Chapter 4

Real-time Target Marketing Using Control Charts

Abstract

Customer-centric firms are actively tracking customer behavior in order to develop and retain customers to increase their CLV. While many studies in the literature on non-contractual customer behavior have focused on the average customer behavior, more recently the variance therein has also become a subject of study. We add to this literature by showing how firms can leverage variance in customer purchase behavior to identify customers at risk of churning. Moreover, our method also guides decision on when to target such at-risk customers as it can operate in real-time. To that end we develop a gamma-gamma control chart approach to model purchase timing. The control chart method is grounded in the statistical quality control literature, and is designed to capture the variance with respect to the mean of a statistical process over time. We extend these methods to deal with the customer heterogeneity found in customer databases. An empirical example in the greetings and gifts industry illustrates our approach. We suggest improvements to the current firm e-mail policy used to reactivate customers at risk of churning. Our findings suggest that by using the proposed approach, the conversion rate of e-mails and the value of orders can be increased.

This chapter is based on Holtrop, Niels, Jaap E. Wieringa (2016), “Real-time target marketing using control charts”, working paper, University of Groningen.
In order to achieve customer centricity, many firms have realized that customers’ intentions and behaviors should be measured to guide the marketing decision making process (Shah et al. 2006). Firms can use metrics such as satisfaction and Net Promoter Score (see e.g. De Haan, Verhoef and Wiesel 2015 for a recent overview of metrics) to monitor customers’ perceptions and link those to firm performance and outcome measures, potentially in real-time through marketing dashboards and related methods (Pauwels et al. 2009; Rust and Huang 2014). Mindset metrics like awareness and affect have also been shown to directly affect performance measures such as brand sales (Hanssens et al. 2014; Srinivasan, Vanhuele and Pauwels 2010).

Besides measuring customers’ perceptions through such metrics, firms can also measure customer behavior directly and link these to firm outcomes. For example, in a contractual setting, Ascarza and Hardie (2013) show that by monitoring service usage, firms can predict customer churn. In non-contractual settings, customer behavior is often measured through statistics such as recency (R), frequency (F), monetary value (M), and more recently clumpiness\(^1\) (C) (Blattberg, Kim and Neslin 2008; Zhang, Bradlow and Small 2014). These measures are then linked to outcomes such as customer churn or purchase volume, two drivers of customer lifetime value (CLV). Virtually all of the above work focuses on average behaviors within or across customers, i.e. summarizing the mean spending and average time between purchases. Recently, Rust, Kumar and Venkatesan (2011) and McCarthy et al. (2014) argued that firms should also pay attention to how variability in customer behavior affects customer value. To achieve this, the latter authors derive a method to compute the variance in customer lifetime value (V(CLV)) which takes into account variability in customer valuation. While this paper shows how to forecast customer behavior and determine the value of the customer base under the uncertainty of variance in customer behavior, it does not directly provide guidance on how to translate these measurements into marketing actions (e.g. as in Hanssens et al. 2014).

In this chapter, we therefore focus on developing an approach that firms can use to guide marketing actions in a non-contractual setting, taking into account the variability in customer behavior. This approach does not only tell firms which customers to target with marketing actions, but also when to target them. Besides behavioral variability, our approach also accounts for the notion that customers are heterogeneous in their behavior whilst their behavior might also

\(^1\) Clumpiness measures the dispersion in purchase time, i.e. whether purchases are closely spaced in time, or more equally divided across time.
vary over time (e.g. Fader, Hardie and Lee 2005a). The development of marketing programs in such a real-time environment is an open question, as indicated by the inclusion of this topic in the research priorities of the Marketing Science Institute (*Marketing Science Institute*, 2016). The potential gains of such an approach can be considerable however, in particular in the online setting we consider (Bijmolt et al. 2010; Goldenberg 2008). As a basis for the development of our approach we rely on techniques developed in the statistical quality control literature (Montgomery 2009). This stream of research is concerned with monitoring and controlling (industrial) processes in the face of process variability, making it ideally suited for our goals. In particular, we focus on a technique called control charts pioneered by Shewhart (1931), which is used to monitor a process variable (e.g. the average concentration of tin in a chemical bath) and to detect situations in time where the process does not obey its requirements (Wieringa 1997). An advantage of our approach compared to advanced methods is its reliance on RFMC statistics, easing the model implementation (e.g. Arora et al. 2008).

We demonstrate our proposed approach in an empirical example where we focus on predicting when customers will purchase again, if ever. Given the non-contractual setting we apply our approach in, knowing which customers will and which customers will not buy again is an important question that is difficult to answer (Fader, Hardie and Lee 2005b; Rust, Lemon and Zeithaml 2004). Subsequently we analyze the benefits such a targeting strategy can bring to an organization. Our empirical application is based on data from a large European company active in the greetings and gifts industry, which provided us with data on customer purchases for the years 2012-2014.

The remainder of the chapter will unfold as follows: In the next section, we will discuss the background to which we develop our research. Next, we outline the development of our model, and show how we deal with the aforementioned challenges of our application in the customer management setting. We shortly discuss the data we have available for our empirical example, and demonstrate the application of our method in the setting of purchase timing. We conclude with a discussion on the implications of our work, and provide directions for future research.
4.1 Research background

Before we outline the development of our approach, we first provide some more background information on target marketing. Next, we show the connection between control charts and problems faced in customer management. Next, we also highlight some challenges we face when translating the control chart approach to the customer management setting, and shortly discuss how we solve them.

