether or not the customer churned in a given time interval. The predictor variables are measured over a specified time period that ends at or before the start of the churn interval. As discussed below, numerous researchers working in the areas of data mining/machine learning, marketing, and statistics have studied the problem of which predictor variables to use and what analysis methodology to use to identify the relationship between churn and the predictor variables.

The predictor variables are typically customer characteristics, measures of customer behavior (e.g., utilization of the service), and their interactions with the firm (e.g., calls to customer service). See Ballings and Van den Poel (2012, Table 1), Lemmens and Croux (2006, Table 1) and Zhang et al. (2012, Table 1) for illustrative lists of the variables commonly used in churn models. Note that these variables focus on the individual customer, ignoring the broader context in which (s)he operates. In recent years, a number of researchers have also considered variables that capture interpersonal influence (e.g., Dasgupta et al. 2008, Haenlein 2013, Verbeke et al. 2014, Zhang et al. 2012),[16] finding that a customer is more likely to churn if individuals with whom (s)he is connected have recently churned from the service provider. Ascarza et al. (2017) show that retention campaigns can have a positive impact (in term of usage and retention) on non-targeted customers who are connected to the targeted customers.

The classic statistical technique used to develop a churn model is logistic regression. Other methods include decision trees (e.g., C4.5, CART), neural networks, support vector machines, and ensemble methods (e.g., random forests, bagging, boosting). Illustrative marketing studies include Coussement and Van den Poel (2008), De Bock and Van den Poel (2011), Larivière and Van den Poel (2005), and Lemmens and Croux (2006). A number of studies have been undertaken, comparing and contrasting the various analysis methods, two recent examples being Verbeke et al. (2011) and Verbeke et al. (2012). Other issues that have received less attention include the length of the time period over which the predictor variables are measured (Ballings and Van den Poel 2012), the "staying power" of the model (Risselada et al. 2010) (i.e., for how long can the estimated model be used before its parame-

[15]Churners are typically categorized as voluntary or involuntary. Voluntary churn occurs when the customer decides to terminate their relationship with the firm, whereas involuntary churn occurs when the firm terminates the relationship (e.g., as a result of nonpayment or fraud). Involuntary churners are typically excluded when developing a churn model or modeling survival (cf. Braun and Schweidel 2011).

[16]Nitzan and Libai (2011) examine such effects in a duration time (i.e., survival) model.

ters need to be re-estimated or different variables added to the model), and the development of churn models in situations where privacy concerns limit the amount of data available to the analyst (Holtrop et al. 2016).

How does the model builder determine the best model specification? Since the standard objective of a churn model is to identify those customers with the highest risk of churning (with the view of targeting them with some proactive retention campaign), it is common to assess the performance of any given model specification on a validation sample in terms of its top-decile lift (which is the proportion of actual churners in the 10% of customers that the model predicts as having the highest risk of churning). Depending on the setting, this can be reduced to the top 5% (or smaller).

Building on Neslin et al. (2006), Blattberg et al. (2008) propose a framework for identifying the tradeoffs inherent in a (single) proactive churn management campaign. With reference to Figure 1, the set of customers at risk of churning is split into those customers that are contacted/targeted with the retention campaign (i.e., those at most risk according to the churn model) and those that are not. Among those contacted (α) at cost c per customer with an incentive valued at δ, a proportion would have been churners (β), and among those, a proportion will be "rescued" (γ) given the company's intervention. (For a customer with lifetime value CLV,[17] the realized value is $CLV - c - \delta$.) The rest of those contacted $(1-\beta)$ would not have been churners, yet some (ψ) might take the incentive with an expected increase in their lifetime value of Δ but at a cost of $c + \delta$. (Note that this ignores the possibility that contacting "not-would-be churners" can actually result in their churning (Ascarza, Iyengar, and Schliecher 2016).) As we consider the profitability of a proactive retention campaign, the tradeoff is between the upside effects of the campaign (coming from the lifetime value (CLV) obtained from the "rescued" customers, $\beta\gamma CLV$, and those would-be non-churners that take the incentive, $(1-\beta)\psi\Delta CLV$ (assuming $\Delta > 0$)) and the downside effects of the campaign (coming from the costs of contacting the customer, c, and the expected cost of the incentive, $[\beta\gamma + (1-\beta)\psi]\delta$).

