



# Investigating the post-complaint period by means of survival analysis

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## Abstract

Firms increasingly view each contact with their customers as an opportunity that needs to be managed. The primary purpose of this article is to gain a better understanding of the customers' post-complaint period. Specific focus is placed on the impact of effective complaint handling on actual customer behavior throughout the time, whereas previous research has mainly focused on time-invariant or intentional measures. Survival analysis techniques are used to investigate the longitudinal behavior of complainants after their problem recovery. The proportionality assumption is tested for each explanatory variable under investigation. In addition, the impact for each variable is estimated by means of survival forests. Survival forests enable us to explore the evolution over time of the effects of the covariates under investigation. As such, the impact of each explanatory variable is allowed to change when the experiment evolves over time, in contrast to 'proportional' models that restrict these estimates to be stationary. Our research is performed in the context of a financial services provider and analyses the post-complaint periods of 2326 customers. Our findings indicate that (i) it is interesting to consider complainants since they represent a typical and rather active customer segment, (ii) furthermore, it is beneficiary to invest in complaint handling, since these investments are likely to influence customers' future behavior and (iii) survival forests are a helpful tool to investigate the impact of complaint handling on future customer behavior, since its components provide evidence of changing effects over time.

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*Keywords:* Data mining; Customer relationship management; Consumer complaint behavior; Actual customer behavior; Proportionality; Survival forests

## 1. Introduction

According to Keaveney (1995), the two major reasons why customers switch service providers are: (1) core service failures and (2) unfavorable service encounters with the company's personnel. When customers face a problem they may respond by exiting (=switching to another provider), loyalty (=staying with the supplier anticipating that 'things will get better') or voicing (=complaining to the firm or word-of-mouth to third-parties) (Levesque & McDougall, 1996; Tax, Brown, & Chandrashekar, 1998). Unfortunately, it is only the tip of the iceberg that complains to the company (Stephens & Gwinner, 1998) since dissatisfied customers tend to remain passive when experiencing a problem (Bougie, Pieters, & Zeelenberg, 2003).

Customers who do not complain to the firm when dissatisfied are of special concern to management for several reasons. First, the company loses the opportunity to

rectify the problem (Fornell & Wernerfelt, 1988; Levesque & McDougall, 1996) and to restore the customer's satisfaction level (Smith, Bolton, & Wagner, 1999). Second, the firm's reputation can be damaged due to the negative word-of-mouth to friends, family or other people external to the customer's social circle, e.g. via newspapers (Bougie et al., 2003; Singh, 1988) which might result in the loss of prospects as well as current customers (Stephens & Gwinner, 1998). Third, the firm is deprived of valuable information about its products and services (Fornell & Wernerfelt, 1987) that is likely to improve the bottom-line performance and to prevent similar problems in the near future.

On the other hand, customers who complain and receive a proper response to their service failures are more likely to stay (e.g. Conlon & Murray, 1996), to buy new products (e.g. Maxham III & Netemeyer, 2003), to pay price premiums (e.g. Zeithaml, Berry, & Parasuraman, 1996), to engage in favorable word-of-mouth and to recommend the company's services to others (e.g. Maxham III, 2001; Maxham III & Netemeyer, 2002). Furthermore, they show higher share-of-wallet behavior (e.g. Bowman & Narayandas, 2001) as well as higher commitment and trust towards the company (e.g. Tax et al., 1998). Finally, they are less vulnerable

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to switch (e.g. Bougie et al., 2003) and less likely to spread negative word-of-mouth to friends (e.g. Blodgett, Granbois, & Walters, 1993), or third-parties, such as other customers (e.g. Zeithaml et al., 1996). In sum, there is overwhelming evidence from previous research that successful complaint handling results in favorable customer outcomes. Additionally, in their study Fornell and Wernerfelt (1988) state that the return on investment in complaint management is likely to reach a 400 percent level.

When considering the consumer complaint behavior (CCB) literature, Stephens and Gwinner (1998) argue that much of the research is dominated by studies trying to understand why customers complain. In their paper, they provide an exhaustive list of investigated antecedents, including individual characteristics, attitudes, situational factors, the cost of complaining, etc. It is only since the last decade that literature has caught up by investigating the consequences of complaint handling (cf. previous paragraph). However, current knowledge is limited in providing insights regarding behavioral intentions or self-reported actual behavior measures resulting from critical incident technique studies in which the respondents are requested to think about their latest service switch (e.g. Keaveney, 1995). As is well known, data on actual behavior are often unavailable. Generally, the only data available are the self-reported intentions of the individuals who completed a post-complaint questionnaire. Nevertheless, many authors argue that intentions are not always translated into subsequent behavior, since respondents typically do not have perfect information about changes that may occur in the future that may affect their behavior (Young, DeSarbo, & Morwitz, 1998).

Unlike previous research, we investigate the impact of complaint handling on customers' *actual* behavior instead of intended behavior (=perceptual information). As a consequence, our research setting implies the need to link complaint data with complainants' behavioral information that is stored in transactional databases.