4.1.1. Managing customers by targeting marketing actions

The starting point for many CRM applications is that customers are “manageable strategic assets of the firm” (Reiman, Schilke and Thomas 2010). This implies that firms can influence CLV (and its components) by using marketing actions on selected customers. To do so, firms need to know which customers to target at what time with which action (Neslin et al. 2013). In this chapter we seek to contribute on the first two points, as we do not have the data to investigate different types of actions.\(^2\) The problem of which customers to target with actions has been investigated quite extensively, most prominently in the direct mailing literature (e.g. Bult and Wansbeek 1995). Studies have acknowledged that taking into account the mailing history of a customer is important to capture dynamics (e.g. Gönul and Shi 1998; Gonül and Ter Hofstede 2006; Simester, Sun and Tsitsiklis 2006), because it might affect the effectiveness of such actions (Van Diepen, Donkers, and Franses 2009). However, few of these studies focus on the variability in the individual response to marketing actions (the latter study being a notable exception), which is one of the contributions we make in this chapter. In terms of timing of marketing actions, the recommendations of these studies are all made in terms of the amount of mailings: After how many mailings should you stop, and what is the optimal number of mailings? (e.g. Neslin et al. 2013; Van Diepen, Donkers and Franses 2009). However, in this study we consider calendar time as our measure of timing, and will propose policies based on this. Thereby we add to more recent literature that is interested in determining calendar time effects to improve marketing policies (e.g. Ascarza and Hardie 2013; Dew and Ansari 2016). In the next section we highlight how we achieve this, and discuss some notable differences with prior work.

\(^2\) In Section 5.2.3 we discuss a potential approach that could account for multiple actions
4.1.2. Control charts and customer management

The statistical quality control literature is concerned with monitoring industrial processes and acting on disturbances to these processes in order to safeguard the continuation of the process (Montgomery 2009). To that end, a variety of methods has been developed. One of the earliest and most prominent examples of such a method is the control chart (Shewhart 1931). Such a chart monitors the process performance through a target variable, for example the average concentration of a chemical. By measuring this target variable at different points in calendar time and plotting the resulting time series, a chart is created. The chart also includes predetermined bounds within which the process is allowed to move. If the target variable crosses these bounds a signal is given, and an intervention can take place to return the process within bounds.

Such situations where the bounds are crossed occur when the process is too variable (i.e. out-of-control) due to what Shewhart (1931) calls special causes, e.g. the concentration of the chemical deviates strongly from the mean (target) concentration. However, a certain amount of variability is allowed, as each process suffers from some normal variation that is natural to the process (common causes, Shewhart 1931). The bounds of the control chart seek to separate the common from the special causes of variation. Importantly, as long as the process is in-control (i.e. moves within the boundaries), one should not interfere in the process (“tampering with the process”, Deming 1982). Doing so would only lead to additional variation and potentially destabilize the process (Deming, 1982). Concluding, control charts provide a natural way to monitor a process mean and variance simultaneously.

The literature on RFMC (Blattberg, Kim and Neslin 2008; Zhang, Bradlow and Small 2014) stresses the importance of taking into account customer behavior by monitoring the recency, frequency, monetary value and clumpiness of customer purchases. The literature shows that these four process variables are highly informative about many customer behaviors, such as customer value and loyalty (e.g. Zhang, Bradlow and Small 2014). Hence, a firm that is interested in monitoring its customer base and managing CLV should focus on these variables to determine on which customers to focus its marketing efforts. In particular, a firm would be interested in divergent behavior as indicated by these variables. For example, customers with a low recency have potentially churned, and could be the target of retention actions (Neslin et al. 2013). Customers with low monetary value could be targets for cross-selling or up-selling initiatives (Blattberg, Kim and Neslin 2008). A control chart would be a potentially powerful tool
to do so, as it also seeks to identify instances of divergent behavior in a process (e.g. purchase timing when talking about recency). In addition, it also recognizes the natural variability in (historic) customer behavior, which has seen scant attention in the literature (a notable exception being McCarthy et al. 2014). However, it should be part of the decision process on which customers to target, as focusing on average behavior ignores the risks that come with variability (Rust, Kumar and Venkatesan 2011).

Moreover, a recent study by Ascarza, Iyengar and Schleicher (2016) also shows that firms should not react on all behavior. These authors found that recommending mobile phone price plans to decrease customer churn would achieve the opposite and increase customer churn instead. The reason for this was that customers who were unaware of their price plan were made aware, and decided to reevaluate their relationship with the telecommunications company. This is a typical example of “tampering with the process”, resulting in the process to destabilize further and resulting in negative consequences (i.e. churn). The control chart approach naturally deals with this situation by separating the common and special causes of variation. In turn, firms should only react on special causes of variation, and not interfere in the stable process. In sum, given the parallels between the issues faced in statistical quality control and customer management, we propose to adapt the control chart approach in order to improve the management of a customer base. In the next section we highlight some challenges we face therein.