This framework was initially used by Neslin et al. (2006) to evaluate a set of models developed in a churn modeling tournament. Verbeke et al. (2012) use this framework to develop a new model selection criterion. Rather than choosing the churn model specification that maximizes lift for some arbitrary fraction of the customer base (10% for the top-decile lift criterion), they propose the maximum profit (MP) criterion, which calculates the profit "generated by including the optimal fraction of customers with the highest predicted probabilities to attrite in a retention campaign" (p. 211). (See Lemmens and Gupta (2013) for a similar approach to model selection.)

[17] Neslin et al. (2006) and Blattberg et al. (2008) use the abbreviation LTV, which we have replaced with CLV. Strictly speaking, this should be $E(RLV)$, but the distinction raised in (1) and (2) is ignored in most of the literature, including the work of Blattberg et al. (2008) and Neslin et al. (2006).

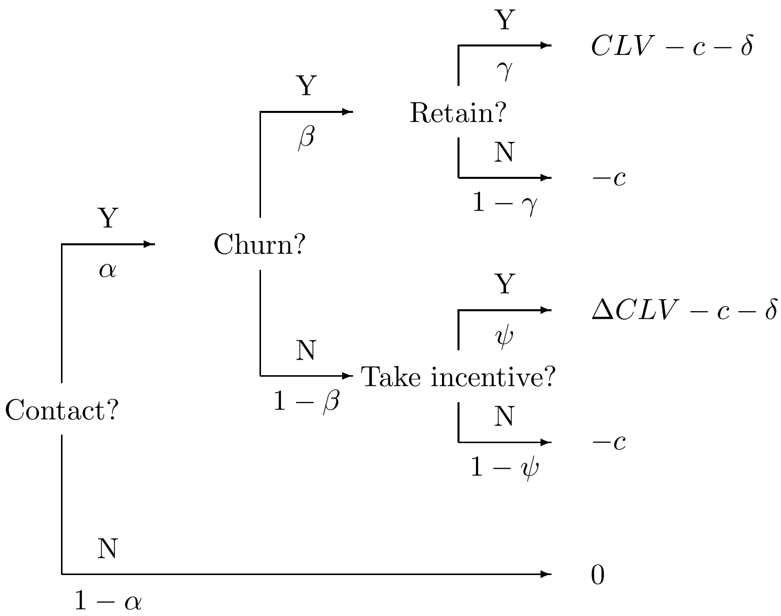

Figure 1: A profitability framework for proactive churn management (after Blattberg et al. (2008, Figure 24.6)).

This is extended by Verbraken et al. (2013) to account for uncertainty in campaign costs and benefits.

Similar profit-based frameworks have been developed by Mozer et al. (2000) and Piatetsky-Shapiro and Masand (1999). Rosset et al. (2003) present a framework for campaign management based on the expected change in CLV resulting from the associated intervention; they explicitly recognize that an intervention could reduce the customer's long-term underlying propensity to churn, or simply lock them in for a fixed period of time without any change in their underlying propensity to churn.

Reflecting on the development of churn models, Hansen (2015) makes the following comment: "The business objective is never 'predict the churners', it is 'reduce the value and rate of churn'. For that, predicting the churner is simply a first step to taking action to dissuade the potential churner. That may sound like two distinct steps but do not waste time improving identification of churners, *focus on identifying those that can be dissuaded* [emphasis added]." At first glance it would appear that profit-based model selection criteria address this. But this is not the case. All this work targets those with the highest risk of churning, but ignores the fact that many of those with a high risk of churning are very dissatisfied and cannot be dissuaded (at least profitably) by the firm's intervention. Recognizing this, Ascarza (2016) proposes an alternative approach to proactive churn management in which the firm targets those customers with the highest sensitivity to the intervention.

Many firms would simply see "lost" customers as re-entering the prospect pool for future acquisition campaigns. Other firms have specific programs that attempt to reacquire/reactivate lost customers, a practice known as "customer winback" (Griffin and Lowenstein 2001, Stauss and Friege 1999). Gerpott and Ahmadi (2015), Kumar et al. (2015), and Thomas et al. (2004) develop models that can be used to guide such decisions; also see Pick et al. (2016).