In this study, we decided to investigate the complainants' 'next-buy' decision. We believe that an effective purchase reflects actual retention behavior (Larivière & Van den Poel, 2004). In contrast to the studies that have investigated intended repeat purchasing behavior by questioning items such as 'In the near future, I intend to buy new products', we consider an actual product opening as a real and executed consequence of such an intention. The variable 'next-buy' expresses whether the customer has bought a new product during the observed period of analysis. The variable is operationalized as a time-varying dependent variable, in which the right-censoring situation is taken into account; that is, customers who have not bought a new product by the end of the observed period of analysis might do so in the future (that is, right-censoring).

Furthermore, we explicitly test whether the impact of complaint handling varies over time by means of survival forests, meaning that we allow for changes in the impact of

complaint handling components on the customers' next-buy decision. In the context of complaints, it is plausible to assume that some effects, such as receiving compensation, fade out after a while. As such, we cannot use conventional 'proportional' models that assume stationary effects of the covariates throughout the observed window of observation.

In sum, we contribute to the existing CCB literature by presenting a framework of *actual* customer behavior in which we account for the right-censoring situation, and we explicitly test for the time-varying impact of explanatory variables by questioning the proportionality assumption.

The rest of this paper is organized as follows. In Section 2 we elucidate both the methodological underpinnings of the proportionality assumption and the survival forests technique. In Section 3, we present the data set and the explanatory variables under investigation. The study results and its implications are reported in Section 4. Section 5 concludes the paper and outlines some directions for further research.

## 2. Methodology

In this study we apply survival analysis techniques because our dependent variable is characterized by both a binary classification ('buy' or 'no buy') and a duration indicator for that purchasing (or censoring) event. First, we present the methodological underpinnings related to the proportionality assumption. Next, we elaborate on the survival forests technique that produces time-varying covariate estimates.

### 2.1. Testing the proportionality assumption

Survival analysis is a class of statistical methods modeling the occurrence and timing of events (in this case: the complainant's next-buy decision).

Survival data have the following form:

$$\{(c_n, t_n, x_n), \quad n = 1, \dots, N\} \quad (1)$$

where  $n$  represents the index to the 2326 ( $N$ ) complainants under investigation in this study;  $c_n$  is the status (or binary classification) indicator which represents whether the complainant repurchased within the period of analysis;  $t_n$  is the duration indicator and represents the time to the event or the censoring time (that is, for the customers who did not experience the event of buying within the period of analysis);  $x_n$  is the vector of covariates for each customer  $n$ , and refers to the complaint handling and control explanatory variables in this study (cf. Section 3.2). The goal of survival analysis is to trace the effects of the covariates on the times to the event; or in this study: the impact of complaint handling on the duration to repurchase.

The field of survival analysis is dominated by the Cox proportional hazard model (Stare, Harrell, & Heinzl, 2001).

The technique is widely used due to its convenient advantages: the technique (i) allows for incorporating time-varying covariates and both discrete and continuous measurements of event times, (ii) can handle observations that did not experience the event (that is, censored observations) and (iii) appears to be very robust and requires few assumptions (Kumar & Westberg, 1997; Van den Poel & Larivière, 2004).

The Cox proportional hazard for customer  $n$  at time  $t$ , given his vector of covariates  $x_n$  can be written as follows:

$$h_n(t, x_n) = h_0 \exp(\beta x_n) \quad (2)$$

in which  $h_0$  represents the baseline hazard.

Despite its convenient advantages, proportional hazard models imply the important key assumption of ‘proportionality’; which is often overlooked when applying the technique (Boucher & Kerber, 2001; Moitra & Lee, 1993; Therneau & Grambsch, 2000). Proportionality means that the hazard for any individual  $i$  is a fixed proportion  $\gamma_{ij}$  of the hazard of any other individual  $j$  (hence the name ‘proportional hazard’):

$$\gamma_{ij} = \frac{h_i(t, x_i)}{h_j(t, x_j)} = \frac{h_0 \exp(\beta x_i)}{h_0 \exp(\beta x_j)} = \exp\{\beta(x_i - x_j)\} \quad (3)$$

As a consequence, during estimation the baseline hazard  $h_0$  cancels out, which is often referred to as the *semi-parametric* estimation of the hazard model.

In this study, we explicitly test for the proportionality assumption with respect to each explanatory variable. In order to do so, we follow Allison’s (1999) suggested approach to compare the graphs of smoothed hazard functions for each covariate’s stratum; parallel curves provide evidence for proportionality. Smoothed hazard functions are produced by means of a kernel smoothing method, as described by Ramlau-Hansen (1983).

## 2.2. Estimating covariates by means of survival forests

In case the proportionality assumption is violated, one needs to use other methods that do not impose restrictions with regard to that assumption. In this study, we choose the novel technique of survival forests proposed by Breiman (2002).

Survival forests represent the newest extension of Breiman’s random forests technique, next to the classification and regression forests (e.g. Larivière and Van den Poel, 2005). The software can be downloaded free of charge from the internet (Breiman, 2003). In his software Breiman proposes two methods for using survival forests: that is, ‘correlations over time’ and ‘time fitting Cox models’. ‘Correlations over time’ compute the correlation between  $\log(\hat{S}(t_k, x_n))$  and each of the covariates at each event time point  $t_k$ ; in which  $\hat{S}$  represents the estimated survival probability. If a Cox model fits the data (that is, the ‘proportionality’ assumption is satisfied), these correlations should be constant over time.