### 4.1.3. Control charts for purchase timing: Challenges and solutions

Our main contribution in this chapter is translating the control chart approach to the customer management setting. To do so, we need to define the process we desire to monitor, and account for the specific characteristics we are faced with in this setting. In this chapter we focus on purchase timing, i.e. when will a customer make a purchase? Purchase timing is an important driver of customer lifetime value (e.g. Blattberg, Kim and Neslin 2008), and is particularly difficult to model in a non-contractual setting (Rust, Lemon and Zeithaml 2004). Moreover, accurate timing can increase the relevance of marketing actions by providing them at a point in time when customers are more receptive to such message, potentially increasing their effectiveness (Goldenberg 2008).
Second, having determined the candidate process, we need to adapt the existing control chart approaches to this specific setting. Particular challenges we face are the selection of the distribution of the data generating process, the presence of customer heterogeneity (Leeflang et al. 2015, ch. 8), and the unavailability of in-control samples for model calibration. We shortly touch upon these issues and our proposed solutions to them here, and expand on them in the model development section. While many control charts assume a normal process distribution (a notable exception is Zhang et al. 2007), for purchase timing this assumption is not valid due to high skewness in this distribution. We therefore adopt a gamma process distribution to accommodate this skewness, following Colombo and Jiang (1999), Fader, Hardie and Lee (2005b), and Platzer and Reutterer (2016). Next, while control charts are usually developed to monitor a single process (e.g. Montgomery 2009), the monitoring of many individual customers gives rise to issues of between-customer heterogeneity affecting the process. We tackle these issues by assuming a gamma heterogeneity distribution on one of the parameters of the gamma process distribution, giving rise to the gamma-gamma distribution as used by Colombo and Jiang (1999) and Fader, Hardie and Lee (2005b). This way, we can use a single method to monitor many individual processes, easing model implementation.

Finally, calibration of control charts requires an in-control sample to determine the boundaries of the control chart which are used to detect out-of-control situations. In the absence of such a sample in most customer management settings, we develop a simulation approach based on the well-known Pareto/NBD model (Schmittlein, Morrison and Colombo 1987) to simulate in-control customers to calibrate our gamma-gamma control charts. Subsequently, we can apply the control chart calibrated on this in-control sample to the full customer database. In the next section, we provide more details on how our approach deals with the above challenges.

### 4.2 Model Development

We start our model development by considering the characteristics of the statistical process underlying our variable of interest: inter-purchase time (IPT). Our model development is based on the following assumptions, which we adapt from Fader, Hardie and Lee (2005b):
- For a given purchase occasion, the time since the last purchase varies around the average customer-specific inter-purchase time
- The average inter-purchase time varies across customers, but does not vary over time for a specific customer

The latter assumption implies that there is a true process mean to be estimated, with noisy variation around the mean. To accurately model the time between purchases, we need to consider the properties of the process distribution. In Table 4-1 we summarize this distribution. We note several things. First, the distribution appears to be right skewed, as indicated by the disparity between mode, median and mean. Second, the time between purchases is non-negative. Both these characteristics indicate that a normal distribution is not feasible to model this process. We therefore adopt the gamma distribution to model this process. This is based on prior work suggesting exponential and Erlang-2 distributions for the time between purchases (e.g. Chatfield and Goodhardt 1973; Morrison and Schmittlein 1988; Schmittlein, Morrison and Colombo 1987), both of which are special cases of the gamma distribution. Recently, Platzer and Reutterer (2016) showed that this specification also helps to capture the notion of clumpiness as defined by Zhang, Bradlow and Small (2014). As noted before, when considering the purchase process of a single customer, this assumption would have been sufficient. However, as we are seeking to model the purchase processes of many customers, it seems unreasonable to assume a similar distribution for each customer (see assumption 2 above). We therefore assume that heterogeneity across the population exists, and that this heterogeneity can be modeled with another gamma distribution. In so doing we follow Fader, Hardie and Lee (2005b), and adapt the gamma-gamma model of Colombo and Jiang (1999) as our model of inter-purchase time. An important advantage hereof is that we can obtain closed-form solutions for some of our key expressions later on.

To develop a control chart that can be used to monitor the IPT process, we first consider the general form of such a chart. Here, we focus on the simplest form due to Shewhart (1931). Such a control chart plots the individual observations in a chart with the mean across these $x$ observations, combined with an upper and lower control limit (Montgomery 2009). This can be denoted as

$$ CC(x) = \mu(x) \pm c \cdot \sigma(x), $$

where $\mu$ and $\sigma$ can be replaced by suitable estimators of this quantity depending on the underlying process distribution. The width of the control chart $c$ is often taken as 3 for both
upper- and lower-bounds, based on the assumptions that the process distribution is normal. This corresponds to a false alarm probability of $1 - 0.9973 = 0.0027$, i.e. a false alarm is highly unlikely and the occurrence of one should be cause for concern (Shewhart 1931). Given our earlier exposition on the non-normality of our underlying distribution, we will seek to replace each of these quantities by forms suitable to our desired application. That is, we will derive expressions for $\mu$ and $\sigma$ based on the gamma-gamma model to deal with the non-normality, and we will propose a procedure to determine $c$ given this data structure as well. For $c$, we will also allow that $c_+ \neq c_-$, i.e. the distance need not be the same for the upper- and lower-bound. This way, we accommodate the non-symmetric nature of the distribution we consider.

**Table 4-1: Summary statistics for the monetary value and inter-purchase time of repeat purchases per customer**

<table>
<thead>
<tr>
<th></th>
<th>Days</th>
<th>€</th>
<th>Days</th>
<th>€</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>0</td>
<td>0.0</td>
<td>Mean</td>
<td>6.17</td>
</tr>
<tr>
<td>25th percentile</td>
<td>0</td>
<td>0.7</td>
<td>Standard Deviation</td>
<td>12.11</td>
</tr>
<tr>
<td>Median</td>
<td>0.71</td>
<td>0.9</td>
<td>Mode</td>
<td>0</td>
</tr>
<tr>
<td>75th percentile</td>
<td>6.18</td>
<td>1.6</td>
<td>Skewness</td>
<td>0.36</td>
</tr>
<tr>
<td>Maximum</td>
<td>100</td>
<td>100</td>
<td>Kurtosis</td>
<td>1.54</td>
</tr>
</tbody>
</table>

The values have been indexed for confidentiality reasons. The index was set to 0 at the 0-point, and to 100 at the maximum inter-purchase time or purchase value.