3.3 Contact Response Models

By definition, attrition is unobserved (and unobservable) in noncontractual settings. As a result, there is no standard attrition-related KPI. Instead, the focus tends to be on purchasing by individuals in the firm's customer database, and this has driven most of the modeling efforts in this space.

In a classic direct marketing setting, mailings are sent out at regular intervals (e.g., quarterly for a charity, monthly for a mail-order company) and the customer may or may not respond (i.e., make a donation or purchase) to the contact. Over time, the firm grows its customer database in which it records the identity of those customers contacted on each mailing and their response. Given printing and mailing costs, budget constraints mean that it may not be possible to contact every customer; even in the absence of any explicit budget constraints, we can assume that it is not profitable to contact every customer. Therefore, for any given campaign, the key decision facing the firm is which customers it should contact.

Historically, the gold-standard approach to supporting this decision was to run an experiment in which the customer base was segmented using some *a priori* scheme and the mailing sent to a sample of customers from each segment. As with the use of experiments for customer acquisition, the firm would "roll out" to those segments where the response rate was above some threshold. A common segmentation scheme is the quintile-based RFM method championed by Hughes (1996). Customers are first ranked on the basis of how recently they made a purchase and are divided into quintiles, with 5 denoting the top quintile (i.e., most recent purchasers) and 1 the bottom quintile (i.e., least recent purchasers). This is repeated on the basis of how many times they made a purchase in a given time period, and then on the basis of their average spend per order in that time period. Thus each customer has a "recency" (R) coding, a "frequency" (F) coding, and a "monetary value" (M) coding, resulting in $5 \times 5 \times 5 = 125$ segments.

However, given the information in the customer database, it is not necessary to undertake such an experiment.[18] For those individuals contacted in

[18]Of course, a firm will make use of experiments to determine the best mailing package (e.g., Bult et al. 1997).

the most recent mailing(s), we know their characteristics and whether or not they responded to the mailing. We can therefore build a contact response model in which response to the mailing (Y/N) is modeled as a function of the customers' purchase histories (often summarized in terms of recency, frequency, and monetary value) and demographics.[19] This can be done using a basic logit or probit model, semiparametric methods such as the Cosslett estimator (Bult and Wansbeek 1995), or one of the other methods used in the development of acquisition scoring and churn models. The whole database can now be scored and customers ranked on the basis of their predicted probability of responding to a mailing. Those customers with a response probability above a certain threshold (often profit-based) are sent the mailing. Bult and Wansbeek (1995) propose a targeting method that seeks to maximize expected profit. Gönül et al. (2000) consider an alternative targeting rule for a catalog-based mail-order company: contact the customer only if the expected profit with the mailing a catalog exceeds the expected profit without the mailing a catalog.[20] Whatever decision rules used, they typically ignore estimation uncertainty in the parameter estimates and can therefore lead to suboptimal decisions. Muus et al. (2002) derive an optimal Bayes decision rule to address this problem.

These standard scoring models often suffer from the problems of selection bias and endogeneity, the first occurring because the firm's targeting rules mean that the model is estimated on a non-random sample of customers, the second typically occurring because of the use of variables that summarize the customer's purchase history (often summarized in terms of RFM variables). The use of a targeting rule that is correlated with the customer's past behavior can lead to biased estimates of the coefficients associated with the RFM variables. Solutions such as the use of instrumental variables, policy functions, and latent trait models have been explored by, amongst others, Cui et al. (2006), Donkers et al. (2006), Hruschka (2010), Rhee and McIntyre (2008, 2009), and Rhee and Russell (2009).

The standard scoring model considers whether or not the contacted customer responds to the mailing. In most situations, we are not just interested in whether or not someone responds but also the nature of their response (e.g., how much they donate/buy). A number of researchers have proposed models of both phenomena (e.g., Donkers et al. 2006, Levin and Zahavi 1998,

[19]In addition to the frequency of response, a number of researchers have considered the impact of contact history (e.g., frequency of contact) on the customer's likelihood of responding to the current mailing, including possible irritation effects; see Schröder and Hruschka (2016) for a review. This is especially an issue in today's permission marketing world where, for example, too much contact could result in the customer opting-out of communications all together (e.g., Drèze and Bonfrer 2008).

