Chapter 5

General Discussion
In a world that is being transformed by the increased richness and detail of data (Wedel and Kannan 2016), new opportunities and challenges arise that firms have to deal with to stay competitive and maintain the value to the firm of their marketing activities. The aim of marketing analytics is to leverage this data richness using model-based approaches to guide the decision making of firms and managers. In this dissertation we showed how firms can use marketing analytics approaches to improve or maintain the value to the firm of their marketing activities at the brand and customer level. We identified several opportunities and challenges associated with data richness, and showed how these affects firms’ activities and the associated value thereof. In the first study, described in chapter 2 of this dissertation, we showed how firms can gain insights on the own and competitive effects of their marketing actions at both the strategic and tactical firm level. Furthermore, we investigated the impact on firm sales of these strategic and tactical actions, which capture the impact on marketing productivity. In the second study of this dissertation in chapter 3, we show how firms can engage in churn prediction to retain customers while also maintaining the privacy of their customers. We thus show to combine two seemingly incompatible objectives by developing a suitable method that encompasses both objectives. The final study in chapter 4 of this dissertation shows how firms can engage in real-time customer targeting by leveraging variation in customer purchase behavior, and demonstrates the value from doing so. The next section highlights the main findings of each study in this dissertation. After that we provide some directions for future research related to each of these three studies. We close this dissertation with some final learnings across the studies.

5.1 Main Findings and managerial implications

In this section we provide the main findings of each of the studies presented in this dissertation. Furthermore, we discuss the managerial implications of each study.

5.1.1. Competitive reactions to strategic and tactical marketing actions

The first study explored the competitive interactions between firms by analyzing strategic and tactical actions initiated by firms in order to acquire and develop customers. Here, we make use of richer data availability to gain a broader view on competitive interaction by considering own and competitive marketing actions, a difference from prior work that is more inward focused (Kamakura et al. 2005). Strategic actions, implemented by higher management, determine the
policies and strategies that govern the acquisition, use and disposition of resources to achieve firm objectives (Anthony 1965; Schultz, Slevin, Pinto 1987; Steiner 1969). On the other hand, tactical actions, which are implemented by more junior management, determine the detailed deployment of these resources. We empirically explore differences between these competitive actions in the setting of the pharmaceutical industry using the sales force as a marketing instrument. Using a unique, single-source panel dataset consisting of 1502 British physicians and covering twenty years of prescriptions and detailing data in combination with time-series methods (i.e. SURECM models) we quantify the short- and long-run strength and sales impact of both types of competitive actions, and provide insights on factors moderating reaction strength.

Our findings suggest three things. First, we find that the competitive response to retaliatory strategic actions (i.e. allocating more resources in response to a competitive increase) is stronger than the response to retaliatory tactical actions. This is in line with Dutton and Jackson (1987), who suggest that the increased competitive threat of strategic actions strengthens the response to these actions. Second, while we find that the response to strategic actions is always justified from a sales point of view, we also show that in a substantial amount of the cases for retaliatory tactical actions the wrong response is chosen. This leads to a loss of sales (Porter 1980). Third, we find distinct differences in the moderators that explain differences between the reaction strength towards strategic and tactical actions. While the former actions are driven by a mix of factors related to awareness, motivation and capability to react, the latter are almost exclusively driven by motivational factors (Chen 1996). This suggest a relative narrow focus in the decision making process surrounding tactical actions, while the decision making process for strategic actions takes a broader view when determining if and how to react to competitive actions.

The managerial implications of our findings are threefold. With respect to strategic actions, given their higher importance and risk to elicit competitive response, careful consideration on whether and how to take such actions should take place. However, managers often fail to consider the competitive response when taking such decisions (Montgomery, Moore and Urbany 2005). Our findings on the moderating effects driving competitive response can ease this process by providing insights on the circumstances under which managers can expect stronger or weaker reactions towards the actions that they take. Furthermore, model-based decision support tools explicitly taking into account competition can also help improve the
decision making process (e.g. Dong, Manchanda and Chintagunta 2009). At the tactical level, two main implications arise. First, given the large amount of actions that are not justified from a sales perspective, assisting junior managers in their decision making process by offering training and coaching can be very valuable to improve decisions (Armstrong and Collopy 1996). Furthermore, offering the same decision support tools as used by higher management can also strengthen the base for decision making of these managers (Zoltners, Sinha and Lorimer 2012). Second, given the strong reliance on motivational factors driving tactical actions, it appears that junior managers are very short-term and self-focused. One way to improve this is to change the incentive scheme for these managers, which is now based on sales goals. Such an outcome based control system stimulates a short-term focus. Instead, a behavior-based control system based on the selling process as a whole instead of its outcomes can be an effective way to stimulate a more long-term focus amongst these junior managers, and improve their decision making (Anderson & Oliver 1987; Cravens et al. 1993).