### 4.2.1 Deriving $\mu$ and $\sigma$ for the gamma-gamma model

In this section, we derive expressions characterizing the mean and standard deviation for the gamma-gamma model. These expressions can be used to determine the average IPT of a customer after $x$ purchases, as well as the variation therein that determines whether an out-of-control situation has occurred.
For a customer with $x$ transactions, let $z_1, z_2, ..., z_x$ denote the time between each transaction$^3$. Define $\bar{z} = \frac{\sum_{i=1}^{x} z_i}{x}$ as an estimate of the (unobserved) average IPT of the customer, denoted as $\xi$ (Fader and Hardie, 2013). We are interested in two quantities related to $\xi$: its conditional mean denoted as $E(Z|\bar{z}, x)$ and its conditional variance denoted as $\text{Var}(Z|\bar{z}, x)$. These two quantities will serve as estimates for $\mu$ and $\sigma$ as desired. To arrive at these expressions, we formalize the model of Colombo and Jiang (1999) as follows:

1. We assume that $z_i \sim \text{gamma}(p, \nu)$, which implies $E(Z_i|p, \nu) = \xi = \frac{p}{\nu}$. This implies that $\bar{z} \sim \text{gamma}(px, vx)$.

2. We assume that $\nu \sim \text{gamma}(q, \gamma)$

Under these conditions, Fader, Hardie and Lee (2005b) show that

$$E(Z|p, q, \gamma, \bar{z}, x) = \frac{p(\gamma + x\bar{z})}{px + q - 1} = \left(\frac{q - 1}{px + q - 1}\right)\frac{p\gamma}{q - 1} + \left(\frac{px}{px + q - 1}\right)\bar{z},$$

which gives our first desired expression. Estimation of the parameters $p$, $q$ and $\gamma$ will be discussed shortly. Note that as $x$ increases, more weight is placed on the actual observed average monetary value or IPT $\bar{z}$, and less weight is placed on the population mean. Deriving an expression for $\text{Var}(Z|\bar{z}, x)$ is more complicated, and no exact closed form solution exists. We therefore resort to a second-order Taylor approximation of this quantity. The full derivation is provided in Appendix 4.A, where it is shown that

$$\text{Var}(Z|p, q, \gamma, \bar{z}, x) = \frac{4p^2(\gamma + x\bar{z})^4(px + q) + q(\gamma + x\bar{z})^4}{(px + q)^6}.$$

To obtain estimates of the parameters $p$, $q$ and $\gamma$, we require the marginal distribution of $\bar{z}$. Fader, Hardie and Lee (2005b) derive that this marginal distribution is equal to

$$f(\bar{z}|p, q, \gamma, x) = \frac{\Gamma(px + q)}{\Gamma(p)\Gamma(q)} \gamma^q \bar{z}^{px-1} x^{px} \left(\gamma + \bar{z}x\right)^{px+q}.$$

Maximum likelihood estimation can then be used to obtain the desired parameter estimates. The likelihood to optimize for $N$ customers given their observed number of purchases $x_i$ and average IPT $\bar{z}_i$ is

$$L(p, q, \gamma|x_i, \bar{z}_i) = \prod_{i=1}^{N} f(\bar{z}_i|p, q, \gamma, x_i).$$

$^3$ We focus on repeat transactions here, hence $z_i$ denotes the time between the first and second purchase. Customers with only one purchase are excluded from the analysis, as it is not certain whether they will make another purchase.
Based on the parameter estimates obtained by maximizing Equation 5 we can compute our other quantities of interest \( E(Z | p, q, \gamma, \bar{z}, x) \) and \( \text{Var}(Z | p, q, \gamma, \bar{z}, x) \).

4.2.2 Estimating \( c \) for the gamma-gamma model

Having obtained estimates for \( \mu \) and \( \sigma \) in Equation 1, all that remains is obtaining an estimate for the width of the control chart boundaries \( c \). In general, this width can be set to a fixed number such as 3 (e.g. Shewhart 1931), but it can also be selected based upon a sample of observations known to be in-control in combination with a suitable false alarm rate (e.g. \( P(\text{false alarm}) = 0.0027 \)). As the number 3 is based on normal distribution theory and we are dealing with non-normal data in our cases, we will use an in-control sample instead to determine the value of \( c \). However, the notion of in-control is hard to define in our case: We do not know a-priori which customers (or observations from these customers) are behaving as ‘normal’ and which observations are not. In addition, given that we do not observe the same number of purchases per customer, we cannot reliably determine a false alarm rate due to short time horizons for many customers.

We therefore rely on a simulation approach whereby we generate our own in-control observations based on the structure of the underlying data, and determine the value for \( c \) based on this sample. In particular, for a given set of simulated customers we need to generate a number of purchases that confirm with the data on purchase timing. To achieve this, we first generate the number of purchases according to the negative binomial model, where the time between purchases is determined according to the BG/NBD model (Fader, Hardie and Lee 2005a), both estimated on the data. This approach allows us to simulate long purchase trajectories for each simulated customer, making it possible to select \( c \) using a grid search such that most of these observations are within the bounds of the control chart (i.e. are in-control). We follow existing theory by requiring that \( c \) is chosen such that 99.73% of the observations are within the bounds of the control chart (Shewhart 1931).
4.3 Empirical application

In this section, we will illustrate the above approach with an empirical application. We first shortly describe the data set that we have available (see also Table 4-1 for summary statistics). Next, we provide our application related to purchase timing.