[20]Whereas the work discussed above implicitly assumes that customers can only place an order (i.e., respond) in a given period if they receive a mailing, Gönül et al. (2000) recognize that customers can place orders from old catalogs, even though they did not receive a catalog in the current period.

Otter et al. 2000, Schröder and Hruschka 2016, van Diepen et al. 2009), with the Type II Tobit being the most common model. Other researchers have gone further, considering the issue of returns (e.g., Baumgartner and Hruschka 2005, Koning et al. 2002).

The decision considered above is who to contact with a given single mailing. However, the reality is that a company is making multiple mailing over a given period of time. Applying selection rules mailing by mailing can lead to suboptimal outcomes for the firm; see, for example, Elsner et al. (2003, Figure 1). As Kestnbaum et al. (1998, p. 58) note, "If a customer is not selected because he or she falls a little below the cutoff point used for the decision criterion, the customer is not contacted. This may happen for every campaign, so the customer is *inadvertently abandoned*. Receiving no contacts for an extended period of time, he or she is not very likely to buy and the poor performance becomes worse. Rather than abandon a customer by default, wouldn't it be better to make a conscious decision to make one or two contacts per year or to stop contacting a customer based on the overall prognosis for that particular customer?" As a result, the decision problem changes from whether or not to contact each customer to one of how many mailings to send to each customer over a given time period. Proposed solutions to this problem include Bitran and Mondschein (1996), Elsner et al. (2003, 2004), Gönül and Ter Hofstede (2006), Jonker et al. (2006), Piersma and Jonker (2004), Neslin et al. (2013), and Simester et al. (2006).

Note that the work reviewed in this section models transactions *given* contact by the firm. Another stream of research models the flow of transactions (and the associated cash flows) in time, without any explicit conditioning on contact by the firm; see, for example, Kumar et al. (2008), Venkatesan and Kumar (2004) and Venkatesan et al. (2007). The more sophisticated models account for underlying dynamics in customer behavior, typically using hidden Markov models (HMMs) (e.g., Chang and Zhang 2016, Mark et al. 2013, Mark et al. 2014, Montoya et al. 2010, Netzer et al. 2008). Work in the tradition of Schmittlein et al. (1987) — as discussed in Section 3.1.2 above — can be viewed as a constrained form of such HMMs (Schwartz et al. 2014).

3.4 Contact Customization

The work discussed above focuses on increasing response rates by using scoring models to improve targeting given an offer. An alternative approach focuses on increasing response rates by improving the relevance of the offer to each customer via some form of customization (Malthouse and Elsner 2006). (Of course these two approaches are not mutually exclusive). The nature and scope of the customization obviously depends on the media used by the firm when contacting the customer; it is obviously far cheaper to customize emails than it is paper mailings.

When talking about customization, we typically think of customizing the offer given the decision to contact. A variant practiced by a number of catalog retailers that have both general and category-specific catalogs considers which subset of all catalogs that will be mailed over a given time period to send to each customer so as to maximze some profit-related objective function (e.g., Campbell et al. 2001, Elsner et al. 2004, George et al. 2013).[21]

Looking beyond catalog retailers, the idea of customization goes hand-in-hand with the concepts of cross-selling and up-selling (which in turn lie the heart of any discussion of "customer development"). Cross-selling is where the firm tries to get the customer to buy products from the firm's product line that the customer does not currently own, and up-selling is where the firm tries to get the customer to buy more expensive variants of (or add-ons to) products they are buying (or currently own). In some digital settings, the goal is simply to increase usage (with no distinction being made between cross- and up-selling); see, for example, Ansari and Mela (2003) and Chung et al. (2016).

The simplest form of cross-selling model is the so-called "next product to buy" model, which models the purchase of a focal product as a function of current product ownership (e.g., Knott et al. 2002) and similarity to other customers (e.g., Moon and Russell 2008). Such a model can be used to identify who to target when next promoting that product. Such an approach to cross-selling is very campaign focused; Li et al. (2011, p. 684) argue that a more customer-centric approach to cross-selling asks "How do we introduce the right product to the right customer at the right time using the right communication channel to ensure long-term success?"

In settings where the decision is which one of several possible products the firm should feature as their recommended product, Bodapati (2008) argues that the firm should not automatically choose the product that has the high probability of purchase (given the customer's purchase history), but rather focus on the product whose purchase probability increases the most with recommendation. (Why recommend a product the customer was going to buy anyhow?)