With respect to ‘time fitting Cox models’, at each event time  $t_k$  the following two equations (3) and (4) are defined:

$$y_n = L(t_k, x_n) \quad (4)$$

$$f(n, t(k), \beta(k)) = t(k) \exp(\beta(k)x_n) \quad (5)$$

in which

$$L(t_k, x_n) = -\log(\hat{S}(t_k, x_n)) \quad (6)$$

and, in which  $\beta(k)$  refers to estimates for the coefficients of the covariates  $x$  at each duration time  $k$  and  $t(k)$  represents the estimate of the integral of the baseline risk. In fact, the right hand side of Eq. (4) is similar to the Cox expression in Eq. (2), with the difference that  $t(k)$  and  $\beta(k)$  need to be determined. Analogously to random forests (Breiman, 2001), a collection of decision trees (i.e. a forest) is grown to estimate  $\hat{S}(t_k, x_n)$ . This is done by minimizing:

$$\sum_n (y_n - f(n, t(k), \beta(k)))^2 \quad (7)$$

If a Cox model fits the data, the  $\beta(k)$  should be constant in time.

In this study we opt for the ‘time fitting Cox models’ tool, since the plot of  $\beta(k)$  enable to investigate the impact of the covariates over time; which is the primary purpose of this study.

## 3. Empirical study

A Belgian financial services provider delivered the data for this study. Its customers have the opportunity to express their complaints to the company whenever they perceive a problem with respect to the products and services they possess. When a customer experiences a (product or) service failure, he has the possibility to formulate his complaint either directly towards the company’s complaint department or to his banking agent who will pass it on to the complaint department. In the latter scenario, it is also plausible that the intermediary is capable himself of recovering the problem, and consequently, the service failure would not reach the complaint department. As such, with respect to the complaints expressed to intermediaries, we assume that especially the more ‘complicated’ failures will be handled by the complaint department.

The complaint handling department of the company under investigation started collecting (and storing) complaint information in January 2000. Our research setting implies the link with the data warehouse information needed to investigate the customer’s subsequent actual behavior. Therefore, we decided to analyze the complaints expressed from January 2000 till 1 February 2003, since the latest release date of data warehouse information is 1 February 2004; as such we ensure a response period (to buy another product) of minimum 12 months for every complainant. Fig. 1 depicts the timeline for this study.

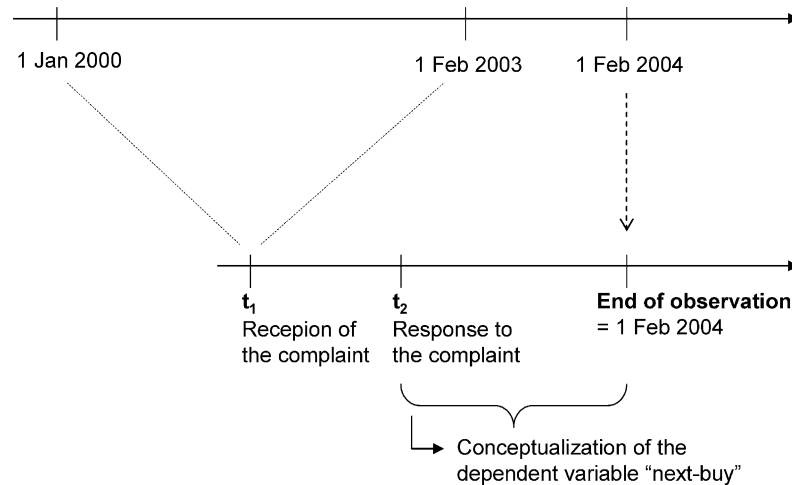


Fig. 1. Period of analysis.

### 3.1. Conceptualization of the dependent variable

In this study we investigate the customers' 'next-buy' decision as the focal actual behavior dependent variable. For each customer, the dependent variable receives two indicators: a status indicator and a duration indicator. The status indicator represents the binary classification and expresses whether the complainant has bought a new product in the subsequent period (that is, between  $t_2$  and 1 February 2004 in Fig. 1); the duration indicator expresses how long it takes before the customer has bought that product. As shown in Fig. 1, the customers under investigation are allowed to have different duration times, since their entry times range from 1 January 2000 to 1 February 2003 as well as their buying dates may differ. More specifically, the complainants who repurchase after their service recovery receive the value of '1' for their buy status indicator and receive the time elapsed since  $t_2$  until the date of buying the new product as duration indicator. On the other hand, the customers who did not repurchase (that is, the right-censored cases) receive the value of '0' for the status indicator and their duration indicator is determined by calculating the time between  $t_2$  and the end of observation (that is, 1 February 2004). All duration terms are expressed in months.

### 3.2. Explanatory variables

The major purpose of this study is to investigate the impact of complaint handling on subsequent actual customer behavior. In the next paragraphs we present the explanatory variables under investigation in this study.

#### 3.2.1. Complaint handling variables

To date, many firms are not well informed on how to deal successfully with service failures or the impact of complaint handling strategies (Tax et al., 1998). Furthermore, the CCB literature suggests that customers are often more dissatisfied

by an organization's failure to recover than by the service failure itself (Keaveney, 1995; Smith et al., 1999). With the complaint handling variables of this study we emphasize the latter attempt. It is our intention to investigate their time-varying impact on the customer's next-buy decision over time.