4.3.1 Data description

Our focal data are provided by an anonymous European on-line retailer in the greetings and gifts industry. The data set covers the first (trial) and repeat purchases of 373,521 customers at the retailer. The first purchase occurred in 2012 (starting January 1) for these customers, and the final order that was recorded in the dataset occurred on December 9, 2014, leading to a total of 1,963,446 orders. Customers can order greetings and gifts at the retailer, with the latter category corresponding to orders with higher value, but more infrequent purchases than the former category. Beyond the date and value of each purchase, we also have information on the number of greetings and gifts per purchase, and whether the purchase was made using a discount voucher. At the customer level, we have information on the age, gender, location, relationship age, and starting purchase (greeting or gift) of most customers. In Table 4-1 we provide summary statistics for the purchase value and purchase timing variables. Note that the values are indexed for confidentiality reasons. We will use the information on purchase value later on, when we consider the value implications of improved targeting.

In the subsequent analyses, we will make use of a sample of 5,000 customers to estimate the model instead of the full database to facilitate the maximum likelihood estimation (e.g. Fader, Hardie, Lee 2005a). Afterwards, we use these estimates to apply the model to each customer in the database.

4.3.2 Predicting purchase timing for customer reactivation

Given the non-contractual setting the retailer is operating in, identifying active from inactive customers is important in directing marketing efforts. Customers that remain active are a source of income for the retailer, while customers that become inactive (churn) can be lost, with all the consequences associated with it (see e.g. Blattberg, Kim and Neslin 2008). Currently, the retailer tries to prevent customers from churning by sending a so-called reactivation mail after a
customer has not purchased for two months (eight weeks). Such an e-mail serves as a reminder to
the customer, and also offers free postage or a discount on the next order. Both these traits aim to
move the customer to purchasing again from the retailer.

However, the current approach has some limitations. Sending such an e-mail after two
months for all customers does not account for the fact that the purchase patterns of individual
customers can differ widely (see also Table 4-1). Some customers might buy once every month,
while others buy once every 6 months. The former group will generally not receive an e-mail, but
if such a customer has not bought for e.g. 1.5 months this could already indicate a break from
past behavior and thus churn. Similarly, a customer in the latter group would receive the e-mail,
but given that she does not need a greeting or gift given her regular purchase cycle, disregards the
e-mail (wasting the opportunity from the firm perspective), or buys something at reduced value
(leading to a loss of revenue for the firm)\(^4\). Our approach can remedy these situations by making
use of the past purchase timing information to derive a date at which the next purchase should
occur given an individual’s purchase pattern (the upper-limit of the control chart). We propose to
send an e-mail once this time has passed, and the customer did not make a purchase by that date.
This increases the relevance of this e-mail, making the likelihood of response larger, and
therefore increasing the effectiveness of the message (Goldenberg 2008).

To that end, we calibrate control charts based on the inter-purchase time (IPT) of our
sample of customers. First, we need to obtain the maximum likelihood estimates based on
Equation (5). These are given as \(\hat{p} = 17.39\), \(\hat{q} = 1.65\) and \(\hat{\gamma} = 3.73\) for our sample. In Figure 4-1
we compare the fit of this distribution against the empirical distribution using a non-parametric
density plot. The plot also includes a simple gamma density, which represents a non-
heterogeneous alternative to our model. In addition, the exponential distribution is a special case
of the gamma distribution, which is a reasonable distribution for the inter-event times when
purchases are made following a Poisson process (Ross, 2007). Both models show some deviation
from the empirical distribution function, which is confirmed by a two-sample Kolmogorov-
Smirnov test which rejects similarity between the gamma-gamma model and the empirical
distribution function \((p < .01)\) and also rejects similarity between the gamma model and the

\(^4\) This assumes that the customer accelerates the next purchase occasion, which is possible given the durable
nature of the product studied here. If an additional purchase occurs on top of the regular purchases, the firm has
created a successful upselling opportunity. However, given the scope of the chapter, we do not discuss the value
implications hereof.
empirical distribution function ($p < .01$). While both models do not show perfect fit to the empirical distribution, we do notice a better fit of the gamma-gamma model when it comes to capturing the largest concentration of mass in the probability distribution, which is underestimated in the gamma model. We therefore continue with the gamma-gamma model. Second, we need to determine the bounds for the control charts. Based on the simulation approach discussed in Section 4.2.2, we find that the value for the upper-bound is $\hat{\phi} = 12$. We do not use the lower bound in this case, as the time between purchases is naturally bounded at 0. With these estimates at hand, the control charts are completely defined for every customer in the sample, and we can analyze the results.

**Figure 4-1: Non-parametric density estimates of the empirical distribution function of inter-purchase times**

As an example of the outcomes produced by our approach, we plot the control chart for a selected customer in Figure 4-2. The control chart depicts the time (in weeks, indexed) since the last purchase on the y-axis. The dotted lines represent the upper control limit of the control chart; the lower bound is omitted as the inter-purchase time is always nonnegative. The figure reveals some salient characteristics of our approach. First, the chart is able to track the customer purchase pattern across time, and is able to classify each observation as within control or out-of-control (based on the upper-bound). Second, the control limit adapts when new information (i.e. a new
purchase) is available. This feature allows the model to learn the behavior of specific customer over time, while less weight is placed on the population-level information (see Equation 2). Due to this adaptability, the approach can be used in a real-time setting to monitor the status of the entire customer base based on the behavior of individual customers. Third, the figure illustrates that there are several points in time where a firm intervention could have taken place. These are the weeks where the time since the last purchase (dots) crosses the upper-limit of the control chart (dotted line). In these instances, the time since the last purchase exceeds what we might expect from that customer based on her own behavior, and the behavior of the population as a whole. At other times, subsequent purchases follow a pattern within the bounds, indicating a ‘normal’ purchasing pattern for that customer.

