Understanding Communication Preferences of Banking Customers

An exploratory study to reveal the underlying factors explaining communication channel preferences of banking customers

MSc. thesis of Albert Bouwmeester

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UNDERSTANDING COMMUNICATION PREFERENCES OF BANKING CUSTOMERS

AN EXPLORATORY STUDY TO REVEAL THE UNDERLYING FACTORS EXPLAINING COMMUNICATION CHANNEL PREFERENCES OF BANKING CUSTOMERS

By

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I hope you all enjoy reading this thesis,

Albert Bouwmeester
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Management summary

Intense competition, technical developments and changing customer demands forced service companies to develop an interaction strategy with its customers that really enables to differentiate from competitors (Payne & Frow, 2004; Rosenbloom, 2007; Verhoef & Donkers, 2005). The resulting interaction strategies strongly contributed to the development of the multi-channel management field (Reis, Amorim, & Melao, 2015). The field of multi-channel management can be described as "the design, deployment, coordination, and evaluation of channels through which firms and customers interact" (Neslin et al., 2006).

Problem analysis and research approach

A large financial institution, called 'bank *X*' in this thesis, made the ability to serve customers by their needs and preferences an important part of the multi-channel strategy. This is a reaction to an acknowledged problem in multi-channel systems: high costs of maintaining a multi-channel system and dissatisfied customers (Moriarty & Moran, 1990; Shih & Venkatesh, 2004). Personalizing the outbound communication strategy is key in solving the identified problems (Godfrey, Seiders, & Voss, 2011). In this thesis the focus was on the outbound perspective of multi-channel management. When the outbound communication strategy is personalized, customers are only contacted through their preferred communication channel. First, this should lead to a reduction of the number of customers who cannot be reached through outbound communication. Second, it should lead to improved customer satisfaction about outbound contact with a bank since customers are served according to their preferences. For implementing personalisation of the outbound communication process, knowledge about the channel preferences of customers is required. The challenge is to identify factors that explain the channel preferences of customers for outbound contact with their bank. Currently no insights in these factors exist within banks and no prior research to outbound communication preferences have been found during extensive literature research.

The communication channels in scope of this study were: landline, mobile phone, online banking account and a mobile bankmobile app. These channels were selected since they are suitable for outbound contact with customers and are currently used for outbound contact. Customers who were in the scope of this study were high valuable customers with savings and/or invested capital exceeding €75.000 and customers who have the potential to become such a valuable customer within five years.

This study aimed to provide an answer to the central question:

What factors can explain outbound communication channel preferences of banking customers and how can these factors contribute to predicting channel preferences of these banking customers?

In order to answer this central question, four research questions were constructed. These research questions subsequently focussed on hypotheses development, analysis design, data analysis, and business relevance. Based on semi-structured interviews with customer interaction experts at ING and literature research into the fields of multi-channel management and channel choice, a conceptual model is proposed. This conceptual model visualizes the hypothesized associations between independent variables *perceived complexity of contact* (operationalized by vignettes developed with interaction experts), *value of time* (operationalized by salary), *technical skills* (operationalized by the use of offline and online interaction channels), *activity* (operationalized by the number of transaction over 12 months), *loyalty* (operationalized by the duration of the relation between a customer and bank), and *age*. To enhance interpretability, the channels e-mail, mobile app and internet banking were grouped into online channels. The landline and mobile channels represent offline channels. Table 1 depicts the hypothesized association of the conceptual model.

Table 1: Hypothesized associations between independent variables and preference for online/offline channels.

	Preference for offline channel (landline, mobile)	**Preference for online channel** (e-mail, mobile app, internet banking)
Positive association	• Perceived contact complexity • Use of offline channels • Loyalty • Age	• Value of time • Use of online channels • Activity
Negative association	• Value of time • Use of online channels • Activity	• Perceived contact complexity • Use of offline channels • Loyalty • Age

To enable data analysis independent variables were collected from databases at a bank, the channel preferences, dependent variables, of customers were collected through a survey. In total 5.500 customers were invited to the survey. After closure of the survey 300 respondents finalized the survey. Since channel preferences were measured by a five point Likert type scale, the dependent variables were assumed to have an ordinal or nominal scale. The easy interpretable technique of linear regression cannot be used with dependent variables of ordinal or nominal scales (Baarda & Goede, 2006). For this reason ordinal logistic regression (OLR) models and multinomial logistic regression (MLR) models were estimated for each communication channel. Based on model diagnostics (model significance, goodness of fit, respecting of assumptions, and pseudo R-squared values the MLR models were selected as best performing model

Main findings

Analysis of the diagnostics of the MLR models showed that all MLR models were significant models that fitted the dataset, and did respect the assumptions of multinomial logistic regression. The results of the MLR models led to accepting about 50% of the hypotheses on a 95% significance level. Translating the results from the hypotheses test to associations between independent variables and preferences for offline and online channels resulted in Table 2. This table shows the significant associations between independent variables and channel preferences found in this study. To enhance interpretability, the channels e-mail, mobile app and internet banking were grouped into online channels. The landline channel represents offline channels. The mobile channel was excluded from this table since this ability of this model to detect relations was strongly reduced due to a large proportion negative preference scores (see section 5.5). The results in Table 2 showed that, when age increased, the preference for an offline channel (landline) increased. At the same time did the preference for online channels decrease when age increased. It can be seen in Table 2 that all independent variables that were positively associated with the preference for offline channels, were negatively associated with online channels, which was in line with the hypotheses. For the independent variables that were negatively associated with the preferences for offline channels, no opposite effect was detected in the preference for online channels.

The associations between moderating variables and channel preference were not included in the table. Results showed that when the level of education increased, the preference for landline decreased and the preference for online channels increased. The results did furthermore show that living in an urban area was negatively associated with the preference for landline and was positively associated with the preference for e-mail. Lastly, results indicated that woman preferred landline more than man and had lower preferences for mobile, e-mail, and mobile app.

Table 2: Associations (at a 95% confidence level) between independent variables and preference for online and offline channels. The channel mobile was excluded from this table since.

	Preference for offline channel (landline)	**Preference for online channel** (e-mail, mobile app, internet banking)
Positive association	• Use of offline channels • Loyalty • Age	• Value of time
Negative association	• Use of online channels • Activity	• Use of offline channels • Loyalty* • Age

*Only applicable for the channel Internet banking

The validation of the MLR models was performed on model diagnostics and the internal validity of predictions made by the MLR models. The model diagnostics of the MLR models have been assessed as valid during the comparisons with OLR models. This provided confidence in the conclusion validity of the hypotheses tests. Internal validity tests showed that only the MLR models for the channels iInternet banking and mobile app were able to deliver valid predictions for channel preferences of respondents. The validity of the channel preference predictions made by the models were only regarded as internally valid when they provided a significantly better accuracy of predictions for channel preferences compared to chance. The accuracy of assigning respondents to a response category by chance is defined as the proportional by chance criterion (PCC). The PCC represents a random classification of samples to groups in proportion to group sizes (McGarigal, Cushman, & Stafford, 2000). The accuracy of predictions made by the mobile app model improved by 27% compared to the PCC (33%/26%). The accuracy of predictions made by the internet banking model improved by 35% compared to the PCC (31%/23%). External validity of the models was not evaluated in this thesis due to time and budget limitations.

Having significant and valid models does not mean they are useful for business. Literature from the field of (big) data governance suggest that the key question in evaluating the business relevance of data is to what extent data from models can be trusted to act upon. To assess the trustworthiness of the generated data five requirements are proposed: *proportionality, accuracy, reliability, credibility,* and *timeliness.* Applying these requirements to the predictions made by the models for internet banking and the mobile app, led to the conclusion that it is currently hard to evaluate the usefulness of the data generated by these models. Main reason for this conclusion is that definitions of success for the criteria are lacking. But even without these criteria, it would have been concluded that the models are not yet useful enough to be employed in practice due to a lack of generated data from the models. For example, data from different time stamps is required to assess the timeliness and reliability of data.

Summarizing, it is concluded that variables depicted in Table 23 can explain channel preferences of banking customers. Validation of the channel preference predictions made by the separate MLR models showed that only the models for mobile app and internet banking can validly predict channel preferences of respondents who are comparable to customers who responded to the survey. Validity of the models to the entire population of high value customers has not been assessed due to time and budget limitations.

Theoretical implications

Current theoretical knowledge about channel preferences for outbound contact is very limited. To gain insights in these preferences professionals and researchers are forced to consult knowledge about channel preferences for inbound interaction in the fields of channel choice and customer behaviour. This study provided various factors that explain channel preferences for outbound contact among banking customers for multiple outbound communication channels. These findings can provide guidance and focus in future research to outbound communication channel preferences. A second theoretical implication of this study is the introduction of a new perspective in multi-channel and channel choice literature. Current multi-channel and channel choice literature mainly focussed on the influence of channel characteristics on channel preference. This study has focussed on customer characteristics instead of channel characteristics. In this way the first step to predicting channel preferences of individual customers was made. Furthermore, this study provided a first step for institutionalizing decision rules on how to act upon model generated predictions of channel preference. The field of (big) data governance provides extensive information for such decision rules. Future scientific research to the application of (big) data governance in the field of multi-channel management and channel choice is therefore recommended.

Societal implications

The societal contributions encompass the contributions for bank and service organisations in general and banking customers. The main societal contribution of this research is that it provides banks, and service companies in general, insights for the personalization of outbound interaction strategies with customers. The identified variables that explain channel preferences of customers can be used as a starting point for predicting channel preferences. To assess the expected impact of using channel preference predictions on the required effort to reach customers and customer satisfaction, it is recommended to start pilots in which predictions for outbound communication channel preferences are used to select a communication channel to reach a customer. In conclusion, this study provides opportunities to turn already available customer data into value. To safeguard that this customer data will be turned in to value, for both companies and customers, it is recommended to institutionalize decision rules on how to trust and rely on channel preference predictions, generated by the models. It is recommended to use the criteria *proportionality, accuracy, reliability, credibility,* and *timeliness* as the base for the decision rules.

Limitations and recommendations for future research

The main findings of this study should be interpreted in the context of the limitations of this study. The limitations of this study can be categorized into three topics: generalizability, methodology, and operationalization of conceptual model. The sampling of respondents from the population and unequal chances of accepting the invitation to participate in the study limited the generalizability of the findings. The generalizability of this study was limited since the population of respondents did not represent the entire population of high value customers. Two causes for non-representativeness were identified: only respondents of whom the e-mail address was known were invited to the survey. Moreover, had older men, who frequently use Internet banking higher probabilities of responding to the survey. To avoid similar problems in future research it is recommended to

- Avoid selection bias by inviting respondents through multiple channels, preferably by the same channels that are included in analysis.
- Avoid non-response bias by correcting the invited population to expected response rates among sub-groups of the invited population.
- Always use a Heckman correction model to assess if non-response bias exists and to correct for non-response bias exists. Furthermore, it is recommended to collect channel preferences through other means than used for collecting data for model development. This data can be used for the validation of the Heckman correction.

Furthermore, the choice to estimate individual models for each channel limited the usability of the MLR models in business. For business usability it might have been better to estimate one model which predicts the preferred communication channel out of a set of communication channels.

- To improve the usability of MLR models in business it is recommended to assess whether a general MLR model for estimating the preferred communication channel is desired. When desired, it is recommended to ask respondents to select their preferred communication channel from a set of channels instead of scoring their preferences for each channel. Since the number of observations would strongly decrease, more respondents would be required.

Another methodological limitation is related to the many non-significant odds values that existed in the models. Reasons for non-significance could be non-existence of relationships between the independent variables and dependent variables, too many parameters to be estimated compared to the number of observations, or a low signal to noise ratio in the dataset.

- If no general model is desired, it is recommended for future research towards channel preferences of customers to use a dependent variable with a maximum of three levels. Using a dependent variable with more levels proved to limit the ability to find relations in the data and limited the predictive power of the models. In addition, collecting more data will increase the likelihood that relations in the data will be detected.

The operationalization of contact complexity is a potential limitation. Results of the MLR models showed that the contact complexity hypothesis (H1) was rejected for all communication channels. Meaning that no relationship between contact complexity and channel preference was found in the dataset. This was unexpected since many authors found a relation between contact complexity and channel preferences. This increases the likelihood that not finding a relation between contact complexity and channel preference can be attributed to the operationalization of contact complexity, compared to the likelihood that there is no relation between contact complexity and channel preference.

- To increase confidence in the operationalization of contact complexity, and attitude based factors in general, in future research towards channel preferences of customers, it is recommended to validate the operationalization through the use of surveys or interviews with customers. In this way results based on the operationalization can be used with more confidence.

Content

1. Introduction

Intense competition, technical developments and changing customer demands forced service companies to develop an interaction strategy with its customers that really enables to differentiate from competitors (Payne & Frow, 2004; Rosenbloom, 2007; Verhoef & Donkers, 2005). The resulting interaction strategies strongly contributed to the development of the multi-channel management field (Reis et al., 2015). The field of multi-channel management can be described as "the design, deployment, coordination, and evaluation of channels through which firms and customers interact" (Neslin et al., 2006). The financial sector has always been an early adapter and innovator in the field of multi-channel management and is therefore a key player for understanding developments in multi-channel management (Cortiñas, Chocarro, & Villanueva, 2010; Reis et al., 2015).

1.1. Problem analysis

A large financial institution in the Netherlands, called 'bank *X'* in this thesis, has set a strategic goal to become a bank where customers can seemingly switch between channels for interaction with the bank, without having to provide already shared information in other channels. Whereas most bank primarily focus the perspective where customers contact a bank, this banks also includes the perspective in which a bank contacts a customer (outbound. In this thesis the focus has been on the outbound perspective of multi-channel management.

The underlying goal of the multi-channel strategy of the bank is to be able to serve customers by their needs and preferences. This strategy is a reaction to an acknowledged problem in multi-channel systems: high costs of maintaining a multi-channel system and unsatisfied customers (Moriarty & Moran, 1990; Shih & Venkatesh, 2004). These issues are especially applicable to outbound contact since reaching customers by different channels requires resources and is usually inefficient due to a large number of customers who cannot be reached. Another potential risk is that customers can become annoyed while being contacted through a channel they dislike. This situation will not exist for inbound contact since customers have the choice to select their preferred communication channel themselves.

Personalizing the outbound communication strategy is key in solving the identified problems (Godfrey et al., 2011). When the outbound communication strategy is personalized, customers are only contacted through their preferred communication channel. This should lead first to a reduction of the number of customers who cannot be reached through outbound communication. Secondly, it should lead to improved customer satisfaction about outbound contact with the bank, since customers are served according to their preferences. For implementing personalisation of the outbound communication process, knowledge about the channel preferences of customers is required. This knowledge is required since the preferred communication channel of a customer needs to be selected. The challenge is to identify factors that explain the channel preferences of customers for outbound contact with the bank. Currently no insights in these factors exist within banks and no prior research to outbound communication preferences have been found during extensive literature research. Therefore, the knowledge gap of the bank overlaps with the scientific knowledge gap and is the main basis for cooperation between both parties in identifying factors that explain channel preferences for outbound contact.

1.1. Scope of study

The scope of this study is determined on three axes: outbound communication process, communication channels, and customers.

The identification of factors that explain communication channel preferences for outbound contact is part of the channel selection process within the larger process of outbound communication at a bank. Figure 1 shows the precise scope of this study. Only the selection of the preferred communication channel for outbound contact was within the scope of this study. Reasons for contacting a customer or actually contacting customers was out of scope.

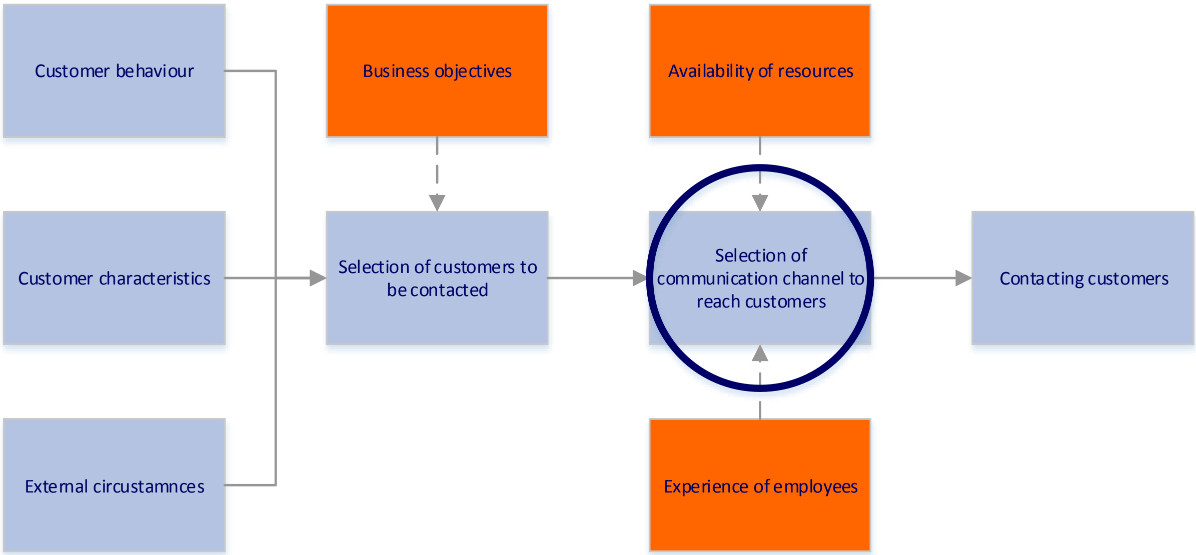

Figure 1: Focus of study within the outbound communication process

The communication channels in scope of this study were: Landline, Mobile phone, E-mail, internet banking & mobile app. These channels were selected since they are suitable for outbound contact with customers and are currently used for outbound contact. For the characteristics of these channels is referred to appendix I.

The customers who were in the scope of this study are high value customers and potential high value customers. Customers in the high value segment are customers with savings and/or invested capital exceeding €75.000. The client group of high value customers is a relatively large group of high value customers and is therefore the first group of clients selected for personalized outbound communication. Additionally, experience showed that these customers are relatively hard to reach and are critical towards the way they are being contacted (Expert, 2015).

1.2. Research questions of study

Based on the described problem the following research question were answered in this thesis:

What factors can explain outbound communication channel preferences of banking customers and how can these factors contribute to predicting channel preferences of these banking customers?

This research question was divided into several sub-questions which are shown below:

1) *What is the current state of knowledge in the overlapping fields of channel choice, customer behaviour and multi-channel management literature and how can it contribute to a better understanding of outbound communication channel preferences of banking customers?*
    i) Deliverable: Conceptual model and hypotheses.

2) *How does an analysis design for testing the hypothesized conceptual model for outbound communication channel preferences of banking customers look like?*
    i) Deliverable: Analysis design.

3) *How well can (outbound) communication channel preferences of high value customers be estimated by combining customer data of banking customers with the proposed conceptual model explaining channel preferences?*
    i) Deliverable: Estimation model for communication channel preferences.
    ii) Overview of what factors that influence outbound communication channel preferences of high value banking customers.
    iii) Assessment of predictive power of estimated models.

4) *What requirements for using predicted customer preferences for outbound communication should be incorporated in a framework for applying personalization in the communication strategy of a bank?*
    i) Deliverable: Set of requirements for using predicted customer preferences for outbound communication.

1.3. Scientific and Societal relevance of study

Societal relevance of this study consisted of both the potential benefits for banking customers and banks that could be achieved with the results of this research. The benefits for banking customers consisted of because the potential improvement of service for customers since they can receive service which better suits their preferences. The benefits for banks existed of the potential to reaching customers in a more efficient manner. Moreover, the benefits for customers are also beneficial for banks since it is likely that customer satisfaction will increase.

Scientific relevance of this study consisted of gaining insights in factors that explain channel preferences for outbound communication in the banking industry. These insights will be added to the current knowledge base about channel choice and multi-channel management, which until now only focussed on inbound communication.

1.4. Outline of thesis

Chapter 2 discussed the research approach of this thesis and provided an overview of the relation between the used methods in this thesis. Chapter 3 focussed on literature and hypothesis development. Chapter 4 covered the analysis design which was applied in the quantitative part of the thesis. Chapter 5 elaborated on the specification of the regression models and results from these models. Chapter 6 presented the validation of the regression models and chapter 7 discussed how the business relevance of the models can be assessed. Conclusions and a discussions were provided in chapter 8.

2. Research approach

In order to answer the research questions of section 0 a structured approach, containing several research methods, is presented. The main goal of the research is to understand the drivers of outbound communication channel preferences among banking customers, and to be able to make predictions about the preference for outbound communication channels. The study can be split into four different stages: Conceptual model construction, data collection, regression analysis, and business relevance. Figure 2 visualizes the stages of this study and the associated activities. The four stages will be discussed in the proceedings of this section.

2.1. Conceptual model construction

For good and up to date understanding of the problem area, the first part of this thesis will focus on available literature and expert knowledge. Insights from available literature were collected through desk research. The desk research subsequently focussed on two areas:

- Multi-channel management
- Channel choice

Knowledge from experts was collected through semi-structured interviews (Gillham, 2000). The semi-structured interviews with experts gained insight in factors that influence channel choice of customers in practice. Secondly, insights were collected about what customer types commonly use the available communication channels.

The results of the desk research and semi-structured interviews created the base for a conceptual model of factors which explain outbound communication channel preferences of banking customers. This conceptual model visualized the expectation of how channel preference for outbound contact is explained (Baarda & Goede, 2006). Furthermore, can the conceptual model be interpreted as the basis for hypotheses.

2.2. Data collection

To investigate to what extent this conceptual model and the accompanying hypotheses had any meaning, a data oriented analysis has been performed. Since the conceptual model relates multiple independent variables to a dependent variable 'channel preference', regression analysis seemed a suitable method for performing the analysis (Baarda & Goede, 2006; Engel, 1988; Petrie & Sabin, 2009; Vocht, 2009). To actually perform the regression analysis two types of data needed to be collected: independent and dependent variables. The independent variables were collected from an ING database with client data. The dependent variables which reveal the actual channel preferences of customers were collected through a survey.

The survey needed to measure to what extent customers preferred being contacted through a communication channel. This could have been done in three ways: selecting the preferred communication channel from a list of channels, ordering channels in increasing order of preference or giving scores to all communication channel in a list of channels. These three methods for measuring communication preferences reveal respectively increasingly more information, but require more time and effort of respondents. For this study the method in which respondents had to score all communication channels on a scale of preference was selected to minimize information loss and collect a maximal amount of information from each respondent. A five point Likert type scale (1= prefer channel not at all, 5= prefer channel very much) is used to measure the preference for communication channels. When introduced, it was intended that multiple questions with Likert type responses were summated to one Likert scale (Likert, 1932). The underlying assumption for the need of a summated score is that the concept to be measured is abstract and can only be measured by multiple indirect questions. In this study the concept of interest was the extent to which a channel is preferred. This was a concrete concept that could be measured by one question with a Likert type scale (Baarda & Goede, 2006).

2.3. Data analysis

The consequence of collecting Likert type data was that the dependent variables had an ordinal or nominal scale. This complicates the data analysis since many statistical test do not accept dependent variables with an ordinal or nominal scale. However, no consensus exists in academic literature about how to treat Likert data. Baarda and Goede (2006) for example found that Likert data is commonly assumed to have an interval scale and can be used for simple and easy to interpret linear regression. In this study simple linear models were constructed to test whether significant models can be constructed when data was regarded as having an interval scale. The focus will however be on regression analysis in which the data is regarded as ordinal. The models that will be used for this are Ordinal Logistic Regression and Multinomial Logistic Regression (Engel, 1988). These models are discussed in more detail in section 4.4, 5.1, and 5.2.

In order to evaluate the predictive performance of the constructed models for predicting channel preferences, a validation sample from the data was required. The data containing responses and information about respondents were split into a training sample and a hold-out validation sample. This was necessary for preventing an overestimation of the predictive performance of the models (Steyerberg et al., 2001). Respondents from the hold-out validation sample were not involved in the model development. Steyerberg et al. (2001) identified three ways of sampling a validation sample from a dataset. The proposed methods are stratified random sampling, cross validation, and bootstrapping. These techniques are increasingly more complex and efficient. However, the simplest technique still proves to be reliable. For this reason, random stratified sampling was used to split the dataset. The validity of the channel preference predictions made by the models were only regarded as valid when they provided a significantly better accuracy of predictions for channel preferences compared to chance. The accuracy of assigning respondents to a response category by chance is defined as the proportional by chance criterion (PCC). The PCC represents a random classification of samples to groups in proportion to group sizes (McGarigal et al., 2000). Significance of the difference between the PCC and the accuracy of the models was tested through a z-test (Cool & Henderson, 1997; McGarigal et al., 2000; White, 2013). If the difference in accuracy of a model and the PCC was significant, the channel preference predictions made by a model were regarded as valid.

2.4. Business relevance

Having significant and valid models does not mean they are useful for business. Therefore, criteria for assessing the business relevance, in terms of both business interests as customer interests, of the models were proposed. To identify these criteria literature research has been performed on (big) data governance.

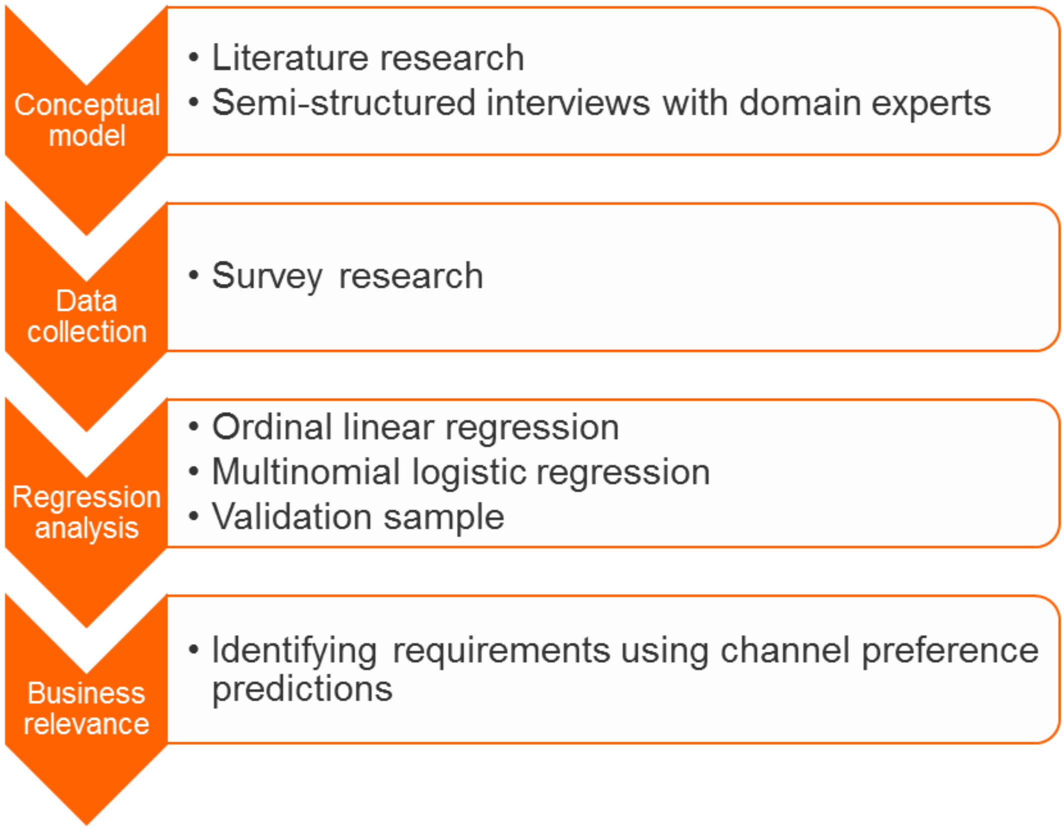

Figure 2: Research structure

3. Theoretical framework for channel preferences of customers

This chapter discusses the overlapping fields of multi-channel management and channel choice. This is followed by a conceptual model which visualizes the hypothesized associations between channel preference and independent variables. The last section provides conclusions on the conceptual model.

3.1. Multi-Channel Management and its role in interaction with customers

As mentioned in the introduction of this document, intense competition, technical developments and changing customer demands forced service companies to develop interaction strategies (Payne & Frow, 2004; Rosenbloom, 2007; Verhoef & Donkers, 2005). These interaction strategies strongly contributed to the development of multi-channel management (Reis et al., 2015). It is not a coincidence that multi-channel management strategies are especially of great importance in the service industry. The main reason for this is that customers perceive services as more risky than tangible goods (Murray, 1991). The intangible nature of services makes the design and implementation of interaction strategies with customers crucial for service providers. This may even hold stronger when customers themselves perform the service task in-home in absence of the service provider, which is the case for many banking services. Therefore, effective communication between service companies and customers becomes crucial as it can be considered as a requirement to successful customer relationships management (Birgelen, Dellaert, & Ruyter, 2012). This link between multi-channel management and customer relationship management introduces the common misinterpretation that multi-channel management only deals with interaction moments between clients and companies, whereas customer relationship management is aimed at the entire process of establishing and maintaining relations. Instead multi-channel management should be regarded as an area which provides great opportunities for gaining better understanding of customers and strengthening relations with them (Payne & Frow, 2004).

Multi-channel management can have many forms and no strict definition of multi-channel management exist. Within literature a distinction between distribution channels to bring products to the market and communication channels exist (Cortiñas et al., 2010). This study only focusses on the communication channels, but insights from the area of distribution channels are still useful, since both have many similarities. To better understand how multi-channel management is mentioned in academic literature a few commonly used definitions are listed below:

- “The use of more than one channel or medium to manage customers in a way that is consistent and coordinated across all the channels in use” (Stone, Hobbs, & Khaleeli, 2002).
- “Multi-channel management can be regarded as a continuum of forms of customer interaction ranging from physical to virtual interaction” (Payne & Frow, 2004).
- “The design, deployment, coordination, and evaluation of channels through which firms and customers interact, with the goal of enhancing customer value through effective customer acquisition, retention, and development” (Neslin et al., 2006).
- “Multi-channel management is the use of alternative modes of contact by customers to interact with and obtain service from an organization” (Cassab & MacLachlan, 2009).

The definitions show that multi-channel management contains the whole system that enables interactions between customers and companies. Rosenbloom (2007) reviewed research from this perspective and identified multiple issues concerning multi-channel management: multi-channel management does not increase the amount of customers who interact with companies, wrong use of channels multi-channel system, high costs of multi-channel systems, multi-channel management system causes customers to be unsatisfied. An important reason for these issues is that companies do not know the drivers which determine the preferred communication channel of their customers. This has the effect that companies use communication channels which are not preferred by customers (Wilson, Street, & Bruce, 2008). Therefore, service industries are looking to the world of online and offline shopping in which extensive research have been performed on channel choice.

However, within the field of channel choice, focus has been on the characteristics of channels and how these channel characteristics explain channel preferences of customers (Birgelen et al., 2012; Konus, Verhoef, & Neslin, 2008; Reis et al., 2015). To gain insight in how customer characteristics can explain channel preferences, a conceptual model is proposed. This model is based on channel choice and customer behaviour literature and visualises how channel choice is explained by customer related characteristics. The conceptual model is discussed in the coming sections of this chapter.

3.2. Conceptual model and hypotheses

Based on literature and semi-structured interviews (see appendix III for the interview template) with experts on the field of outbound communication within a bank, five drivers for *channel preference for outbound contact* are identified. The identified drivers are: *perceived complexity of contact, value of time, technological skills, activity* and *loyalty.* Additionally, some moderating effects are expected to explain *channel preference for outbound contact.* Figure 3 visualizes the conceptual model.