When considering previous complaint studies that analyzed the impact on future intended behavior, it is clear that the investigation of 'perceived justice' or 'satisfaction with recovery' dominates the literature, whereas other antecedents of customer outcome that are related to the complaint handling encounter are often ignored in previous research (e.g. Blodgett et al., 1993; Maxham III, 2001; Maxham III & Netemeyer, 2002; Tax et al., 1998; Zeithaml et al., 1996). A notable exception is the study by Conlon and Murray (1996) who examine the impact of (1) the type of explanation, (2) the presence of compensation, (3) problem severity and (4) the speed of the company's reply on both customers' satisfaction level with the explanation and their willingness to do business with the company in the near future.

With respect to the complaint handling variables that are analyzed in this study, we use the information that is stored by the complaint handling department during the service recovery process. All complaint handling variables are gathered at  $t_1$  or  $t_2$  (cf. Fig. 1). The next paragraphs present the complaint handling variables that are investigated in this study (the information between brackets indicates whether the information is gathered at  $t_1$  or  $t_2$ ). Table 1 summarizes the explanatory variables of this study, whereas Table 2 reports their intercorrelations.

**3.2.1.1. Severity of the complaint ( $t_1$ ).** Fear of opportunistic customers is an important reason why firms are reluctant towards customers' demands (Wirtz & Kum, 2004). In the context of complaints, it is realistic that not every service failure is equally severe or even justified. In their study, Conlon and Murray (1996) analyzed two surrogate



Maxham III & Netemeyer, 2002; Tax et al., 1998; Zeithaml et al., 1996). In this study, we investigate the impact of satisfaction with recovery on customer's actual buying behavior. The satisfaction indicator is gathered at the time of formulating a reply to the customer (that is,  $t_2$  in Fig. 1). The variable 'sat\_rec' is a dummy variable reflecting the employee's perception of the customer's reaction with regard to the complaint answer; that is, when the employee perceived that the customer agreed with the final solution, he coded the corresponding complaint record with a 'satisfied=yes' label. We believe that 'sat\_rec' represents a good proxy for the customers' satisfaction level with respect to the recovery of his complaint.

### 3.2.2. Control variable

Since our research investigates actual buying behavior instead of repeat purchase intentions, which implies the necessity to combine complaint records with the company's data warehouse, we decided to control for the recency of the customer's previous purchase. In the context of complaints, it is plausible to assume that some customers perceive failures with respect to the products they just acquired: as such, investigating a next-buy decision longitudinally without considering this type of information would result in biased conclusions. In this study, we explicitly account for the variable 'recency' and we hypothesize that complainants who just acquired a new product are less likely to buy another one, although they might be satisfied about their problem recovery. The variable 'recency' represents the time elapsed until  $t_1$  (cf. Fig. 1) and is expressed in months.

## 4. Findings

The next paragraphs contain the findings of the study. First, we report survival estimates for satisfied versus dissatisfied complainants, and we benchmark them against a random sample of non-complainants. Then, we present the findings of the proportionality investigation and the time-varying parameter estimates resulting from the survival forests. Finally, we suggest how one can

approximate non-proportionality in conventional Cox regression.

### 4.1. Complainants versus non-complainants

Since our research setting integrates complaint handling records with data warehouse information, we have the possibility to analyze the actual behavior of non-complainants. As in previous research (e.g. Zeithaml et al., 1996) we compare three groups: (i) no complaint, (ii) complaint with satisfactory recovery and (iii) complaint with unsatisfactory recovery. We randomly selected 2500 customers who did not complain within the period of analysis (that is, between 1 January 2000 and 1 February 2003, cf. Fig. 1) and we observed them for the same period with respect to their next-buy behavior.

We investigate the timing of the next-buy decision for the three groups by means of Kaplan–Meier survival estimates. The Kaplan–Meier estimator—also known as the product-limit estimator—is the most widely used method for estimating survival functions (Efron, 1988). Survival probabilities are presented as a survival curve. The 'curve' is a step function with sudden changes in the estimated probability corresponding to times at which events are observed (Bland & Altman, 1998). In Fig. 2 we present survival probabilities for the three groups. Our findings indicate significant differences with respect to the three repurchase times since the Log-Rank statistics report  $p$ -values between  $<0.0001$  and  $0.0009$  for each  $2 \times 2$  comparison.

It is clear from Fig. 2 that satisfied complainants experience shorter repurchase times than their opponents who are dissatisfied about the service recovery, since the survival line of the former group decreases faster toward the horizontal axis. Survival probabilities represent 'the likelihood of surviving' or in this context: 'the likelihood of *not* experiencing the purchase incident'. Therefore, lower survival rates stand for higher repeat-purchase behavior. Hence, our study reveals the logical relationship between satisfied and dissatisfied complainants with respect to their *actual* repurchase behavior and finds support for previous CCB studies that were restricted to examine behavioral intentions.