**Figure 4-2: Control chart for inter-purchase times of a selected customer**

*(y-axis indexed for anonymity reasons)*

A firm can thus separate potential churners from non-churners in two ways. First, when a customer is unlikely to purchase again (based on the average of the customer base and its own past), the control limit for this customer will be high, and the firm will not act on any signal of this customer. Second, customers that have crossed the control limit for a long-time without repurchasing could also be considered as lost. However, this would require determining a cut-off for this distance, which we do not pursue in this chapter.
As we use historical data, the firm did not act upon the out-of-control signals identified by the control chart. Thus, we cannot evaluate the effectiveness of such responses. However, we can evaluate the characteristics of such an intervention, and compare these to the current policy of sending a reactivation e-mail after two months.

Figure 4-3 shows the distribution of e-mails sent under the policy recommended by the control chart approach we develop. A few things are of note. First, there is a substantial shift in the timing of the e-mails sent. The median time to send an e-mail is reduced to 5.0 weeks, instead of the current time of eight weeks across all customers. Second, however, there is also a substantial amount of heterogeneity in the time to send an e-mail, as indicated by the standard deviation of 9.5 weeks of the distribution. For a large portion of customers (31.9%), e-mails are sent beyond the current threshold of eight weeks, indicating that these customers were targeted to early under the existing policy. Finally, there is slight increase in the amount of e-mails sent overall. While under the existing policy 13,074 e-mails would have been sent over the period investigated, under the proposed policy this would amount to 15,964 e-mails. Combined with a different distribution of these e-mails across customers, this suggests a substantial change to the current policy. Therefore, this analysis does illustrate the potential of our approach for more effective deployment of marketing resources. To evaluate the consequences of our approach, we provide some implications in the next section.

Figure 4-3: Distribution of reactivation e-mails sent under control-chart policy, compared to current policy of sending an e-mail after two months (vertical line)
4.3.3 The consequences of improved targeting

In this section we aim to show the value that improved targeting can have in relation to firms’ marketing actions. We focus on two measures of effectiveness: response to marketing actions, in this case e-mail, and value of purchases.

First, we consider the response to marketing actions, in this case the e-mail that is sent. Sending an e-mail closer to the point in time when it becomes relevant to a customer (i.e. when the customer is thinking of purchasing again) will increase the effectiveness of such a message (e.g. Chen, Narasimhan and Zhang 2001; Goldenberg 2008). To investigate whether targeting improvements give rise to improved responses to mailings, we compare the conversion rates of mails sent under the eight weeks policy with the model predicted purchase time. By comparing these predicted purchase dates to the actual purchase date, and relating these to the current e-mail policy, we can gain some insights in the effectiveness of this policy. We achieve this by dividing customers into three groups based on our model predictions: those targeted too late (e-mail sent more than 1 week after the predicted purchase date), those targeted on time (e-mail sent 1 week before or after predicted purchase date), and those targeted too soon (e-mail sent more than 1 week before the predicted purchase date). We then compare the conversion rates of the e-mails (sent after eight weeks) across these groups to investigate potential between-group differences.

Here, conversion is defined as purchasing within one week after receiving the e-mail, in line with the definition used by the focal firm.

As we are considering conversion rates, interpreting these rates directly between groups could lead to biased results if we do not account for between-group differences that could influence conversion behavior. We therefore first apply a hybrid matching procedure (e.g. Gensler, Leeflang and Skiera 2012) to match the three groups on purchase behavior (value and timing), and customer characteristics. As a consequence, the matched customers should be comparable, and we can measure the effect that receiving an e-mail (vs. not receiving an e-mail) has on conversion. We take the on-time group as our reference group, and match customers that were targeted too soon or too late with customers in this reference group.

The matching procedure yields 2607 matched purchase occasions for the too late and on-time group, while yielding 1391 matched purchase occasions for the too soon and on-time group. If we compare the conversion rates across groups, we find that compared to the on-time group, customers that were targeted too late have a significantly higher conversion rate (0.42 vs 0.53, p
< .05). Furthermore, compared to the on-time group, customers that were targeted too soon have a significantly lower conversion rate (0.40 vs 0.15, p < .01). Note that there is no difference in conversion rate between the two different on-time groups (0.42 vs 0.40, p > 0.10), assuring that these reference groups are comparable.

We thus find that customers that were targeted too late have an 11% higher conversion in response to e-mails compared to those targeted on time. This could indicate that these customers were already willing to purchase before, but did not get around to doing so. Given the higher response of this group, it seems that these customers are highly willing to purchase at the focal firm, and did not do so at another firm for example. Hence, there seems to be no loss in response associated with sending e-mails too late. Instead, the effectiveness is increased. However, sending e-mails too soon dramatically reduces the response rate by 25%. Customers receiving these e-mails are not yet willing to purchase again from the focal firm, and seem to disregard the e-mail sent. This finding does indicate a loss in marketing effectiveness for the firm, and this is the area where improved targeting could improve the timing of e-mails, thereby potentially increasing their effectiveness. Concluding, in terms of response to marketing actions the gains of improved targeting are likely to be made for customers that were approached too soon, and not for customers that were approached too late.

When we consider the value implications of improved targeting, we noted before (i.e. footnote 4) that when a customer receives an e-mail while he normally would not make a purchase yet, (s)he has the possibility to accelerate his/her purchase pattern by purchasing in response to the e-mail. However, given the acceleration in the purchase pattern, it is possible that the value of this purchase will be lower than otherwise would have occurred. Repeating this several times would result in potentially substantial losses in customer value. Similarly, sending an e-mail too late might lead to loss of purchase value due to the customer purchasing elsewhere, given the non-contractual setting we consider (e.g. Rust, Lemon and Zeithaml 2004). In general, the value implications of better (individually) targeted marketing actions is found to be positive compared to the case of more aggregate targeting, in both the off-line (e.g. Rossi, McCulloch and Allenby 1996) as well as the on-line world (e.g. Ansari and Mela 2003; Zhang and Wedel 2009).