A number of researchers have explored the idea that consumers acquire certain non-consumable products (e.g., financial products, durables) in the same order (e.g., Kamakura et al. 1991, Paas 1998). Building on such acquisition pattern analysis, a number of researchers have developed models that aim to predict which product will be acquired next by each customer (e.g.,

[21]Note that most of this work has focused on which *products* to offer to the firm's customers. Khan et al. (2009) develop a model for determining which *promotions* to offer, if any, over a finite planning horizon. The promotions they consider are transaction, not product, specific (i.e., free shipping offers, discount coupons, and loyalty program rewards).

Li et al. 2005, Prinzie and Van den Poel (2006) and when (e.g., Prinzie and Van den Poel 2007), the output of which can be used to customize the next mailing sent to each customer.

Implicit in most of the work on cross-selling is the idea that the objective of the solicitation is to generate an immediate purchase. Li et al. (2011) suggest that cross-selling solicitations can have an educational and advertising effect in addition to the immediate promotional effect. Furthermore, customers differ in their preference for communication channels (e.g., mail versus email). They develop a model for making decisions about *when* to promote *which* product to *which* customer via *which* communication channel that takes into consideration the short- and long-term effects of any solicitation.

The issue of up-selling has received less direct attention. Working in a single category setting, Kim and Kim (1999) use a stochastic frontier model to estimate the inefficiency of the firm's customer-specific marketing activities, from which an estimate of each customer's upselling potential is calculated. Verhoef and Donkers (2001) look at predicting customer potential value in a multicategory setting; this is, of course, identifying customers with both cross-selling and up-selling potential. In the same spirit is the work on estimating share of wallet (e.g., Chen and Steckel 2012, Du et al. 2007). Ballings and Van den Poel (2015) consider the task of identifying Facebook users who are expected to increase their usage frequency, with the view that those predicted not to increase their usage can be targeted with campaigns designed to increase their engagement with the social network. In all cases, the goal is identifying who to target, rather than what should be promoted as part of any up-selling campaign.

More generally, the question of what offer the customer should receive (be it for the purpose of cross-selling or up-selling) is a recommendation problem. Since the mid-1990s, a large number of researchers in both academia and industry (especially those with a computer science background) have focused on the problem of developing computer-based systems that generate recommendations, i.e., recommender systems. (Ansari et al. (2000) and Ying et al. (2006) are early examples of such work by marketing researchers. See Adomavicius and Tuzhilin (2005) for a survey of the early literature, and Ricci et al. (2015) for a comprehensive coverage of current methods and applications.) While such system are used to generate a set of products to offer as part of a cross-selling or up-selling campaign (i.e., to customize communications from the firm), they are more widely used to customize the recommendations a customer sees when on the firm's website.[22]

Generally speaking, researchers in marketing have downplayed the optimization-related challenges associated with the design of large-scale cross-

[22]Once at the firm's website, a further form of customization matches the "look and feel" of a website to each customer (e.g., Hauser et al. 2014, Hauser et al. 2009).

selling and up-selling campaigns. Various solutions have been proposed by operations researchers and computer scientists — see, for example, Cohen (2004), Delanote et al. (2013), Lu and Boutilier (2014), and Nobibon et al. (2011) — and these deserve consideration by marketing scientists (probably working with experts in optimization).

4 Coordinating Acquisition and Retention

While acquiring customers and managing acquired customers are important activities, they do not occur independently, isolated from one another. A fundamental question facing the manager of a customer-centric firm is how to allocate their marketing budget across various acquisition, retention, and development activities.

Several researchers have explored the trade-off between acquisition and retention spend using analytical models, with Fruchter and Zhang (2004) and Musalem and Joshi (2009) considering the case of a competitive environment, Lianos and Sloev (2013) considering the case of a monopolistically competitive industry, and Ovchinnikov et al. (2014) investigating the case of a firm facing capacity constraints.