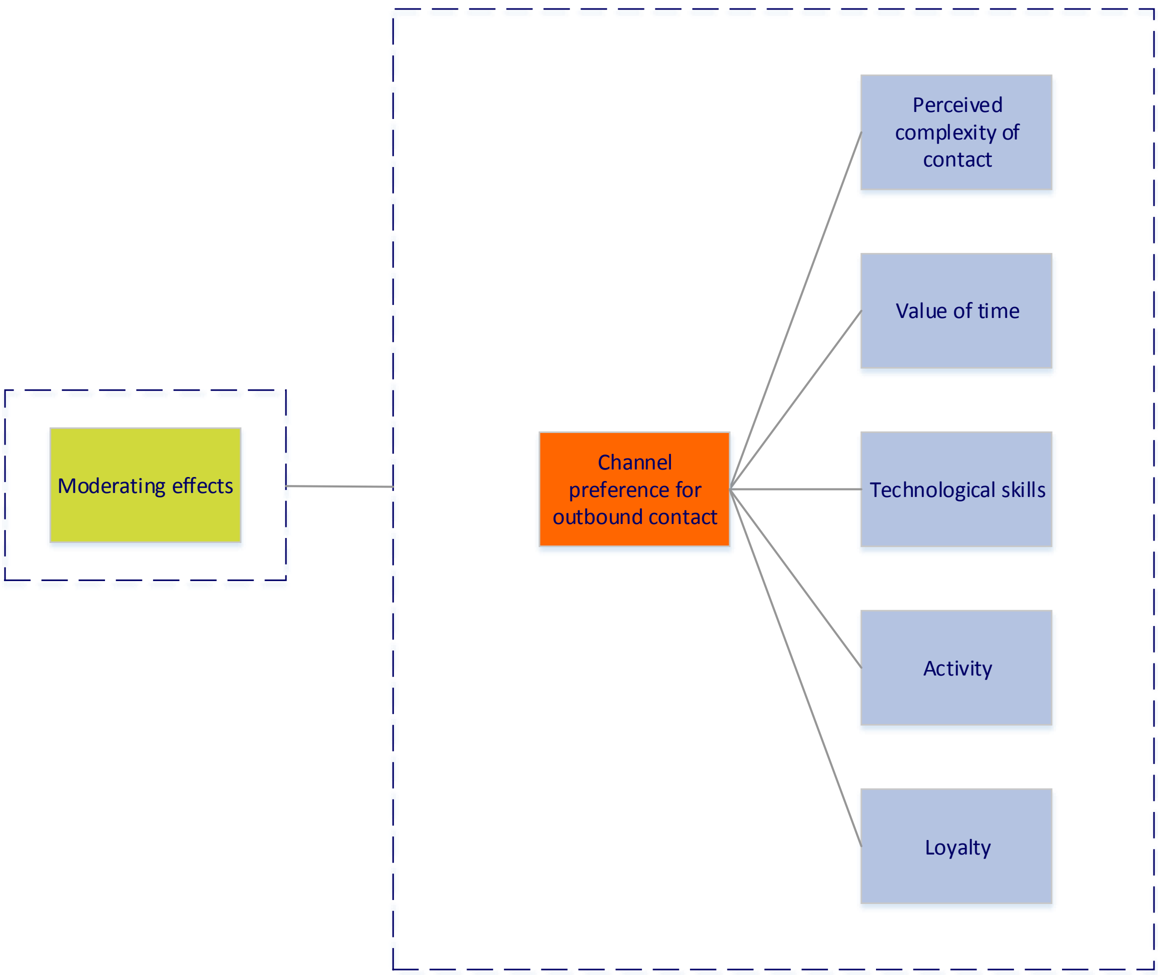

Figure 3: Conceptual model for channel preference for outbound contact.

This conceptual model forms the basis for hypotheses about what factors explain channel preference for outbound contact. As in most multi-channel research a distinction between offline channels (landline and mobile phone) and online channels (E-mail, Internet banking and Mobile app) has been made in the hypotheses. The **H0** hypothesis for each driver is: there is no association with 'driver' and preference for channel 'x' in the context of outbound communication. In the remaining of this sections the conceptual model and hypotheses will be discussed.

3.2.1. Perceived complexity of contact

Service complexity has been found to explain channel choice in a comparison between online and offline shopping (Simon & Usunier, 2007). It is expected that complexity can also explain channel preferences for outbound contact. The main reasoning for this expectation is that the substantive complexity of contact between a customer and a firm is not the same for each situation and that this influences channel preference. Birgelen, Jong, and Ruyter (2006) for example stated that channel preferences are dynamic since routine situations involve standardized procedures with relatively simple decisions, whereas more complex situations require higher involvement and knowledge intensive communication. It is therefore reasoned that customers may have different channel preferences for different situations (Dijk, Minocha, & Laing, 2007; Patricio, Fisk, & Cunha, 2003). Pieterson and Dijk (2007) even observed that citizens tend to prefer face-to-face communication channels for communication with municipal institutions when the perceived complexity of contact increases. Based on the presented arguments it seems likely that a higher perceived complexity of contact increases the chance that a customer prefers an offline communication channel. This is even more likely if the logic of Birgelen et al. (2006) is considered: "the delivery of non-routine financial services, such as mortgage and investment consulting, is more likely to lead to a positive customer evaluation through a face-to-face contact than routine services, such as credit applications, for which customers increasingly use internet banking". The arguments discussed lead to the following hypothesis:

H1: Perceived contact complexity is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound communication.

Operationalization

Complexity is operationalized in three levels: high, medium and low. This is a common way for measuring complexity in channel management (IntelliResponse & Oracle, 2011). However, just operationalizing complexity by asking *'To what extent do you prefer being contacted through communication channel A in a low/medium/high complex situation'* will not provide reliable data because people will interpret complexity differently. Alexander and Becker (1978) described ambiguity as a major problem in public opinion and survey research. They identified abstract and limited information in questions as the main cause of perceived ambiguity of questions among respondents. To overcome these issues, the use of vignettes is proposed. "Vignettes help to standardize the social stimulus across respondents and at the same time makes decision-making situations more real" (Alexander & Becker, 1978). In this study two vignettes per level of complexity (low, medium and high) are used to make complexity concrete and collect channel preferences for different levels of complexity. Each vignette deals with a situation about a financial product. For the construction of the vignettes 25 experts where consulted to help assigning financial products to the complexity levels. The financial products that are selected for the vignettes are: Insight in spending & income and savings account for low complexity, Insurance portfolio and mortgage for medium complexity, retirement related products and investments account for high complexity. The detailed results of this session can be found in appendix IV.

3.2.2. Value of time

Value of time (VoT) is the monetary value that a person assigns to a unit of time (Dijst, Rietveld, & Steg, 2009). VoT is commonly used in transportation to explain the monetary value of travel and is mainly determined by the money a person could have earned in the time he/she was traveling. Research in the transportation field showed that travellers use the VoT to select a preferred mode of transportation in which travellers with a high VoT select the transportation mode with the lowest travel time to minimize the lost earnings (Dijst et al., 2009; Schoemaker, 2002). It is expected that the same logic accounts for the relation between channel preference and VoT. This means that customers with a high VoT would like to minimize the time spent on interaction with the bank and therefore prefer communication channels with low interaction time. Offline communication usually requires more interaction time and are harder to postpone to a moment when the VoT is lower. The minimization of interaction time by customers with a high VoT has been observed in the comparison between offline and online shopping behaviour of Bitner, Brown, and Meuter (2000); Verhoef and Langerak (2001) where shoppers with a high VoT preferred the online channel. The arguments discussed lead to the following hypothesis:

H2: Value of time is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization

VoT is commonly operationalized by someone's salary (Dijst et al., 2009; Schoemaker, 2002). The VoT is therefore operationalized by the monthly salary that a customer receives on his/her checking account.

3.2.3. Technological skills

The role of habits in human behaviour has been widely researched in the social sciences. And there is strong evidence that habits influence future behaviour (Aarts & Dijksterhuis, 2000; Birgelen et al., 2012). It is expected that previous behaviour in the context of channel usage also influences preferences for future channel use. Since previous behaviour in the context of channel preference is based on channel choices (for inbound contact) of customers made in the past, the assumption has been made that channel preference for inbound contact is similar to the preference for outbound contact. The logic of this reasoning is that when people use a particular communication channel more often, they are apparently satisfied with the channel. This higher satisfaction with a channel reduces the perceived risk of using this channel (Venkatesan, Kumar, & Ravishanker, 2007). This low perceived risk of channel usage makes it more likely that a customer will use or prefers to use that channel in future interaction with a firm. In the same way does a lack of familiarity with a communication channel and dissatisfying experiences increase the perceived risk of using a channel (Valentini, Montaguti, & Neslin, 2011). The increased perceived risk will reduce the chance that a customer will use or prefer a channel in future interaction with a firm. It is expected that previous usage of online communication channels makes it more likely that an online communication channel is preferred for future interaction. The same accounts for previous usage of offline communication channels. The arguments discussed lead to the following hypotheses:

H3: Inbound usage of online communication channels is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

H4: Inbound usage of offline communication channels is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization

Technological skills in multi-channel literature are commonly measured by the usage of applications to use a channel (Carlson & Zmud, 1999). A remark is that only data available at the database of bank *X* can be used. Usage of online communication channels is measured by the number of *logins to internet banking* and *logins to the mobile app* over a period of 3 months. Usage of offline communication channels is measured by the *usage of bank offices* and *usage of the call centre of bank X* over a period of 12 months. A longer period for these channels is used since they are used less frequently than the online channels.

3.2.4. Activity

Insights from the semi-structured interviews (Expert, 2015) and internal customer behaviour databases of bank *X* show that customers that are actively using financial products, make less use of offline communication channels compared to customers that are less actively using their financial products. It is expected that this logic also accounts for the channel preference for outbound contact. Reason for this expectation is two folded. The first reason is that customers who are actively using their financial products are online oriented (Gensler, Leeflang, & Skiera, 2012). The online orientation can be explained by the fact that active usage of financial products is mainly facilitated by the rise of online banking services (Payne & Frow, 2004). The second reason is that customers who are actively using financial products understand these products better than customers who do not use their financial products frequently (Birgelen et al., 2012). Consequently, this better understanding of financial products makes it less likely that active customers prefer offline communication for outbound contact. The arguments discussed lead to the following hypotheses:

H5: Activity is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization

Financial activity is regularly measured by the number of transactions performed by a customer (Dholakia, Zhao, & Dholakia, 2005; Gensler et al., 2012). Here the *total number of transactions* over a period of 12 months is measured.

3.2.5. Loyalty

Loyalty is a phenomenon which develops slowly and is not solely limited to interaction moments between customer and a firm (Lemke, Clark, & Wilson, 2011). Since loyalty is build up during a long period, customers who are long-time customers can be regarded as loyal to a bank. Client data of bank *X* shows that loyal customers appear to make more use of offline communication channels compared to less loyal customers. An explanation of this could be that at the time more loyal customers became client, online communication channels were almost not available. Therefore, they are used to using offline communication channels (Valentini et al., 2011). This makes that it is expected that more loyal customers prefer offline communication channels for outbound contact. A second reason for the expectation is that more loyal customers expect a more personal treatment since they are long-time customers, stored large amount of money at the bank and have multiple financial products of the bank (Expert, 2015). Offline communication channels can fulfil this expected treatment. The arguments discussed lead to the following hypotheses:

H6: Loyalty is positively associated with the preference landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization

In multi-channel research loyalty is commonly measured by the *length of relationship* between the customer and a firm (Birgelen et al., 2006). For this reason, loyalty is measured by the *length of relationship* between a customer and the bank.

3.2.6. Moderating effects

Moderating effects that are commonly recognised in the area of multi-channel management and channel choice are included in this conceptual framework. The moderating effects that are included are: *age, education, habitat* and *customer type* (Cortiñas et al., 2010; Dholakia et al., 2005; Pieterson & Dijk, 2007; Strebel, Erdem, & Swait, 2004). Based on the semi-structured interviews some additional moderating variables are included: *number of financial products* a customer possesses, the summation of *the average amount of savings and investments* over a period of 3 months, *possession of internet banking,* and *possession of mobile app*. Special attention goes to the age variable since it has been found to be a major predictor of channel preferences for inbound contact, where age was positively associated with offline communication channels (Birgelen et al., 2012; Simon & Usunier, 2007). This leads to the last hypothesis:

H7: Age is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound communication.

For the other moderating variables no specific hypotheses are drawn.

3.3. Conclusions on theoretical framework

This chapter was aimed at exploring and collecting available academic literature on the fields of channel management, channel choice and customer behaviour to better understand what factors can explain channel preferences among banking customers in the context of outbound contact. Furthermore, have multiple experts on the field of outbound contact been interviewed to complement the academic knowledge. This process was guided by the following research question:

> *What is the current state of knowledge in the overlapping fields of channel choice, customer behaviour and multi-channel management literature and how can it contribute to a better understanding of outbound communication channel preferences of banking customers?*

Effective communication between service companies and customers is crucial since it can be considered as a requirement to successful customer relationships management (Birgelen et al., 2012). From this perspective multi-channel management should be regarded as a concept which provides opportunities for gaining better understanding of customers and strengthening relations with them

(Payne & Frow, 2004). Rosenbloom (2007) reviewed large amounts of multi-channel management research and identified multiple issues concerning multi-channel management: multi-channel management does not increase the amount of customers who interact with companies, high costs of multi-channel systems, multi-channel management systems causes customers to be unsatisfied. An important reason for these issues is that companies do not know the drivers which can explain the communication channel preferences of their customers. This has the effect that companies use communication channels which are not preferred by customers (Wilson et al., 2008). Therefore, service industries are looking to the world of online and offline shopping in which extensive research have been performed on channel choice.

However, within the field of channel choice, focus has been on the characteristics of channels and how these channel characteristics explain channel preferences of customers (Birgelen et al., 2012; Konus et al., 2008; Reis et al., 2015). To gain insight in how customer characteristics can explain channel preferences, a conceptual model is proposed. This model visualised how channel preference can be explained by customer related characteristics and is based on channel choice literature, customer behaviour literature, and interviews with outbound contact experts. The combined insights from literature and interviews with experts led to hypothesized relations between channel preference and the independent variables *perceived complexity of contact, value of time, technical skills, activity, loyalty,* and *age*. To enhance interpretability, the channels e-mail, Mobile app and Internet banking were grouped into online channels. The landline and mobile channels represent offline channels. Table 3 depicts the hypothesized relations of the conceptual model.

Table 3: Hypothesized associations between independent variables and preference for online/offline channels.

	Preference for offline channel (landline, mobile)	**Preference for online channel** (e-mail, mobile app, internet banking)
Positive association	• Perceived contact complexity • Use of offline channels • Loyalty • Age	• Value of time • Use of online channels • Activity
Negative association	• Value of time • Use of online channels • Activity	• Perceived contact complexity • Use of offline channels • Loyalty • Age

4. Analysis design and descriptive information from survey and client data

This chapter addresses the analysis design for testing the hypotheses which were derived from the conceptual model in section 3.2. The subjects that will be discussed are: survey design, data collection, data inspection, effects of data on data analysis, tools for analysis, sample representativeness and the construction of a hold-out validation sample.

4.1. Survey design

The survey design was strongly influenced by insights which the survey should provide. The required insights which this survey should provide were split into two components: *complexity* and *channel preference*. Section 2.2 already explained that *channel preference* was measured by asking respondents to rate channels on a scale from 1 to 5. Section 3.2.1 described that *complexity* was measured by vignettes. Two vignettes per level of complexity (high, medium & low) were used to measure channel preferences for different levels of complexity. Vignette 1 is an example of a low complex situation:

> *Imagine that the bank X would like to invite you for an interview with an advisor to review your current financial situation so you can make the right financial choices based on good insight and overview in your situation* (Vignette 1).
>
> *Would you like to be contacted about this subject? (Y/N)*
>
> **If answer to previous question was Y:**
>
> *You indicated that you would like to be contacted about this situation by bank X. Please enter below on a scale of 1 to 5 how you rate the following communication channels for being contacted. A 1 equals "Do not prefer at all" and a 5 indicates "I prefer very much." If desired, you explain your answer.*

For a complete overview of all vignettes, appendix V can be consulted. Furthermore, an overview of the whole survey can be found in appendix VI

For the implementation of all components in the survey design, special attention is required to ensure only valid channel preferences of customers were measured. The issue of validity was particularly applicable for the vignettes. Concerns about the validity of collected channel preferences was caused by the fact that respondents were asked to rate channels in a situation where bank *X* wants to contact them about a financial product that was discussed in a vignette. When for example a respondent did not want to be contacted about this situation, he/she would have probably rated all channels with a 1. In that case channel ratings do not reflect channel preference but the unwillingness of being contacted about this situation. Therefore, respondents were not forced to rate the communication channels, since this would have provided biased channel preferences. To avoid biased channel ratings a respondent was first asked whether he/she wants to be contacted in a situation. If the respondent did not want to be contacted, no rating had to be provided (see Figure 4). This safeguarded that if a respondent scored a communication channel with a 1 (do not prefer at all) this really reflected his/her attitude towards the channel and not that he or she did not want to be contacted in that specific situation.

Table 4: Example of possible data structure for communication preferences per vignette

Respondent	Vignette	Willing to be contacted	Preference Mobile app (1-5)
AA	1	Yes	3
AA	2	Yes	4
AA	3	No	MISSING VALUE
AA	4	Yes	3
AA	5	No	MISSING VALUE
AA	6	Yes	5

A drawback of this structure is that when a respondent was not willing to be contacted, no score for any communication channel was recorded and missing values were created. This is visualized in Table 4. The handling of this missing values is discussed in section 4.4. Table 4 also shows that each vignette can be found back in the data as single case and all respondents are represented by six rows in the data.

Additionally, assigning the financial products to levels of complexity has been performed by experts. To verify if respondents perceived the complexity of the financial products in the same manner as the experts, respondents were asked to rate the financial products on a scale from 1 to 5 in which a score of 1 represented 'not complex at all' and a score of 5 'very complex'

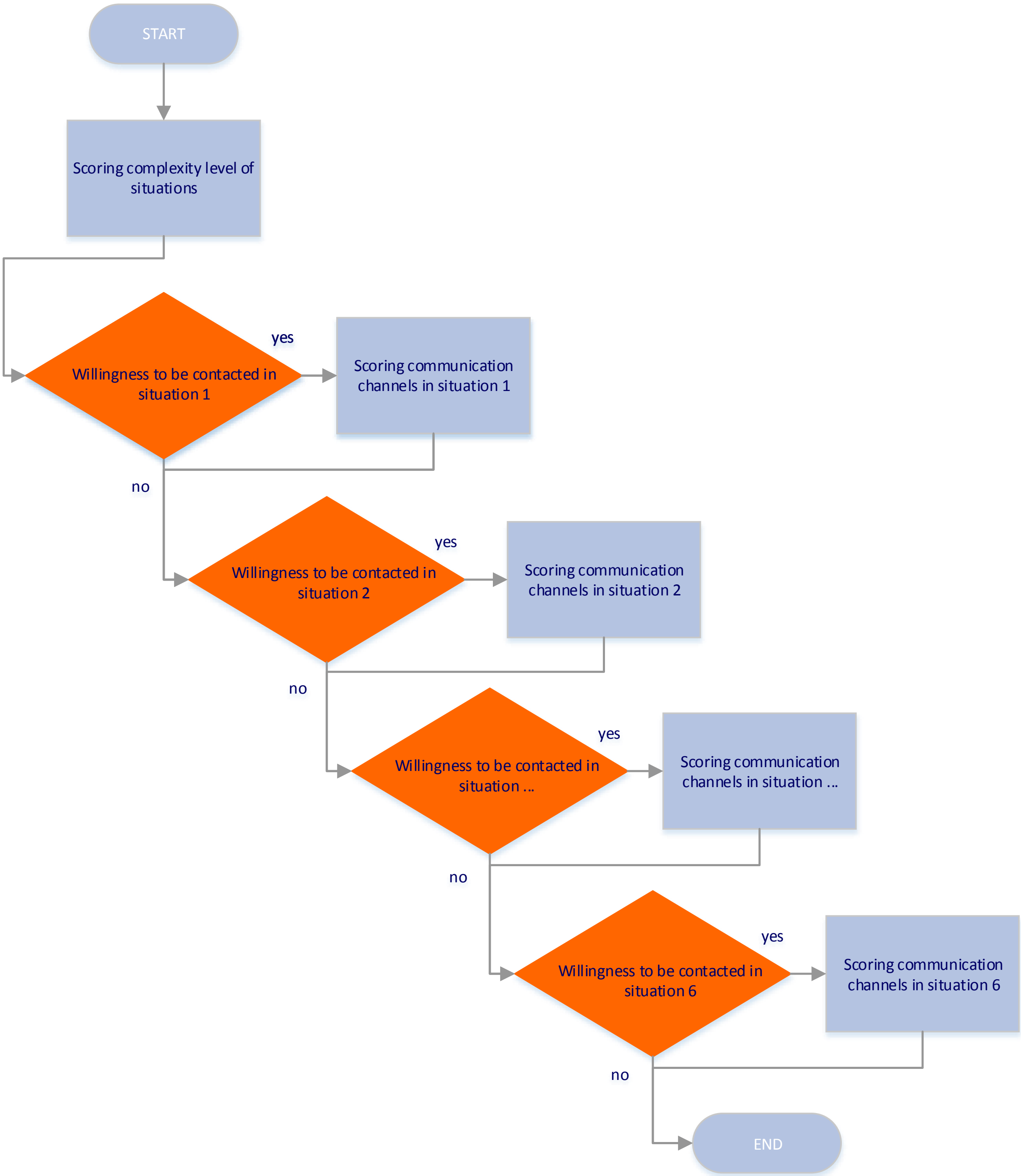

Figure 4: Survey design

4.2. Data collection approach

Due to time constrains, policy constrains at bank *X*, and budget constrains 250 valid responses could be collected. Experience form earlier surveys at bank *X* learned that a response rate between 4% and 5% was to be expected. Therefore, under the assumption of a 4.5% response rate, the survey has been sent to 5.500 customers from the Personal Banking segment (2750) and Personal Banking Prospects segment (2750). A response sample of 250 respondent corresponds to a Margin of Error of 6.2% at a significance level of 95%. The MOE expresses the amount of random sampling error in a survey and provides a likelihood that parameters found in the sample represent the real parameters of the population (Kotz, Read, Balakrishnan, Vidakovic, & Johnson, 2004). For the calculation of the MOE is referred to appendix VII.

After the approval of the Human Research Ethical Committee (HREC) of the Delft University of Technology, the operational activities were started. The collecting of data was outsourced to the research company [redacted]. The market research company [redacted] applied the ESOMAR world research codes & guidelines on market and social research which guarantied the ethical processing and collection of data (ESOMAR, 2009). [redacted] worked under supervision of the researcher [redacted] department of bank *X*. Respondents received an e-mail with an explanation of the survey and why they were selected for participation in the survey. The invitation mail has been sent at the start of week 39 (22nd of September 2015). Respondents were able to reply to the survey until the beginning of week 42 (13th of October 2015).

As mentioned before, respondents were invited by e-mail. This makes that information was collected by passive collection of data. The fact that respondents were only invited to participate by e-mail probably biased the results of the survey since e-mail is a communication channel itself. This could have potentially favoured online channels. However, customers seldom use only one channel (Wilson et al., 2008). It is therefore expected that not only e-mail users are included in the survey Due to time and budget limitations it was not possible to approach customers by other means.

4.3. Descriptive information of from survey data and client data

Three weeks after invitation 419 customers responded to the survey. In Figure 5 an overview of the response rate to the questions in the survey can be found. A small drop-off can be seen between each question. The drop-out from the introduction question to the first substantive question (about complexity of products) is an exception. Here a drop-off of 19% is recorded, these respondents did not answer any question. The total drop-out of respondents for the important questions (starting with the complexity question) is 12% (1-(300/339) * 100).

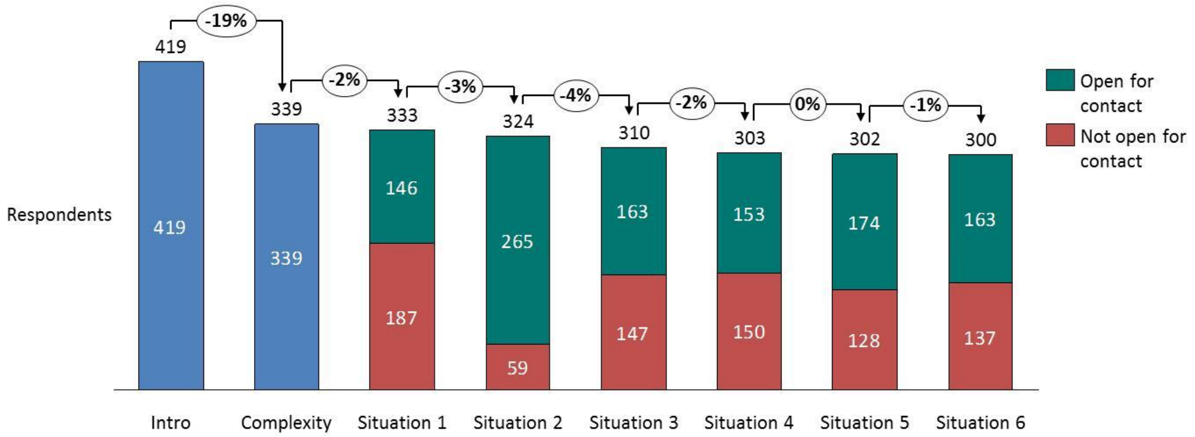

Figure 5: Response funnel of survey

In total 300 respondents went through all questions of the survey. This is higher than the expected 250 respondents and improved the MOE. The MOE decreased from 6.2% to 5.7% (see appendix VII for the calculation of the MOE). Furthermore, Figure 5 shows that a substantial part of customers was not willing to be contacted in the hypothetical situations. When respondents were not open for contact about a situation, they did not have to score their preference for communication channels as can be seen in Figure 4. A consequence of this was that many missing values were created in the data. The handling of missing data will be dealt with in section 4.4.

The independent variables which were included in the analysis have been selected in section 3.2. Appendix IX provides a descriptive overview of the mean, variance, skewness, kurtosis, minimum and maximum of the independent variables. Especially the skewness and kurtosis required attention, since they might reveal abnormal distributions of variables. Skewness indicates the degree of symmetry in the distribution of variables and kurtosis indicates the 'tailedness' of a distribution. Normal values of both skewness as kurtosis lay between -1 and 1. The variables POSESSION OF INTERNET BANKING, SALARY, LOGIN MOBILE APP, OFFICE VISITS and INBOUND CALLS had a skewness and/or kurtosis larger than 5. Further inspection of theses variables resulted in excluding the independent variable POSSESSION OF INTERNET BANKING (skewness -5.484 & kurtosis 28.093) since 97% of respondents possessed the online banking account. Therefore, the variable would have had low predictive value. For the other independent variables, it is decided to include them in the analysis, since the skewness and kurtosis could be fully explained by the characteristics of the data.

The distributions of the dependent variables in appendix VIII (preference ratings for channels) show that for the channels mobile, landline and e-mail, respondents a either preferred the channels very much or not at all. Variability in these dependent variables is therefore limited. This could potentially hamper the ability of the models to find relations between the independent variables and dependent variables.

4.4. Effects on data analysis

This and previous chapters learned that the collected data carries multiple potential threats for further analysis. The potential threats and the way these threats were handled is presented below:

Scale of dependent variables

The dependent variables were measured by a Likert type scale. The methods chapter already discussed the effects of dealing with Likert scaled data in regression analysis. Consequence of the Likert type scale of the dependent variables was that dependent variables are assumed to have an ordinal or nominal scale. The exploration of dependent variables in section 4.3 further showed that on average respondents either had strong preferences or no preferences for the channels landline, mobile and e-mail. The variability in these dependent variables was therefore limited, potentially making it harder to find relations with the independent variables.

Regression analysis

The assumed ordinal or nominal scale of the dependent variables had large effects on the possible regression techniques that could be used. The easy interpretable technique of linear regression for example does only allow a dependent variable to have an interval or ratio scale (Baarda & Goede, 2006) and was therefore not suitable in this study. Issues with dependent variables with an ordinal or nominal scale have been researched by many authors since the 80' of the previous century. McCullagh (1980) and Engel (1988) strongly contributed to the development of alternative regression techniques for dependent variables with ordinal and nominal scales. This resulted in the Ordinal Logistic Regression (OLR) technique and the Multinomial Logistic Regression (MLR) technique. The OLR models do assume that the dependent variables have an ordinal scale and therefore use cumulative probabilities to relate independent variables to dependent variables. The MLR models do not assume any order in the different levels of the nominal variables. For this reason, can MLR be regarded as a combination of multiple binary logistic regression models in which each level of the nominal dependent variable is compared to the one specific level of the nominal dependent variable, the reference level. Due to the multiple models that are created by the MLR models, interpretation of MLR models is hard. The assumptions of MLR models are however less restrictive than the assumptions of the OLR models (Williams, 2008). Therefore both models were estimated as can be seen in Figure 6.

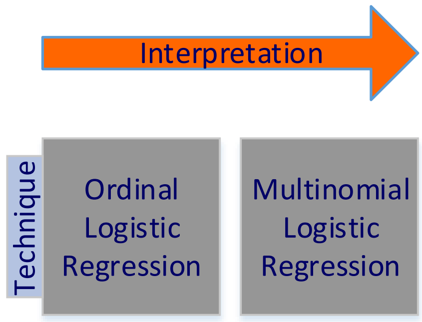

Figure 6: Plan for regression analysis. Direction of arrow indicates increasing interpretation complexity.

Missing values in the dependent variables

Several options exist for dealing with missing values. Examples are to remove cases with missing values, substitute missing values with the mean or to perform imputation (Tabachnick & Fidell, 2000). However, all these methods imply that missing values exist due to errors or mistakes made by respondents. This was not the cause of missing values in this dataset. A missing value was created when a respondent did not want to be contacted in specific situation. Therefore, replacing missing values with estimations/new values would have been incorrect. For this reason, it was decided to exclude cases with missing values from analysis.

4.5. Analysis tool

For the execution of data analysis, the software package Statistical Package for the Social Sciences (SPSS) of IBM has been used. SPSS has been selected because of its user friendly interface and the ability to customize reports of statistical tests. Furthermore, Microsoft Excel has been used to estimate the predictive value of regression models.

4.6. Non-response model and bias

The distribution of the non-response versus response to the invitation for participation in the survey required attention. If there was a significant difference between customers who did participate and customers who did not participate in the survey two populations exist. This means that the customers who did respond are not representative for the invited population and biased results from the survey could be produced (Bartlett, Kotrlik, & Higgins, 2001; Scheuren, 2004). Low response rates are a strong indicator for non-response bias (Montaquila & Olson, 2012). The response rate of the survey used in this study was low (7%), therefore non-response bias was examined. For this study a simple non-response model was constructed to test whether non-respondents and respondents were different populations. A logistic regression model was used to construct this model. Non-respondents were coded with a 0 and respondents were coded with a 1. Due to unreliable data in the database bank *X* 100 invitees were not included in this model, 5401 invites were included in the non-response model.

Table 5: Binary logistic regression model for non-response

Parameter	Beta	P-value	Exp
Gender	-0.392	0.001	0.676
AGE	0.036	0.000	1.037
Login internet banking	0.003	0.006	1.003
Constant	**-4.963**	**0.000**	**0.007**

The logistic regression model was significant (Chi-square of 103, 15df and p-value of 0.000) compared to an intercept only model, but has a very low **Nagelkerke R Squared of 4.6%.** Despite this low pseudo R-squared significant parameters were found (see Table 5), the odds values (exp) show that female (0=male, 1=female) had 32.4% less chance of responding to the survey. Furthermore, did each extra year of age increase the odds that an invitee responded with 3.7% and did each login to internet banking increase the odds of responding with 0.3%. Most influential was the constant since it shows that invitees did not prefer to participate. The results of this model showed that there is a risk for biased results since it was likely that on average older men who are actively using internet banking did respond to the survey.

Several action could be taken to deal with the unequal probabilities for responding to the survey. The ideal action upon a non-response bias is to avoid non-response. For avoiding non-response bias, insights in the expected response probabilities are required. These insights can be used to adjust the sampling of respondents. Hansen and Hurwitz (1946) suggested to correct the amount of invitations to a survey to the expected response rates of subgroups within the survey. For example, Table 5 shows that woman had 32.4% less chance of responding to the survey. Assuming there is a population of 100 people consisting of 50 men and 50 women. When the whole population would be invited to respond to the survey and all men were expected to respond. It can be expected that 34 (50*0.676) woman will respond. To keep the same ratio between men and woman in the response sample as in the population, the number of men being invited to respond should be decreased by 32.6%. Since they will all respond, the same amount of woman and men can be expected to respond. Since no information about expected response was available at the time of inviting respondents, no corrections in the amount of invitees for different subgroups were made. Due to time and budget limitations it was decided not redo the data collections with corrected amounts of invitees to avoid a non-response bias.