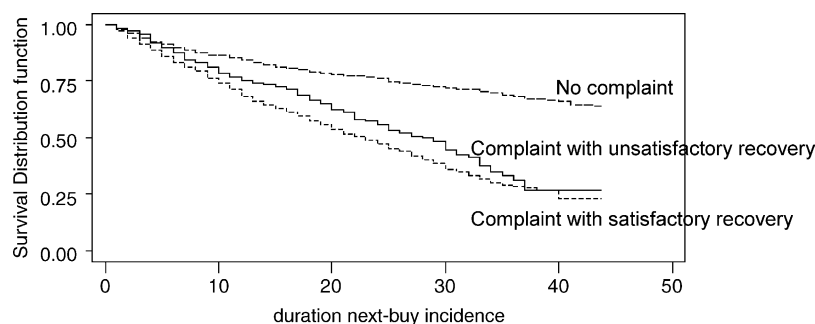


Fig. 2. Survival probabilities for (dis)satisfied complainants versus non-complainants.

A second, and more intriguing finding of Fig. 2 concerns the fact that non-complainants report the lowest repurchase behavior. As such, complainants with an unsatisfactory service recovery show evidence of higher repeat-purchase behavior than the group of non-complainants. Generally, non-complainants consist of customers who do not experience a service problem as well as customers who do not complain about the problem they encounter. A possible explanation might be that complainants represent more ‘active’ customers who are not only more inclined to complain when they experience a service failure, but also more likely to buy (even when they are dissatisfied about the service recovery) compared to the more ‘passive’ customers who do not buy as often and are less likely to communicate with the company. As such, we assume that (i) ‘being an active customer’ has a stronger impact on future behavior than the satisfaction level with the service recovery and that (ii) complaining is a result of being active. Further research is warranted on this issue.

#### 4.2. Investigation of the proportionality assumption

In order to test the proportionality assumption for each explanatory variable, we investigate the smoothed hazard functions for each covariate’s stratum as suggested by Allison (1999). With respect to the ‘recency’ variable we decided to create an ‘aggregated’ stratum variable ‘rec\_cat’ since the original variable (‘recency’) contains more than two (or  $n$  distinct category) values. We decided to categorize the ‘recency’ variable into four groups based on its quartiles. As such, the stratum variable ‘rec\_cat’ contains four different values; that is, representing the four quartiles. In Fig. 3 we present the plots for each explanatory variable.

As stated in the methodology section (cf. Section 2.1): parallel curves provide evidence for proportionality. It is clear from Fig. 3 that the proportionality assumption is not satisfied for the complaint handling and control variables in this study. Hence, we find evidence that the impact of

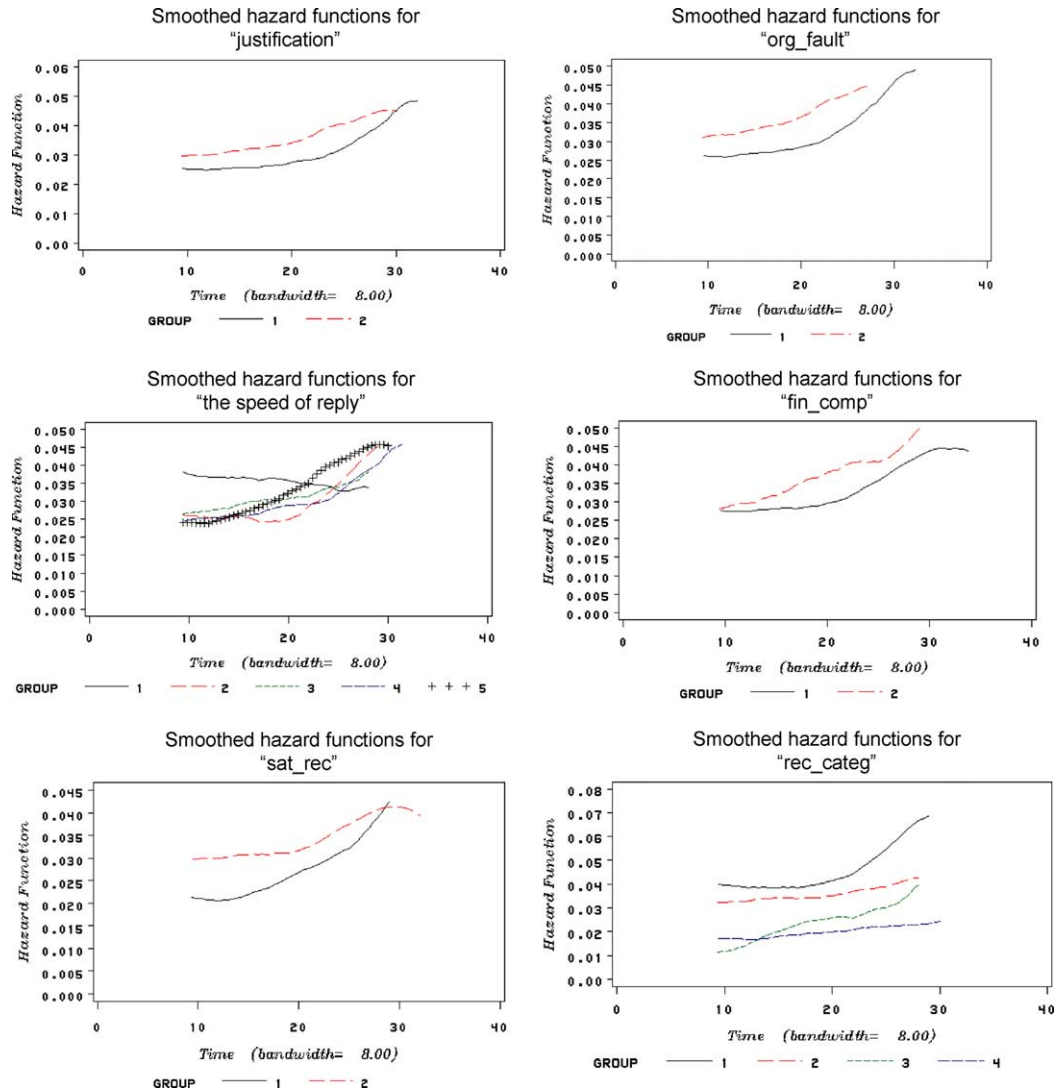


Fig. 3. Graphs of smoothed hazard functions for the explanatory variables.