In their classic paper that introduced the idea of customer equity, Blattberg and Deighton (1996) present side-bar examples in which a simple decision calculus model is used to determine the optimal level of acquisition spending and another simple decision calculus model is used to determine the optimal level of retention spending. Berger and Bechwati (2001) build on this work to develop a model for optimizing the allocation of a promotion budget between spending on acquisition and retention. An real-world application of this model is presented in Berger and Bernstein (2002), and it is extended in Dong et al. (2007) to accommodate the notion of (acquisition) channel quality, which captures dependencies between acquisition and retention. Building on Dong et al., Swain et al. (2014) develop a model that allows the decision maker to explore the impact of margin-reducing incentives (such as discounts) that increase acquisition rates, but which may attract the “wrong” types of customers, on customer equity maximization.

This basic formulation is somewhat artificial in nature as it is a static/single-period formulation in which we have a fixed prospect pool, and the firm is looking at how much to spend this period per prospect. The assumption is that the firm will spend the same amount on retention in perpetuity, but the optimality of this is ignored given the static nature of the problem formulation. Fan and Berger (2001) consider the problem of how to allocate the fixed promotion budget over a finite time horizon with the objective of maximizing customer equity. Other research that builds on the primitives of Blattberg and Deighton (1996) includes Blattberg et al. (2008, Chapter 28), Calciu (2008), Pfeifer (2005), and Pfeifer and Ovchinnikov (2011).

All this work models each period's retention rate as a function of "retention spend" in that period (ignoring the phenomenon of cohort-level dynamics in retention rates); as such, it only applies to contractual settings. The analog formulation for noncontractual setting is not immediately obvious.[23] We also note that any customer development-related activities are excluded from the resource allocation exercise.

This work has a macro view, looking at high-level resource allocation. The more micro view considers the tradeoff at the level of the mailing (or, more generally, contact) decision. Bitran and Mondschien's (1996) model for the development of optimal mailing policies explicitly considers the tradeoff between mailing to prospects on rented lists and mailing to existing customers. Mailing to prospects may not be profitable in the short term but is an investment for the future; mailing to existing customers allow the firm to reap the rewards of past such investments. In a fundraising setting, Stanford et al. (1996) present a linear programming model for determining the number and type of mailings to send to different groups of prospects and current donors. The goal is to maximize funds raised given various constraints, including the size of the marketing budget and various prospecting goals.

In addition to the obvious dependency created by a budget constraint, we would intuitively expect there to be some additional relationship between acquisition and retention that should be taken into consideration when considering this resource allocation problem. For example, customer acquisition campaigns designed to acquire as many customers as possible may come back to haunt the firm when the retention team tries to retain what turns out to be the "wrong types" of customers. Research suggests these two processes are not independent. Thomas (2001) finds that the duration of a customer's relationship with the firm is correlated with their likelihood of being acquired in the first place; the same result is found by Reinartz et al. (2005). Schweidel et al. (2008b) find that a customer's relationship duration is correlated with the speed with which they were acquired (having entered the prospect pool). (In particular, customers who are acquired more quickly tend to have shorter relationships than those who took longer to start their "relationship" with the first.) As discussed in Section 2.2, the value of customers can be a function of acquisition channels and type of acquisition-related promotion. These issues are largely ignored in the

[23] At first glance, it may appear that the work that embeds Blattberg and Deighton's (1996) model in a brand-switching framework (e.g., Tsao et al. 2014, Williams and Williams 2015) would work in a noncontractual setting. However, this is not the case; the fact that someone purchases from a competitive firm between two purchases from the focal firm should not necessarily mean that they churned after the first purchase and were acquired (again) when they made their second purchase. The notions of acquisition and retention implicit in such models are quite different from those implict in most of the literature reviewed in this chapter. (See Fader and Hardie (2014a) for a further discussion of issues related to the treatment of competition in noncontractual settings.)

existing literature and deserve consideration in future work.

5 Discussion

We have reviewed the key data-based tools and methods that have been developed by researchers to assist a customer-centric firm in its customer acquisition, retention, and development activities. It is clear that while certain topics and/or industries have received a lot of attention, there are many opportunities for further research.

The whole topic of customer acquisition is under-addressed, with much of the published work coming from traditional direct mail settings. Given the recognition that customer retention and value varies across method and channel of acquisition, acquiring the "right" customers in the first place is of vital importance. Today's multichannel world poses a number of challenges. Which channels should be used? How should the message be tailored across channels and over time in recognition of the prospect's path to acquisition? How do we integrate online and offline activities? How do we integrate "direct" and "broadcast" activities? How do we account for the impact on non-acquisition-specific marketing activities on customer acquisition? How do we trade off the desire to acquire "quality" customers with the pressure for "quantity"?