When non-response bias was not avoided it is possible to correct for the non-response bias. The Heckman correction model can be used for assessing and correcting the non-response bias (Sales, Plomondon, Magid, Spertus, & Rumsfeld, 2004). In 2000 James Heckman won the Nobel Prize for economy with his correction model which suggested that problems with non-response bias or selection bias in survey data can be allocated to truncation. "Truncation occurs when sample data is only drawn from a subset of a larger population. Thus, a truncated distribution is part of larger, untruncated distribution. In the data from such a survey, the dependent variable will be observed only for a portion of the whole distribution" (Guo & Fraser, 2015). The task of the Heckman correction model is to analyse the truncated dependent variable to infer the untruncated dependent variable for the whole population. The Heckman correction model does this in two steps. First it develops a selection equation. This selection equation is a model with factors associated the non-response to a survey. The residuals of the selection equation are used form a new variable which is used in the second step. In the second step this newly created variable is included as an independent variable in the original linear or logistic regression model (Guo & Fraser, 2015; Sales et al., 2004). This new independent variable assesses bias and tries to correct for it. If it a significant independent variable, the original model was biased (Sales et al., 2004). The concept of explicitly including selection bias in the regression equation instead of throwing it away or assuming it to be random is seen as crucial in thinking about selection bias (Guo & Fraser, 2015; Puhani, 2000).

Table 5 showed that data from older men, who frequently use internet banking is overrepresented in the data. A Heckman correction model could be used to assess the effect and make corrections. For two reasons it was decided not to apply the Heckman correction model. First reason is that it is not possible to evaluate the effect of the Heckman correction model. This not possible since the channel preference s of customers that did not respond to the survey are unknown. Therefore, it is not possible to assess if the effect of the Heckman correction would be valid. The second reason for not applying the Heckman correction model is related to the first reason. It would require substantial amounts of time and funds to perform the correction and collect channel preferences of customers who did not respond to the survey. This time and funds were not available. It should be noted that the Heckman correction model could also help to correct for the sampling bias which was caused by only inviting customers of whom the e-mail address was known for participation in the survey. Since no corrections for non-response bias was performed, results from this study should be interpreted with the caution that the data included an overrepresentation of older men which frequently use Internet banking.

4.7. Creation of validation hold-out sample

In order to evaluate the predictive performance of the constructed models for predicting channel preferences a hold-out validation sample from the data was required. The data containing responses and information about respondents has been split into a training sample and a hold-out validation sample. Not performing this would have resulted in an overestimation of the predictive performance of the models (Steyerberg et al., 2001). First the design of the validation sample is discussed. In the second part of this section the construction of the validation sample was discussed.

4.7.1. Validation hold-out sample design

Steyerberg et al. (2001) identified three ways of sampling a hold-out validation sample from the dataset. The proposed methods are stratified random sampling, cross validation, and bootstrapping. The techniques are increasingly more complex and efficient. However, the simplest technique still proves to be reliable. For this reason, random stratified sampling is used to split the dataset.

Stratified random sampling is a technique which allows that with few draws a representative sample from a population can be drawn (Cochran, 1977). The data is divided into non-overlapping groups (strata) and data points are drawn from these strata based on the proportional size of the strata in the population.

For each communication channel a model has been constructed in this study. This means that for each model a hold-out validation sample is required. This could be either a separate hold-out validation sample for each channel or one hold-out validation sample for all models which can be used for all models. For this study it was decided to draw one hold-out validation sample for all models. Only respondents who were willing to be contacted for all situations (presented in vignettes) were selected for the hold-out validation sample. With the hold-out validation sample drawn from this group, the validation and development was fully independent since none of the respondent in the hold-out validation sample was included in the development of any model. In case of separate hold-out validation samples, respondents could be part of the validation sample for channel A and be part of the training sample for channel B. This might cause issues with the comparability of the performance of the different models.

4.7.2. Construction of validation hold-out sample

In total 59 respondents did answer all questions. These respondents were divided into four strata. No more strata were constructed since the group of 59 respondents was too small for more than four strata. Due to the small population strata were based on dichotomous variables GENDER and POSSESION OF MOBILE APP. These variables were selected because they are expected to be important predictors for channel preference. Therefore, these variables must be well represented in the validation sample. As can be seen in Table 6, the proportions of strata were almost the same in total group (not willing to have contact in all situations) and subgroup (willing to have contact in all situations) from which the validation sample was drawn. This means that the hold-out validation sample is regarded as a stratified random sample from respondents that answer all questions.

In total 30% of the 59 respondents which answered all questions were used for the hold-out validation sample. This was equal to 11% of all cases of the dataset. The number of respondents from each stratum to be selected can be found in the last column of Table 6. The validation with the hold-out sample was performed in chapter 6.

Table 6: Overview random stratified validation sample

Strata			# respondents within strata (*)	Proportion of respondents (*)	# of respondents in validation sample
1	Man	Without Mobile app	167 (24)	40% (41%)	59*0.30*0.40 = 7 respondents
2	Man	With Mobile app	125 (18)	30% (31%)	59*0.30*0.30 = 5 respondents
3	Woman	Without Mobile app	34 (8)	9% (14%)	59*0.30*0.09 = 2 respondents
4	Woman	With Mobile app	89 (9)	21% (15%)	59*0.30*0.21 = 4 respondents
Total			415 (59)	100% (100%)	18 respondents

* Information within brackets is based on respondents which answered all questions.

4.8. Conclusions on analysis design for testing the hypothesized conceptual model

The previous chapters contributed to the creation of an analysis design for testing the hypothesized conceptual model which is proposed in chapter 3 of this document. The analysis design is an answer to the second research question of this thesis:

How does an analysis design for testing the hypothesized conceptual model for outbound communication channel preferences of banking customers look like?

The previous sections showed that the analysis design for testing the hypothesized conceptual model should consist of the five steps which are visualized in Figure 7. First the identified factors of the conceptual model need to be *operationalized* (1). A complication in this step is that the operationalized variables must be measurable in databases. This is required to predict the channel preferences of customers in the future, without having to collect new data from customers. Next step is to m*easure* channel preferences of banking customers (2). These preferences are used to develop models which should be validated in a later step. The third step is to *retrieve customer data from databases* (3). These are the attribute values of operationalized factors from step 1. The fourth step is to perform the *regression analysis* (4). The final step is to *validate* the models to assess the generalizability of the models for high value customer population of bank *X*.

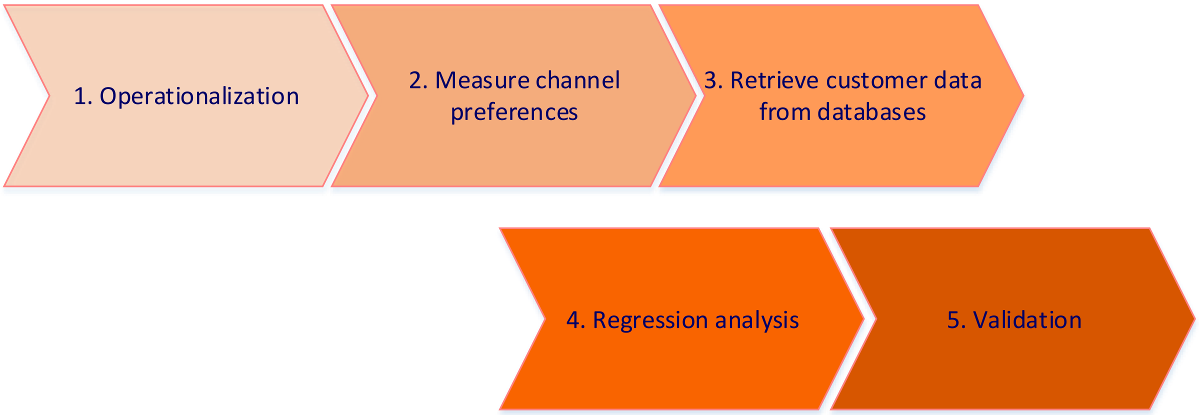

Figure 7: Analysis design for testing the hypothesized conceptual model

The analysis design had limiting effects on the generalizability of the results from this study. The limited generalizability of the results is caused by non-response bias and only inviting customers for the survey of whom the e-mail address was known. Due to time and budget limitations these issues were not treated. Therefore, results should be interpreted with the caution of these problems.

5. Model results

As discussed in section 2.3 and 4.4 the non-ratio scale of the dependent variables caused that estimating linear regression models was not appropriate. However, while probably not capable of estimating valid models, linear regression models may still provide useful information about the effect of independent variables on the dependent variable assuming that the dependent variable has an interval scale (Winship & Mare, 1984). For this reason and the good interpretability of linear regression, linear regression models have been estimated. All of these models found significant relations between the independent variables and channel preference as can be found in appendix X. However, the models had little validity since all models violated the assumptions of linearity, normally distributed residuals and homoscedasticity. Only the assumption of independence of observations was respected. Furthermore, the models explained only small parts of the variance since the models had relative low R-square values (between 0,093 and 0,234). Despite of the identified issues with the linear models, confidence in the conceptual model had grown, since the models provided an indication of relations between independent and dependent variables within the available data.

In the remaining of this chapter two types of models for the preference of the communication channels (landline, mobile, e-mail, mobile app, and internet banking) are discussed: ordinal logistic regression (OLR) models and multinomial logistic regression (MLR) models. First the specification of both OLR and MLR models is presented. Secondly, based on the statistical significance, goodness of fit, pseudo R-squared and respecting of model assumptions the MLR models was selected for hypotheses testing.

5.1. Specification of Ordinal Logistic Regression Model

Ordinal logistic regression assumes the existence of a latent continuous variable Y^*. This latent variable consist of multiple contiguous sections representing categories 1,..., *k*. While Y^* is latent, the distributions of responses to the *k* categories are known since they were measured in the survey among customers. Therefore, a link is required between Y^* and the observed *k* response categories. The concept of *thresholds* makes it possible to link the observed responses to the *k* response categories to the latent variable Y^* (McCullagh, 1980; Tutz & Hennevogl, 1996). The thresholds ($\theta_1, \dots, \theta_{k-1}$) are the cut points between two adjacent contiguous sections representing two of the *k* response categories. The logistic ordinal regression model estimates both these threshold values and parameters for independent variables.

The formal description of the ordinal logistic regression model has extensively been described by McCullagh (1980). In his formal description of the ordinal logistic regression model McCullagh (1980) formalized the ordered response categories as integers from 1 to *k*. The multinomial probability of being in each of the response categories is described by π_j, with $j = 1, \dots., k$. The π_j depends on the value of a vector of independent variables *x* through regression parameters (Armstrong & Sloan, 1989). Since the response categories are ordinal, the model is based on cumulative probabilities. The following equation and Figure 8 show this: $\gamma_j = \pi_1 + \cdots + \pi_j$ is the cumulative probability of being in one of the first j response categories, in this way the ordering of response categories is incorporated. The odds of γ_j is then(Bender & Grouven, 1997):

$$\gamma_j = \frac{P(\gamma \leq j)}{(1 - P(\gamma \leq j))}$$

Figure 8 visualizes the odds of γ_j. A j of 2 would for example correspond with the row where the first two blocks are orange. Since the logit link function is used in this thesis the regression model can be formalised by the following equation in which θ and β are unknown parameters (McCullagh, 1980; Tutz & Hennevogl, 1996):

$$logit(\gamma_j) = \ln\left(\frac{\gamma_j}{1-\gamma_j}\right) = \theta_j - \beta^T * x \qquad (j = 1 \ldots\ldots k-1)$$

The β is a linear vector of parameters for the independent variables, the θ is used for assigning response categories. Thus the cumulative ordinal regression model is thus given by:

$$\begin{aligned} logit(\gamma_j) = \theta_j - \beta_1 * Complexit - \beta_2 * Education - \beta_3 * Gender - \beta_4 * Urbanity - \beta_5 \\ * Possession\ ING\ app - \beta_6 * Age - \beta_7 * Duration\ relation - \beta_8 * Salary - \beta_9 \\ * Transactions - \beta_{10} * Login\ Mijn\ ING - \beta_{11} * Login\ ING\ app - \beta_{12} \\ * Office\ visit - \beta_{13} * Inbound\ call - \beta_{14} * Number\ of\ products - \beta_{15} \\ * Average\ savings\ \&\ investments \end{aligned}$$

$$with \quad (j = 1, \ldots, 4)$$

It can be seen that each response category has a specific threshold value and regression parameters are equal for all response categories. This causes that the odds of the *k* response categories only depend on the threshold values. Therefore this model is also called the proportional odds model (Bender & Grouven, 1997). Another difference with linear functions is that the parameters have negative signs. These negative signs improve the interpretability of parameters with regards to probability. The parameters are log values and high negative numbers have large effects and the same direction when the exp(-parameter) is used to calculated the effect on the probability (Christensen, 2015). Furthermore, it can be seen that no noise term is included in this function, when performing ordinal regression this is normally accepted (Tutz & Hennevogl, 1996).

When actually calculating the probabilities of belonging to a response category or lower, the logit link function describes the following function (Stock & Watson, 2007):

$$\gamma_j = \frac{1}{1 + e^{-(\theta j - \beta^T * x)}}$$

The assumptions for ordinal logistic regression are: the dependent variable should be at the ordinal level, one or more of the independent variables need to be either continuous, ordinal or nominal, no multicollinearity and the key assumption of ordinal logistic regression is the assumption of proportional odds (parallel lines). This key assumption assumes that all parameters of the independent variables are equal for each level of the *k-1* response categories (Bender & Grouven, 1997).

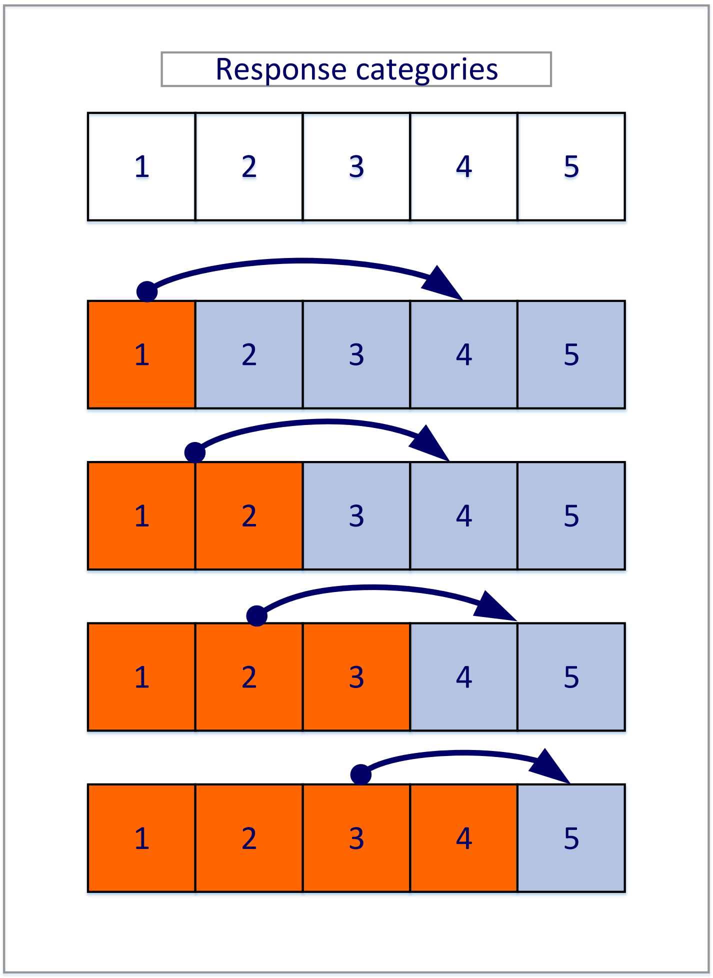

Figure 8: Conceptual overview of Ordinal Logistic Regression

5.2. Specification of Multinomial Logistic Regression Model

Ordinal regression assumes the existence of a latent continuous variable of which the observed response variable is a coarse approximation. Multinomial logistic regression does not assume the existence of a latent continuous variable. It does not require such an assumption since it assumes no ordinal scale of the response categories (Bender & Grouven, 1997). Since no ordinal scale of the dependent variable is assumed, the multinomial logistic regression (MLR) model does not use the cumulative probabilities but instead performs multiple binary logistic regressions. It is supposed that the nominal scale response variable (Y) has *k* response categories. To avoid performing multiple binary logistic regressions the MLR creates *generalized logits* in which response category *k* is selected as a reference category. In the *generalized logits* the probability π_j, with $j = 1, \ldots, k-1$, is described as the probability of belonging to response category *j* compared to the reference category *k* (see Figure 9). The π_j depends on the value of a vector of independent variables *x* through regression parameters (Armstrong & Sloan, 1989). The *generalized odds* are defined by:

$$\pi_j = \frac{P(Y = j)}{P(Y = k)} \qquad (j = 1 \ldots . . k - 1)$$

The *generalized logits* are with *m* independent variables is defined by:

$$logit(\pi_j) = \ln\left(\frac{\pi_j}{\pi_k}\right) = \alpha_j + \beta_{j1} * x_1 + \ldots + \beta_{jm} * x_m \qquad (j = 1 \ldots\ldots k-1)$$

Since the proportional odds assumptions is not applicable for MLR, the MLR model is given by *k -1* equations. This has the effect that each level *k* of the response variable *Y* has its own parameters. So the effect having less strict assumptions is that interpretation becomes harder.

$$\begin{aligned} logit(\pi_j) = \alpha_j + \beta_{j1} * Complexit + \beta_{j2} * Education + \beta_{j3} * Gender + \beta_{j4} * Urbanity + \beta_{j5} \\ * Possession\ ING\ app + \beta_{j6} * Age + \beta_{j7} * Duration\ relation + \beta_{j8} * Salary \\ + \beta_{j9} * Transactions + \beta_{j10} * Login\ Mijn\ ING + \beta_{j11} * Login\ ING\ app + \beta_{j12} \\ * Office\ visit + \beta_{j13} * Inbound\ call + \beta_{j14} * Number\ of\ products + \beta_{j15} \\ * Average\ savings\ \&\ investments \end{aligned}$$

$$with \quad (j = 1, \ldots, 4)$$

When actually calculating the probabilities of belonging to a response category or lower, the logit function describes the following function (Stock & Watson, 2007):

$$\pi_j = \frac{e^{(\alpha_j + \beta_{j1} * x_1 + \ldots + \beta_{jm} * x_m)}}{1 + e^{(\alpha_1 + \beta_{11} * x_1 + \ldots + \beta_{1m} * x_m)} + \ldots + e^{(\alpha_k + \beta_{k1} * x_1 + \ldots + \beta_{km} * x_m)}}$$

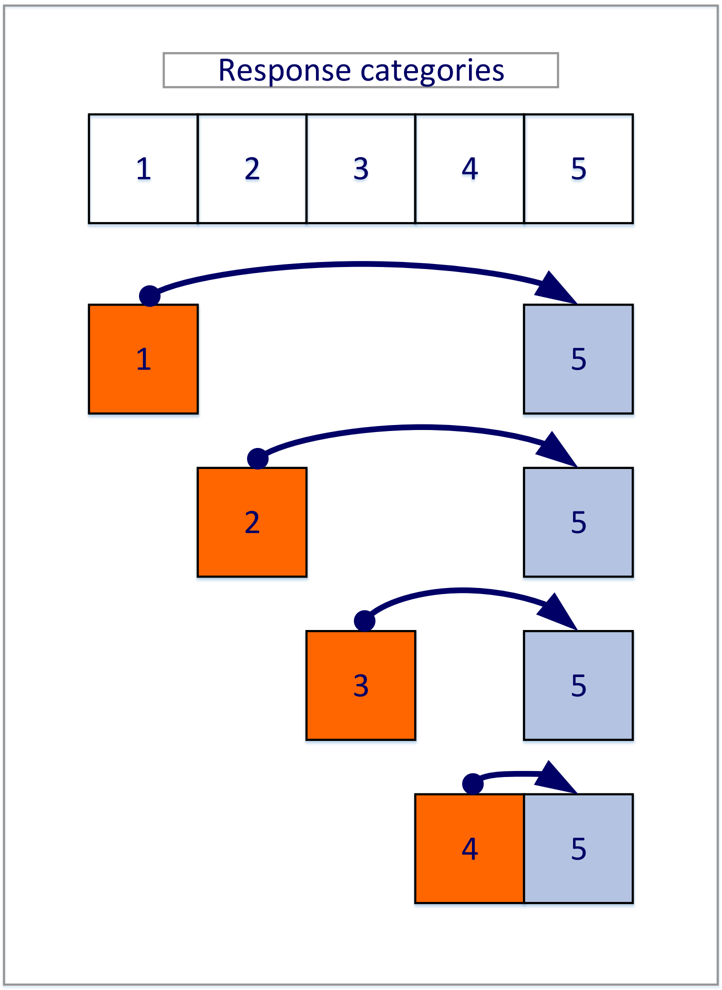

Figure 9: Conceptual overview of Multinomial Logistic Regression

5.3. Diagnostics of ordinal- and multinomial logistic regression models

This section discussed diagnostics of both the OLR and MLR models. Based on these model diagnostics one of these models is selected as best performing model.

5.3.1. Ordinal logistic regression models

The model information in Table 7 shows that the pseudo explained variance (Nagerkerke R-Squared) of all models was quite low, but were still an improvement compared to the linear regression models in appendix X. More important was that all models were significant and did significantly fit the data. A drawback was that only the model for the preference for Mobile app respects the important assumption of proportional odds (Parallel lines). This assumption assumes that the coefficients are equal at all levels of the response categories. Meaning that the coefficients are capable of distinguishing all response categories from each other. For more elaborate explanations of this assumption is referred to Bender and Grouven (1997); McCullagh (1980). The SPSS output of the ordinal logistic regression models can be found in appendix XI.

Table 7: Diagnostic information of ordinal logistic regression models

Channel	Significant model? (Chi-square df=21)	Goodness of fit (Chi-square df-3555)	Nagelkerke R-squared (OLR)	Respecting assumption of parallel lines?
Landline	208,165**	3416,578	0,219	No
Mobile	127,348**	3636,906	0,145	No
E-mail	94,557**	3418,679	0,109	No
Mobile app	240,427**	3612,206	0,249	Yes
Internet banking	129,088**	3520,054	0,141	No

5.3.2. Multinomial logistic regression models

The advantage of multinomial logistic regression is that it does not make many assumptions. MLR does not make any assumptions of normality, linearity, and homogeneity of variance for the independent variables. The assumptions for MLR are: the dependent variable should have a nominal scale, no multicollinearity and independent variables should not be able to predict the dependent variable perfectly. When the dependent variables can be predicted perfectly, unrealistic coefficients will be estimated. The dependent variables are assumed to have a nominal scale here and no multicollinearity was detected (see appendix IX). For the mobile and Mobile app models the independent variable *education* caused perfect predictions. This variable had three levels: high, medium and low education. The low education group was very small (only 5% of respondents) and caused the perfect predictions. The problem was resolved by merging the medium and low education categories for both models.

Table 8: Diagnostic information of multinomial logistic regression models (Diagnostic validation)

Channel	**Significant model? (Chi-square df=84)**	**Goodness of fit (Pearson chi-square df-3492)**	**Nagelkerke R squared (MLR)**	**Respecting perfect predictions assumption?**
Landline	357,766**	3373,108	0,348	Yes
Mobile	217,390**	3662,363*	0,236	Yes
E-mail	281,933**	3756,007**	0,294	Yes
Mobile app	416,691**	4794,412**	0,393	Yes
Internet banking	332,433**	3769,568**	0,326	Yes

Table 8 shows that all models are significantly better in predicting the dependent variable, compared to intercept only models. The pseudo R-squared values were considerably higher compared to the OLR models. However, estimating a MLR model, compared to an OLR model, always leads to a higher pseudo R-squared value since more parameters need to be estimated. This was the case because in an OLR model only one parameter is estimated for each independent variable and in the MLR models multiple (k-1 parameters for a dependent variable with k levels) parameters need to be estimated for each independent variable. Therefore, higher pseudo R-squared values should do not have to indicate a better explanation of the variance in the dependent variable. Caution is therefore required by the Interpretation of the higher pseudo R-squared values. Furthermore, all models respect the important assumption of no perfect predictions. The goodness of fit of the models is only acceptable (at a 95% confidence level) for the landline model. Meaning that only the landline model fits the data well and the other models do not fit the data well. These outcomes should be interpreted with great care since the goodness of fit test with Chi-Square is very sensitive to independent variables with a ratio level, which are included in the models (Allison, 2014; McCullagh, 1980). An alternative goodness of fit test for multinomial logistic regression models is the accuracy of predictions made by the models (Hoetker, 2007).

Hoetker (2007) shows that MLR models can be regarded to have a good fit when their overall accuracy rate is significantly better than the proportional chance criterion (PCC). The PCC represents a random classification of samples to groups in proportion to group sizes (McGarigal et al., 2000). The PCC can then be computed by:

$$Proportional\ by\ chance\ criterion = \boldsymbol{p_1}^2 + \boldsymbol{p_2}^2 + \boldsymbol{p_3}^2 + \boldsymbol{p_4}^2 + \boldsymbol{p_5}^2$$

Where $\boldsymbol{p_1}$ is the proportion of samples in the first group (response category 1) and $\boldsymbol{p_2}$ is the proportion of samples in the second group (response category 2), etc.. The difference between the PCC and the accuracy rate for the predictions in the training sample were standardised in a z-score and tested for significance by a right sided z-table (Marcoulides & Hershberger, 1997). Negative z values indicated that the model performed worse than the PCC and was not fitting the data. As can be seen in Table 9 all models had significant z-values and therefore all had a good fit with the data. The calculations for these goodness of fit can be found in appendix XIV.

Table 9: Goodness of fit test with predictive value of models

Channel	Proportional by chance criterion (PCC)	Accuracy of predictions	Z-value (if negative model invalid)	P-value (α=0,05)	Goodness of fit?
Landline	27%	49%	15,08	0,000**	Yes
Mobile	39%	60%	12,95	0,000**	Yes
E-mail	36%	57%	7,76	0,000**	Yes
Mobile app	26%	53%	18,16	0,000**	Yes
Internet banking	23%	43%	14,10	0,000**	Yes

5.3.3. Comparison OLR models and MLR models

Comparison of the diagnostics of both models led to the conclusion that the MLR models performed better than the OLR models. This conclusion was based on the following criteria: significance, goodness of fit, pseudo R-squared and assumptions. Regarding significance of the models both the OLR and MLR models were significantly better compared to intercept only models. The same accounted for the goodness of fit of both the OLR and MLR models. It was observed that the Nagelkerke R squared values were considerably higher for the MLR models compared to the ordinal regression model. The pseudo R-squared values (Nagelkerke) of both models could not be compared since it was not clear how much of the extra explained variance of the MLR models can be attributed to just having more parameters to be estimated. Lastly, four out of five OLR models violated the important assumption of parallel lines, indicating that the coefficients of parameters cannot be assumed to have the same value at all levels of the response categories. Contrary, all MLR models did respect the important assumption of not perfectly predicting outcomes. Taking into account all diagnostics of both the OLR models and MLR models, the better performance of the MLR models regarding respecting of essential assumptions, led to the conclusion that the MLR models were selected as best performing models. For this reason, hypotheses tests were only discussed for the MLR models.

5.4. Results of Multinomial Logistic Regression Model

As discussed in section 5.2 the consequence of not having the proportional odds assumption is that each independent variable has *k-1* separate coefficient for *k* response categories. This means that for this study 96 coefficients were estimated per channel ((intercept + 14 ratio scale + 2 ordinal scales with in total 9 levels) * *4)*. For all models in total, 480 coefficients were estimated. This was too much information to present in one table. For that reason, separate tables were presented for each hypothesis. If an independent variable had a significant relation with the dependent variable the odds values were presented. If there was no significant relation, no odds values were presented. If the presented odds values significantly contributed to distinguishing between response categories *(95%) or **(99%) were used to indicate significance levels. The significance of the odds values was determined by the Wald test. For the output results of SPSS is referred to appendix XIV.

H7: Age is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, Internet banking and the mobile app in the context of outbound communication.

Table 10 shows for each channel the odds of the independent variable age for the response scores 1,2,3 and 4 compared to scoring a 5 (preferring a channel very much). For the channel landline the odds of scoring a 1 (not preferring landline at all) compared to scoring a 5 (preferring landline very much) decrease by 9.1% per unit of age, controlled for other variables. This means that older people have a higher probability of preferring landline. No significant relation between age and preference for mobile was found. It can be seen that for the online communication channels the odds of scoring a 1 (not preferring a channel) compared to scoring a 5 (preferring a channel very much) favour scoring a 1 (not preferring a channel at all). This effect is the strongest for the e-mail channel (5.7% increase of the odds of scoring a 1 instead of a 5). Furthermore, when someone scores a communication channel higher (e.g. 2,3 or 4), the effect of age becomes weaker but still has the same direction. Meaning that the effect (positive or negative) of age on channel preference was consistent. For example, the odds for scoring a 3 compared to a 5 for landline decrease by 6.9% per unit of age whereas the comparison between a score of 1 compared to 5 provided a decrease of 9.1% in odds. The effect is weaker but still in the same direction. In summary, for all channels except mobile, significant parameters were estimated which were in line with H7. This all leads to **accepting** H7 for the channels **landline, e-mail, mobile app,** and **internet banking** and **rejecting** H7 for the channel **mobile.**

Table 10: Hypothesis 7: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (sig. at 95% confidence interval;** sig. at 99% confidence interval)*

		Landline	Mobile	E-mail	Mobile app	Internet banking
Age	Response score 1	,909**	-	1,057**	1,036**	1,047**
	Response score 2	,895**	-	-	-	-
	Response score 3	,931**	-	1,039*	-	1,034*
	Response score 4	-	-	-	-	-
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✓	✓	✓

H1: Perceived contact complexity is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound communication.

The ratio likelihood test for the models of all channels showed that there was no significant relation between complexity and channel preference. This had the consequence that the comparisons between response categories cannot be interpreted (University-of-Texas-at-Austin, 2006) (see appendix XIV for details). **H1 is rejected for all channels** due to the lack of a significant relation between complexity and channel preference**.**

Table 11: Hypothesis test conclusions for hypothesis 1. X represent a rejection of the hypothesis at a 95% confidence interval

Landline	Mobile	E-mail	Mobile app	Internet banking
✘	✘	✘	✘	✘

H2: Value of time is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Table 12 shows the odds of the independent variable salary from the MLR models for each channel. The odds in the models for offline communication channel were almost never significant. Only for the landline channel the odds comparing response category 3 and 4 to response category 5 were significant. However, these odds were opposite to what was expected. They indicate that customers with high incomes have higher odds of scoring a 5 (preferring landline). The online communication channel e-mail has only one significant odds value for scoring a 4 compared to a 5 which favours the odds of scoring a 5. The other online communication channels do show odds that were as expected. Almost all odds values for these channels were significant. And show for both the Mobile app and Internet banking that the odds of scoring a 1 (preferring these channels not at all) compared to a 5 (preferring these channels very much) decrease with about 8% per €1.000 of salary. In summary, the results show that salary cannot explain the preference for offline channels in the expected direction. As expected is salary positively associated with the preference for online channels. Based on the significance of the odds values **H2 is rejected** for the channels **landline** and **mobile,** and **H2 is accepted** for the channels **e-mail, mobile app,** and **internet banking.**

Table 12: Hypothesis 2: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (sig. at 95% confidence interval;** sig. at 99% confidence interval)*

		Landline	Mobile	E-mail	Mobile app	Internet banking
Salary (per €1000)	Response score 1	-	-	-	,912**	,920**
	Response score 2	-	-	-	,942*	-
	Response score 3	,940*	-	-	,949**	,932**
	Response score 4	,937*	-	,910*	,934**	,950**
	Response score 5	0	0	0	0	0
Conclusion		✘	✘	✓	✓	✓

H3: Inbound usage of online communication channels is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Table 13 shows that the odds for the independent variables *login internet banking* and l*ogin mobile app* were more often significant in the models for online channels compared to offline communication channels. In the model for the offline channel landline, login to internet banking was only significant in comparing response category 1 to 5 and confirmed that logins to internet banking increased the odds of scoring a 1 compared to a 5 with 1.3% per login to internet banking, controlled for other variables. However, the results in the offline communication channels were not consistent. The effect in the mobile channel, also an offline channel, showed opposite results compared to effect in the landline model. The logins to internet banking increased the odds of preferring the channel mobile. This is opposed to what was expected. For the online channels e-mail and mobile app, logins to internet banking did surprisingly increase the odds of scoring lower scores compared to 5. This means that logins to internet banking decrease the probability of preferring the online channel e-mail and mobile app. In addition, the effect of the logins to internet banking on the preference for internet banking are confusing since they show mixed effects (both positive and negative). The effect of logins to the mobile app on offline channels was as expected, it decreases the odds of preferring landline.