5.1.2. Predicting churn in the face of customer privacy

The second study focuses on one of the challenges that firms face when trying to leverage the richness in modern databases. In particular, we focus on the increased concerns that customers have about their privacy, which was identified as one of the top research priorities by the Marketing Science Institute (Marketing Science Institute 2016). In this study we investigate how firms can preserve the privacy of their customers in the setting of customer churn prediction (which aims to improve customer retention), which has emphasized the use of detailed customer panel data sets recently (e.g. Ascarza and Hardie 2013). The common perception is that firms lose analytical capabilities when they try to preserve customer privacy (Blattberg, Kim and Neslin 2008, p. 78; Verhoef, Kooge and Walk 2016). This is mainly due to firms’ “self-policing” in response to customer demand for privacy, by only storing data for a limited amount of time (data minimization, Wedel and Kannan 2016). This renders panel data methods infeasible. In this study we develop an approach, which we dub the generalized mixture of Kalman filters (GMOK) model, which allows us to capture the relevant customer information before it is deleted and stores it within the model parameters. In this way, we do not need the data anymore in future periods, but can still use the information contained in it. Beyond achieving data minimization, by
aggregating the data we also achieve data anonymization with our approach (Wedel and Kannan 2016).

We compare our model to a variety of benchmarks which have been used to predict customer churn. In particular, we compare our approach to simpler benchmarks (logistic regression and classification tree) as well as more advanced models (hidden Markov model, Ascarza and Hardie 2013). We do so in two settings: the panel data world and the cross-sectional world. While in the former world the full data history is available for models, in the latter world this is not the case. Consequently, we cannot estimate the advanced HMM, but other models (including ours) remain viable. Our comparisons take place using data on customer churn for ~1 million customers from the healthcare insurance industry covering the years 2004-2012. In the cross-sectional world, we also replicate our findings using data from the Internet service provided industry using data on ~300k customers covering four quarters in 2006.

In the panel data world, we establish that our approach performs comparably to the HMM, while both models outperform simpler benchmarks. Thus, while all past data is available, our approach shows a good performance and does not reduce predictive ability. This good performance with respect to simpler benchmarks remains in the cross-sectional world, when past data is unavailable. The unavailability of past data renders the HMM inestimable, while our approach remains valid. Here, we also find that our model predictions deteriorate at a slower pace over time than those of other models (i.e. our model has better staying power). Finally, we document the faster estimation time of the GMOK model compared to the HMM and other benchmarks, which is in excess of 41%. We therefore conclude that preserving customer privacy does not have to come at the cost of analytical operations, provided the right methods are applied.

5.1.3. Real-time target marketing using control charts

In the third study of this dissertation we explored the possibilities of firms to engage in real-time marketing, one of the top priorities identified by the Marketing Science Institute (Marketing Science Institute 2016). We investigate these possibilities in the setting of targeting of marketing actions, aimed to develop and retain customers. The promise of real-time marketing in this setting is that marketing actions become more relevant by targeting the right customers on the right time with the right marketing actions (Goldenberg 2008). In this study we develop an
approach that firms can use to this end. Our approach is based on the control chart method from the statistical quality control literature (Montgomery 2009). These control charts are based on identifying variation in a statistical process (in this case purchase timing), and separating special from common causes of variation (Shewhart 1931). When variation becomes too high due to special causes, action must be taken to bring the process back into control (Deming 1982). Our focus on variation in customer purchase behavior aligns with a recent stream of research emphasizing that firms should not only focus on average customer behavior, but also the variation therein (Rust, Kumar and Venkatesan 2011; McCarthy et al. 2014). This way, the negative consequences of wrong targeting can be mitigated; see Ascarza, Iyengar and Schleicher (2016) for a recent example of such consequences.

Based on historical purchase data from an online firm in the greetings and gifts industry, we develop a control chart approach to track customer purchase timing. To that end, we design a gamma-gamma control chart, which captures the dynamics and customer heterogeneity in the underlying purchase timing process (e.g. Colombo and Jiang 1999). We calibrate this control on purchase data from 373,521 customers of this firm, which cover all the purchases made between 2012 and 2014. Next, we demonstrate how this control chart can be used to target customers. For each customer, we determine an upper-bound for purchase time, based on the average historical purchase time and the variation therein. Once this bound is crossed (i.e. the time since the last purchase lies too far in the past), we suggest that firm should take action in order to avoid customer churn.