complaint handling on subsequent behavior varies over time, such that one needs techniques that can handle non-proportionality in order to investigate the longitudinal impact of the explanatory variables on the complainants' next-buy decision.

4.3. The impact of the explanatory variables throughout the time

In the previous section we found evidence that the effects of the explanatory variables vary over time, which implies that conventional proportional hazard models are less attractive to fit our data since they restrict these effects to be stationary.

By means of survival forest, we are able to fit Cox models at each time  $t_k$ , meaning that the parameter estimates for the covariates are allowed to change at each time  $t_k$ . (cf. Section 2.2). In sum, the use of survival forests enables us to investigate the time-varying impact of each of the explanatory variables on the dependent variable of this study: that is, the complainant's next buy decision. Table 3 and Fig. 4 summarize the output of the survival forests: Table 3 reports the average parameter estimates for each explanatory variable, whereas Fig. 4 presents the parameter estimates throughout the time.

It is clear from Table 3 that all complaint variables have a positive parameter estimate, meaning that they have a positive association with the dependent variable. On the other hand, for the 'recency' variable we observe a negative relationship with the complainant's next buy decision. With respect to the time-varying effects of the explanatory variables we observe the most dramatic changes for the 'reply\_d1', 'recency' and 'fin\_comp' variables (cf. Fig. 4). Hence, our findings highlight the benefits of using non-proportional estimation techniques when analyzing survival data, since the impact of some explanatory variables are likely to change when the experiment evolves in time.

In the next paragraphs, we elaborate on the direction of the covariate's impact and we examine its time-varying impact on the next-buy decision, by exploring the plots of the  $\beta(k)$  (cf. Section 2.2) in Fig. 4.

Table 3  
Average survival forests estimates for the explanatory variables

Variables	Average $\beta(k)$
Justification	0.028
org_fault	0.045
reply_d1	0.300
reply_d2	0.039
reply_d3	0.269
reply_d4	0.010
fin_comp	0.059
sat_rec	0.040
Recency	-0.589

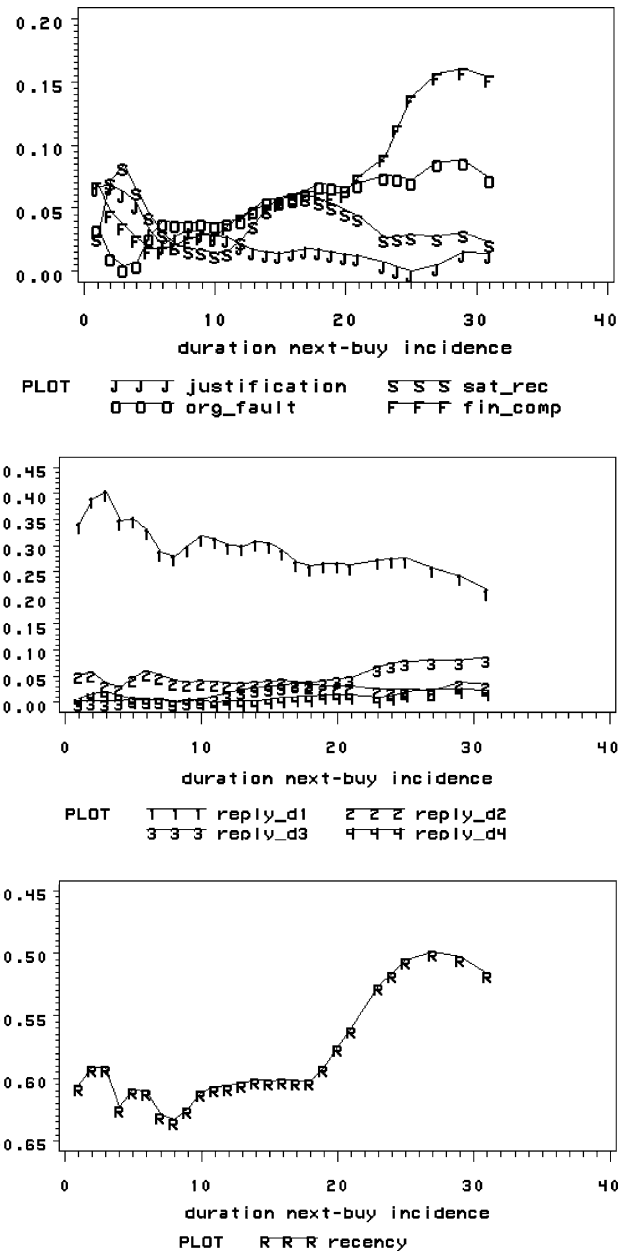


Fig. 4. Time-varying parameter estimates of the explanatory variables by means of survival forests.