---

5 We obtain two on-time groups, because the matching procedure used only allows matching of two groups, as a logistic regression approach is used. The on-time groups are similar on the matching variables however, and this result shows that they also do not differ on the outcome variable of interest.

6 Note that we do not assume that a customer is lost for good if no purchase occurs (e.g. Schmittlein, Morrison and Colombo 1987), but that a customer can return in the future to purchase again (e.g. Berger and Nasr 1998).
To investigate whether these assertions hold, we compare the eight week policy to our model predicted policy. We do so by considering the same three groups as before (targeted too late, targeted on time and targeted too soon), and comparing the value of orders within these groups. To that end we estimate a linear regression model relating these groups to the value of each purchase, while controlling for the size and timing of the order. Specifically, we estimate the following model for the $j$-th purchase occasion of customer $i$:

$$
Value_{ij} = a_0 + \beta_1 \text{Targeted. too. soon}_{ij} + \beta_2 \text{Targeted. too. late}_{ij} + \beta_3 \text{E - mail. sent}_{ij} \\
+ \beta_4 (\text{Targeted. too. soon}_{ij} \times E - \text{mail. sent}_{ij}) + \beta_5 \text{Targeted. too. late}_{ij} \times E \\
- \text{mail. sent}_{ij} + \beta X_{ij} + \epsilon_{ij}
$$

Here, targeted too soon and targeted too late refer to the groupings based on our model, while the e-mail sent variable measures whether an e-mail was sent preceding that order or not. The control variables $X_{ij}$ contain measures for the amount of greetings and gifts ordered in a specific purchase occasion, whether a conversion (measured as purchasing within a week after the e-mail) took place on that purchase occasion, and the inter-purchase time since the last purchase occasion. The dependent variable is operationalized as an index to maintain data confidentiality, where the base of the index is taken as the mean (model 1 and 3) or the median (model 2 and 4) spending per purchase occasion. To control for customer heterogeneity, in model 3 and model 4 we include a full set of customer fixed effects. The results of our estimations can be found in Table 4-2.

The results consistently show that sending an e-mail before the predicted purchasing date results in decreasing purchase values, compared to sending it on time. This is indicated by the negative coefficient $\beta_4$ of the interaction term. The losses are sizable, with a 5% loss in mean purchasing value, and an 8.5% loss in median purchase value (based on the models including fixed effects). In contrast, sending an e-mail after the predicted purchase date does not lead to any change in purchase value compared to the case where an e-mail is sent on time. Hence, we find support for the notion that reaching out to customers too quickly can be detrimental to firm

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7 The advantage of the fixed effects model over a random effects model is that it captures both the main effects across groups (i.e. targeted too late vs. targeted too soon), as well as the interactions (Goldfarb and Tucker 2011). Moreover, given the large number of observations per customer, fixed effects are also not prohibitive.

8 The main effect in models 1 and 2 is positive, but the total effect is negative. When controlling for customer heterogeneity, the significant main effect disappears.
Leveraging Data Rich Environments

profits. Reassuringly, no evidence is found for the notion that e-mails sent too late will lead to a loss in profits, mitigating concerns that customers might shop elsewhere at the cost of the focal firm.

### Table 4-2 Overview of estimated models

<table>
<thead>
<tr>
<th></th>
<th>(1) DV purchase value mean index</th>
<th>(2) DV purchase value median index</th>
<th>(3) DV purchase value mean index</th>
<th>(4) DV purchase value median index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Targeted too late</td>
<td>-1.021</td>
<td>-1.746</td>
<td>-2.144*</td>
<td>-3.667*</td>
</tr>
<tr>
<td></td>
<td>(1.063)</td>
<td>(1.819)</td>
<td>(1.228)</td>
<td>(2.100)</td>
</tr>
<tr>
<td>Targeted too soon</td>
<td>2.809**</td>
<td>4.804**</td>
<td>1.110</td>
<td>1.899</td>
</tr>
<tr>
<td></td>
<td>(1.172)</td>
<td>(2.005)</td>
<td>(1.267)</td>
<td>(2.167)</td>
</tr>
<tr>
<td>E-mail sent</td>
<td>3.869*</td>
<td>6.618*</td>
<td>3.138</td>
<td>5.367</td>
</tr>
<tr>
<td></td>
<td>(2.183)</td>
<td>(3.734)</td>
<td>(2.136)</td>
<td>(3.653)</td>
</tr>
<tr>
<td>Converted</td>
<td>0.348</td>
<td>0.595</td>
<td>0.821</td>
<td>1.403</td>
</tr>
<tr>
<td></td>
<td>(1.586)</td>
<td>(2.712)</td>
<td>(1.557)</td>
<td>(2.663)</td>
</tr>
<tr>
<td>Number of greetings</td>
<td>27.896***</td>
<td>47.717***</td>
<td>27.889***</td>
<td>47.705***</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.095)</td>
<td>(0.059)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Number of gifts</td>
<td>266.957***</td>
<td>456.636***</td>
<td>256.966***</td>
<td>439.546***</td>
</tr>
<tr>
<td></td>
<td>(0.917)</td>
<td>(1.568)</td>
<td>(1.008)</td>
<td>(1.725)</td>
</tr>
<tr>
<td>Inter-purchase time</td>
<td>0.227***</td>
<td>0.389***</td>
<td>0.200***</td>
<td>0.342***</td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td>(0.072)</td>
<td>(0.044)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>Targeted too late x E-mail sent</td>
<td>-3.785</td>
<td>-6.475</td>
<td>-2.247</td>
<td>-3.845</td>
</tr>
<tr>
<td></td>
<td>(2.458)</td>
<td>(4.206)</td>
<td>(2.393)</td>
<td>(4.094)</td>
</tr>
<tr>
<td>Targeted too soon x E-mail sent</td>
<td>-6.058***</td>
<td>-10.362***</td>
<td>-5.001**</td>
<td>-8.544**</td>
</tr>
<tr>
<td></td>
<td>(2.299)</td>
<td>(3.932)</td>
<td>(2.259)</td>
<td>(3.865)</td>
</tr>
<tr>
<td>Constant</td>
<td>31.664***</td>
<td>54.161***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.016)</td>
<td>(1.738)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Customer fixed effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>70,547</td>
<td>70,547</td>
<td>70,547</td>
<td>70,547</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.825</td>
<td>0.825</td>
<td>0.844</td>
<td>0.844</td>
</tr>
</tbody>
</table>