Table 13: Hypothesis 3: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (sig. at 95% confidence interval;** sig. at 99% confidence interval)*

		Landline	Mobile	E-mail	Mobile app	Internet banking
Login internet banking	Response score 1	1,013**	-	-	1,023**	,993*
	Response score 2	-	,987*	1,011*	1,036**	1,015**
	Response score 3	-	-	-	1.019**	,989**
	Response score 4	-	-	-	1.019**	-
	Response score 5	0	0	0	0	0
Login mobile app	Response score 1	1,028*	-	,964*	,990*	-
	Response score 2	-	-	-	0,964*	-
	Response score 3	1,027*	-	-	-	-
	Response score 4	1,024*			1,006*	
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✗	✗	✗

The effects for the mobile and internet banking preference were not significant. Furthermore, logins to the mobile app increased the odds of preferring the mobile app and e-mail, confirming the idea that previous behaviour is a good indicator for future behaviour. In summary, the model results only show consistent and expected results for the landline model. This leads to the conclusion that **H3 is accepted** for the channel **landline** and **H3 is rejected** for the channels**, mobile, e-mail, mobile app,** and **internet banking.**

H4: Inbound usage of offline communication channels is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Table 14 shows the odds of the independent variable *office visit* and *inbound call* from the MLR models for each channel. For the offline communication channels both variables were only significant in the landline model and just for one odds value. These values show that usage offline channels makes it more likely you prefer the landline channel. For example, a visit to an office decreases the odds that you score landline with a 1 compared to a 5 with 26.8%, controlled for other variables. The odds do also show that usage of offline channels makes it less likely that you prefer an online channel like e-mail, mobile app or internet banking. Based on the significance of the odds values **H4 is accepted** for the channels **landline, e-mail, mobile app** and **internet banking,** and **H4 is rejected** for the channel **mobile.**

Table 14: Hypothesis 4: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (sig. at 95% confidence interval;** sig. at 99% confidence interval)*

		Landline	**Mobile**	**E-mail**	**Mobile app**	**Internet banking**
Office visits	Response score 1	,742**	-	1,290*	-	-
	Response score 2	-	-	-	-	1,495**
	Response score 3	-	-	-	-	1,200*
	Response score 4	-	-	-	-	-
	Response score 5	0	0	0	0	0
Inbound calls	Response score 1	-	-	-	-	1,145*
	Response score 2	.748*	-	1,355**	-	-
	Response score 3	-	-	1,197**	1,195*	1,230**
	Response score 4	-	-	1,229**	-	1,272**
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✓	✓	✓

H5: Activity is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

No significant relation between the number of transactions in the last 12 months and channel preference for mobile app and internet banking was found as can be seen in Table 15. Furthermore, the odds in the landline and mobile model showed that each transaction decreases the odds that a respondent prefers one of these channels. For the online channels only on odds value for the e-mail channel was significant. It showed that each transactions decreases the odds that a respondent prefers e-mail, this is opposite to what was expected. Based on the significance of the odds values **H5 is accepted** for the channels **landline** and **mobile, H5 is rejected** for the channels **e-mail, mobile app,** and **internet banking.**

Table 15: Hypothesis 5: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (sig. at 95% confidence interval;** sig. at 99% confidence interval). In mobile app and iInternet banking relation was not significant.*

		Landline	Mobile	E-mail	Mobile app	Internet banking
Trans-actions in 12 months (per 10 trans-actions)	Response score 1	-	-	-	-	-
	Response score 2	1,013**	-	-	-	-
	Response score 3	-	-	-	-	-
	Response score 4	1,017**	1,012*	1,007**	-	-
	Response score 5	0	0	0	0	0
Conclusion		✓	✓	✗	✗	✗

H6: Loyalty is positively associated with the preference landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

shows the odds of the independent variable *duration of relation* from the MLR models for each channel. First observation is that the variable did not have a significant relation in the models for the channels mobile, e-mail and Mobile app. The effect of the duration of the relation in the landline model seems weak since the odds of scoring a 1 compared to a 5 decrease by 0,2% per month of the relation, taking into account that the average relationship length of respondents is 436 months learns that small odds values can have strong effects. Overall does the variable duration of relation show a positive relation with the preference for the landline channel. The effect of the duration of relationship with the preference for the online channel internet banking was negative. The odds values showed that for each month of the relationship, the odds of preferring internet banking decrease. Based on the significance of the odds values **H6 is accepted** for the channels **landline** and **internet banking, H6 is rejected** for the channels **mobile, e-mail,** and **mobile app.**

Table 16: Hypothesis 6: Odds of voting a response score compared to scoring a 5 (preferring a channel very much); (sig. at 95% confidence interval; ** sig. at 99% confidence interval)*

		Landline	Mobile	E-mail	Mobile app	Internet banking
Duration relation (per month)	Response score 1	,998*	-	-	-	-
	Response score 2	-	-	-	-	-
	Response score 3	-	-	-	-	1,003*
	Response score 4	,996**	-	-	-	1,002*
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✗	✗	✓

5.5. Discussion on model results

The tables with the odds values of the MLR models and the conclusions on the hypotheses tests in the previous paragraph provided interesting insights in what factors can explain channel preferences of banking customers for outbound contact. The results also showed some (unexpected) patterns. Five of them are discussed here.

First pattern is that the contact complexity hypothesis (H1) was rejected for all communication channels. Meaning that no relationship between contact complexity and channel preference was found in the dataset. Based on section 3.2.1, which describes that many authors found a relation between contact complexity and channel preferences, the outcome of the hypothesis tests was not expected. This increases the likelihood that not finding a relation between contact complexity and channel preference can be attributed to the operationalization of contact complexity, compared to the likelihood that there is no relation between contact complexity and channel preference. Contact complexity was operationalized by using financial products in vignettes. The financial products were categorized into three levels of complexity (low, medium, and high) with the help from experts. The usage of vignettes is an accepted technique in surveys (Alexander & Becker, 1978). However, the categorization of financial products into different levels of contact complexity might have limited the measurement of contact complexity. An indication of this is: when asked, respondents appeared to perceive the contact complexity, related to financial products in the vignettes, less complex than the experts. With the consequence that only a limited range of contact complexity is measured and finding a relation became harder.

Secondly, the hypotheses concerning the mobile channel were in many cases (5 out of 7) rejected due to a lack of significant relations between the independent variables and channel preference for mobile. For other channels this happened at maximum in 2 out of 7 cases. The probable reason for the lack of significant relations in the mobile channels is that most respondents (59%) scored a 1 (not preferring at all) for the mobile channel. The proportion of scores to the other response categories is therefore much lower. This also applies to the reference score 5, only 7% of the respondents scored a 5 (preferring very much) for the mobile channel. It would have been better to have a larger proportion of scores to the reference categories. Possible alternatives to achieve this is increasing the number of respondents or decreasing the levels of the scale for the dependent variable. Since the aim of this study was to understand channel preferences of customers, a scale in which at least a negative, neutral, and positive attitude can be distinguished would have been sufficient. In future research it should therefore be considered to decrease the scale of the dependent variable from a five point scale to a three point scale. Decreasing the scale from a five point scale to a three point scale reduces the amount of parameters to be estimated, increases the proportions of scores to the response categories, and can reduce noise in the dataset. With the consequence that the data can be used more efficiently for finding relations between independent variables and dependent variables.

Third point of discussion is about the difference in outcomes between the OLR and MLR models. Although the MLR models were selected as the models with the best performance, the hypothesis tests have also been performed for the OLR models (see appendix XII). These hypotheses tests have been performed to check whether the choice for a model leads to different conclusions. Less hypotheses were confirmed in the OLR models as can be seen in appendix XII. In most cases this was caused by a lack of significant parameters. In one case the OLR and MLR model provided contradicting results. In the OLR model the relation between activity and preference for mobile was positive. The relation between both variables in the MLR model was negative, as was expected. Since these contradicting results did occur only once and only in the mobile model, which has scale issues as discussed before, it was not seen as a threat. However, the lack of significant parameters in the OLR models did show that conclusions on hypotheses are dependent on the choice for either the OLR or MLR technique. This supports the selection of the MLR models (based on diagnostics) as better performing models compared to the OLR models in section 5.3.3.

Last point of discussion is the relation between the usage of online channel internet banking and the preference for the channel mobile app. Against expectations, logins to internet banking decreased the odds of preferring online channel mobile app. Consulting customer experts explained that using internet banking reduces the probability of preferring the mobile app. This indicates that the independent variable login to internet banking is not only measuring channel preferences for online and offline channels, but simultaneously represents a negative attitude towards mobile app usage. Therefore, conclusions based on the usage of Internet banking should be interpreted with great care.

6. Validation of MLR models

In this section the validation of the MLR models is discussed. Ideally the validation of a MLR model is performed on three levels: diagnostic, internal, and external (Steyerberg & Harrell, 2002). The diagnostic validation concerns the performance of a MLR model on a training sample and gives an indication for the conclusion validity of models (Trochim, 2006). The internal validation deals with the validity of a MLR model on a hold-out validation sample from the same underlying population as the training sample. Lastly, external validation is about the validity of a MLR model for the general population (Bourennane et al., 2014). The training and validation hold-out sample are drawn from this general population. The diagnostic validation has been discussed in section 5.3.2 and section 5.3.3. These sections showed that the MLR models were all statistically valid models. Table 8 (page 30) and Table 9 (page 31) provided an overview of the diagnostic validation of all MLR models. Both tables showed that all MLR models were significant improvements compared to intercept-only models; fitted the dataset well, did not violate the assumptions of multinomial logistic regression, and explained a considerable part of the variance in the dependent variables. Furthermore, the MLR models were able to find relations between independent variables and the dependent variables, based on a Wald test with 95% confidence interval. This information provided confidence in the conclusion validity of the hypothesis tests in section 5.4. However, a considerable amount of coefficients was not found to be significant is not known what the signal to noise ratio is in the data. This might indicate there is still a substantive amount of noise in the data. This increases the possibility that (weak) relations between independent variables and the dependent variables were not detected, potentially threatening conclusion validity. This should be kept in mind while interpreting the results of the hypotheses tests.

To assess whether the current state of the MLR models allowed them to validly predict responses, the hold-out validation sample was used (Wang, 2005). The coefficients from the constructed MLR models were used to predict the response of respondents in the hold-out validation sample. The hold-out validation sample is a random stratified sample from the sample of respondents (see chapter 4.7 for more detailed information). Since the training sample and the hold-out validation sample shared the same underlying population, the tests with the hold-out validation sample assessed the internal validity of the MLR models (Steyerberg & Harrell, 2002). The internal validation sets an upper limit to performance which might be expected in the external validation.

Due to time and budget limitations, this study only evaluated the internal validity of the MLR models. The assessment of the external validity required that coefficients of the constructed MLR models were used to predict the response / channel preference of customers who did not participate in the survey (Bourennane et al., 2014; Steyerberg & Harrell, 2002). To assess the validity of the predictions, the actual responses/channel preferences of these customers should be collected, time and budget limitations did not allow for this.

6.1. Internal validity of predictions: Approach

In this section the hold-out validation sample was used to test the internal validity of the predictions made by the constructed MLR models from section 5.4. The coefficients from the constructed models, based on the training sample, were used to calculate the logits for the response categories 1,2,3 and 4 (*k -1)* for each respondent in the hold-out validation sample. These logits were used to calculate the probability that a respondent from the hold-out validation sample scored a channel by response category 1,2,3,4 or 5 (*k).* The equations used to calculate the logits and probabilities can be found in section 5.2. The response category with the highest probability was selected as the predicted response.

The MLR models were regarded as internally valid when their overall accuracy rate of predicted responses was significantly better than the proportional chance criterion (PCC). The PCC represents a random classification of samples to groups in proportion to group sizes (McGarigal et al., 2000). Since it was tested whether the predictions made by the models (based on the training sample) were valid, group proportions in the training sample were used to calculate the PCC (Cool & Henderson, 1997). In this way it was tested whether the constructed MLR models can provide response predictions with significantly higher accuracy, compared to the PCC, for respondents who were not included in the development of the MLR models. The PCC can then be computed by:

$$Proportional\ by\ chance\ criterion = \boldsymbol{p_1}^2 + \boldsymbol{p_2}^2 + \boldsymbol{p_3}^2 + \boldsymbol{p_4}^2 + \boldsymbol{p_5}^2$$

Where $\boldsymbol{p_1}$ is the proportion of samples in the first group (response category 1) and $\boldsymbol{p_2}$ is the proportion of samples in the second group (response category 2), etc.. The difference between the PCC and the accuracy rate for the prediction in the hold-out validation sample were standardised into a z-score and tested for significance through a right sided z-table (Marcoulides & Hershberger, 1997). Negative z values indicated that the model performed worse than the PCC and is not capable of providing internally valid predictions. The internal validity test for predictions made by the multinomial logistic regression model for the preference of internet banking is presented in the next section. The validation tests for all multinomial logistic regression models can be found in appendix XVI.

6.2. Internal validity of predictions: Example

In the training sample 22.9% of the respondents scored a 1, 6.5% scored a 2, 18.5% scored a 3, 21.7% scored a 4 and 30.4% scored a 5 for the channel internet banking. The PCC is therefore $0.229^2 + 0.065^2 + 0.185^2 + 0.217^2 + 0.304^2 = 0.23$ (23%). As can be seen in Table 17 the overall accuracy rate of the predictions for preference for internet banking was 31%. The accompanying z-value with this score is:

$$z = \frac{(Accuracy * \#cases) - (PCC * \#cases)}{\sqrt{(\frac{(PCC * \#cases) * \left(\#cases - (PCC * \#cases)\right)}{\#cases}}}$$

$$z = \frac{(0.,31 * 108) - (0.23 * 108)}{\sqrt{(\frac{(0.23 * 108) * \left(108 - (0.23 * 108)\right)}{108}}}$$

$$z = 1.85$$

The accompanying p-value with z-value of 1.85 from a right sided z-table at a 95% confidence interval is 0.0322. This is smaller than 0.05, therefore predictions made by the multinomial logistic regression model for the preference of internet banking is regarded as internally **valid**.

Table 17: Classification table internet banking model with hold-out sample. 1 = not preferring at all, 5 = prefer very much

		predicted					
		1	2	3	4	5	Recall
observed	1	6	0	2	0	8	38%
	2	2	0	0	0	3	0%
	3	11	0	11	3	19	25%
	4	2	0	4	5	13	21%
	5	4	0	4	0	11	58%
	Precision	24%	0%	52%	63%	20%	*31%* Total accuracy

6.3. Overview of internal validation results: Multinomial logistic regression models

Table 18 presents the validation results of the predictions made by multinomial logistic regression models. The results show that the accuracy of predictions for the hold-out sample was worse than the proportion by chance criterion for the landline, mobile, and e-mail model. This means that these models perform worse than randomly classifying cases to groups in proportion to group sizes. The predictions made by the multinomial logistic regression models for landline, mobile, and e-mail were therefore regarded as internally **invalid.** Only the discussed MLR model for internet banking in section 6.2 and the model for the preference of the mobile app had higher accuracy rates than the PCC value. The z-value for both models showed that the difference between accuracy and PCC value was significant. The accuracy of predictions in the mobile app model was improved by 27% compared to the PCC (33/26). The accuracy of predictions in the internet banking model was improved by 35% compared to the PCC (31/23). Therefore, only predictions made by the MLR models for mobile app and internet banking were regarded as internally **valid**.

Table 18: Summary of validation tests for multinomial logistic regression models

Channel	**Proportional by chance criterion (PCC)**	**Accuracy for hold-out sample**	**Z-value (if negative model invalid)**	**P-value (α=0.05)** ***= significant**	**Valid?**
Landline	27%	19%	Negative	-	No
Mobile	39%	35%	Negative	-	No
E-mail	36%	23%	Negative	-	No
Mobile app	26%	33%	1.73	0.0418*	Yes
Internet banking	23%	31%	1.85	0.0322*	Yes

6.4. Summary and discussion of validation MLR models

The previous two sections of this chapter presented the results and conclusions about the validity of the individual MLR models. Diagnostics of the MLR models led to the conclusion that all MLR models were statistically valid, providing confidence in the conclusion validity of the hypotheses tests in section 5.4. However, a considerable amount of coefficients was not found to be significant. Reasons for non-significance could be non-existence of relationships between the independent variables and dependent variables, too many parameters to be estimated compared to the number of observations, or a low signal to noise ratio in the dataset. Noise in the dataset and too much parameters increase the possibility that (weak) relations between independent variables and the dependent variables were not detected, potentially threatening conclusion validity. This should be kept in mind while interpreting the results of the hypotheses tests.

Internal validity tests showed that only the MLR models for the channels internet banking and mobile app were able to deliver valid predictions for channel preferences of respondents. External validity of the models was not evaluated in this thesis. Evaluating the external validity of the models would have required to collect channel preferences from customers, who did represent the whole population of high value customers of bank *X*. The collection of channel preferences from customers to develop the MLR models resulted in a non-representative sample due to only inviting respondents by e-mail and unequal probabilities of responding to the invitation to participate in the survey. To avoid collecting channel preferences a group of non-representative customers for the evaluation of external validity, customers should be approach through multiple channels and unequal response probabilities should be avoided and/or corrected for. Due to time and budget limitations this has not been performed. It is recommended to perform this in future research.

Noise in the dataset and too much parameters increase the possibility that (weak) relations between independent variables and the dependent variables were not detected, potentially threatening conclusion validity. Not detecting relations in the dataset also affect the ability of the MLR models to correctly predict responses of channel preferences. Therefore, reducing the number of parameters and noise in the data seems an effective measure to improve the overall validity of the MLR models. The noise in the data could be attributed to multiple sources like measurement unreliability, model type, or the unpredictable nature of human attitudes. Reducing the scale of the dependent variables from a five point scale to a three point scale has been suggested in section 5.5 as a solution for using the data more efficiently for detecting relationships. Since it will reduce the number of parameters to be estimated and potentially reduces noise in the data, it is recommended to replicate this research with dependent variables which have a scale with less levels.

6.5. Conclusions on data analysis sections

Chapters 5 and 6 focussed on the regression analysis step in this thesis. This step served to answer the following research question:

> *How well can (outbound) communication channel preferences of high value customers be estimated by combining customer data of banking customers with the proposed conceptual model explaining channel preferences?*

The answer to this question was expected to contain three deliverables: models for estimating communication channel preferences, an overview of what factors explain outbound communication channel preferences for the channels: landline, mobile, e-mail, mobile app, and internet banking, and lastly an assessment of the predictive power of estimated models

For the first deliverable multinomial logistic regression models were constructed to estimate channel preference for outbound contact. A separate multinomial logistic regression model was constructed for the communication channels internet banking, mobile app, e-mail, mobile phone, and landline. Analysis of the diagnostics of the MLR models showed that the MLR models were significant models that fitted the dataset, and did respect the assumptions of multinomial logistic regression.

The hypotheses tests based on the MLR models provided the input for the second deliverable. All hypotheses were analysed per communication channel. The objective was to assess whether the identified factors in the conceptual model had the same effect as was expected in the hypotheses. The hypotheses consisted of an expected effect of factors on the preference for offline channels (landline and mobile) and the preference for online channels (e-mail, mobile app, and internet banking). The results of the MLR models led to accepting about 50% of the hypotheses about the relation between factors from the conceptual model and channel preference for outbound contact. Table 19 provides an overview of the accepted and rejected hypotheses per communication channel.

Table 19:Overview of results from hypotheses tests (red indicates a rejection of the hypothesis, green indicates acceptance of the hypothesis, conclusions were drawn at a 95% confidence interval).

	Landline	**Mobile**	**E-mail**	**Mobile app**	**Internet banking**
H1 (complexity)					
H2 (VoT)					
H3 (use of online channels)					
H4 (use of offline channels)					
H5 (active)					
H6 (loyal)					
H7 (age)					

The overall view of Table 19 shows that:

- No association between perceived contact complexity and channel preference was detected for any channel (hypothesis 1).
- Almost all hypotheses were rejected in the MLR model for the mobile channel. This was mainly caused by large differences in the proportions of scores (1,2,3,4 or 5), limiting the ability of the MLR model to find relations in the data.
- Value of time is not associated with the preference for offline channels. It is positively associated with the preference for online channels.
- Usage of online channels is negatively associated with the preference for landline, it not associated with the preference for other channels.
- Usage of offline channels is positively associated with the preference for landline and negatively associated with the preference for online channels.
- Activity is negatively associated with the preference for offline channels. It is not associated with the preference for online channels.

- Loyalty is positively associated with the preference of landline, negatively associated with the preference for internet banking and not associated with the preference for other channels.
- Age is positively associated with the preference for landline and negatively associated with the preference for online channels.

Besides the independent variables that belonged to hypotheses, moderating variables were included in the MLR models. Table 20 shows how they are associated with the preference for each channel. The table shows that when the level of education increases, the preference for landline decreases and the preference for online channels increases. The results do furthermore show that living in an urban area is negatively associated with the preference for landline and positively associated with the preference for e-mail. Lastly, results indicate that woman prefer landline more than man and have lower preferences for mobile, e-mail, and mobile app.

Table 20: Association of moderating variables with channel preference. A '+' indicates a positive association and a '-' indicates a negative association (both at a 95% confidence interval). A 'ns' indicates non-significant relations.

Moderating variables	Landline	Mobile	E-mail	Mobile app	Internet banking
Being low educated compared to high educated	+	ns	-	-	-
Living in urban area compared to non-urban	-	ns	+	ns	ns
Influence of being male compared to female	-	+	+	+	ns

The validation of the MLR models was performed on model diagnostics and the internal validity of predictions made by the MLR models. Based on the diagnostics of the MLR models, all MLR models were evaluated as valid. This provided confidence in the conclusion validity of the hypotheses tests. However, a potential threat to conclusion validity is the considerable amount of coefficients that were not significant. Reasons for non-significance could be non-existence of relationships between the independent variables and dependent variables, too many parameters to be estimated compared to the number of observations, or a low signal to noise ratio in the dataset.

Internal validity tests showed that only the MLR models for the channels internet banking and mobile app were able to deliver valid predictions for channel preferences of respondents. The accuracy of predictions made by the mobile app model improved by 27% compared to the PCC (33/26). The accuracy of predictions made by the internet banking model improved by 35% compared to the PCC (31/23). External validity of the models was not evaluated in this thesis due to time and budget limitations.

7. Relevance of estimated models for business

Having evaluated the different models and results, the question arises how to turn insights into value for business. To assess the usefulness of the generated data by the models it is helpful to look back at the purpose of the insights. Figure 1 at page 2 shows that the purpose of understanding the factors explaining channel preferences was to improve the selection of a communication channel to reach a customer. The validation of the estimated models showed that only the models for predicting channel preference for the mobile app and internet banking provided significantly better predictions, compared to the proportional chance criterion. Both models resulted in respectively 27% and 35% more accurate predictions compared to the proportion by chance criterion. While the improvements in accuracy proved to be significant, the relevance of the models is still questionable since the final accuracy rates of the models are still rather low (33% and 31%). Malik (2013) stated in his framework for data governance that the main goal of creating and using customer data is to reduce risk and more importantly extract value from data. Multiple requirements are proposed for evaluating the generated data from the perspective of Malik (2013). The proposed requirements are: *proportionality, accuracy, reliability, credibility,* and *timeliness.*

Table 21: Requirements for good data governance

Channel	Definition
Proportionality	Degree to which relying on the models is justifiable compared to alternative methods
Accuracy	Data precisely reflects the object is describes
Reliability	Data is consistent across multiple samples
Credibility	The degree to which decision makers trust both the accuracy and reliability of the data
Timeliness	Extent to which data represents the real world at a given time point in time

The proportionality requirement is connecting all other requirements and serves to think about the consequences of totally relying on predictions of the models. What does it for example mean for a customer if the Mobile app model predicts he/she prefers being contacted by the mobile app and bank *X* decides to only contact that customer through the mobile app. For this customer it will have the consequence that he/she is only contacted through this channel and is excluded from other channels. Totally relying on model predictions would effectively exclude many customers from being contacted trough channels that where not predicted as preferred. Therefore, decisions rules are required to decide when it is proportional to rely on a prediction from a model. These decision rules should at least include accuracy, reliability and credibility of data as requirements. The National Association of State Chief Information Officers (NASCIO) of the United States included these requirements in their data governance strategies (NASCIO, 2008). The definitions of their requirements can be found in Table 21. Only the timeliness requirement does not originate from NASCIO. Timeliness of data concerns the 'extent to which data represents the real world at a given time point in time' (Otto & Ebner, 2010). It is for example likely that channel preferences change over time. This would make older data less valuable and suitable for selecting the preferred communication channel of a customer.

Applying these requirements to the estimated models for the preference for internet banking and the mobile app, lead to the conclusion that it is currently hard to evaluate the usefulness of the generated data since definitions of success for the criteria are lacking. For the accuracy requirement it should for example be decided what is more important, maximizing the true positive rate of predictions or minimizing the false negative rate of predictions. Likewise, are criteria for assessing the proportionality, reliability, credibility and timeliness required.

However, based on the availability of data generated by the models it is concluded that they are not yet useful enough to be employed in practice. Main reason for this conclusion is that more data from the models is required to assess how useful the models are for business. Both reliability and timeliness for example require that the models are used to make predictions for multiple samples at multiple time moments. Furthermore, to assess the credibility of the models it is required to actually implement or test the models in reality. Due to time and budget limitations this was not possible in this study. In summary, the models are not regarded as useful at this moment due to a lack of criteria to assess the usefulness and a lack of available data to assess the usefulness of the models.

7.1. Conclusion upon relevance of estimated models

With the knowledge from this chapter the last research question can be answered:

> *What requirements for using predicted customer preferences for outbound communication should be incorporated in a framework for applying personalization in the communication strategy of a bank?*

Key point of this question is to what extent data generated by the models can be trusted to act upon. To assess the trustworthiness of the generated data five requirements are proposed: *proportionality, accuracy, reliability, credibility,* and *timeliness.*

Applying these requirements to the predictions made by the models for internet banking and the mobile app, led to the conclusion that it is currently hard to evaluate the usefulness of the data generated by these models. Main reason for this conclusion is that definitions of success for the criteria are lacking. But even without these criteria, it would have been concluded that the models are not yet useful enough to be employed in practice due to a lack of generated data from the models. For example, data from different time stamps is required to assess the timeliness and reliability of data.

8. Conclusions and Discussion

This final chapter discusses the main findings, theoretical implications, societal implications and limitations of the study. Section 8.1 focusses on the main findings of the study and is structured by the initial research questions from section 0. Section 8.2 covers the theoretical implications of the performed research, followed by the societal implication of this study in section 8.3. The final section presents the recommendation limitations of this research.

8.1. Main findings

This study aimed to provide an answer to the general question:

What factors can explain outbound communication channel preferences of banking customers and how can these factors contribute to predicting channel preferences of these banking customers?

Four research questions structured the study to find an answer to the general research question. The research questions subsequently focussed on hypotheses development, analysis design, regression analysis, and business relevance. A brief conclusion on each research question is provided and in the end of this section the main research question is answered.

RQ1 *What is the current state of knowledge in the overlapping fields of channel choice, customer behaviour and multi-channel management literature and how can it contribute to a better understanding of outbound communication channel preferences of banking customers?*

Effective communication between service companies and customers is crucial since it can be considered as a requirement to successful customer relationships management (Birgelen et al., 2012). From this perspective multi-channel management should be regarded as a concept which provides opportunities for gaining better understanding of customers and strengthening relations with them (Payne & Frow, 2004). Rosenbloom (2007) reviewed large amounts of multi-channel management research and identified multiple issues concerning multi-channel management: multi-channel management does not increase the amount of customers who interact with companies, high costs of multi-channel systems, multi-channel management systems causes customers to be unsatisfied. An important reason for these issues is that companies do not know the drivers which can explain the communication channel preferences of their customers. This has the effect that companies use communication channels which are not preferred by customers (Wilson et al., 2008). Therefore, service industries are looking to the world of online and offline shopping in which extensive research have been performed on channel choice.

Table 22: Hypothesized associations between independent variables and preference for online/offline channels.

	Preference for offline channel (landline, mobile)	**Preference for online channel** (e-mail, mobile app, internet banking)
Positive association	• Perceived contact complexity • Use of offline channels • Loyalty • Age	• Value of time • Use of online channels • Activity
Negative association	• Value of time • Use of online channels • Activity	• Perceived contact complexity • Use of offline channels • Loyalty • Age

However, within the field of channel choice, focus has been on the characteristics of channels and how these channel characteristics explain channel preferences of customers (Birgelen et al., 2012; Konus et al., 2008; Reis et al., 2015). To gain insight in how customer characteristics can explain channel preferences, a conceptual model is proposed. This model visualised how channel preference can be explained by customer related characteristics and is based on channel choice literature, customer behaviour literature, and interviews with outbound contact experts from bank *X*. The combined insights from literature and interviews with experts led to hypothesized relations between channel preference and the independent variables *perceived complexity of contact, value of time, technical skills, activity, loyalty,* and *age*. To enhance interpretability, the channels e-mail, mobile app and internet banking were grouped into online channels. The landline and mobile channels represent offline channels. Table 22 depicts the hypothesized relations of the conceptual model.

An analysis design for testing the hypothesized associations between independent variables and channel preferences provided the answer to the second research question of this thesis:

RQ2 *How does an analysis design for testing the hypothesized conceptual model for outbound communication channel preferences of banking customers look like?*

A five step analysis design for testing the hypothesized conceptual model is proposed. First the identified factors of the conceptual model need to be *operationalized* (1). A complication in this step is that the operationalized variables must be measurable in databases. This is required to enable that channel preferences of customers can be predicted in the future, without having to collect new data from customers. Next step is to m*easure* channel preferences of banking customers (2). These preferences are used to develop models and validate these models in a later stage. Third step is to *retrieve customer data from databases* (3). These are the actual values of operationalized factors from step 1. The fourth step is to perform the *regression analysis* (4). Final step is the validation of the models to assess the generalizability of the models for the high value customer population of bank *X*.

RQ3 *How well can (outbound) communication channel preferences high value customers be estimated by combining customer data of banking customers with the proposed conceptual model explaining channel preferences?*

The answer to this question was expected to contain three deliverables: models for estimating communication channel preferences, an overview of what factors explain outbound communication channel preferences for the channels: landline, mobile, e-mail, mobile app, and internet banking, and lastly an assessment of the predictive power and validity of predictions made by the estimated models. For the first deliverable multinomial logistic regression models were constructed for the channels landline, mobile, e-mail, mobile app, and internet banking. Analysis of the diagnostics of the MLR models showed that all MLR models were significant models that fitted the dataset, and did respect the assumptions of multinomial logistic regression. The hypotheses tests, based on the MLR models, provided the input for the second deliverable. All hypotheses were analysed per communication channel. The results of the MLR models led to accepting about 50% of the hypotheses. The results showed two unexpected patterns: (1) no association between perceived contact complexity and channel preference was detected for any channel (hypothesis 1); (2) almost all hypotheses were rejected in the MLR model for the mobile channel. This was mainly caused by large differences in the proportions of scores (1,2,3,4 or 5), limiting the ability of the MLR model to find relations in the data. These two patterns will be discussed in the limitations (section 8.4) of this thesis.

Translating the results from the hypotheses test to associations between independent variables and preferences for offline and online channels resulted in Table 23. This table shows the significant associations between independent variables and channel preferences found in this study. To enhance interpretability, the channels e-mail, mobile app and internet banking were grouped into online channels. The landline channel represents offline channels. The mobile channel was excluded from this table since this ability of this model to detect relations was strongly reduced due to a large proportion negative preference scores (see section 5.5). For example, when age increases, the preference for an offline channel (landline) increases. At the same time does the preference for online channels decrease when age increases. It can be seen in Table 23 that variables that were positively associated with the preference for offline channels, were negatively associated with online channels, which was in line with the hypotheses. For the variables which are negatively associated with the preferences for offline channels, no opposite effect was detected at the preference for online channels.

Table 23: Associations (at a 95% confidence level) between independent variables and preference for online and offline channels. The channel mobile was excluded from this table.

	Preference for offline channel (landline)	**Preference for online channel** (e-mail, mobile app, internet banking)
Positive association	• Use of offline channels • Loyalty • Age	• Value of time
Negative association	• Use of online channels • Activity	• Use of offline channels • Loyalty* • Age

*Only applicable for the channel internet banking

The associations between moderating variables and channel preference were not included in the table. Results showed that when the level of education increased, the preference for landline decreased and the preference for online channels increased. The results did furthermore show that living in an urban area was negatively associated with the preference for landline and positively associated with the preference for e-mail. Lastly, results indicated that woman preferred landline more than man and had lower preferences for mobile, e-mail, and Mobile app.