4.3.1. Severity of the complaint

The variable 'justification' has a positive average parameter estimate and its impact is decreasing within the first 6 months after the service recovery, followed by a more stationary impact after this 6-month period. With respect to the 'justification' variable we hypothesized a positive relationship with the complainants' next-buy decision since we assumed more favorable recoveries for more justified service failures. The survival forests findings support this hypothesis. Especially during the first 6 months a 'better' complaint recovery results in higher repeat-purchase behavior. Afterwards the effect is fading out (but still positive).



#### 4.3.2. Organization's fault

The complainants who expressed a service failure which is due to the company's fault reveal a decrease in subsequent purchase behavior within the first 3 months, followed by a slight increase. Furthermore, the average parameter estimate is positive. As such, our findings indicate that failures caused by the company may result in negative customer outcomes since these customers are likely to experience anger. Nevertheless, an appropriate service recovery is likely to absorb this negative feeling and to restore the negative customer behavior into a favorable one. As hypothesized for the 'justification', we assumed that customers who experienced an 'organization's fault' service failure received a more favorable response to their complaint. Our survival forests findings indicate that such responses meet their purpose after the third month.

#### 4.3.3. Speed of the company's reply

The four dummy variables 'reply\_d1', 'reply\_d2', 'reply\_d3' and 'reply\_d4' all have a positive average parameter estimate. The former variable ('reply\_d1') has the strongest impact, whereas the other variables are hovering close to the horizontal axis. The variable 'reply\_d1' expresses whether the complaint is recovered within the same day. It is clear from Fig. 4 that an immediate reply to the customer's service failure is very important. Although, its impact is decreasing within certain periods, the variable supports the hypothesis that the speed of the company's reply has a positive impact on the complainant's subsequent behavior.

#### 4.3.4. Financial compensation

Table 3 and Fig. 4 reveal that (i) financial compensations for service failures result in favorable repeat-purchase behavior and that (ii) its impact is increasing over time. As such, we find support for this conclusion in the study by Conlon and Murray (1996) who found that customers who received coupons report greater willingness to do business with the company in the future.

#### 4.3.5. Satisfaction with recovery

With respect to our 'sat\_rec' variable we find evidence of a positive impact on actual purchase behavior. Furthermore, we observe an increasing positive impact during the first 3 months after the service recovery, followed by a lower and slightly fluctuating impact in the subsequent period.

#### 4.3.6. Recency

In this study, we explicitly control for the impact of the customer's previous purchase (cf. Section 3.2.2). Contrary to what was hypothesized we find that complainants who recently bought a new product are even more likely to buy another one in the subsequent period, since the average parameter estimate is negative. As a consequence, we find evidence that some complainants belong to the most 'active' segment of the company's customer base: they are constantly buying new products, and they complain

whenever they perceive a problem. Furthermore, Fig. 4 indicates that this negative impact is decreasing over time, meaning that the 'interactive' customers are more likely to buy sooner than later.

In the previous sections, we discussed the parameter estimates of the explanatory variables under investigation in this study. Since survival forests are a rather novel technique, we decided to additionally test for the impact of multicollinearity in this study. As well-known, multicollinearity (i) makes the parameter estimates unreliable and (ii) inflates the standard errors (Leeflang et al., 2000; Morrow-Howell, 1994). Table 2 revealed some rather high intercorrelations between 'org\_fault' and 'justification' (0.556) and between 'org\_fault' and 'fin\_comp' (0.416). Therefore, we decided to run an extra survival forests model without the variable 'org\_fault'. The findings of this analysis are reported in Table 4.

It is clear from Table 4 that the level of intercorrelations in this study does not dramatically change the parameter estimates (similar findings were found when plotting the parameter estimates over time). Additionally, we simulated a new variable 'rec\_corr' which correlates 0.97 with the variable 'recency' in order to better understand the impact of higher intercorrelations on the time-varying parameter estimates produced by survival forests. The results in Table 4 reveal that the introduction of the highly correlated 'rec\_corr' variable dramatically changes the parameter estimate of the variable 'recency' which increases by 0.309. As a consequence, our additional findings indicate that survival forests also suffer from the effects of multicollinearity (like traditional statistical techniques), such that researchers need to be cautious when interpreting the survival forests estimates of highly intercorrelated variables.

#### 4.4. Approximating non-proportionality in cox regression

In this section we elaborate on how researchers can approximate non-proportionality in Cox regression and by doing so, we demonstrate the pernicious consequences of applying Cox regression without testing (and controlling) for proportionality in the analysis sample.