*p<0.1 **p<0.05 ***p<0.01
4.4 Discussion

Customer centric firms have an interest in learning about customer behavior in order to serve customers better, thereby potentially increasing their value to the firm (Shah et al. 2006). These insights can be used to explain the value of a customer to the firm (e.g. through customer lifetime value, CLV) and select customers to focus marketing actions on (Rust, Lemon and Zeithaml 2004). While much of the prior work in this field has linked the average customer behavior to drivers of CLV (e.g. Fader, Hardie and Lee 2005b), recently McCarthy et al. (2014) and Rust, Kumar and Venkatesan (2009) emphasized the need to focus on the variation in this behavior as well. The former authors extend the RFMC framework, which focuses on average behavior of a customer, with information about the variance in this behavior in order to derive what they call V(CLV). However, while this work shows how to value customers taking into account the variance in their behavior, it does not guide the decision making process regarding the execution of marketing actions. In this work we therefore develop an approach that not only provides firms with the information on which customers to target, but also when to target them.

Our approach takes into account and leverages the variation in customer behavior in order to guide these decisions. Our approach, which derives from the control chart methodology used in the statistical quality control literature, captures the variation in behavior over time within a customer, and controls for the heterogeneity between customers. We show how to develop such control charts in the setting of purchase timing, using data on the inter-purchase time (IPT) of customers. We tackle challenges surrounding the non-normality of the IPT distribution by using a gamma distribution instead, capture heterogeneity in this distribution through another gamma distribution (arriving at what we call a gamma-gamma control chart), and develop a method to efficiently calibrate these control charts on data from a customer database. We illustrate our approach with an application in targeting reactivation e-mails for a company in the greetings and gifts industry. We discuss the alternative policy recommended by our model, and compare our approach with the current policy of sending an e-mail after eight weeks of customer inactivity.

Our findings suggest that our model fits the inter-purchase time data reasonably well, and is better able to capture the mass of the distribution than a model without heterogeneity. We show how the control chart identifies when to target which customers by making use of control limits, which present an upper-bound on the variation in the process. Once this bound is crossed, it has taken too long for a customer to purchase again, and a firm intervention should take place (see
Figure 4-2). Another salient feature of our approach is that once a new purchase takes place, the model automatically updates the upper-bound with this information, making the model highly adaptable to changing circumstances and applicable for real-time marketing (Goldenberg 2008).

Given our calibrated model, in the empirical application we compare our targeting policy based in individual level control charts to the current firm policy of sending an intervention (reactivation) e-mail after eight weeks without a purchase occurring. We find that under the new policy, the median time is reduced to five weeks. However, in a substantial amount of cases (31.9%) e-mails should be sent later than eight weeks. We also shed some light on the consequences of this new policy. We find that there are no negative consequences of targeting customers too late (after their predicted purchase date) in terms of conversion rate in response to e-mails, but this conversion rate drops with 25% when customers are targeted too soon (before their predicted purchase date). Targeting customers too soon also has negative value implications: The mean purchase value drops by 5% for these customers. Again, targeting customers too late has no negative consequences. We thus find managerially relevant consequences associated with using our method over existing methods.

4.5 Limitations and future research

Within the scope of this chapter there are still some limitations remaining which could not be addressed. While the recommendations we made with respect to the current firm policy suggest improvements to this policy, we cannot measure the causal impact of these changes given the use of historical data. These data do not allow us to evaluate a change in the intervention strategy, because we cannot execute these interventions; we can only suggest what the firm should have done in the past. To further deepen our understanding on the consequences of our proposed change, a field experiment could be performed to measure the impact of our proposed changes, and validate our findings with regards to the implications thereof.

Second, our policy recommendations assume that customers are not forward looking and adjust their behavior based on the observed change in the policy (Meyer and Hutchinson 2016). However, we argue that learning in this case is limited, as customers would find it difficult to observe the policy and refine their reactions accordingly. This is due to the full e-mail policy of the focal firm, which includes other promotional messages (brand building mails, new product introduction mails) beyond the reactivation mail message. While the latter message is distinct in
that it offers an activating message, it is also one of multiple messages a customer is exposed to, adding noise to consumer learning. As this is one of the causes that prohibits consumer learning (Meyer and Hutchinson 2016), we expect limited adjustment to occur.

Third, we only apply our approach in the specific setting of the greetings and gifts industry. Extensions to other industries could help generalize our findings and the validity of our approach. Given the general outline of our approach given here, such implementations should be straightforward.