The validation of the MLR models was performed on model diagnostics and the internal validity of predictions made by the MLR models. Based on the diagnostics of the MLR models, all MLR models were evaluated as valid. This provided confidence in the conclusion validity of the hypotheses tests. However, a potential threat to conclusion validity was the considerable amount of coefficients that were not significant. Reasons for non-significance could be non-existence of relationships between the independent variables and dependent variables, too many parameters to be estimated compared to the number of observations, or a low signal to noise ratio in the dataset. This is discussed in the limitations section of this chapter.

Internal validity tests showed that only the MLR models for the channels internet banking and mobile app were able to deliver valid predictions for channel preferences of respondents. The accuracy of predictions made by the mobile app model improved by 27% compared to the PCC (33/26). The accuracy of predictions made by the internet banking model improved by 35% compared to the PCC (31/23). External validity of the models was not evaluated in this thesis due to time and budget limitations.

The last research question was answered to assess whether the models had business relevance:

RQ4 *What requirements for using predicted customer preferences for outbound communication should be incorporated in a framework for applying personalization in the communication strategy of a bank?*

Key point of this question is to what extent data generated by models can be trusted to act upon. To assess the trustworthiness of the generated data five requirements are proposed: *proportionality, accuracy, reliability, credibility,* and *timeliness.* Applying these requirements to the predictions made by the models for internet banking and the mobile app, led to the conclusion that it is currently hard to evaluate the usefulness of the data generated by these models. Main reason for this conclusion is that definitions of success for the criteria are lacking. But even without these criteria, it would have been concluded that the models are not yet useful enough to be employed in practice due to a lack of generated data from the models. For example, data from different time stamps is required to assess the timeliness and reliability of data.

Summarizing, it is concluded that variables depicted in Table 23 can explain channel preferences of banking customers. Validation of channel preference predictions made by the MLR models showed that only the models for mobile app and internet banking validly predicted channel preferences of respondents who are comparable to customers who responded to the survey. Validity of the models for all high value customers of bank *X* has not been assessed due to time and budget limitations.

8.2. Theoretical implications

Current theoretical knowledge about channel preferences for outbound contact is very limited. Theoretical insights in channel preferences, for outbound contact, of banking customers is even non-existent. To estimate outbound channel preferences of banking customers, professionals and researchers consult knowledge about channel preferences for inbound interaction in the fields of channel choice and customer behaviour. This study provided various factors that can explain channel preferences for outbound contact of banking customers. These findings can provide guidance and focus in future research to outbound communication channel preferences. The conceptual model of this study can be used as a starting point for future research. Suggestion for improvement of the conceptual model is to include interaction variables. Interaction variables were not included in this study since this would have made the complex interpretation of MLR models even more complex.

A second theoretical implication of this study is the introduction of a new perspective on multi-channel and channel choice literature. Current multi-channel and channel choice literature mainly focus on how channel characteristics and situational factors can explain channel preference. This perspective contributes to understanding how customer select communication channels. However, it does not allow for predicting preferences of individual customers, since most predictors are attitude based variables which are mostly unknown. This study focussed on customer characteristics instead of channel characteristics, providing opportunities for predicting individual channel preferences.

Furthermore, this study provided a first step to institutionalizing decision rules on how to act upon model generated predictions for channel preference. Since the fields of multi-channel management and channel choice do not yet include work on channel preference predictions, no framework for using channel preference predictions exists. The field of (big) data governance provides extensive information for developing such a framework. Therefore, future research into the application of (big) data governance in the field of multi-channel management and channel choice is recommended.

8.3. Societal implications

The societal contributions encompass the contributions for bank *X* as well as contributions to organisations in general and banking customers. The main societal contribution of this research is that it provides bank *X*, and service companies in general, insights for the personalization of outbound interaction strategies with customers. The insights in variables that explain channel preferences of customers can be used as a starting point for predicting channel preferences. This provides bank *X* with the opportunity to personalize the selection of a communication channel to reach customers. The ability to personalize the outbound communication with customers also enables bank *X* to implement its interaction strategy discussed in section 1.1. Based on research from Payne and Frow (2004), Wilson et al. (2008) and Neslin et al. (2006) it is expected that reaching customers through their preferred communication channel will require less effort compared to reaching them through non-preferred communication channels. Furthermore, can bank *X* allocate resources more efficiently to communication channels, since effort to reach customers is expected to decrease. To assess the expected impact of using channel preference predictions on the required effort to reach customers, it is recommended to start pilots in which predictions for outbound communication channel preferences are used to select a communication channel to reach a customer. These same pilots can provide information about how customer satisfaction about outbound contact is affected by reaching them through preferred communication channels. Higher customer satisfaction can be expected when customers are treated based on their preferences.

From the above it can be concluded that this study provides opportunities to turn already available customer data into value. To safeguard that customer data will be turned into value, for both companies and customers, it is recommended to institutionalize decision rules. These decision rules based on *proportionality, accuracy, reliability, credibility,* and *timeliness* of channel preference predictions ensure that the predictions can be trusted to act upon.

Furthermore, did this study show that for similar research or pilots (SQL) programming skills are required to retrieve customer data from databases. Also statistical knowledge combined with skills to use statistical software is required to perform similar research. Finally, a substantial budget for collecting channel preferences should be allocated.

8.4. Limitations & future research

The main findings of this study should be interpreted in the context of the limitations of this study. The limitations are discussed for three topics: generalizability, methodology, and operationalization of conceptual model. Future research is proposed to deal with the limitations of this study.

Generalizability

Design choices of this study caused two main threats to the generalizability of the findings from this study. The first threat to validity is the representativeness of the invited population to participate in the survey. Due to time, budget and policy constrains of bank *X* it was decided to only invite customers by e-mail. Since e-mail was one of the communication channels under review in this study, it is likely that the preference for the e-mail channel is overestimated in the constructed models. Besides it caused that the probability of being selected for participation in the study was not equal within the population, since customers from whom no e-mail address was available had no chance of participating in the survey. The response patterns in the survey also showed that the e-mail channel was a preferred channel for most respondents (about 70%). The degree of overestimation of preferences for e-mail was not investigated. Consequence of this problem is that the results of this study can only be generalized to the population of high value customers of whom the e-mail addresses is known. *To avoid this problem in future research is it recommended to invite respondents through multiple channels, preferably by the same channels that are included in analysis.*

A second threat to generalizability is the unequal probability of responding to the survey invitation. The non-response model from chapter 4.6 showed that older men who actively use the online banking account have higher probabilities of responding to the survey than other invitees. This indicates that the results might be more applicable to older men who are actively using internet banking than to the whole population of high value customers. Several action could be taken to deal with the unequal probabilities for responding to the survey. The ideal action upon a non-response bias is to avoid non-response. For avoiding non-response bias, insights in the expected response probabilities are required. These insights can be used to correct the amount of invitations to a survey for the expected response rates of subgroups within the survey. Since no information about expected response was available at the time of inviting respondents, no corrections in the amount of invitees for different subgroups were made. When non-response bias was not avoided it is possible to correct for the non-response bias. The Heckman correction model can be used for assessing and correcting the non-response bias (Sales et al., 2004). For two reasons it was decided not to apply the Heckman correction model. First reason is that it is not possible to evaluate the effect of the Heckman correction model, since the channel preferences of customers that did not respond to the survey are unknown. Therefore, it is not possible to assess if the effect of the Heckman correction would be valid. The second reason for not applying the Heckman correction model is related to the first reason. It would require substantial amounts of time and funds to perform the Heckman correction and collect channel preferences of customers who did not respond to the survey. This time and funds were not available. Since no corrections for non-response bias was performed, results from this study should be interpreted with the caution that the data included an overrepresentation of older men which frequently use internet banking. *For future research it recommended to avoid non-response bias by correcting the invited population to expected response rates. Furthermore, it is recommended to use the Heckman correction model to assess if non-response bias and correct for it when necessary. Lastly, it is recommended to collect channel preferences through other means than a survey that is used for model development. This data can be used for the validation of the Heckman correction.*

Methodological

Regarding methodological limitations of this study three limitations will be discussed. First limitation is caused by the choice to estimate a separate model for each communication channel. A consequence of this choice is that for each communication channel the degree of preference is predicted (1,2,3,4, or 5). For usability of the MLR models in business it might have been better to estimate one model which predicts the preferred communication channel out of a set of communication channels. Consequence of estimating such a model is that channel preference should be measured in a different manner. Since only one dependent variable (channel preference) is allowed in MLR, customers should select their preferred channels instead of scoring their preference for each channel on a five point scale. This results in a nominal dependent variable with 5 levels (landline, mobile, e-mail, mobile app, and internet banking). With this dependent variable one MLR model can be estimated. This model provides the odds of preferring a channel compared to a reference channel. A consequence of asking respondent to select one preferred channel instead of scoring each channel, is that the amount of observations strongly decreases. So, to have enough observations more customers should participate in the survey. Other model types that are commonly used in customer behaviour or channel choice literature are segmentation models and structural equation modelling. While both have advantages compared to MLR models, both models require substantial larger sample sizes than MLR. For this reason, both models are not seen as usable in this research for the near future.

The second limitation is related to the many non-significant odds values that existed in the models. Reasons for non-significance could be non-existence of relationships between the independent variables and dependent variables, too many parameters to be estimated compared to the number of observations, or a low signal to noise ratio in the dataset. Noise in the dataset and too much parameters increase the possibility that (weak) relations between independent variables and the dependent variables were not detected, potentially threatening conclusion validity and the ability of the models to correctly predict channel preferences. Channel preferences were measured at a five point scale. A scale with less levels, a three point scale (negative, neutral, and positive), might have been sufficient since the aim of this study was to understand channel preferences of customers. A three point scale would have reduced that parameters to be estimated in the MLR models and could have potentially reduced noise in the data. This would have enabled the models to use data more efficiently for finding relations between independent variables and dependent variables. To test whether reducing the scale of the dependent variables would have improved the models and their ability to predict channel preference, the MLR model for the preference for Mobile app was re-estimated. The dependent variable was recoded: 1 and 2 → 1 (negative), 3 →2 (neutral), 4 and 5 → 3 (positive). The Nagelkerke pseudo R-squared value decreased from 39%, in the model with a five point dependent variable, to 33% in the three point dependent variable. This was expected since the number of parameters decreased. The model with the three point dependent variable was significant (Chi-square = 301 with df=42). Furthermore, did the new model detect a relationship between the preference for Mobile app and loyalty (duration of relation) and education, which were not detected in the model based on a five point dependent variable. Table 24 shows the classification table of the channel predictions, made by the new model, for respondents in the hold-out validation sample. The predictions made by this model were a significant (z-value = 2.43; p-value = 0.0075) improvement compared to the proportional chance criterion (39%, see appendix XVII). Additionally, the table shows that the overall accuracy (49%) of predictions was a substantial improvement compared to the accuracy (33%, see Table 33) of prediction based on the five point dependent variable. Just as in the model based on a five point dependent variable, the new had poor ability to predict a neutral preference for Mobile app.

Table 24: Classification table mobile app preference with 3 level dependent variable

		predicted				
		1	2	3	Recall	
observed	1	34	0	7	83%	
	2	23	0	12	0%	
	3	12	1	19	59%	
	Precision	49%	0%	50%	*49%*	Total accuracy

This might indicate that a dichotomous dependent variable (positive, negative) might be even more appropriate. This model was not estimated due to time constrains. *For future research it is recommended to use a dependent variable with a maximum of three levels. Using a dependent variable with more levels proved to limit the ability to find relations in the data and limited the predictive power of the models. Besides, collecting more data will increase the likelihood that relations in the data will be detected.*

Third potential limitation concerns the validation of channel preference predictions. To minimize the loss of respondents for the training sample and maximize the number of cases in the hold-out validation sample, it was decided to draw the hold-out validation sample from respondents who scored communication channels in all situations (see section 4.7.2). This sample consisted only of 59 respondents and 18 (30%) of these respondents were included in the hold-out validation sample through random stratified sampling. These 18 respondents represented 11% of all cases and about 5% of all respondents. The rather small hold-out validation sample potentially limits the robustness of the validation results. *Therefore, it is recommended for future research to increase the sample size of respondents to allow for a larger hold-out validation sample and increase robustness of the validation.*

Operationalization of the Conceptual model

The operationalization of the factors in the proposed conceptual model of section 3.2 had several limitations on the study. First limitation was that all variables which represent factors (like value of time) from the conceptual model, had to be available in the database of bank *X*. These variables had to available in the database of bank *X* since the models will eventually be used to predict channel preferences of customers.

The operationalization of contact complexity is a second limitation. Results of the MLR models showed that the contact complexity hypothesis (H1) was rejected for all communication channels. Meaning that no relationship between contact complexity and channel preference was found in the dataset. This was unexpected since many authors found a relation between contact complexity and channel preferences. This increases the likelihood that not finding a relation between contact complexity and channel preference can be attributed to the operationalization of contact complexity, compared to the likelihood that there is no relation between contact complexity and channel preference. Contact complexity was operationalized by using financial products in vignettes. The financial products were categorized into three levels of complexity (low, medium, and high) with the help from experts. The usage of vignettes is an accepted technique in surveys (Alexander & Becker, 1978). However, the categorization of financial products into different levels of contact complexity might have limited the measurement of contact complexity. An indication of this is: when asked, respondents appeared to perceive the contact complexity, related to financial products in the vignettes, less complex than the experts. With the consequence that only a limited range of contact complexity is measured and finding a relation became harder. *To increase confidence in the operationalization of contact complexity, and attitude based factors in general, it is recommended to validate the operationalization through the use of surveys or interviews with customers. In this way results based on the operationalization can be used with more confidence.*

8.5. Recommendations the future research

Whereas the societal implications in section 8.3 provided recommendations about how to use the findings of this study to improve the outbound interaction strategy of bank *X*, this section provides recommendations about how to improve future research within bank *X* towards understanding channel preferences of its customers. The recommendations in this section are based on the identified limitations of this study. The recommendation to improve future research towards understanding channel preferences of customers are:

- To avoid generalizability problems with the results of future research it is recommended to*:*

    - Avoid selection bias by inviting respondents through multiple channels, preferably by the same channels that are included in analysis.
    - Avoid non-response bias by correcting the invited population to expected response rates among sub-groups of the invited population.
    - Always use a Heckman correction model to assess if non-response bias exists and to correct for non-response bias exists. Furthermore, it is recommended to collect channel preferences through other means than used for collecting data for model development. This data can be used for the validation of the Heckman correction*.*

- To improve the usability of MLR models in business it is recommended to assess whether a general MLR model for estimating the preferred communication channel is desired. When desired, it is recommended to ask respondents to select their preferred communication channel from a set of channels instead of scoring their preferences for each channel. Since the number of observations would strongly decrease, more respondents would be required.

- If no general model is desired, it is recommended for future research towards channel preferences of customers to use a dependent variable with a maximum of three levels. Using a dependent variable with more levels proved to limit the ability to find relations in the data and limited the predictive power of the models. In addition, collecting more data will increase the likelihood that relations in the data will be detected.

- To improve the robustness of the validation of channel preference predictions made by MLR models in future research, it is recommended to increase the number of respondents to allow for a larger hold-out validation sample.

- To increase confidence in the operationalization of contact complexity, and attitude based factors in general, in future research towards channel preferences of customers, it is recommended to validate the operationalization through the use of surveys or interviews with customers. In this way results based on the operationalization can be used with more confidence.

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10. Appendices

This chapter provides all appendices mentioned in the thesis.

I. Appendix: Outbound communication channels at bank *X*

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

II. Appendix: Customer segments at bank *X*

[redacted]

III. Appendix: Semi-structured interview template

Interviewer:	Albert Bouwmeester, A. (Albert)
Geinterviewde:	xxxxx
Datum/tijd:	24-4-15 – 10:00-10:45
Kanaal:	xxxxx

I. Kun je vertellen wat de doelen zijn van het klantcontact dat je zoal hebt?

II. Wat voor type klanten kom je voornamelijk tegen bij ## communicatie kanaal ## ?

III. In welke situaties zijn deze klanten tevreden over de bandering bij via dit kanaal (outbound)?

IV. Wat voor factoren spelen naar jouw idee een rol in de tevredenheid van klant over de benadering via ## communicatie kanaal ## ?

V. Los van de tevredenheid, welke criteria gebruik je om te bepalen of je een klant gaat benaderen of niet?

VI. Kun je een patroon herkennen in klanten die je niet/moeilijk kunt bereiken?

VII. In welke situaties zijn deze klanten ontevreden over de bandering bij via dit kanaal?

VIII. (Niet) Aansprekende elementen van ## communicatie kanaal ## ?

IV. Appendix: Categorization of financial products in complexity categories

This appendix shows how financial experts at bank *X* categorized situations concerning specific financial products. The first table shows the situations with financial products. The second table shows the scores for each situation. The green colour represents low complex financial products, yellow represents medium complex financial products and orange represents high complex financial products. In total 25 experts participated in this process. From each complexity level 2 products were selected (appendix V).

[redacted]

[redacted]

V. Appendix: Vignettes used to operationalize complexity

Below an overview of the constructed vignettes can be found. For the first vignette the total question is shown. The other vignettes are used in the same manner. For a complete overview of the survey appendix VI can be consulted. The following vignettes are constructed:

For low complexity:

- *Imagine that the bank X would like to invite you for an interview with an advisor to review your current financial situation so you can make the right financial choices based on good insight and overview in your situation (Vignette 1).*

  Would you like to be contacted about this subject? (Y/N)

  If answer to previous question was Y:
  You indicated that you would like to be contacted about this situation by bank X. Please enter below on a scale of 1 to 5 how you rate the following communication channels for being contacted. A 1 equals "Do not prefer at all" and 5 indicates "I prefer very much." If desired, you explain your answer.

	1 Prefer not at all	2	3	4	5 Prefer very much	I do not use/know this communication channel
Landline						
Mobile						
Social Media (private message)						
Mobile app						
Internet banking						
E-mail						
SMS						

Figure 13: Example survey question

- *Imagine that you have a considerable amount of savings on your savings account and bank X believes that another type of savings account is more interesting for you because of interest rates* (Vignette 2).

For medium complexity:

- *Imagine that you have several home insurance products and bank X sees that, in combination with your with your mortgage, your coverage of risks is not optimal* (Vignette 3).

- *Imagine that you have a mortgage with ING and you have repaid extra last year. bank X sees this and wants to inform you about policies which offer the possibility to repay without penalty* (Vignette 4).

For high complexity:

- *Imagine that you have retirement related products at bank X and retirement legislation changes* (Vignette 5).

- *Imagine that you have an investment account with bank X and bank X wants to inform you about your options as an investor in due to fluctuations in the stock market* (Vignette 6).

Assigning the financial products to levels of complexity has been performed by experts. To verify if respondents perceive the complexity of the financial products in the same manner as the experts, respondents are asked to rate the financial products on a scale from 1 to 5 in which a score of 1 represents ‘not complex at all’ and a score of 5 ‘very complex’. An overview of the total survey design can be found in Figure 4.

Research company [redacted] performed a pre-test of the survey among 50 respondents. The pre-test required some textual adjustments of the survey. Furthermore, the pre-test showed that respondent required 10-15 min to finish the survey. Based on the few survey questions presented here, this duration might be longer than would be expected. Main reason for the longer duration of the survey is that some questions were added for another department of bank *X*. These questions are out of scope of this thesis.

VI. Appendix: Final survey design of implemented by research company

Vragenlijst [redacted]

Doelgroep: [redacted]

- Vermogende Nederlanders: High value klanten met een credit vermogen bij bank *X* van €75.000 of meer.
- Nederlanders met de potentie om toekomstig vermogend te worden: [redacted] die de potentie hebben om toekomstig vermogend te worden. Vooralsnog houden we hiervoor [redacted] aan die een stijging hebben laten zien in inkomen en vermogen en waarbij het vermogen op dit moment rond de Vermogensvrijstellingsgrens valt.

Minimale N=250 (uitgaande van 4,5% respons; bruto steekproef 5.500)

Respons opleveren in Excel; iedere respondent moet identificeerbaar zijn bijvoorbeeld obv e-mailadres.

Inlogscherm (bij online, alleen als het automatisch inloggen niet werkt):

Hartelijk welkom bij dit onderzoek van de bank *X*. Vul hieronder uw usercode in. Deze staat helemaal onderaan de uitnodigingsmail die u heeft ontvangen.

Vragenlijst:

(1 antwoord mogelijk vraag)

1. **Volgens onze gegevens bent u klant van bank X klopt dat?**
   - o Ja
   - o Nee → *Screenout*

<antwoorden randomiseren>

(stellingvraag)

2. **Hieronder ziet u een aantal financiële thema's. Geeft u alstublieft aan in welke mate u deze thema's moeilijk vindt. Hiermee bedoelen we de mate waarin u dit thema lastig vind om mee aan de slag te gaan en inzicht in te krijgen. U kunt antwoorden op**

een schaal van 1 tot 5 waarbij een 1 staat voor 'helemaal niet moeilijk' en een 5 voor 'zeer moeilijk'.

Helemaal niet moeilijk (1)	(2)	(3)	(4)	Zeer moeilijk (5)

a) Inzicht krijgen in uw inkomsten en uitgaven
b) Vermogen opbouwen door te sparen
c) Optimale dekking van uw verzekeringen
d) In kaart brengen van uw pensioensituatie
e) (Extra) Aflossen op uw hypotheek
f) Oversluiten van uw hypotheek
g) Vermogen opbouwen door te beleggen

(dummyvraag)

3. **Hierna volgt een zestal hypothetische situaties. We vragen u om u in te leven in de situatie en vanuit die gedachte uw antwoorden te geven. Indien de situatie niet op u van toepassing is, vragen we u toch om u in te leven in de situatie.**

(1 antwoord mogelijk vraag)

4. **Situatie 1/6: Stelt u zich eens voor dat de bank *X* u wil uitnodigen voor een gesprek met een adviseur om uw huidige financiële situatie eens door te nemen, zodat u op basis van een goed inzicht en overzicht in uw situatie de juiste financiële keuzes kunt maken.**

   Zou u door de bank *X* benaderd willen worden voor een dergelijk gesprek?

   o Ja
   o Nee

(stellingvraag)[alleen stellen als vraag 4 = Ja]

5. **Situatie 1/6:**
   *Stelt u zich eens voor dat **bank X** u wil uitnodigen voor een gesprek met een adviseur om uw huidige financiële situatie eens door te nemen, zodat u op basis van een goed inzicht en overzicht in uw situatie de juiste financiële keuzes kunt maken.*

   U heeft aangegeven dat u in deze situatie door de bank *X* benaderd zou willen worden voor een dergelijk gesprek.
   Geef hieronder op een schaal van 1 tot 5 aan in hoeverre u onderstaande communicatiemiddelen waardeert voor deze benadering. Hierbij staat een 1 voor 'Heeft absoluut geen voorkeur' en een 5 voor 'Heeft absoluut voorkeur'. Indien gewenst kunt uw antwoord toelichten.

Heeft absoluut geen voorkeur (1)	(2)	(3)	(4)	Heeft absoluut voorkeur (5)	*Ik ken/heb dit communicatie middel niet* (999)

   a) Gebeld worden op mijn vaste telefoon <open invoer niet verplicht>
   b) Gebeld worden op mijn mobiele telefoon <open invoer niet verplicht>
   c) Een privébericht op social media (zoals LinkedIn of Facebook) <open invoer niet verplicht>
   d) Een bericht in de **bank *X*** bankieren app <open invoer niet verplicht>
   e) Een bericht in internet banking <open invoer niet verplicht>
   f) Een e-mail <open invoer niet verplicht>
   g) Een SMS <open invoer niet verplicht>

(1 antwoord mogelijk vraag)

6. **Situatie 2/6 Stelt u zich eens voor dat u een aanzienlijk bedrag op uw spaarrekening heeft en de bank *X* ziet dat een ander type spaarrekening qua rente interessanter is voor u.**

   Zou u door de bank *X* benaderd willen worden om u hierop te wijzen?

   o Ja
   o Nee

(stellingvraag)[alleen stellen als vraag 7 = Ja]

7. **Situatie 2/6:**
   Stelt u zich eens voor dat u een aanzienlijk bedrag op uw spaarrekening heeft en de **bank *X*** *ziet dat een ander type spaarrekening qua rente interessanter is voor u.*

   U heeft aangegeven dat u in deze situatie door de bank *X* benaderd zou willen worden om u hierop te wijzen.
   Geef hieronder op een schaal van 1 tot 5 aan in hoeverre u onderstaande communicatiemiddelen waardeert om hiervoor benaderd te worden. Hierbij staat een 1 voor 'Heeft absoluut geen voorkeur' en een 5 voor 'Heeft absoluut voorkeur'. Indien gewenst kunt uw antwoord toelichten.

Heeft absoluut geen voorkeur (1)	(2)	(3)	(4)	Heeft absoluut voorkeur (5)	*Ik ken/heb dit communicatie middel niet* (999)

a) Gebeld worden op mijn vaste telefoon <open invoer niet verplicht>
b) Gebeld worden op mijn mobiele telefoon <open invoer niet verplicht>
c) Een privébericht op social media (zoals LinkedIn of Facebook) <open invoer niet verplicht>
d) Een bericht in de **bank *X*** bankieren app <open invoer niet verplicht>
e) Een bericht in internet banking <open invoer niet verplicht>
f) Een e-mail <open invoer niet verplicht>
g) Een SMS <open invoer niet verplicht>

(1 antwoord mogelijk vraag)

8. Situatie 3/6: Stelt u zich voor dat u verscheidene [redacted] heeft en de bank *X* ziet door de combinatie met uw hypotheek dat deze mogelijk niet de optimale dekking geven.

Zou u door de bank *X* <u>benaderd</u> willen worden om u hierop te wijzen?

- o Ja
- o Nee

(stellingvraag)[alleen stellen als vraag 10 = Ja]

9. Situatie 3/6:
Stelt u zich voor dat u verscheidene [redacted] *heeft en de **bank X** ziet door de combinatie met uw hypotheek dat deze mogelijk niet de optimale dekking geven.*

U heeft aangegeven dat u in deze situatie door de bank *X* <u>benaderd</u> zou willen worden om u hierop te wijzen.
Geef hieronder op een schaal van 1 tot 5 aan in hoeverre u onderstaande communicatiemiddelen waardeert om hiervoor benaderd te worden. Hierbij staat een 1 voor 'Heeft absoluut geen voorkeur' en een 5 voor 'Heeft absoluut voorkeur'. Indien gewenst kunt uw antwoord toelichten.

Heeft absoluut geen voorkeur (1)	(2)	(3)	(4)	Heeft absoluut voorkeur (5)	*Ik ken/heb dit communicatie middel niet* (999)

a) Gebeld worden op mijn vaste telefoon <open invoer niet verplicht>
b) Gebeld worden op mijn mobiele telefoon <open invoer niet verplicht>
c) Een privébericht op social media (zoals LinkedIn of Facebook) <open invoer niet verplicht>
d) Een bericht in de **bank *X*** bankieren app <open invoer niet verplicht>
e) Een bericht in internet banking <open invoer niet verplicht>
f) Een e-mail <open invoer niet verplicht>
g) Een SMS <open invoer niet verplicht>

(1 antwoord mogelijk vraag)

10. Situatie 4/6: Stelt u zich voor dat u pensioen gerelateerde producten bij de bank *X* heeft en de pensioenwetgeving verandert.

Zou u door de bank *X* benaderd willen worden over deze wijzigingen en de gevolgen ervan voor uw persoonlijke situatie?

o Ja
o Nee

(stellingvraag)[alleen stellen als vorige vraag 13 = Ja]

11. Situatie 4/6:
Stelt u zich voor dat u pensioen gerelateerde producten bij de ***bank X*** *heeft en de pensioenwetgeving verandert.*

U heeft aangegeven dat u in deze situatie door de bank *X* benaderd zou willen worden over deze wijzingen en de gevolgen ervan voor uw persoonlijke situatie. Geef hieronder op een schaal van 1 tot 5 aan in hoeverre u onderstaande communicatiemiddelen waardeert om hierover geïnformeerd te worden. Hierbij staat een 1 voor 'Heeft absoluut geen voorkeur' en een 5 voor 'Heeft absoluut voorkeur'. Indien gewenst kunt uw antwoord toelichten.

Heeft absoluut geen voorkeur (1)	(2)	(3)	(4)	Heeft absoluut voorkeur (5)	*Ik ken/heb dit communicatie middel niet* (999)

a) Gebeld worden op mijn vaste telefoon <open invoer niet verplicht>
b) Gebeld worden op mijn mobiele telefoon <open invoer niet verplicht>
c) Een privébericht op social media (zoals LinkedIn of Facebook) <open invoer niet verplicht>
d) Een bericht in de **bank *X*** bankieren app <open invoer niet verplicht>
e) Een bericht in internet banking <open invoer niet verplicht>
f) Een e-mail <open invoer niet verplicht>
g) Een SMS <open invoer niet verplicht>

(1 antwoord mogelijk vraag)

12. Situatie 5/6: Stelt u zich voor dat u een hypotheek bij de bank *X* heeft en u het afgelopen jaar extra heeft afgelost. De bank *X* ziet dit en wil u graag informeren over een actie waarin de mogelijkheid is verruimd om boetevrij af te lossen.

Zou u hierover door de bank *X* benaderd willen worden?

o Ja
o Nee

(stellingvraag)[alleen stellen als vraag 16 = Ja]

13. Situatie 5/6:

Stelt u zich voor dat u een hypotheek bij de ***bank X*** *heeft en u het afgelopen jaar extra heeft afgelost.* ***bank X*** *ziet dit en wil u graag informeren over een actie waarin de mogelijkheid is verruimd om boetevrij af te lossen.*

U heeft aangegeven dat u in deze situatie door de bank *X* benaderd zou willen worden.
Geef hieronder op een schaal van 1 tot 5 aan in hoeverre u onderstaande communicatiemiddelen waardeert om hierover geïnformeerd te worden. Hierbij staat een 1 voor 'Heeft absoluut geen voorkeur' en een 5 voor 'Heeft absoluut voorkeur'. Indien gewenst kunt uw antwoord toelichten.

Heeft absoluut geen voorkeur (1)	(2)	(3)	(4)	Heeft absoluut voorkeur (5)	*Ik ken/heb dit communicatie middel niet* (999)

a) Gebeld worden op mijn vaste telefoon <open invoer niet verplicht>
b) Gebeld worden op mijn mobiele telefoon <open invoer niet verplicht>
c) Een privébericht op social media (zoals LinkedIn of Facebook) <open invoer niet verplicht>
d) Een bericht in de **bank *X*** bankieren app <open invoer niet verplicht>
e) Een bericht in internet banking <open invoer niet verplicht>
f) Een e-mail <open invoer niet verplicht>
g) Een SMS <open invoer niet verplicht>

(1 antwoord mogelijk vraag)

14. Situatie 6/6: Stelt u zich voor dat u een beleggingsrekening heeft bij de bank *X* en de bank *X* wil u graag informeren over uw mogelijkheden als belegger i.v.m. schommelingen op de aandelenbeurs.

Zou u hierover door de bank *X* benaderd willen worden?

o Ja
o Nee

(stellingvraag)[alleen stellen als vraag 19 = Ja]

15. Situatie 6/6:

Stelt u zich voor dat u een beleggingsrekening heeft bij de ***bank X*** *en de* ***bank X*** *wil u graag informeren over uw mogelijkheden als belegger i.v.m. schommelingen op de aandelenbeurs.*

U heeft aangegeven dat u in deze situatie door de bank *X* <u>benaderd</u> zou willen worden.
Geef hieronder op een schaal van 1 tot 5 aan in hoeverre u onderstaande communicatiemiddelen waardeert om hierover geïnformeerd te worden. Hierbij staat een 1 voor 'Heeft absoluut geen voorkeur' en een 5 voor 'Heeft absoluut voorkeur'. Indien gewenst kunt uw antwoord toelichten.