The managerial implications of our approach are illustrated with a case study. Here, we compare our control chart approach for customer targeting with the firm policy of sending a reactivation e-mail after eight weeks of inactivity of a customer. Our alternative approach reduces this time to a median of five weeks. However, substantial variation in timing is present as well (standard deviation = 9.5 weeks), resulting in 31.9% of the customers being approached later than under the current policy. The alternative approach also has substantial implications for response to marketing actions (i.e. conversion) and purchase value. For conversion we find a drop in conversion rate of 25% when customers are targeted too soon (as implied by our model) compared to when they are targeted on time. Surprisingly, we find that the conversion rate increases by 11% when customers are targeted too late (as implied by our model) compared to when they are targeted on time. The latter finding suggests that customers were ready to make a
purchase, but without a reminder of the firm did not translate this intention into behavior at the focal firm. In terms of purchase value, we report drops of 5% in mean purchase value and 8% in median purchase value for customers that were targeted too soon compared to customers targeted on time. No loss of value for customers targeted too late was found. These findings suggest that moving purchases forward by targeting customers earlier than their regular purchase pattern suggests results in loss of customer value. Concluding, we find that our approach to targeting using individual level information improves both the response to marketing actions and the value of purchases, highlighting the benefits of our approach.

5.2 Future research opportunities

In the three studies of this dissertation we have discussed how firms can react to the opportunities and challenges presented by data richness. However, many opportunities and challenges still remain (for a more extensive overview, see Leeflang et al. 2014). In this section we highlight some of these research opportunities, and relate them to each of the chapters of this dissertation.

5.2.1 Future research opportunities on strategic and tactical actions

In the first study we investigated the difference between strategic and tactical actions, and the sales implications of these actions. While we provided useful insights on the strength of reactions to these actions, evaluated the sales impact of these actions and investigated factors moderating the reaction strength, other opportunities for research in this field exist. For example, our study is only concerned with personal selling, which is one particular marketing instrument. More common instruments such as advertising and price promotions were not considered, and the difference between action types has been ignored in these studies so far (e.g. Nijs et al. 2001; Steenkamp et al. 2005). Extending our work to these settings could help improve the strategic planning for a broader range of firms than considered in this dissertation, for example to FMCG manufacturers and retailers. Besides extending our work to other marketing instruments, another possibility would be to extend our work to different industries within the personal selling field.

1 We cannot investigate whether they would have bought at competing firms instead given the limitation of our data to one firm only
While the pharmaceutical industry is a typical example of an industry using this marketing instrument, it is also an industry with distinct characteristics in terms of industry structure (Stremersch and Van Dyck 2009). Other settings that widely use personal selling as a marketing instrument are for example military recruiting and media selling (Albers, Mantrala and Shridhar 2010). Extension of our work to such settings could help improve the generalizability of our findings.

Another promising avenue for future research in this field lies in the investigation of more complex reaction patterns. While we only consider reactions within the same category, many firms within the pharmaceutical industry, but also in many other industries, have a portfolio of products which are simultaneously marketed (Zoltners and Sinha 2005). Decisions on where to allocate resources (i.e. strategic actions) and how deploy these resources effectively (i.e. tactical actions) are affected by the presence of multiple products in the portfolio, and firms seek to balance the allocation of resources between products. This can also have consequences for competitive actions. Increased competitive activity in one category could lead a firm to shift focus to a different category, foregoing a reaction in the same category. Alternatively, retaliation could take place in a different category where the defending firm has a stronger presence. While the data available do not allow us to infer such differences across categories, investigating such multicategory reactions is important to understand the full palette of actions occurring within industries (Jayachandran, Gimeno and Varadarajan 1999; Yu and Cannella 2013).

### 5.2.2 Future research opportunities on churn and customer privacy

The second study in this dissertation illustrated how firms can balance their interest to predict churn with the customer interest of preserving privacy. There are however more opportunities to expand on this research.

One of those opportunities rests in the selection of variables. The approach we develop relies on a stable set of variables that are tracked over time. This assumption places more pressure on the selection of variables to track over time and include in the model. Therefore, developing approaches that can make this selection would be an important avenue for further research. Related to the selection of variables for the model, determining the right model structure is also important. Our model assumes a number of clusters that assures data can be processed
anonymously (i.e. at the segment level instead of the individual level). We currently assume that the number of segments is fixed over time, and select this number at the time of the first model estimation. However, this number could well change over time given changing market circumstances. Dynamically selecting the number of segments would then be a solution, e.g. through the reversible MCMC technique highlighted in Bruce, Peters and Naik (2012).