As we reflect on the management of acquired customers, it is important to make the distinction between contractual and noncontractual settings. In contractual settings, the vast majority of research has focused on the problem of predicting churn. As we reflect on the management problem these models are supposed to address, we realize that developing a model that best-predicts churn could be missing the point. Managers need support in developing the best interventions to *reduce* churn, which may see them ignoring those customers with a high risk of churning (Ascarza 2016). The whole issue of product and service usage while under contract has received little attention (cf. Ascarza and Hardie 2013). Similarly, the task of customer development has received little attention in contractual settings. A notable exception is the work of Thomas et al. (2015), which looks at the effects of two different types of campaigns (one focusing on retention, the other on customer development) in an opt-out setting. Customer development in contractual settings will typically involve signing up for a higher level of service and/or multiple services offered by the same firm. The associated modeling issues, including that of modeling switching between contracts of different lengths, have received little attention (cf. Heitz et al. 2011, Schweidel et al. 2011).

In noncontractual settings, much of the work has been very campaign oriented in nature, developing a model of customer response to a contact (typically some form of direct mail) and using that to decide on who to target. While such a campaign orientation reflects the realities of marketing practices in most firms, this work has typically ignored the possible distinction between retention- and development-oriented activities. Furthermore, it is typically the case that the objective of the contact is to trigger an immediate purchase. We need to think more broadly, considering the advertising and educating roles of the firm's communications (e.g., Li et al. 2011), including simply keeping the firm in top-of-mind. In today's multichannel world, an added challenge is determining which channel and message to use to contact each customer (which could vary according to the objective of the communication). All this raises a number of optimization-related issues when implemented in real-world settings. Furthermore, while technological developments have created a data-rich world in online settings, the challenge is how to integrate online and offline activities, especially as omnichannel operations become more and more the norm. Finally, there is the challenge of controlling for selection bias and endogeneity when developing the response models that underpin such work.

An additional challenge in today's multichannel world is that of allocating "proportional credit to marketing communications and media activity across all channels, which ultimately leads to the desired customer action" (Moffett 2014, p. 3). How much credit should be given to the first- versus last-touch and the touchpoints in-between the two on the customer's path to purchase? This complex attribution problem is starting to receive the attention of researchers in both marketing and computer science (e.g., Abhishek et al. 2015, Li and Kannan 2014, Shao and Li 2011, Xu et al. 2014). Most of this work has focused on trying to attribute credit for a given transaction, failing to make the distinction between the first purchase that signals the start of the customer's relationship with the firm and subsequent transactions. A customer-centric firm will want attribution models that allow it to understand the impact of its activities (and the impact of other customers) on the acquisition, retention and development of its customers. (See Kannan et al. (2016) for an introduction to the topic.)

Reflecting on the methods developed to assist customer-centric firms in their targeting decisions, we want to bring attention to the use of incremental (or uplift) modeling. Rather than merely estimating the likelihood of a customer engaging in a certain behavior (e.g., churning), uplift models estimate the incremental impact of the firm's actions on such behavior (e.g., the difference in churn probability with and without the marketing intervention). Furthermore, they also recognize customer heterogeneity with respect to the incremental impact of the marketing intervention, identifying customers who will be most sensitive to specific marketing campaigns. While the literature has made some steps in this direction (e.g., Gönül et al. (2000) in the context of catalog mailing, Bodapati (2008) in the context of product recommendations, and Ascarza (2016) in the context of proactive churn management), an explicit focus on the incremental effect of targeted marketing campaigns has been more the exception than the norm. We encourage managers and researchers to re-orient their focus and seek to maximize the effectiveness of the marketing actions by comparing the expected behavior given the action to the counterfactual of what the behavior would have been in the absence of the intervention.

Finally, the issue of balancing the firm's acquisition and retention (let alone development) activities has received little attention, especially in non-contractual settings. There are questions of how to allocate a budget across various activities, as well as setting the size of the budget in the first place, at both the macro- and micro-level of the firm, while accounting for underlying dependencies between the activities.

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