Heeft absoluut geen voorkeur (1)	(2)	(3)	(4)	Heeft absoluut voorkeur (5)	*Ik ken/heb dit communicatie middel niet* (999)

a) Gebeld worden op mijn vaste telefoon <open invoer niet verplicht>
b) Gebeld worden op mijn mobiele telefoon <open invoer niet verplicht>
c) Een privébericht op social media (zoals LinkedIn of Facebook) <open invoer niet verplicht>
d) Een bericht in de **bank *X*** bankieren app <open invoer niet verplicht>
e) Een bericht in internet banking <open invoer niet verplicht>
f) Een e-mail <open invoer niet verplicht>
g) Een SMS <open invoer niet verplicht>

Stijl en opmaak: conform [redacted]
Afzender: Onderzoek van [redacted]
Subject: Uw voorkeur in communicatiemiddelen van bank *X*

Geachte [heer/mevrouw xxx],

Bank *X* vindt het belangrijk haar klanten pro actief te adviseren en informeren op belangrijke momenten, bijvoorbeeld omdat wetgeving wijzigt, financiële producten die u afneemt veranderen of nieuwe financiële producten mogelijk interessanter zijn dan uw huidige. Bank *X* gaat hier graag met u over in gesprek via de communicatiemiddelen van uw voorkeur. Wij willen u daarom uitnodigen voor een onderzoek naar uw communicatievoorkeuren als het gaat om financieel advies en informatie.

- **Tijdsduur**: ongeveer 5 minuten
- **Onderwerp**: Uw communicatievoorkeuren
- **Vragenlijst starten**: klik hier

Het onderzoek blijft beschikbaar **tot en met 12 oktober**, zou u de vragenlijst voor die datum kunnen invullen?

Wanneer u halverwege de vragenlijst geen tijd meer hebt om verder te gaan, dan kunt u de vragenlijst verlaten en op een ander moment de link in deze mail opnieuw gebruiken. De vragenlijst zal dan beginnen bij de vraag waar u de vorige keer was gebleven.

Bij voorbaat dank voor uw deelname!

[redacted]

P.S. Het onderzoek wordt uitgevoerd en gerapporteerd door een onafhankelijk onderzoeksbureau, [redacted]. Uw antwoorden worden anoniem en vertrouwelijk verwerkt.

VII. Appendix: Calculation of the Margin Of Error (MOE) of survey

For practical and financial reasons it is not possible to apporach all Perba and Perba prospect customers. Due to time constrains, policy contrains of bank *X*, and budget contrains 250 valid responses could be collected. Experience form earlier surveys at bank *X* learned that a response rate between 4 and 5% can be expected. Therefore, under the assumption of a 4,5% response rate, the survey has been sent to 5.500 customers from the high value customer segment. The number of valid resopnses influences the Margin of Error (MOE) of the survey. The MOE expresses the amount of random sampling error in a survey and provides a likelihood that parameters found in the sample reflect the real parameters of the population (Kotz et al., 2004). The MOE of a survey with 250 valid responses can calculated by equation (1) from (Kotz et al., 2004; Scheuren, 2004) with probability of proportion of population (p) = 0,5; sample size (n) = 250 and population size (N) = 400.000. Since the population is very large the last section of the eqation is irrelevant and not included (2). Finally the expected MOE for the survey is 6,2%. This MOE comes close to the general accepted MOE of 5% (Bartlett et al., 2001) and is therefore found appropiate.

$$\mathrm{MOE} = 1{,}96 * \sqrt{\left(\frac{\mathrm{p}*(1-\mathrm{p})}{\mathrm{n}}\right)} * \sqrt{\left(\frac{\mathrm{N}-\mathrm{n}}{N-1}\right)} \qquad (1)$$

$$\mathrm{MOE} = 1{,}96 * \sqrt{\left(\frac{\mathrm{p}*(1-\mathrm{p})}{\mathrm{n}}\right)} \qquad (2)$$

$$\mathrm{MOE} = 1{,}96 * \sqrt{\left(\frac{0{,}5*(1-0{,}5)}{250}\right)} \qquad (3)$$

$$\mathrm{MOE} = 0{,}0619 \approx 6{,}2\%$$

VIII. Appendix: Distributions of dependent variable

This appendix shows the distributions of the dependent variables. It provides an overview on how respondents rated their preference for the channels landline, mobile, e-mail, mobile app, and internet banking.

IX. Descriptive overview of independent variables

This appendix shows the descriptive information of the independent variables in the first table. The second table shows the correlations between the independent variables. This tables is provided to check for multicollinearity.

[redacted]

Correlations

[redacted]

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

X. Appendix: SPSS output linear regression models

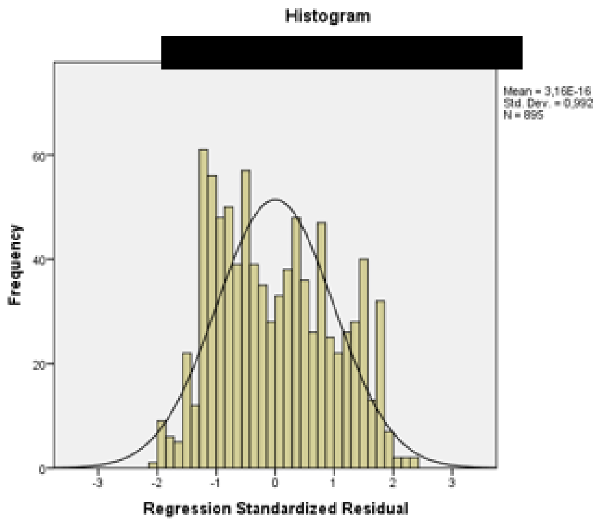
This appendix provides the relevant output of the estimated linear regression models. The inspection of assumptions for each model shows that the assumption of linearity, normality and homoscedasticity are violated. Therefore, these models are not used for further analysis.

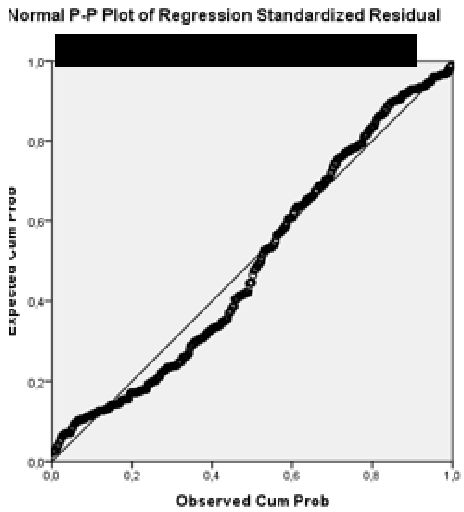
Linear regression model for LANDLINE

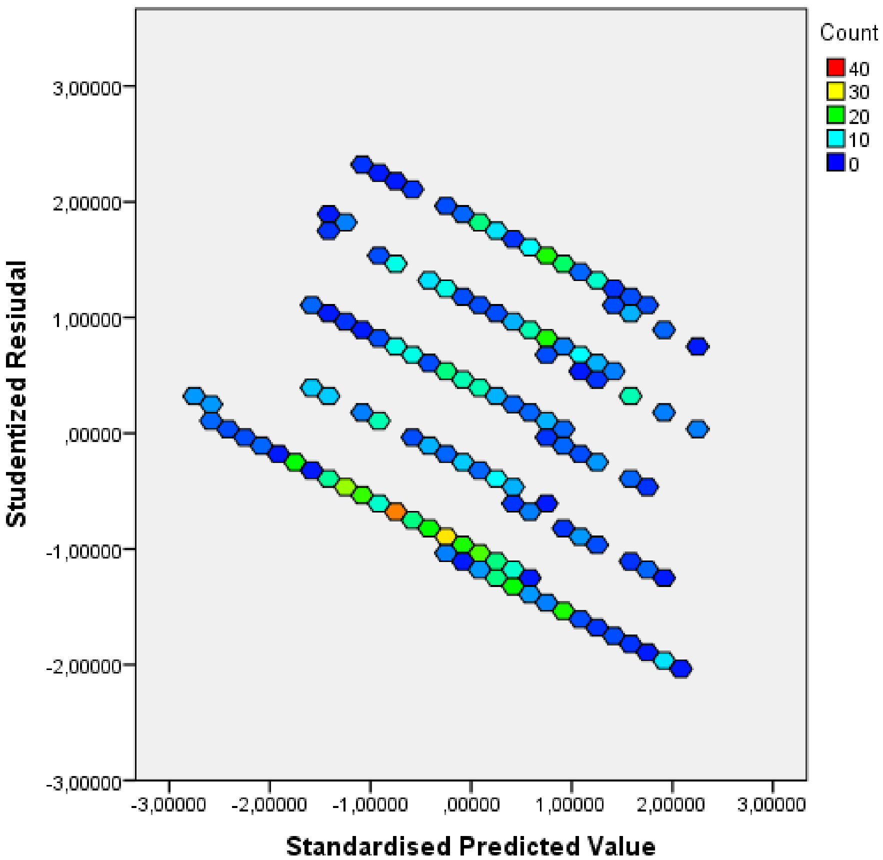
R Square	Std. Error of Estimate	p-value R square	Confidence interval for model
0,187	1,380	0,000	95%

Independent variable	Beta	Standardized beta	t-value	p-value
[redacted]	-0,716	-	-1,641	0,101
[redacted]	-0,101	-0,038	-1,180	0,238
[redacted]	0,202	0,066	1,495	0,135
[redacted]	0,389	0,114	3,562	0,000
[redacted]	0,045	0,319	7,286	0,000
[redacted]	-5,273E-5	-0,005	-0,123	0,902
[redacted]	0,180	0,156	4,918	0,000
[redacted]	-0,519	-0,170	-4,533	0,000
[redacted]	-5,970E-7	-,003	-0,095	0,925
[redacted]	0,000	0,055	1,315	0,189
[redacted]	-0,008	-0,170	-5,190	0,000
[redacted]	-0,004	-0,083	-2,461	0,014
[redacted]	0,134	0,112	3,559	0,000
[redacted]	0,022	0,026	0,830	0,407
[redacted]	0,027	0,078	2,017	0,044
[redacted]	9,607E-7	0,054	1,237	0,216

Assumpties


Histogram
[redacted]
Mean = 3,16E-16
Std. Dev. = 0,992
N = 895
Frequency
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
[redacted]
Observed Cum Prob

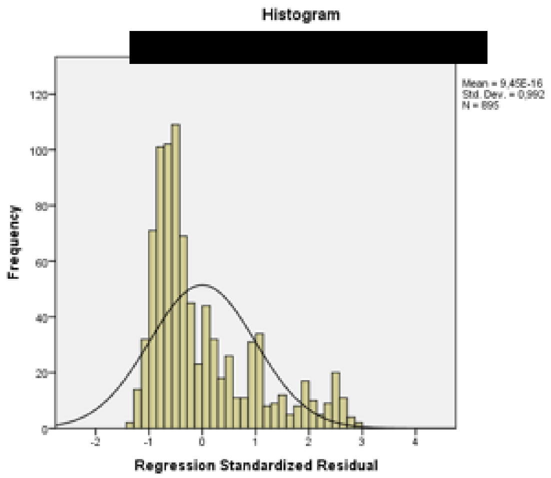

Count
40
30
20
10
0
Studentized Resiudal
3,00000
2,00000
1,00000
,00000
-1,00000
-2,00000
-3,00000
-3,00000
-2,00000
-1,00000
,00000
1,00000
2,00000
3,00000
Standardised Predicted Value

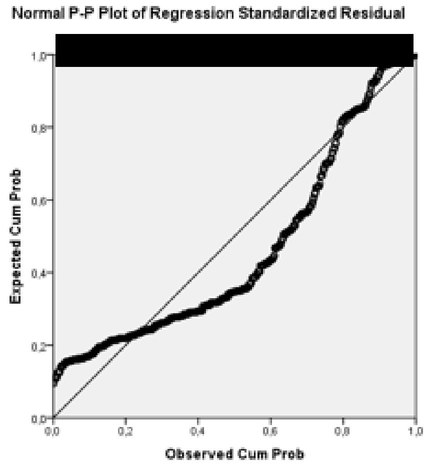
Linear regression model for MOBILE

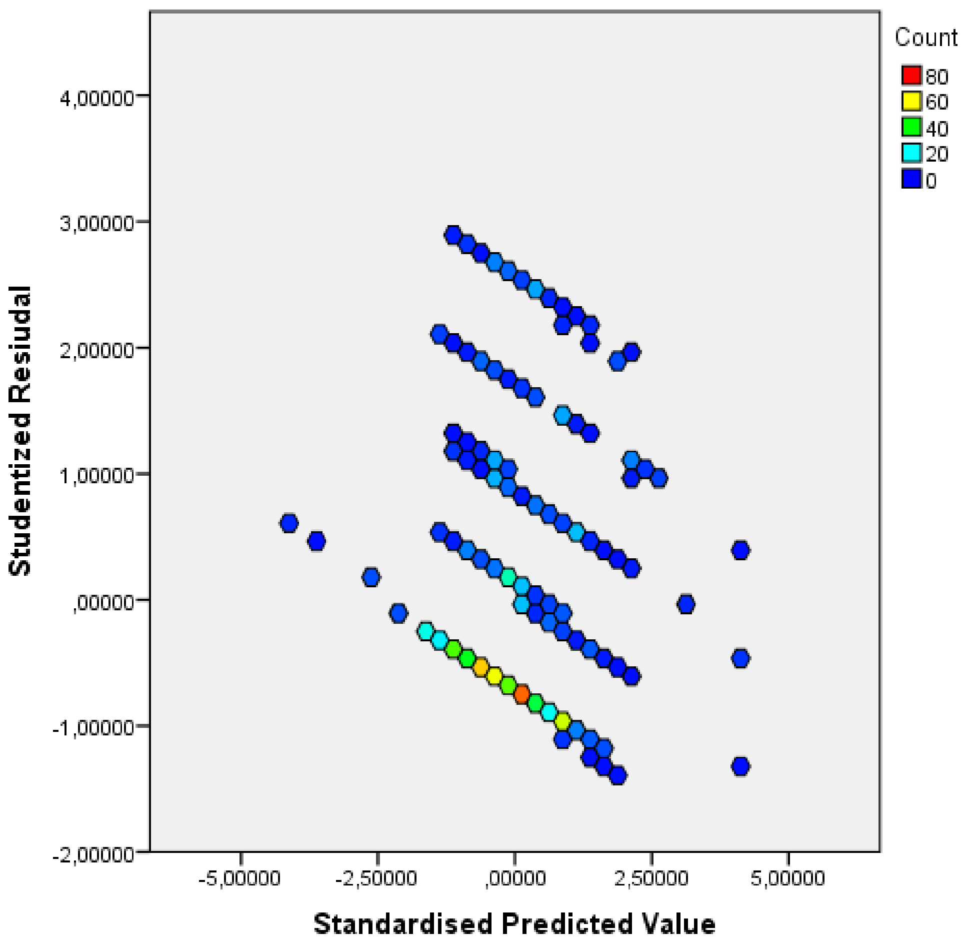
R Square	Std. Error of Estimate	p-value R square	Confidence interval for model
0,093	1,229	0,000	95%

Independent variable	Beta	Standardized beta	t-value	p-value
[redacted]	2,698	-	6,938	,000
[redacted]	-,019	-,008	-,248	,804
[redacted]	-,069	-,027	-,575	,566
[redacted]	-,339	-,118	-3,482	,001
[redacted]	-,003	-,024	-,516	,606
[redacted]	-,001	-,152	-3,665	,000
[redacted]	,032	,033	,975	,330
[redacted]	-,264	-,102	-2,590	,010
[redacted]	-1,820E-5	-,112	-3,243	,001
[redacted]	,000	,101	2,299	,022
[redacted]	,000	-,006	-,165	,869
[redacted]	,004	,096	2,684	,007
[redacted]	,019	,019	,568	,570
[redacted]	,020	,029	,880	,379
[redacted]	,011	,038	,942	,346
[redacted]	-1,808E-6	-,121	-2,613	,009

Assumpties



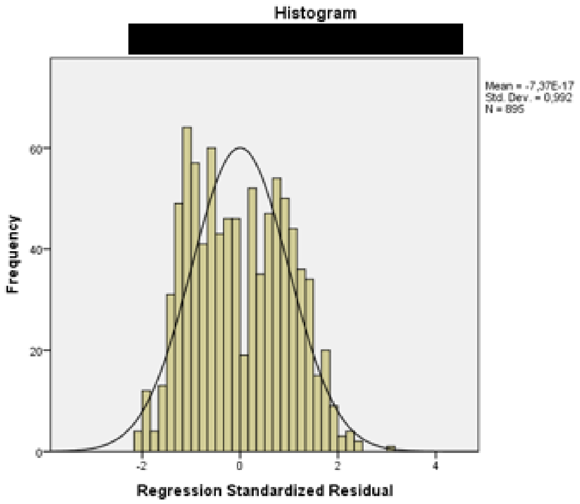


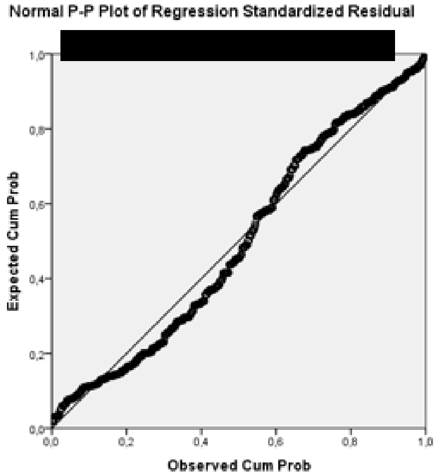


<u>**Linear regression model for MOBILE APP**</u>

R Square	Std. Error of Estimate	p-value R square	Confidence interval for model
0,235	1,430	0,000	95%

Independent variable	**Beta**	**Standardized beta**	**t-value**	**p-value**
[redacted]	4,607	-	10,187	,000
[redacted]	-,441	-,155	-4,987	,000
[redacted]	-,043	-,013	-,305	,760
[redacted]	-,260	-,072	-2,302	,022
[redacted]	-,019	-,126	-2,972	,003
[redacted]	,000	-,030	-,794	,427
[redacted]	,088	,071	2,317	,021
[redacted]	,660	,202	5,564	,000
[redacted]	3,859E-5	,187	5,912	,000
[redacted]	9,418E-5	,026	,642	,521
[redacted]	-,006	-,122	-3,833	,000
[redacted]	,004	,086	2,628	,009
[redacted]	-,054	-,042	-1,387	,166
[redacted]	-,044	-,050	-1,642	,101
[redacted]	,017	,046	1,235	,217
[redacted]	-1,307E-6	-,069	-1,624	,105

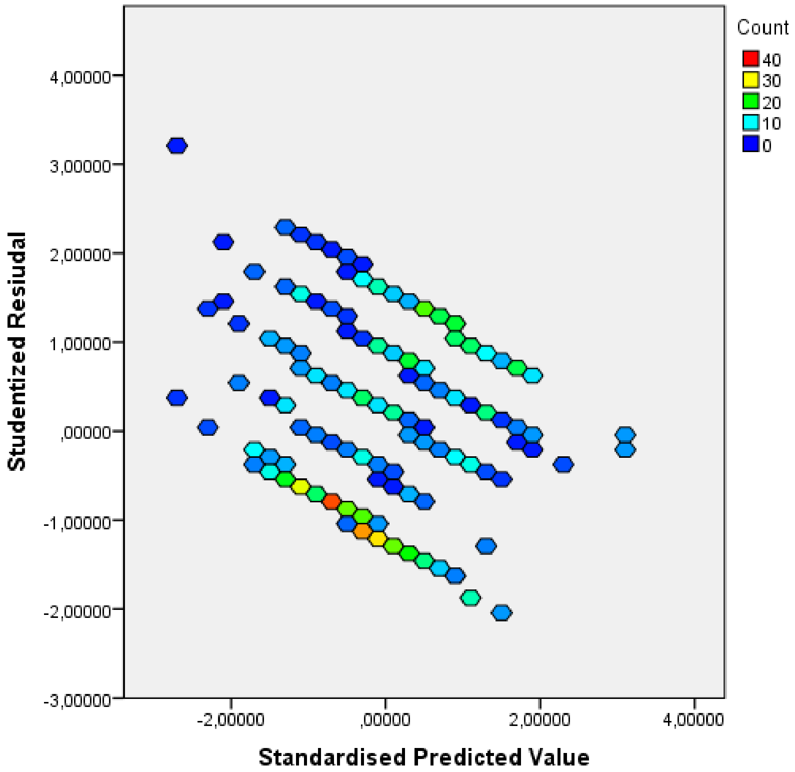




Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Studentized Residual	,073	895	,000	,973	895	,000

a. Lilliefors Significance Correction

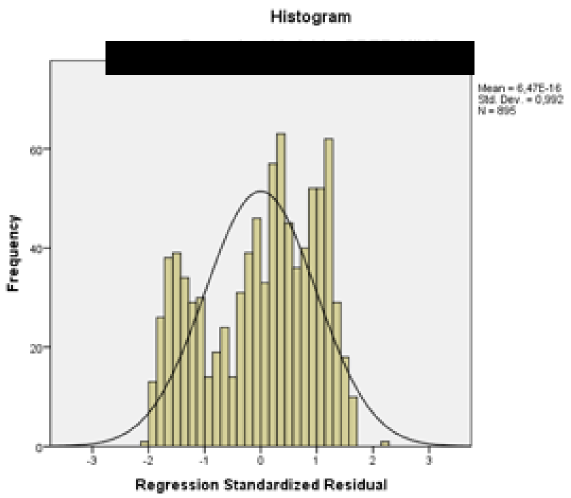


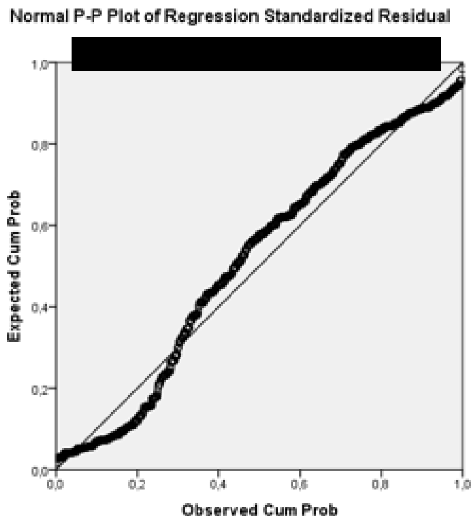
Linear regression model for INTERNET BANKING

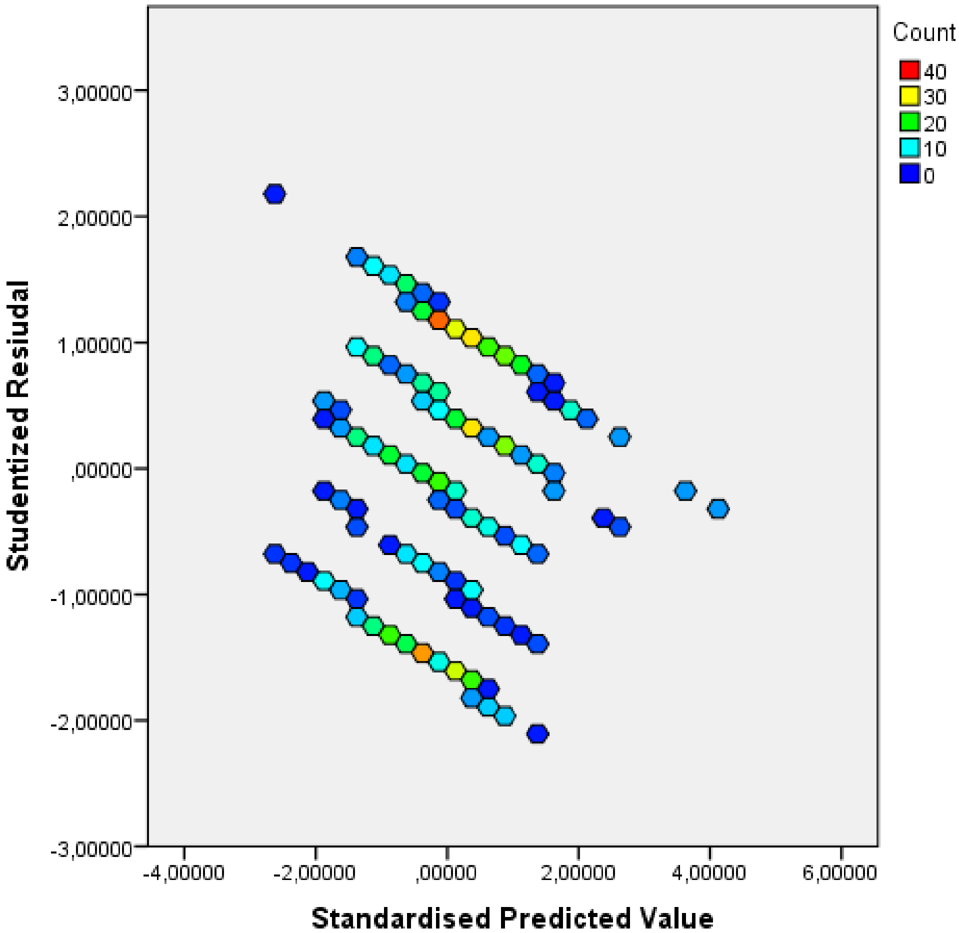
R Square	Std. Error of Estimate	p-value R square	Confidence interval for model
0,119	1,444	0,000	95%

[redacted]	Beta	Standardized beta	t-value	p-value
[redacted]	4,476	-	9,801	,000
[redacted]	-,243	-,091	-2,719	,007
[redacted]	-,217	-,071	-1,540	,124
[redacted]	-,211	-,062	-1,848	,065
[redacted]	-,024	-,168	-3,693	,000
[redacted]	,000	,037	,893	,372
[redacted]	,082	,071	2,141	,033
[redacted]	,276	,090	2,306	,021
[redacted]	2,671E-5	,138	4,053	,000
[redacted]	,000	,041	,956	,339
[redacted]	,002	,052	1,538	,124
[redacted]	,003	,062	1,766	,078
[redacted]	-,053	-,044	-1,344	,179
[redacted]	-,015	-,018	-,552	,581
[redacted]	,039	,110	2,748	,006
[redacted]	-1,321E-6	-,074	-1,625	,104

Assumpties


Histogram
[redacted]
Mean = 6,47E-16
Std. Dev. = 0,992
N = 895
Frequency
Regression Standardized Residual


Normal P-P Plot of Regression Standardized Residual
[redacted]
Expected Cum Prob
Observed Cum Prob


Count
40
30
20
10
0
Studentized Resiudal
Standardised Predicted Value

Group Statistics

	Standardized Predicted Value	N	Mean	Std. Deviation	Std. Error Mean
Studentized Residual	>= ,00000	427	-,0191551	,95622094	,04627477
	< ,00000	468	,0172620	1,03883347	,04802009

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Studentized Residual	Equal variances assumed	9,784	,002	-,544	893	,587	-,03641710	,06694130	-,16779770	,09496350
	Equal variances not assumed			-,546	892,929	,585	-,03641710	,06668796	-,16730051	,09446631

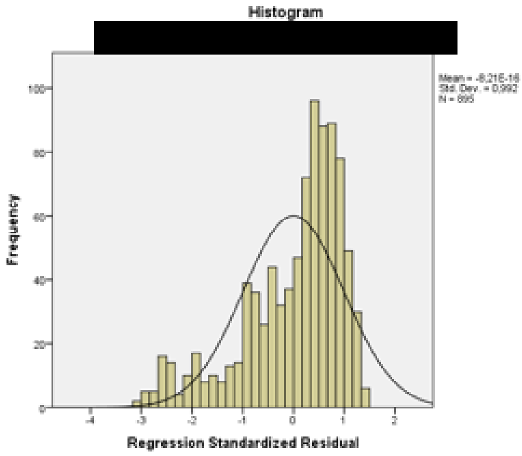
Linear regression model for E-MAIL

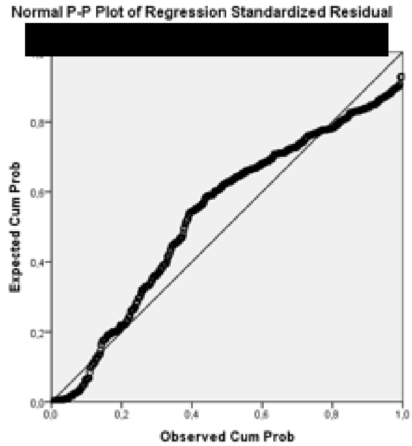
R Square	Std. Error of Estimate	p-value R square	Confidence interval for model
0,104	1,168	0,000	95%

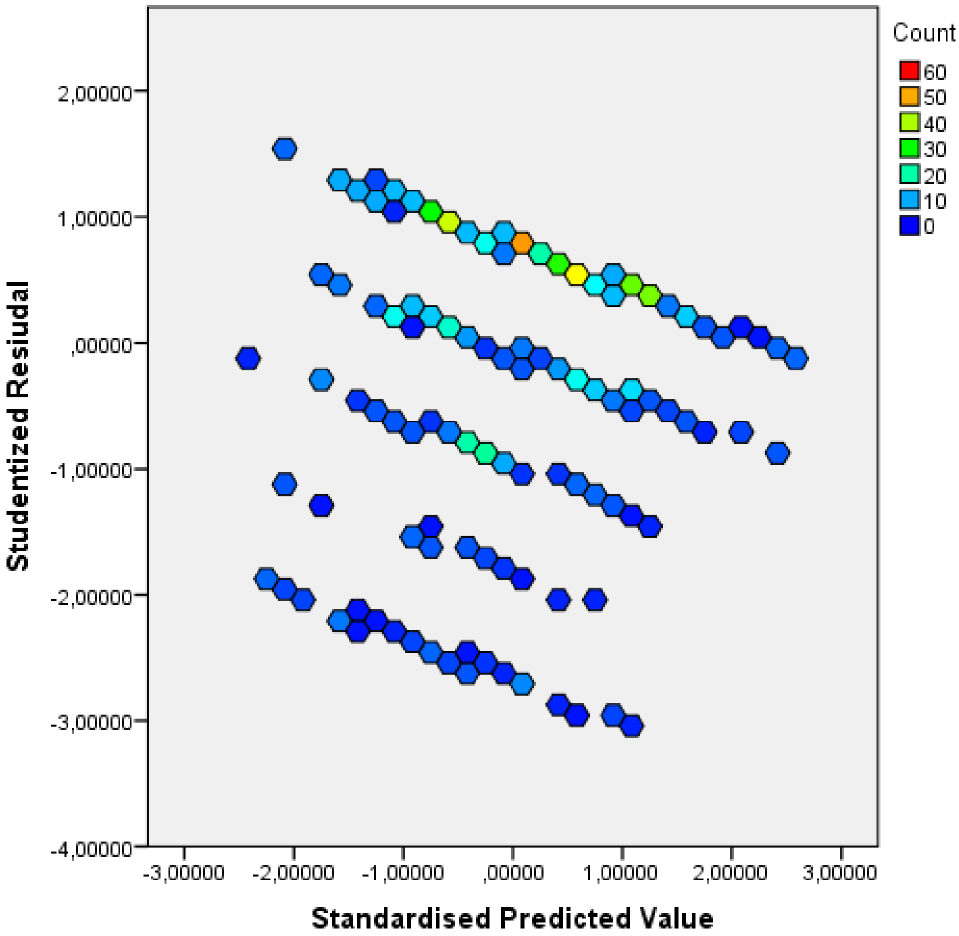
Independent variable	Beta	Standardized beta	t-value	p-value
[redacted]	4,748	-	12,848	,000
[redacted]	,268	,125	3,704	,000
[redacted]	-,388	-,159	-3,404	,001
[redacted]	-,422	-,154	-4,571	,000
[redacted]	-,010	-,084	-1,825	,068
[redacted]	,000	-,033	-,799	,425
[redacted]	-,084	-,090	-2,699	,007
[redacted]	,112	,045	1,153	,249
[redacted]	5,805E-6	,037	1,088	,277
[redacted]	,000	,110	2,522	,012
[redacted]	,000	-,010	-,281	,779
[redacted]	,001	,036	1,030	,304
[redacted]	-,098	-,101	-3,059	,002

[redacted]	-,061	-,093	-2,787	,005
[redacted]	-,046	-,161	-3,978	,000
[redacted]	5,895E-7	,041	,896	,370

Assumpties







Count
60
50
40
30
20
10
0
2,00000
1,00000
,00000
-1,00000
-2,00000
-3,00000
-4,00000
Studentized Resiudal
-3,00000
-2,00000
-1,00000
,00000
1,00000
2,00000
3,00000
Standardised Predicted Value

XI. SPSS output of Ordinal Logistic Regression

PLUM - Ordinal Regression [redacted]

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2606,557			
Final	2398,393	208,165	21	,000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3416,578	3555	,951
Deviance	2398,393	3555	1,000

Link function: Logit.