5.2.3 Future research opportunities on real-time target marketing

The final study investigated the value of a control chart approach to target marketing, which can be used to target the right customers at the right time. While we showed substantial improvement in the response to marketing actions (i.e. e-mail) and the value of purchases, opportunities for the future remain.

One major opportunity lies in the extension of our control chart framework to other metrics. We focused on modeling purchase timing to improve customer retention. However, it is very well possible to model purchase value using the same framework, with the aim of identifying customer development opportunities. Such an approach would be closer to the original use of the gamma-gamma model, which was developed with purchase value in mind (e.g. Fader, Hardie and Lee 2005b), although extensions to purchase timing as in our application have been made as well (Platzer and Reutterer 2016). An additional extension would be to consider both processes simultaneously in one control chart. Such an approach can be motivated by the fact that substantial correlations between purchase timing and purchase value can exist, depending on the dataset under consideration (Glady, Lemmens, Croux 2015). One appropriate choice would be the Hotelling $T^2$ control chart, which can consider the mean and variation therein for two focal processes (Wierda 1994).

Further extensions of the control chart approach can also go beyond the gamma-gamma model we apply. While this model provides a flexible way to model many different distributions, other distributions are well possible depending on the context. In discrete time settings for example, a beta-geometric distribution (Fader, Hardie and Shang 2010) could provide an alternative for the continuous time gamma-gamma model. Alternatively, a non-parametric approach which does not make distributional assumptions could provide a generalized framework to model varying processes. In the setting of purchase value, the assumption of equidistance
between time intervals is potentially violated. Future research could investigate how to deal with this situation in the setting of control charts, which assume regular intervals between points in time.

To investigate the value of real-time targeting further, future research should also focus on testing such approaches in the field. Only then will it be possible to investigate the consequences fully, as such a test would allow the researcher to observe changes in customer behavior which cannot be captured using historical data. While our findings suggest that there can be substantial value in using our approach, it also identified a lot of opportunities where a firm should have reacted, but did not do so. In the field, a firm could react immediately, and the consequences of such a reaction can be observed and attributed to the action themselves. In turn, this would allow us to infer the consequences for conversion and purchase value directly.

5.3 Overall conclusion

Having summarized the main findings from each chapter, we will return to the question posed in Chapter 1: *How can firms maintain or improve the value to their firm of their marketing activities through the use of marketing analytics in the face of increasing data richness?* Across the chapters, we have shown that through the deployment of marketing analytics solutions, firms are in a position to gain deeper insights from data, or can attenuate the loss of information due to data limitations. In turn, when applied in practice these benefits can translate into competitive advantages that can lead to an increase in the value delivered to the firm. Hence, the value of data richness does not consist of just possessing the data, but requires active analysis and interpretation of the insights gained to succeed. However, this translation also hinges on the actual implementation and usage of the insights and methods that we propose, which can be challenging due to limitations in for example the technical and knowledge capabilities of firms (Day 2011; Leeflang et al. 2014). Addressing such issues is beyond the scope of this dissertation however.

One of the salient characteristics that all the applications have in common is that value gains are obtained by taking into account the dynamics of processes in new or improved ways. This highlights that one of the important characteristics of *big data* is not so much the size of the data (i.e. bigger N), but that gains are be made by disentangling cause-and-effect relationships in a better way, or by building up more or improved knowledge on the way the world works over
time. It also aligns well with the notion that the movement speed of data generation has increased, necessitating analysis tools to follow pace and account for this phenomenon (McAfee and Brynjolfsson 2012). Concluding, it is important that firms focus on new or better insights that can be obtained from data rich environments in the discussed and other applications, and don’t stare blindly on having more data available per se. Only in this way can value to the firm be improved (e.g. Pauwels 2014).

While the cases investigated in this dissertation were motivated by current issues in the marketing science landscape, as indicated by their inclusion in the research priorities of the Marketing Science Institute, the far-reaching consequences of data richness reach beyond these cases. It will therefore be important to continue to focus on research in this area, and identify new opportunities and challenges as they emerge. These can range from more general issues (i.e. Leeflang et al. 2014) to more specific problems (i.e. Wedel and Kannan 2016). Only in this way will we truly be able to gain advantage of the transformative powers of big data.