Table 4  
Testing for the impact of multicollinearity

Variables	Multicollinearity tests	
	Average $\beta(k)$	Average $\beta(k)$
Justification	0.026	0.034
org_fault	/	0.057
reply_d1	0.319	0.285
reply_d2	0.054	0.029
reply_d3	0.023	0.014
reply_d4	0.024	0.016
fin_comp	0.060	0.042
sat_rec	0.034	0.034
Recency	-0.587	-0.280
rec_corr	/	-0.320

Table 5  
Approximating non-proportionality in Cox regression

Cox regression models			
Variable	Parameter estimate	Pr>ChiSq	Hazard ratio
<i>Model 1</i>			
fin_comp	0.08290	0.28	1.086
<i>Model 2</i>			
fin_comp	−0.01837	0.84	0.982
fin_comp_period	0.34422	0.03	1.411

In general, when applying conventional proportional hazard models one assumes that the estimates of the explanatory variables do not vary over time. By means of an example we first run a Cox regression with ‘fin\_comp’ as independent variable (cf. Model 1 in Table 5). Next, we create two new variables: A dummy variable ‘period’ that is coded as ‘1’ when the duration time is between 15 and 26 months (and coded as ‘0’ in the other case) and an interaction variable ‘fin\_comp\_period’ which is the product of the former dummy variable and ‘fin\_comp’. In Model 2, the new interaction variable ‘fin\_comp\_period’ is introduced into the Cox model. In sum: in Model 1, we apply a proportional hazard model in which we test for the impact of ‘fin\_comp’ and in which we neglect the proportionality assumption; on the other hand, in Model 2 we explicitly account for a ‘sensitive’ period for which we observed a greater impact of a financial compensation. The period ranging from 15 to 26 months is determined based on the smoothed hazard functions (cf. Fig. 3) as well as the survival forests graphs (cf. Fig. 4) with respect to the ‘fin\_comp’ variable; Fig. 3 revealed an increased difference between the two graphs within this period, whereas Fig. 4 showed the dramatic increase of the value for the corresponding parameter estimate. In Table 5 we report the results of the two models.

It is clear from Table 5 that the impact of ‘fin\_comp’ is not statistically significant in Model 1. On the other hand, in Model 2 we observe a significant impact of the ‘fin\_comp\_period’ variable, meaning that financial compensation has a significant and positive impact on customers’ subsequent buying behavior within this time period. In sum, our findings reveal the importance of both (i) testing for proportionality and (ii) accounting for it during the estimation process, since neglecting proportionality is likely to bias the results, and as consequence, might lead to wrong managerial decisions and actions.

## 5. Conclusion and further research directions

This study investigates the post-complaint period of the customers of a financial services provider. Unlike previous CCB studies that mainly focused on behavioral intentions, we analyze the impact of complaint handling on *actual* purchase behavior. Moreover, the dependent variable (that is, the complainant’s next-buy decision) is conceptualized

longitudinally by means of a status and a duration indicator, such that we are able to account for right-censored observations. The primary purpose of this article is to gain a better understanding of the role of a company’s complaint handling department by investigating the impact of its components on customers’ subsequent behavior. In this study, we investigate five complaint handling variables: severity of the complaint, organization’s fault, speed of the company’s reply, financial compensation and satisfaction with recovery. Furthermore, we explicitly control for the recency of the complainant’s previous purchase. We apply survival analysis techniques to investigate the longitudinal behavior of the complainants after their service recovery. First, the proportionality assumption is tested for each covariate by means of smoothed hazard functions. Our findings provide evidence that the effects of the explanatory variables in this study vary over time (that is, non-proportionality) which implies that conventional ‘proportional’ hazard models are less attractive to fit our data, since they restrict these estimates to be stationary. Therefore, we decided to use the novel technique of survival forests, since the technique enables us to fit Cox regression at each observed event time, such that the estimates are allowed to vary over time. To the best of our knowledge, this study is the first in adopting the survival forests technique for analyzing a customer relationship management (CRM) topic.

### 5.1. A number of interesting findings emerge from our study

First, it is clear that complainants represent a rather ‘active’ customer segment, since our findings indicate that customers dissatisfied with the service recovery are even more likely to repurchase than non-complainants. Moreover, our findings provide evidence that complainants who just bought another product, are more inclined to repurchase in the near future, since the parameter estimate of the control variable ‘recency’ reveals a negative and decreasing impact on the customer’s next-buy decision. For future research it offers an opportunity to elaborate on the active customer segment. Although they might be dissatisfied about their problem recovery, they are still likely to continue their buying behavior. A first avenue for further research concerns a profound investigation of the customer’s activeness—communication encounter (e.g. complaining)—future behavior triad.

Second, besides the intriguing ‘non-complainant’ versus ‘complaint with unsatisfactory recovery’ findings of this study, our results confirm previous findings in the CCB literature: complainants who are satisfied about their service failure report higher repeat-purchase behaviors than dissatisfied customers. Similar findings result from the other complaint handling variables. With respect to the most important complaint handling variables, it is clear from Table 3 and Fig. 4 that a fast problem recovery and a financial compensation have the greatest impact on the complainant’s subsequent behavior. As such, we can

ascertain the value of a complaint handling department with respect to favorable customer behavior.

Third, it is clear from our analyses that the impact of complaint handling variables on customers' future behavior is likely to change over time. In this study, we observed the most dramatic changes for the speed of the reply, the financial compensation and the recency of the latest purchase. Even though a Cox regression can be adapted to take into account violations of the proportionality assumption (cf. Section 4.4), survival forests provide a more general approach by investigating the impact of covariates at each event time point. In doing so, the user does not need to know in advance nor to specify (i) for which periods the effect of each covariate differs as well as (ii) their exact time frame. As such, we conclude that the survival forests technique is a promising tool for analyzing survival data.

## Acknowledgements

The authors would like to thank the anonymous company and its complaint handling department that supplied the data to perform this research study. Moreover, we are grateful to Leo Breiman for the public availability of the survival forests software.

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