Pseudo R-Square

Cox and Snell	,208
Nagelkerke	,219
McFadden	,080

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[redacted]	3,433	,533	41,544	1	,000	2,389	4,477
		3,982	,537	55,032	1	,000	2,930	5,035
		4,701	,543	74,938	1	,000	3,636	5,765
		5,855	,554	111,784	1	,000	4,770	6,941
Location		,063	,009	47,803	1	,000	,045	,080
		,001	,001	1,127	1	,288	-,001	,002
		-3,058E-06	9,410E-06	,106	1	,745	-2,150E-05	1,538E-05
		,000	,000	2,122	1	,145	-9,732E-05	,001
		-,010	,002	21,715	1	,000	-,014	-,006
		-,006	,002	6,715	1	,010	-,010	-,001
		,174	,051	11,676	1	,001	,074	,274
		,021	,036	,331	1	,565	-,049	,091
		,033	,019	3,169	1	,075	-,003	,070
		7,300E-07	1,037E-06	,495	1	,482	-1,303E-06	2,763E-06
		,125	,236	,279	1	,597	-,338	,588
		-,445	,203	4,786	1	,029	-,843	-,046
		-,278	,227	1,501	1	,220	-,723	,167
		-,310	,229	1,840	1	,175	-,759	,138
		-,235	,220	1,141	1	,286	-,667	,197
		0[a]			0			
		-,300	,285	1,105	1	,293	-,859	,259
		,815	,171	22,599	1	,000	,479	1,151
		0[a]			0			
		-,276	,186	2,195	1	,138	-,640	,089
		0[a]			0			
		-,584	,151	14,889	1	,000	-,881	-,287
		0[a]			0			
		-,595	,135	19,353	1	,000	-,860	-,330
		0[a]			0			
		,651	,161	16,423	1	,000	,336	,967
		0[a]			0			

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	2398,393			
General	2222,291[b]	176,101[c]	63	,000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

PLUM - Ordinal Regression [redacted]

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2206,555			
Final	2079,206	127,348	21	,000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3636,906	3555	,166
Deviance	2079,206	3555	1,000

Link function: Logit.

Pseudo R-Square

Cox and Snell	,133
Nagelkerke	,145
McFadden	,058

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[redacted]	-,279	,514	,295	1	,587	-1,287	,729
		,484	,515	,886	1	,346	-,524	1,493
		1,277	,517	6,089	1	,014	,263	2,291
		2,182	,526	17,198	1	,000	1,151	3,214
Location		-,009	,009	,992	1	,319	-,026	,008
		-,002	,001	7,277	1	,007	-,003	,000
		-4,978E-05	1,692E-05	8,658	1	,003	-8,294E-05	-1,662E-05
		,000	,000	4,431	1	,035	2,934E-05	,001
		-,003	,002	1,222	1	,269	-,007	,002
		,004	,002	4,100	1	,043	,000	,008
		,086	,052	2,754	1	,097	-,016	,188
		,048	,037	1,692	1	,193	-,024	,119
		,004	,019	,041	1	,840	-,034	,042
		-2,940E-06	1,357E-06	4,691	1	,030	-5,600E-06	-2,796E-07
		,434	,245	3,136	1	,077	-,046	,915
		-,194	,218	,797	1	,372	-,621	,232
		-,316	,246	1,652	1	,199	-,798	,166
		-,296	,248	1,428	1	,232	-,781	,189
		-,214	,237	,815	1	,367	-,678	,250
		0[a]			0			
		-,750	,353	4,504	1	,034	-1,442	-,057
		,402	,179	5,062	1	,024	,052	,753
		0[a]			0			
		-,068	,206	,111	1	,739	-,472	,335
		0[a]			0			
		,672	,166	16,342	1	,000	,346	,999
		0[a]			0			
		,038	,143	,070	1	,792	-,242	,317
		0[a]			0			
		,318	,166	3,697	1	,055	-,006	,643
		0[a]			0			

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	2079,206			
General	1940,111[b]	139,096[c]	63	,000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

PLUM - Ordinal Regression [redacted]

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2242,047			
Final	2147,490	94,557	21	,000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3418,679	3555	,948
Deviance	2147,490	3555	1,000

Link function: Logit.

Pseudo R-Square

Cox and Snell	,100
Nagelkerke	,109
McFadden	,042

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[redacted]	-3,431	,534	41,249	1	,000	-4,478	-2,384
		-2,954	,529	31,164	1	,000	-3,991	-1,917
		-1,995	,523	14,542	1	,000	-3,020	-,970
		-,931	,520	3,208	1	,073	-1,949	,088
Location		-,013	,009	1,913	1	,167	-,030	,005
		-,001	,001	1,390	1	,238	-,002	,000
		3,720E-05	1,544E-05	5,810	1	,016	6,951E-06	6,746E-05
		,000	,000	2,817	1	,093	-5,653E-05	,001
		,000	,002	,026	1	,873	-,004	,005
		,000	,002	,040	1	,842	-,005	,004
		-,169	,051	11,136	1	,001	-,269	-,070
		-,117	,035	11,203	1	,001	-,186	-,049
		-,064	,019	11,618	1	,001	-,101	-,027
		1,650E-06	1,144E-06	2,079	1	,149	-5,928E-07	3,892E-06
		-,264	,246	1,152	1	,283	-,745	,218
		-,068	,212	,103	1	,749	-,483	,347
		-,044	,236	,034	1	,854	-,506	,419
		-,080	,239	,113	1	,737	-,548	,387
		,023	,231	,010	1	,922	-,430	,476
		0[a]			0			
		-,588	,282	4,339	1	,037	-1,141	-,035
		-,460	,174	6,988	1	,008	-,802	-,119
		0[a]			0			
		,606	,193	9,847	1	,002	,227	,984
		0[a]			0			
		,556	,153	13,140	1	,000	,255	,856
		0[a]			0			
		,102	,137	,558	1	,455	-,166	,370
		0[a]			0			
		-,236	,161	2,138	1	,144	-,552	,080
		0[a]			0			

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	2147,490			
General	1952,142[b]	195,349[c]	63	,000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

PLUM - Ordinal Regression - [redacted]

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2628,307			
Final	2387,880	240,427	21	,000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3612,206	3555	,247
Deviance	2387,880	3555	1,000

Link function: Logit.

Pseudo R-Square

Cox and Snell	,236
Nagelkerke	,249
McFadden	,091

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[redacted]	-2,023	,492	16,906	1	,000	-2,987	-1,059
		-1,652	,491	11,343	1	,001	-2,613	-,691
		-,863	,488	3,127	1	,077	-1,820	,094
		,036	,488	,005	1	,941	-,920	,992
Location		-,020	,008	5,731	1	,017	-,037	-,004
		-,001	,001	4,098	1	,043	-,002	-3,796E-05
		6,738E-05	1,251E-05	28,989	1	,000	4,285E-05	9,191E-05
		7,232E-05	,000	,141	1	,707	,000	,000
		-,007	,002	10,056	1	,002	-,011	-,003
		,004	,002	3,636	1	,057	,000	,008
		-,081	,052	2,380	1	,123	-,183	,022
		-,078	,038	4,326	1	,038	-,152	-,004
		,033	,019	3,073	1	,080	-,004	,069
		-2,131E-06	1,179E-06	3,269	1	,071	-4,441E-06	1,790E-07
		-,104	,242	,185	1	,667	-,578	,370
		,275	,204	1,816	1	,178	-,125	,675
		,139	,228	,374	1	,541	-,307	,585
		-,051	,231	,049	1	,824	-,504	,402
		,095	,222	,182	1	,670	-,341	,530
		0^a			0			
		1,410	,281	25,141	1	,000	,859	1,961
		,261	,173	2,269	1	,132	-,079	,600
		0^a			0			
		,033	,190	,030	1	,863	-,339	,404
		0^a			0			
		,375	,153	5,975	1	,015	,074	,675
		0^a			0			
		-,167	,133	1,570	1	,210	-,427	,094
		0^a			0			
		-,804	,156	26,477	1	,000	-1,110	-,498
		0^a			0			

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	2387,880			
General	2313,587[b]	74,293[c]	63	,156

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

PLUM - Ordinal Regression - [redacted]

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2722,204			
Final	2593,116	129,088	21	,000

Link function: Logit.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3520,054	3555	,658
Deviance	2593,116	3555	1,000

Link function: Logit.

Pseudo R-Square

Cox and Snell	,134
Nagelkerke	,141
McFadden	,047

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[redacted]	-2,095	,481	19,008	1	,000	-3,037	-1,153
		-1,736	,479	13,140	1	,000	-2,675	-,797
		-,857	,476	3,236	1	,072	-1,790	,077
		,170	,475	,128	1	,721	-,762	1,102
Location		-,028	,008	11,879	1	,001	-,045	-,012
		,000	,001	,046	1	,829	-,001	,001
		5,500E-05	1,284E-05	18,348	1	,000	2,984E-05	8,017E-05
		,000	,000	,333	1	,564	,000	,000
		,003	,002	2,957	1	,086	,000	,007
		,003	,002	1,480	1	,224	-,002	,007
		-,084	,050	2,844	1	,092	-,182	,014
		-,032	,034	,873	1	,350	-,098	,035
		,056	,018	9,471	1	,002	,020	,092
		-1,594E-06	1,025E-06	2,417	1	,120	-3,604E-06	4,157E-07
		-,329	,231	2,033	1	,154	-,782	,123
		,114	,196	,337	1	,561	-,271	,499
		,109	,219	,245	1	,620	-,321	,538
		-,062	,221	,080	1	,778	-,495	,370
		-,114	,214	,287	1	,592	-,533	,304
		0[a]			0			
		,578	,274	4,471	1	,034	,042	1,115
		,473	,169	7,808	1	,005	,141	,805
		0[a]			0			
		,307	,179	2,949	1	,086	-,043	,657
		0[a]			0			
		,187	,144	1,674	1	,196	-,096	,470
		0[a]			0			
		-,098	,128	,584	1	,445	-,348	,153
		0[a]			0			
		-,425	,152	7,825	1	,005	-,723	-,127
		0[a]			0			

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	2593,116			
General	2380,455[b]	212,661[c]	63	,000

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

XII. Appendix: Ordinal logistic regression results + conclusions

Estimating ordinal regression models has a drawback compared to linear regression models that the interpretability of the coefficients becomes harder. Reason for this is that the ordinal regression model is a logistic regression model. Therefore estimated coefficients in ordinal regression are logits (Hoetker, 2004, 2007). Another drawback is that the coefficients for different groups cannot be compared in most cases. Hoetker (2007) explains that comparability of coefficients is only possible when the unobserved variation in groups is equal. If this is not the case, 'differences in the estimated coefficients tell us nothing about the difference in the underlying impact of x between groups' (Allison, 1999). When different models are estimated (here a separate model for each channel), coefficients can be qualitatively compared at the level of being significant and the direction of the coefficients (Hoetker, 2007). A consequence for answering the hypotheses from the conceptual model is that quantitative/statistical conclusions can only be drawn at the level of individual. Therefore, the effects of the independent variables are statistically evaluated by H0: Coefficient of independent variable = 0 and H1: Coefficient of independent variable ≠ 0.

Table 25: Model information of ordinal regression models including unstandardized logit coefficients with: (sig. at 95% confidence interval;** sig. at 99% confidence interval)*

		Variable	Landline	Mobile	E-mail	Mobile app	Internet banking
Thresholds		Response category 1 (θ_1)	3,433**	-,279	-3,431**	-2,023**	-2,095**
		Response category 2 (θ_2)	3,982**	,484	-2,954**	-1,652**	-1,736**
		Response category 3(θ_3)	4,701**	1,277*	-1,995**	-,863	-,857
		Response category 4 (θ_4)	5,855**	2,182**	-,931	,036	,170
Parameters		Age	0,063**	-,009	-,013	-,020*	-,028**
		Duration relation	,001	-,002**	-,001	-,001*	1,23E-04
		Salary (x1000)	-0,004	-0.005	0.003*	0.007**	0.005**
		Transactions 12MND (x10)	0.003	0.004*	0.003	0.007	0.001
		Login internet banking 3MND	-,010**	-,003	0.003	-,007**	,003
		Login mobile app 3MND	-,006*	,004*	-0.004	,004	,003
		Office visits 12MND	,174**	,086	-,169**	-,081	-,084
		Inbound calls 12MND	,021	,048	-,117**	-,078*	-,032
		Number of products	,033	,004	-,064**	,033	,056**
		Average savings & investments 3MND (x1000)	0.000	-0.003*	0.002	-0.002	-0.002
	Ref = Complexity situation 6 (high)	Complexity situation 1 (low)	,125	,434	-,264	-,104	-,329
		Complexity situation 2 (low)	-,445*	-,194	-,068	,275	,114
		Complexity situation 3 (medium)	-,278	-,316	-,044	,139	,109
		Complexity situation 4 (medium)	-,310	-,296	-,080	-,051	-,062
		Complexity situation 5 (high)	-,235	-,214	,023	,095	-,114
	Ref= education (high) (high)	Education (low)	-,300	-,750*	-,588*	1,410**	,578*
		Education (medium)	.815**	,402*	-,460**	,261	,473**
		Segment (personal banking) (ref = prospect)	-,276	-,068	,606**	,033	,307
		Gender (male) (ref = female)	-,584**	,672**	,556**	,375*	,187
		Urbanity (high) (ref = low)	-,595**	,038	,102	-,167	-,098
		Possession mobile app (ref= possession of mobile	,651**	,318	-,236	-,804**	-,425**
Model information		Nagelkerke R-Squared	,219	,145	,109	,249	,141
		Model fitting information – Intercept only vs. Final model (Chi-Square) (df=21)	208,165**	127,348**	94,557**	240,427**	129,088**
		Goodness of Fit (Pearson Chi-Square) (df=3555)	3416,578	3636,906	3418,679	3612,206	3520,054

	Respecting assumption of Parallel Lines?	No	No	No	Yes	No

A remark for interpreting the coefficients in Table 25 is that they represent a constant change in odds and not a constant change in probabilities (Hoetker, 2007). For example: the coefficient for age (0,063 → odds exp(-0,063) = 0,939) in the landline model means that for each year in age the odds that someone is in a lower a category decrease with (1-0,939) 6,1% controlled for other variables. Figure 8 helps to understand the interpretation of 'the odds that someone is in a lower category.

Table 26: Hypotheses tests; green = confirmed, red = rejected at a 95% confidence level

Hypothesis	Landline	Mobile	E-mail	Mobile app	Internet banking
H1 (complexity)					
H2 (VoT)					
H3 (use of online channels)					
H4 (use of offline channels)					
H5 (active)					
H6 (loyal)					
H7 (age)					

Table 26 shows the conclusions about the hypotheses for all individual models. The conclusions per hypothesis are discussed below.

H1: Perceived contact complexity is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound communication.

Only one parameter of complexity was significant for channel preference. This was the case in the Landline model and concerned the (situation 2(low complexity)) compared to (situation 6 (high complexity)). It showed that in a low complex situation the odds of being in a lower response category was 56% higher compared to being in a higher response category, controlled for other variables. However, none of the other parameters were significant. For this reason, **H1 is rejected for all channels.**

H2: Value of time is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

The VoT hypothesis was accepted in all models except the model for landline. Table 25 shows that coefficient for salary was negative for the mobile phone communication channel and positive for offline communication channels. For this reason, **H2 is accepted** for the channels **mobile, e-mail, mobile app,** and **internet banking** and **H2 is rejected** for the channel **landline.**

H3: Inbound usage of online communication channels is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

All independent variables (*login internet banking, Login mobile app)* for this hypotheses were only significant and as expected in the landline model: logins to internet banking and the app increased the chance of disliking landline. For the channels mobile app and internet banking login to app was not significant and login to internet banking was only significant for the preference for the mobile app. However, the direction of this effect is opposite to the expected direction. A login to internet banking decreases the odds that a customer belongs to a lower response category (not liking the mobile app) by 0,7%. This was not expected according to the hypothesis. Consulting an expert answered this event: customers that use internet banking tend to use the mobile app less. Since only the results for the channel landline were significant and as expected **H3 is only accepted for the channel landline and rejected for the other channels.**

H4: Inbound usage of offline communication channels is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

The independent variables (*office visits* and *inbound calls)* for this hypotheses were only both significant in the e-mail model and decreased the odds of liking e-mail. In the landline communication channel, only office visits were significant. It decreased the odds of belonging to a lower response category (not liking landline) by 16% per visit. For the Mobile app communication channels only the inbound calls variable had a significant variable. It increased the odds of belonging to a lower response category (not liking mobile app) with 8,1% per visit. Based on the significance of the coefficients **H4 is accepted** for the channels **landline, e-mail,** and **mobile app, H4 is rejected** for the channels **mobile** and **internet banking.**

H5: Activity is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

The number of transactions was only significant in the mobile model. In this model it increased the odds of belonging to a higher response category (liking mobile) by 0,4% per transaction. This effect was opposite to what was expected. Combined with a lack of significant coefficients in the models for the other channels **H5 is rejected for all channels.**

H6: Loyalty is positively associated with the preference landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

The independent variable *duration of relation* was only significant and as expected in the mobile app model. **H6 is therefore accepted** for the **mobile app** channel and **H6 is rejected** for the channels **landline, mobile, e-mail,** and **internet banking.**

H7: Age is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound communication.

Age was found to be significant in the models for landline, Mobile app, and Internet banking. For the landline model it increased the odds of belonging to a higher response category (liking landline) by 6.1% per year, controlled for other variables. For the Mobile app it increased the odds of belonging to a lower response category (not liking the Mobile app) by 2% per year, controlled for other variables. This rate was even 2.8% per year for internet banking channel. Based on these results **H7 is accepted** for the channels **landline, mobile app,** and **internet banking** and **H7 is rejected** for the channels **mobile** and **e-mail.**

XIII. Appendix: Overview of Odds values for coefficients from ordinal regression

Table 27: Odds values of OLR models (sig. at 95% confidence interval;** sig. at 99% confidence interval)*

		Variable	Landline	Mobile	E-mail	Mobile app	Internet
Thresholds		Response category 1 (θ1)	0,032**	1,322	30,908**	7,561**	8,125**
Thresholds		Response category 2 (θ2)	0,019**	0,616	19,183**	5,217**	5,675**
Thresholds		Response category 3(θ3)	0,009**	0,279*	7,352**	2,370	2,356
Thresholds		Response category 4 (θ4)	0,003**	0,113**	2,537	0,965	0,844
Parameters		Age	0,939**	1,009	1,013	1,020*	1,028**
Parameters		Duration relation	0,999	1,002**	1,001	1,001*	1,000
Parameters		Salary (per 1000€)	1,003	1,049**	0,963*	0,933**	0,945**
Parameters		Transactions 12MND	0,997	0,996*	0,997	0,999	0,999
Parameters		Login internet banking 3MND	1,010**	1,003	1,000	1,007**	0,997
Parameters		Login mobile app 3MND	1,006**	0,996*	1,000	0,996	0,997
Parameters		Office visits 12MND	0,840**	0,918	1,184**	1,084	1,088
Parameters		Inbound calls 12MND	0,979	0,953	1,124**	1,081*	1,033
Parameters		Number of products	0,968	0,996	1,066**	0,968	0,946**
Parameters		Ave. savings & investments 3MND (per 1000€)	0,999	1,003*	0,998	1,002	1,002
Parameters	Ref = Complexity situation 6 (high)	Complexity situation 1 (low)	0,882	0,648	1,302	1,110	1,390
Parameters	Ref = Complexity situation 6 (high)	Complexity situation 2 (low)	1,560*	1,214	1,070	0,760	0,892
Parameters	Ref = Complexity situation 6 (high)	Complexity situation 3 (medium)	1,320	1,372	1,045	0,870	0,897
Parameters	Ref = Complexity situation 6 (high)	Complexity situation 4 (medium)	1,363	1,344	1,083	1,052	1,064
Parameters	Ref = Complexity situation 6 (high)	Complexity situation 5 (high)	1,265	1,239	0,977	0,909	1,121
Parameters	Ref= education (high)	Education (low)	1,350	2,117*	1,800*	0,244**	0,561*
Parameters	Ref= education (high)	Education (medium)	0,443**	0,669*	1,584**	0,770	0,623**
Parameters		Segment (personal banking) (ref = prospect)	1,318	1,070	0,546**	0,968	0,736
Parameters		Gender (male) (ref = female)	1,793**	0,511**	0,573**	0,687*	0,829
Parameters		Urbanity (high) (ref = low)	1,813**	0,963	0,903	1,182	1,103
Parameters		Possession mobile app (ref= possession of mobile	0,522**	0,728	1,266	2,234**	1,530**
Model information		Nagelkerke R-Squared	,219	,145	,109	,249	,141
Model information		Model fitting information – Intercept only vs. Final model (Chi-Square) (df=21)	208,165**	127,348**	94,557**	240,427**	129,088**
Model information		Goodness of Fit (Pearson Chi-Square) (df=3555)	3416,578	3636,906	3418,679	3612,206	3520,054
Model information		Respecting assumption of Parallel Lines?	No	No	No	Yes	No

XIV. Appendix: Calculations for goodness of fit tests of MLR models

Landline

In the training sample 44.1% scored a 1, 11.5% scored a 2, 13.9% scored a 3, 16.5% scored a 4 and 14.0% scored a 5. The PCC is therefore $0.441^2 + 0.115^2 + 0.139^2 + 0.165^2 + 0.140^2 = 0.27$. As can be seen in Table 28, the overall accuracy rate of the predictions for preference for landline was 49%. The accompanying z-value with this score is:

$$z = \frac{(Accuracy * \#cases) - (PCC * \#cases)}{\sqrt{(\frac{(PCC * \#cases) * \left(\#cases - (PCC * \#cases)\right)}{\#cases}}}$$

$$z = \frac{(0.49 * 895) - (0.27 * 895)}{\sqrt{(\frac{(0.27 * 895) * \left(895 - (0.27 * 895)\right)}{895}}}$$

$$z = 15.08$$

The accompanying p-value with z-value of 15.08 from a right sided z-table at a 95% confidence interval is 0.000. This is smaller than 0.05, therefore the **goodness of fit** of the multinomial logistic regression model for the preference of landline is regarded as **valid**.

Table 28: Classification table of Landline. 1=not preferred at all, 5=very much preferred.

Classification Landline

	Predicted					
Observed	1	2	3	4	5	Percent Correct
1	335	5	3	29	23	84,8%
2	80	5	2	9	7	4,9%
3	87	4	10	13	10	8,1%
4	80	0	1	45	22	30,4%
5	56	0	2	20	47	37,6%
Overall Percentage	71,3%	1,6%	2,0%	13,0%	12,2%	49,4%

Mobile

In the training sample 58.7% scored a 1, 14.7% scored a 2, 11.5% scored a 3, 8.0% scored a 4 and 6.9% scored a 5. The PCC is therefore $0.587^2 + 0.147^2 + 0.115^2 + 0.08^2 + 0.069^2 = 0.39$. As can be seen in Table 29, the overall accuracy rate of the predictions for preference for mobile was 60%. The accompanying z-value with this score is: 12.95. The accompanying p-value with z-value of 12.95 from a right sided z-table at a 95% confidence interval is 0.000. This is smaller than 0.05, therefore the **goodness of fit** of the multinomial logistic regression model for the preference of mobile is regarded as **valid**.

Table 29: Classification table of mobile. 1=not preferred at all, 5=very much preferred.

Classification Mobile

Observed	Predicted 1	2	3	4	5	Percent Correct
1	512	8	3	2	0	97,5%
2	116	10	2	5	0	7,5%
3	87	5	5	6	0	4,9%
4	56	1	2	12	1	16,7%
5	58	1	2	1	0	0,0%
Overall Percentage	92,6%	2,8%	1,6%	2,9%	0,1%	60,2%

E-mail

In the training sample 7.6% scored a 1, 3.9% scored a 2, 12.8% scored a 3, 21.9% scored a 4 and 53.7% scored a 5. The PCC is therefore $0.076^2 + 0.039^2 + 0.128^2 + 0.219^2 + 0.537^2 = 0.36$. As can be seen in Table 30, the overall accuracy rate of the predictions for preference for e-mail was 57%. The accompanying z-value with this score is: 7.76. The accompanying p-value with z-value of 7.76 from a right sided z-table at a 95% confidence interval is 0.000. This is smaller than 0.05, therefore the **goodness of fit** of the multinomial logistic regression model for the preference of e-mail is regarded as **valid**.

Table 30: Classification table of e-mail. 1=not preferred at all, 5=very much preferred.

Classification E-mail

Observed	Predicted 1	2	3	4	5	Percent Correct
1	9	1	3	10	45	13,2%
2	0	5	0	3	27	14,3%
3	0	1	2	10	102	1,7%
4	1	0	7	54	134	27,6%
5	0	1	5	37	438	91,1%
Overall Percentage	1,1%	0,9%	1,9%	12,7%	83,4%	56,8%

Mobile app

In the training sample 40.0% scored a 1, 7.7% scored a 2, 15.5% scored a 3, 14.6% scored a 4 and 22.1% scored a 5. The PCC is therefore $0.400^2 + 0.077^2 + 0.155^2 + 0.146^2 + 0.221^2 = 0.26$. As can be seen in Table 31, the overall accuracy rate of the predictions for preference for the mobile app was 53%. The accompanying z-value with this score is: 12.95. The accompanying p-value with z-value of 12.95 from a right sided z-table at a 95% confidence interval is 0.000. This is smaller than 0.05, therefore the **goodness of fit** of the multinomial logistic regression model for the preference of the mobile app is regarded as **valid**.

Table 31: Classification table of mobile app. 1=not preferred at all, 5=very much preferred.

Classification [redacted]

Observed	Predicted					
	1	2	3	4	5	Percent Correct
1	301	5	3	4	45	84,1%
2	43	15	2	0	9	21,7%
3	99	0	11	1	28	7,9%
4	72	1	3	14	41	10,7%
5	55	0	9	4	130	65,7%
Overall Percentage	63,7%	2,3%	3,1%	2,6%	28,3%	52,6%

Internet banking

In the training sample 22.9% scored a 1, 6.5% scored a 2, 18.5% scored a 3, 21.7% scored a 4 and 30.4% scored a 5. The PCC is therefore $0.229^2 + 0.065^2 + 0.185^2 + 0.217^2 + 0.304^2 = 0.23$. As can be seen in Table 32, the overall accuracy rate of the predictions for preference for internet banking was 43%. The accompanying z-value with this score is: 14.10. The accompanying p-value with z-value of 14.10 from a right sided z-table at a 95% confidence interval is 0.000. This is smaller than 0.05, therefore the **goodness of fit** of the multinomial logistic regression model for the preference of internet banking is regarded as **valid**.

Table 32: Classification table of Internet banking. 1=not preferred at all, 5=very much preferred.

Classification [redacted]

Observed	Predicted					
	1	2	3	4	5	Percent Correct
1	74	4	42	19	66	36,1%
2	7	19	9	7	16	32,8%
3	30	0	61	22	53	36,7%
4	39	6	16	53	80	27,3%
5	37	6	26	23	180	66,2%
Overall Percentage	20,9%	3,9%	17,2%	13,9%	44,1%	43,2%

XV. Appendix: SPSS output of multinomial logistic regression models

Nominal Regression - [redacted]

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2614,557	2633,745	2606,557			
Final	2424,791	2846,911	2248,791	357,766	84	,000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3373,108	3492	,924
Deviance	2248,791	3492	1,000

Pseudo R-Square

Cox and Snell	,330
Nagelkerke	,348
McFadden	,137

Likelihood Ratio Tests

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	2424,791	2846,911	2248,791[a]	0,000	0	
[redacted]	2481,621	2884,555	2313,621	64,830	4	,000
	2437,577	2840,510	2269,577	20,786	4	,000
	2429,115	2832,048	2261,115	12,324	4	,015
	2438,893	2841,826	2270,893	22,102	4	,000
	2441,993	2844,926	2273,993	25,202	4	,000
	2432,863	2835,796	2264,863	16,072	4	,003
	2437,647	2840,581	2269,647	20,856	4	,000
	2433,452	2836,385	2265,452	16,661	4	,002
	2431,017	2833,950	2263,017	14,226	4	,007
	2419,368	2822,301	2251,368	2,577	4	,631
	2405,534	2731,718	2269,534	20,743	20	,412
	2439,449	2823,195	2279,449	30,658	8	,000
	2423,312	2826,245	2255,312	6,521	4	,163
	2437,315	2840,248	2269,315	20,524	4	,000
	2438,403	2841,336	2270,403	21,612	4	,000
	2437,931	2840,864	2269,931	21,140	4	,000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

PR[redacted]		B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
								Lower Bound	Upper Bound
1	[redacted]	7.053	1.088	42.054	1	.000			
		-.095	.018	27.180	1	.000	.909	.877	.942
		-.002	.001	3.834	1	.050	.998	.996	1.000
		.000	.000	2.265	1	.132	1.000	1.000	1.000
		.001	.000	1.774	1	.183	1.001	1.000	1.001
		.013	.004	10.782	1	.001	1.013	1.005	1.021
		.028	.011	6.501	1	.011	1.028	1.006	1.051
		-.298	.101	8.754	1	.003	.742	.610	.904
		-.022	.069	.097	1	.756	.979	.855	1.121
		-.102	.034	9.280	1	.002	.903	.845	.964
		.000	.000	.016	1	.898	1.000	1.000	1.000
		-.019	.416	.002	1	.963	.981	.434	2.215
		.751	.359	4.383	1	.036	2.118	1.049	4.277
		.628	.411	2.331	1	.127	1.873	.837	4.192
		.662	.417	2.526	1	.112	1.939	.857	4.386
		.386	.386	.996	1	.318	1.471	.690	3.136
		0[b]			0				
		.951	.606	2.466	1	.116	2.589	.790	8.483
		-1.314	.310	17.969	1	.000	.269	.146	.493
		0[b]			0				
		.263	.334	.621	1	.431	1.301	.676	2.503
		0[b]			0				
		.935	.271	11.933	1	.001	2.548	1.499	4.333
		0[b]			0				
		1.129	.261	18.709	1	.000	3.094	1.855	5.161
		0[b]			0				
		-.604	.331	3.330	1	.068	.547	.286	1.046
		0[b]			0				
2		5.052	1.270	15.820	1	.000			
		-.111	.023	24.343	1	.000	.895	.856	.935
		.000	.002	.005	1	.942	1.000	.997	1.003
		.000	.000	3.604	1	.058	1.000	1.000	1.000
		.001	.000	7.772	1	.005	1.001	1.000	1.002
		.009	.005	3.367	1	.067	1.009	.999	1.019
		.018	.012	2.353	1	.125	1.018	.995	1.043
		.025	.105	.058	1	.810	1.026	.835	1.260
		-.291	.115	6.441	1	.011	.748	.597	.936
		-.095	.040	5.627	1	.018	.909	.839	.983
		.000	.000	.022	1	.883	1.000	1.000	1.000
		.243	.525	.215	1	.643	1.276	.455	3.572
		.823	.454	3.281	1	.070	2.278	.935	5.551
		.509	.523	.947	1	.331	1.664	.597	4.640
		.854	.509	2.811	1	.094	2.349	.866	6.374
		-.096	.521	.034	1	.855	.909	.327	2.524
		0[b]			0				
		.766	.747	1.049	1	.306	2.150	.497	9.303
		-.696	.374	3.461	1	.063	.499	.240	1.038
		0[b]			0				
		-.094	.418	.051	1	.822	.910	.401	2.065
		0[b]			0				
		1.436	.359	16.042	1	.000	4.205	2.082	8.492
		0[b]			0				
		.720	.321	5.028	1	.025	2.054	1.095	3.855
		0[b]			0				
		-.110	.390	.080	1	.778	.896	.417	1.922
		0[b]			0				
3		4.421	1.247	12.564	1	.000			
		-.071	.021	11.043	1	.001	.931	.893	.971
		.000	.001	.015	1	.904	1.000	.998	1.003
		.000	.000	4.893	1	.027	1.000	1.000	1.000
		.001	.000	3.264	1	.071	1.001	1.000	1.002
		.007	.005	2.284	1	.131	1.007	.998	1.016
		.027	.011	5.827	1	.016	1.027	1.005	1.050
		-.079	.108	.528	1	.467	.924	.748	1.143
		.087	.077	1.280	1	.258	1.091	.938	1.268
		-.152	.042	13.095	1	.000	.859	.791	.933
		.000	.000	.487	1	.485	1.000	1.000	1.000
		.069	.474	.021	1	.885	1.071	.423	2.715
		.294	.415	.502	1	.479	1.341	.595	3.023
		.449	.466	.931	1	.335	1.567	.629	3.902
		-.091	.508	.032	1	.858	.913	.337	2.474
		.089	.448	.039	1	.843	1.093	.455	2.627
		0[b]			0				
		1.220	.655	3.464	1	.063	3.386	.937	12.232
		-.214	.336	.405	1	.525	.807	.418	1.561
		0[b]			0				
		-.533	.383	1.938	1	.164	.587	.277	1.243
		0[b]			0				
		.432	.307	1.984	1	.159	1.541	.844	2.813
		0[b]			0				
		.828	.298	7.725	1	.005	2.288	1.276	4.100
		0[b]			0				
		-.263	.373	.499	1	.480	.768	.370	1.598
		0[b]			0				
4		.518	1.248	.172	1	.678			
		-.005	.020	.055	1	.815	.995	.957	1.035
		-.004	.001	11.227	1	.001	.996	.994	.998
		.000	.000	6.117	1	.013	1.000	1.000	1.000
		.002	.000	14.585	1	.000	1.002	1.001	1.003
		-.003	.005	.350	1	.554	.997	.987	1.007
		.023	.011	4.362	1	.037	1.024	1.001	1.046
		.030	.091	.104	1	.747	1.030	.861	1.232
		.009	.075	.014	1	.905	1.009	.871	1.169
		-.081	.039	4.266	1	.039	.923	.855	.996
		.000	.000	1.398	1	.237	1.000	1.000	1.000
		.433	.446	.945	1	.331	1.542	.644	3.693
		.246	.410	.361	1	.548	1.279	.573	2.856
		.368	.463	.631	1	.427	1.445	.583	3.579
		.597	.461	1.676	1	.195	1.816	.736	4.480
		.274	.434	.399	1	.528	1.315	.562	3.078
		0[b]			0				
		.507	.692	.537	1	.464	1.661	.427	6.452
		-.808	.340	5.642	1	.018	.446	.229	.868
		0[b]			0				
		-.152	.368	.170	1	.680	.859	.418	1.766
		0[b]			0				
		.668	.303	4.856	1	.028	1.950	1.077	3.532
		0[b]			0				
		.597	.295	4.095	1	.043	1.816	1.019	3.238
		0[b]			0				
		.607	.374	2.645	1	.104	1.836	.883	3.817
		0[b]			0				

a. T[redacted]

b. This parameter is set to zero because it is redundant.

Nominal Regression - [redacted]

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2214,555	2233,742	2206,555			
Final	2157,165	2560,098	1989,165	217,390	80	,000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3662,363	3496	,025
Deviance	1989,165	3496	1,000

Pseudo R-Square

Cox and Snell	,216
Nagelkerke	,236
McFadden	,099

Likelihood Ratio Tests

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	2157,165	2560,098	1989,165[a]	0,000	0	
[redacted]	2154,507	2538,253	1994,507	5,342	4	,254
	2164,515	2548,261	2004,515	15,350	4	,004
	2164,622	2548,368	2004,622	15,457	4	,004
	2164,232	2547,978	2004,232	15,067	4	,005
	2159,144	2542,890	1999,144	9,979	4	,041
	2161,607	2545,353	2001,607	12,442	4	,014
	2159,545	2543,290	1999,545	10,380	4	,034
	2155,892	2539,638	1995,892	6,727	4	,151
	2153,321	2537,067	1993,321	4,156	4	,385
	2162,386	2546,132	2002,386	13,221	4	,010
	2147,827	2454,824	2019,827	30,662	20	,060
	2151,714	2535,460	1991,714	2,549	4	,636
	2158,136	2541,882	1998,136	8,971	4	,062
	2170,631	2554,377	2010,631	21,466	4	,000
	2149,436	2533,182	1989,436	,271	4	,992
	2156,516	2540,262	1996,516	7,351	4	,118

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Parameter Estimates

[redacted]

B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
.519	1.091	.226	1	.634			
.017	.018	.949	1	.330	1.018	.983	1.054
.002	.001	2.820	1	.093	1.002	1.000	1.005
.000	.000	2.698	1	.100	1.000	1.000	1.000
.000	.000	.199	1	.656	1.000	.999	1.001
-.004	.004	.688	1	.407	.996	.988	1.005
-.001	.007	.017	1	.895	.999	.986	1.012
.061	.129	.220	1	.639	1.063	.824	1.370
.041	.078	.272	1	.602	1.041	.894	1.212
-.064	.037	3.058	1	.080	.938	.873	1.008
.000	.000	4.470	1	.034	1.000	1.000	1.000
-.042	.480	.008	1	.930	.959	.374	2.454
.476	.405	1.388	1	.239	1.610	.728	3.560
1.655	.665	6.195	1	.013	5.234	1.422	19.272
.779	.503	2.399	1	.121	2.179	.813	5.841
.319	.430	.551	1	.458	1.376	.592	3.200
0a			0				
.461	.319	2.089	1	.148	1.586	.849	2.962
0a			0				
-.372	.452	.677	1	.411	.690	.285	1.671
0a			0				
-1.002	.368	7.390	1	.007	.367	.178	.756
0a			0				
-.070	.291	.058	1	.810	.932	.527	1.649
0a			0				
-.624	.348	3.218	1	.073	.536	.271	1.060
0a			0				
.300	1.244	.058	1	.810			
-.011	.021	.265	1	.607	.989	.950	1.030
.002	.001	1.874	1	.171	1.002	.999	1.005
.000	.000	.714	1	.398	1.000	1.000	1.000
.000	.000	.135	1	.714	1.000	.999	1.001
-.014	.005	6.284	1	.012	.987	.976	.997
.002	.007	.096	1	.757	1.002	.988	1.016
.261	.135	3.753	1	.053	1.298	.997	1.691
.031	.093	.109	1	.741	1.031	.860	1.237
-.044	.041	1.142	1	.285	.957	.882	1.038
.000	.000	5.090	1	.024	1.000	1.000	1.000
.868	.546	2.530	1	.112	2.382	.817	6.939
.420	.490	.735	1	.391	1.522	.582	3.979
1.884	.720	6.839	1	.009	6.578	1.603	26.990
.863	.580	2.209	1	.137	2.370	.760	7.391
.388	.514	.570	1	.450	1.474	.538	4.039
0a			0				
.380	.369	1.058	1	.304	1.462	.709	3.013
0a			0				
-1.147	.505	5.161	1	.023	.318	.118	.854
0a			0				
-.095	.421	.051	1	.822	.909	.398	2.077
0a			0				
-.097	.332	.085	1	.771	.908	.473	1.742
0a			0				
-.272	.394	.477	1	.490	.762	.352	1.649
0a			0				
-.343	1.310	.069	1	.793			
.021	.021	1.005	1	.316	1.021	.980	1.064
-.001	.001	.130	1	.718	.999	.997	1.002
.000	.000	1.065	1	.302	1.000	1.000	1.000
.000	.000	.350	1	.554	1.000	.999	1.001
-.005	.005	1.013	1	.314	.995	.984	1.005
.007	.007	1.034	1	.309	1.007	.994	1.020
.081	.146	.307	1	.580	1.084	.814	1.444
.157	.086	3.324	1	.068	1.170	.988	1.386
-.078	.045	3.017	1	.082	.925	.846	1.010
.000	.000	.001	1	.971	1.000	1.000	1.000
.811	.559	2.107	1	.147	2.250	.753	6.723
.568	.497	1.307	1	.253	1.764	.667	4.670
1.458	.745	3.827	1	.050	4.298	.997	18.525
.596	.609	.957	1	.328	1.815	.550	5.993
-.072	.554	.017	1	.896	.930	.314	2.755
0a			0				
.214	.380	.317	1	.574	1.238	.588	2.609
0a			0				
-.295	.552	.285	1	.593	.745	.252	2.197
0a			0				
-.305	.436	.490	1	.484	.737	.314	1.732
0a			0				
-.149	.348	.185	1	.667	.861	.436	1.703
0a			0				
-.647	.403	2.570	1	.109	.524	.237	1.155
0a			0				
-1.512	1.432	1.115	1	.291			
.014	.022	.385	1	.535	1.014	.970	1.060
-.001	.002	.664	1	.415	.999	.996	1.002
.000	.000	.102	1	.749	1.000	1.000	1.000
.001	.001	5.750	1	.016	1.001	1.000	1.002
-.009	.006	2.217	1	.136	.991	.979	1.003
.010	.007	2.258	1	.133	1.010	.997	1.023
.228	.145	2.453	1	.117	1.256	.944	1.669
.134	.093	2.060	1	.151	1.143	.952	1.372
-.082	.050	2.694	1	.101	.922	.836	1.016
.000	.000	2.211	1	.137	1.000	1.000	1.000
.838	.607	1.904	1	.168	2.311	.703	7.597
.138	.567	.059	1	.807	1.148	.378	3.486
1.722	.772	4.971	1	.026	5.594	1.231	25.412
.669	.655	1.043	1	.307	1.953	.541	7.057
.085	.598	.020	1	.887	1.088	.337	3.514
0a			0				
.441	.436	1.023	1	.312	1.555	.661	3.656
0a			0				
-.261	.590	.196	1	.658	.770	.242	2.448
0a			0				
-.564	.462	1.490	1	.222	.569	.230	1.407
0a			0				
-.009	.388	.000	1	.982	.991	.463	2.122
0a			0				
.000	.448	.000	1	1.000	1.000	.416	2.407
0a			0				

a. [redacted]

Nominal Regression [redacted]

Model Fitting Information

Model	Model Fitting Criteria AIC	BIC	-2 Log Likelihood	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept Only	2250,047	2269,235	2242,047			
Final	2136,115	2558,235	1960,115	281,933	84	,000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3756,007	3492	,001
Deviance	1960,115	3492	1,000

Pseudo R-Square

Cox and Snell	,270
Nagelkerke	,294
McFadden	,126

Likelihood Ratio Tests

Effect	Model Fitting Criteria AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Likelihood Ratio Tests Chi-Square	df	Sig.
Intercept	2136,115	2558,235	1960,115[a]	0,000	0	
[redacted]	2145,449	2548,382	1977,449	17,334	4	,002
	2136,526	2539,459	1968,526	8,411	4	,078
	2150,559	2553,492	1982,559	22,444	4	,000
	2145,289	2548,222	1977,289	17,174	4	,002
	2138,729	2541,662	1970,729	10,615	4	,031
	2144,551	2547,484	1976,551	16,436	4	,002
	2141,584	2544,517	1973,584	13,469	4	,009
	2154,491	2557,424	1986,491	26,376	4	,000
	2148,991	2551,924	1980,991	20,876	4	,000
	2131,104	2534,037	1963,104	2,989	4	,560
	2109,852	2436,036	1973,852	13,737	20	,844
	2157,699	2541,445	1997,699	37,585	8	,000
	2143,638	2546,572	1975,638	15,524	4	,004
	2162,274	2565,208	1994,274	34,160	4	,000
	2147,299	2550,233	1979,299	19,185	4	,001
	2134,957	2537,890	1966,957	6,843	4	,144

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Parameter Estimates

[redacted]

B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
-4.509	1.246	13.086	1	.000			
.055	.021	6.757	1	.009	1.057	1.014	1.101
-.001	.001	.191	1	.662	.999	.997	1.002
.000	.000	.040	1	.842	1.000	1.000	1.000
-.001	.000	2.636	1	.104	.999	.998	1.000
.001	.005	.014	1	.906	1.001	.991	1.010
-.037	.016	5.526	1	.019	.964	.935	.994
.254	.102	6.175	1	.013	1.290	1.055	1.576
.064	.088	.535	1	.465	1.066	.898	1.266
.150	.036	17.312	1	.000	1.162	1.083	1.247
.000	.000	.376	1	.540	1.000	1.000	1.000
.207	.549	.143	1	.705	1.231	.420	3.606
.336	.455	.545	1	.460	1.399	.573	3.415
.424	.491	.747	1	.387	1.528	.584	3.999
.213	.517	.170	1	.680	1.237	.449	3.406
-.146	.525	.077	1	.781	.864	.309	2.417
0a			0				
1.343	.559	5.774	1	.016	3.831	1.281	11.458
1.045	.341	9.399	1	.002	2.842	1.458	5.543
0a			0				
-1.104	.414	7.097	1	.008	.331	.147	.747
0a			0				
-1.375	.322	18.243	1	.000	.253	.135	.475
0a			0				
-.582	.320	3.313	1	.069	.559	.298	1.046
0a			0				
-.183	.379	.232	1	.630	.833	.397	1.750
0a			0				
-1.803	1.709	1.113	1	.292			
-.042	.038	1.264	1	.261	.959	.890	1.032
.007	.003	4.953	1	.026	1.007	1.001	1.013
.000	.000	2.824	1	.093	1.000	1.000	1.000
-.001	.001	3.589	1	.058	.999	.997	1.000
.011	.005	5.053	1	.025	1.011	1.001	1.020
.010	.006	3.191	1	.074	1.010	.999	1.022
.133	.146	.823	1	.364	1.142	.857	1.521
.304	.093	10.756	1	.001	1.355	1.130	1.626
.038	.064	.360	1	.549	1.039	.917	1.178
.000	.000	.251	1	.616	1.000	1.000	1.000
.454	.781	.338	1	.561	1.574	.341	7.272
.589	.646	.832	1	.362	1.802	.508	6.390
-.018	.763	.001	1	.981	.982	.220	4.377
.240	.730	.108	1	.742	1.271	.304	5.311
.569	.673	.715	1	.398	1.767	.472	6.612
0a			0				
.861	.651	1.752	1	.186	2.365	.661	8.465
-1.629	1.058	2.371	1	.124	.196	.025	1.560
0a			0				
-1.903	.649	8.591	1	.003	.149	.042	.532
0a			0				
-.673	.478	1.979	1	.160	.510	.200	1.303
0a			0				
-.940	.445	4.469	1	.035	.390	.163	.934
0a			0				
.760	.505	2.265	1	.132	2.138	.795	5.751
0a			0				
-3.865	.928	17.350	1	.000			
.038	.016	5.799	1	.016	1.039	1.007	1.071
.001	.001	1.293	1	.255	1.001	.999	1.003
.000	.000	1.204	1	.272	1.000	1.000	1.000
.000	.000	.544	1	.461	1.000	.999	1.000
-.008	.004	3.812	1	.051	.992	.984	1.000
.001	.004	.054	1	.816	1.001	.993	1.009
.129	.093	1.929	1	.165	1.137	.949	1.363
.180	.062	8.560	1	.003	1.197	1.061	1.351
.078	.032	5.714	1	.017	1.081	1.014	1.151
.000	.000	1.049	1	.306	1.000	1.000	1.000
-.161	.404	.158	1	.691	.852	.386	1.881
-.207	.326	.403	1	.525	.813	.429	1.540
-.435	.390	1.243	1	.265	.647	.301	1.391
-.050	.370	.018	1	.893	.951	.460	1.966
-.351	.371	.894	1	.345	.704	.340	1.457
0a			0				
.644	.432	2.219	1	.136	1.903	.816	4.439
.871	.266	10.731	1	.001	2.390	1.419	4.025
0a			0				
-.398	.313	1.609	1	.205	.672	.364	1.242
0a			0				
-.852	.253	11.359	1	.001	.427	.260	.700
0a			0				
.020	.227	.008	1	.929	1.020	.654	1.593
0a			0				
.347	.279	1.546	1	.214	1.414	.819	2.443
0a			0				
-1.587	.681	5.426	1	.020			
-.015	.012	1.463	1	.226	.985	.962	1.009
.001	.001	.872	1	.350	1.001	.999	1.003
.000	.000	8.500	1	.004	1.000	1.000	1.000
.001	.000	6.695	1	.010	1.001	1.000	1.001
-.001	.003	.132	1	.716	.999	.993	1.005
.005	.003	3.126	1	.077	1.005	1.000	1.010
.227	.071	10.362	1	.001	1.255	1.093	1.441
.206	.049	17.615	1	.000	1.229	1.116	1.353
-.001	.027	.001	1	.977	.999	.948	1.053
.000	.000	2.006	1	.157	1.000	1.000	1.000
.795	.339	5.509	1	.019	2.215	1.140	4.302
.137	.310	.195	1	.658	1.147	.624	2.107
.303	.333	.828	1	.363	1.354	.705	2.603
.225	.342	.435	1	.509	1.253	.641	2.447
.248	.327	.578	1	.447	1.282	.676	2.433
0a			0				
-.736	.500	2.165	1	.141	.479	.180	1.277
-.363	.272	1.786	1	.181	.695	.408	1.185
0a			0				
-.154	.282	.299	1	.584	.857	.494	1.489
0a			0				
.323	.226	2.038	1	.153	1.381	.886	2.153
0a			0				
.519	.191	7.386	1	.007	1.680	1.156	2.442
0a			0				
.417	.218	3.663	1	.056	1.518	.990	2.328
0a			0				

Nominal Regression - [redacted]

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2636,307	2655,494	2628,307			
Final	2379,616	2782,549	2211,616	416,691	80	,000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	4794,412	3496	,000
Deviance	2211,616	3496	1,000

Pseudo R-Square

Coxand Snell	,372
Nagelkerke	,393
McFadden	,159

Likelihood Ratio Tests

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	2379,616	2782,549	2211,616[a]	0,000	0	
[redacted]	2391,034	2774,780	2231,034	19,419	4	,001
	2377,217	2760,963	2217,217	5,602	4	,231
	2412,388	2796,134	2252,388	40,772	4	,000
	2377,484	2761,230	2217,484	5,869	4	,209
	2417,330	2801,076	2257,330	45,715	4	,000
	2400,812	2784,558	2240,812	29,196	4	,000
	2378,195	2761,941	2218,195	6,579	4	,160
	2382,838	2766,583	2222,838	11,222	4	,024
	2378,494	2762,240	2218,494	6,878	4	,142
	2386,365	2770,111	2226,365	14,749	4	,005
	2355,891	2662,888	2227,891	16,276	20	,699
	2398,171	2781,917	2238,171	26,556	4	,000
	2382,601	2766,347	2222,601	10,985	4	,027
	2386,948	2770,694	2226,948	15,332	4	,004
	2389,555	2773,301	2229,555	17,940	4	,001
	2397,791	2781,537	2237,791	26,175	4	,000

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Parameter Estimates

[redacted]	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
	-2.413	.845	8.160	1	.004			
	.036	.013	6.965	1	.008	1.036	1.009	1.064
	.001	.001	.901	1	.342	1.001	.999	1.003
	.000	.000	20.828	1	.000	1.000	1.000	1.000
	.000	.000	.211	1	.646	1.000	.999	1.000
	.022	.005	19.660	1	.000	1.023	1.013	1.033
	-.010	.005	3.957	1	.047	.990	.979	1.000
	.175	.097	3.230	1	.072	1.191	.984	1.441
	.131	.069	3.576	1	.059	1.140	.995	1.307
	-.044	.030	2.200	1	.138	.957	.902	1.014
	.000	.000	3.311	1	.069	1.000	1.000	1.000
	.187	.400	.218	1	.641	1.205	.550	2.641
	-.556	.326	2.902	1	.088	.574	.303	1.087
	-.205	.372	.304	1	.582	.815	.393	1.689
	.044	.376	.014	1	.906	1.045	.500	2.184
	-.155	.358	.187	1	.665	.856	.424	1.729
	0[a]			0				
	.968	.246	15.476	1	.000	2.633	1.625	4.264
	0[a]			0				
	-.321	.331	.942	1	.332	.725	.379	1.388
	0[a]			0				
	-.631	.255	6.110	1	.013	.532	.323	.877
	0[a]			0				
	.196	.220	.793	1	.373	1.216	.790	1.871
	0[a]			0				
	1.307	.268	23.755	1	.000	3.695	2.185	6.250
	0[a]			0				
	-3.156	1.347	5.489	1	.019			
	-.035	.023	2.402	1	.121	.965	.923	1.009
	.002	.002	.762	1	.383	1.002	.998	1.005
	.000	.000	5.233	1	.022	1.000	1.000	1.000
	.000	.000	.069	1	.793	1.000	.999	1.001
	.036	.006	37.766	1	.000	1.036	1.025	1.048
	-.037	.016	5.474	1	.019	.964	.935	.994
	.302	.131	5.322	1	.021	1.353	1.047	1.749
	.058	.094	.385	1	.535	1.060	.882	1.274
	-.038	.046	.683	1	.408	.963	.881	1.053
	.000	.000	9.492	1	.002	1.000	1.000	1.000
	.769	.625	1.517	1	.218	2.158	.635	7.340
	-.084	.558	.023	1	.880	.919	.308	2.741
	.451	.589	.586	1	.444	1.570	.495	4.979
	.418	.598	.489	1	.484	1.519	.470	4.908
	.244	.587	.172	1	.678	1.276	.404	4.034
	0[a]			0				
	2.150	.581	13.714	1	.000	8.582	2.751	26.775
	0[a]			0				
	-1.041	.496	4.402	1	.036	.353	.134	.934
	0[a]			0				
	-.091	.381	.057	1	.812	.913	.432	1.929
	0[a]			0				
	1.144	.353	10.504	1	.001	3.141	1.572	6.275
	0[a]			0				
	.802	.402	3.981	1	.046	2.230	1.014	4.904
	0[a]			0				
	-2.626	1.037	6.413	1	.011			
	.020	.018	1.291	1	.256	1.020	.986	1.056
	.003	.001	4.975	1	.026	1.003	1.000	1.005
	.000	.000	9.247	1	.002	1.000	1.000	1.000
	.000	.000	1.181	1	.277	1.000	1.000	1.001
	.019	.005	12.196	1	.000	1.019	1.008	1.030
	-.013	.007	3.194	1	.074	.987	.974	1.001
	.181	.111	2.643	1	.104	1.198	.963	1.490
	.178	.077	5.359	1	.021	1.195	1.028	1.390
	-.094	.037	6.491	1	.011	.910	.846	.978
	.000	.000	.430	1	.512	1.000	1.000	1.000
	.571	.455	1.579	1	.209	1.770	.726	4.316
	-.403	.388	1.079	1	.299	.668	.313	1.429
	-.188	.440	.182	1	.670	.829	.350	1.962
	-.021	.443	.002	1	.962	.979	.411	2.333
	-.383	.436	.771	1	.380	.682	.290	1.603
	0[a]			0				
	.929	.303	9.409	1	.002	2.531	1.398	4.581
	0[a]			0				
	-.682	.393	3.006	1	.083	.506	.234	1.093
	0[a]			0				
	-.748	.291	6.599	1	.010	.473	.267	.838
	0[a]			0				
	-.280	.265	1.118	1	.290	.756	.450	1.270
	0[a]			0				
	1.136	.313	13.135	1	.000	3.114	1.685	5.756
	0[a]			0				
	-1.589	.938	2.869	1	.090			
	-.008	.015	.301	1	.583	.992	.963	1.021
	.001	.001	.336	1	.562	1.001	.999	1.003
	.000	.000	9.166	1	.002	1.000	1.000	1.000
	.001	.000	2.414	1	.120	1.001	1.000	1.001
	.019	.006	11.992	1	.001	1.019	1.008	1.031
	.006	.003	4.557	1	.033	1.006	1.001	1.012
	.194	.105	3.382	1	.066	1.214	.987	1.492
	-.031	.084	.137	1	.711	.969	.821	1.144
	-.034	.033	1.038	1	.308	.967	.906	1.032
	.000	.000	.248	1	.619	1.000	1.000	1.000
	-.087	.480	.033	1	.857	.917	.358	2.348
	-.272	.383	.503	1	.478	.762	.360	1.614
	.214	.418	.261	1	.609	1.238	.546	2.811
	-.118	.453	.069	1	.794	.888	.366	2.157
	.176	.407	.188	1	.664	1.193	.537	2.648
	0[a]			0				
	.533	.276	3.726	1	.054	1.703	.992	2.925
	0[a]			0				
	.314	.386	.663	1	.416	1.369	.643	2.914
	0[a]			0				
	.160	.310	.268	1	.605	1.174	.640	2.155
	0[a]			0				
	.018	.257	.005	1	.945	1.018	.615	1.684
	0[a]			0				
	.954	.295	10.457	1	.001	2.595	1.456	4.626
	0[a]			0				

Nominal Regression - [redacted]

Model Fitting Information

Model	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC	BIC	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	2730,204	2749,391	2722,204			
Final	2565,770	2987,891	2389,770	332,433	84	,000

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	3769,568	3492	,001
Deviance	2389,770	3492	1,000

Pseudo R-Square

Cox and Snell	,310
Nagelkerke	,326
McFadden	,122

Likelihood Ratio Tests

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	2565,770	2987,891	2389,770[a]	0,000	0	
[redacted]	2582,074	2985,007	2414,074	24,304	4	,000
	2569,765	2972,698	2401,765	11,995	4	,017
	2586,919	2989,852	2418,919	29,148	4	,000
	2562,570	2965,503	2394,570	4,799	4	,309
	2598,470	3001,403	2430,470	40,700	4	,000
	2571,450	2974,383	2403,450	13,680	4	,008
	2569,743	2972,677	2401,743	11,973	4	,018
	2582,867	2985,800	2414,867	25,096	4	,000
	2572,454	2975,387	2404,454	14,683	4	,005
	2572,460	2975,393	2404,460	14,690	4	,005
	2538,715	2864,899	2402,715	12,945	20	,880
	2588,991	2972,737	2428,991	39,221	8	,000
	2565,536	2968,470	2397,536	7,766	4	,101
	2567,152	2970,085	2399,152	9,382	4	,052
	2564,828	2967,761	2396,828	7,058	4	,133
	2570,462	2973,396	2402,462	12,692	4	,013

The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

a. This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.

Parameter Estimates

[redacted]

	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B) Lower Bound	Upper Bound
1	-1.231	.781	2.488	1	.115			
	.046	.013	12.193	1	.000	1.047	1.021	1.075
	.000	.001	.009	1	.925	1.000	.998	1.002
	.000	.000	11.856	1	.001	1.000	1.000	1.000
	.000	.000	.373	1	.542	1.000	.999	1.000
	-.007	.004	3.896	1	.048	.993	.986	1.000
	-.011	.006	3.096	1	.078	.989	.978	1.001
	.077	.087	.788	1	.375	1.080	.911	1.282
	.136	.068	4.003	1	.045	1.145	1.003	1.308
	-.106	.033	10.563	1	.001	.899	.844	.959
	.000	.000	.975	1	.323	1.000	1.000	1.000
	.437	.380	1.324	1	.250	1.548	.735	3.260
	-.245	.309	.627	1	.429	.783	.427	1.435
	-.341	.357	.911	1	.340	.711	.354	1.431
	.002	.353	.000	1	.995	1.002	.502	2.002
	.077	.340	.051	1	.821	1.080	.555	2.102
	0[b]			0				
	-.642	.390	2.710	1	.100	.526	.245	1.130
	-.598	.268	4.977	1	.026	.550	.325	.930
	0[b]			0				
	-.266	.291	.836	1	.361	.766	.433	1.356
	0[b]			0				
	-.309	.235	1.730	1	.188	.734	.463	1.164
	0[b]			0				
	.272	.210	1.670	1	.196	1.312	.869	1.982
	0[b]			0				
	.214	.261	.673	1	.412	1.238	.743	2.064
	0[b]			0				
2	-3.709	1.326	7.818	1	.005			
	-.007	.025	.085	1	.770	.993	.946	1.042
	.002	.002	.842	1	.359	1.002	.998	1.005
	.000	.000	1.686	1	.194	1.000	1.000	1.000
	.000	.000	.001	1	.971	1.000	.999	1.001
	.014	.004	11.199	1	.001	1.015	1.006	1.023
	-.032	.021	2.258	1	.133	.968	.928	1.010
	.402	.118	11.723	1	.001	1.495	1.188	1.883
	-.038	.105	.133	1	.715	.962	.783	1.183
	.035	.045	.624	1	.429	1.036	.949	1.131
	.000	.000	3.904	1	.048	1.000	1.000	1.000
	1.067	.665	2.571	1	.109	2.906	.789	10.707
	.220	.608	.131	1	.717	1.246	.379	4.104
	.631	.630	1.005	1	.316	1.880	.547	6.458
	.671	.631	1.129	1	.288	1.956	.567	6.744
	1.024	.603	2.882	1	.090	2.784	.854	9.077
	0[b]			0				
	-2.182	1.133	3.712	1	.054	.113	.012	1.038
	-1.245	.544	5.242	1	.022	.288	.099	.836
	0[b]			0				
	-1.074	.473	5.149	1	.023	.342	.135	.864
	0[b]			0				
	-.274	.366	.560	1	.454	.761	.371	1.558
	0[b]			0				
	.898	.352	6.521	1	.011	2.455	1.232	4.890
	0[b]			0				
	1.242	.474	6.876	1	.009	3.462	1.368	8.759
	0[b]			0				
3	-2.556	.846	9.125	1	.003			
	.034	.015	4.906	1	.027	1.034	1.004	1.066
	.003	.001	6.479	1	.011	1.003	1.001	1.005
	.000	.000	10.695	1	.001	1.000	1.000	1.000
	.000	.000	.398	1	.528	1.000	.999	1.000
	-.011	.004	7.189	1	.007	.989	.981	.997
	-.008	.006	1.925	1	.165	.992	.982	1.003
	.182	.090	4.063	1	.044	1.200	1.005	1.432
	.207	.069	9.113	1	.003	1.230	1.075	1.407
	-.031	.032	.950	1	.330	.970	.912	1.032
	.000	.000	3.703	1	.054	1.000	1.000	1.000
	.603	.402	2.250	1	.134	1.828	.831	4.019
	-.152	.339	.200	1	.655	.859	.442	1.671
	.080	.373	.046	1	.830	1.083	.521	2.251
	.162	.380	.182	1	.670	1.176	.558	2.479
	-.082	.381	.046	1	.830	.921	.436	1.945
	0[b]			0				
	-3.025	.778	15.105	1	.000	.049	.011	.223
	-.961	.304	9.984	1	.002	.382	.211	.694
	0[b]			0				
	.094	.322	.085	1	.770	1.099	.584	2.067
	0[b]			0				
	-.284	.250	1.292	1	.256	.753	.461	1.229
	0[b]			0				
	.208	.226	.844	1	.358	1.231	.790	1.919
	0[b]			0				
	.741	.274	7.308	1	.007	2.097	1.226	3.589
	0[b]			0				
4	-.949	.741	1.640	1	.200			
	-.015	.014	1.232	1	.267	.985	.959	1.012
	.002	.001	4.150	1	.042	1.002	1.000	1.004
	.000	.000	7.939	1	.005	1.000	1.000	1.000
	.000	.000	2.289	1	.130	1.000	1.000	1.001
	.005	.003	2.147	1	.143	1.005	.998	1.011
	.003	.003	1.156	1	.282	1.003	.998	1.008
	.091	.089	1.066	1	.302	1.096	.921	1.304
	.241	.061	15.380	1	.000	1.272	1.128	1.435
	-.048	.028	2.937	1	.087	.953	.902	1.007
	.000	.000	.436	1	.509	1.000	1.000	1.000
	.402	.385	1.092	1	.296	1.495	.703	3.178
	-.017	.316	.003	1	.956	.983	.529	1.825
	.017	.350	.002	1	.962	1.017	.512	2.021
	.064	.362	.031	1	.860	1.066	.525	2.166
	.199	.343	.337	1	.562	1.220	.623	2.389
	0[b]			0				
	-.622	.418	2.213	1	.137	.537	.237	1.218
	-.463	.265	3.050	1	.081	.629	.374	1.058
	0[b]			0				
	.129	.298	.187	1	.666	1.138	.634	2.042
	0[b]			0				
	.386	.252	2.348	1	.125	1.471	.898	2.411
	0[b]			0				
	.221	.207	1.137	1	.286	1.247	.831	1.872
	0[b]			0				
	.382	.237	2.589	1	.108	1.465	.920	2.334
	0[b]			0				

a. The reference category is: 5.

b. This parameter is set to zero because it is redundant.

XVI. Appendix: Calculations for validation tests of MLR models

Mobile app

In the training sample 40.0% scored a 1, 7.7% scored a 2, 15.5% scored a 3, 14.6% scored a 4 and 22.1% scored a 5. The PCC is therefore $0.400^2 + 0.077^2 + 0.155^2 + 0.146^2 + 0.221^2 = 0.26$. As can be seen in Table 33 the overall accuracy rate of the predictions for preference of mobile app was 33%. The accompanying z-value with this score is:

$$z = \frac{(Accuracy * \#cases) - (PCC * \#cases)}{\sqrt{(\frac{(PCC * \#cases) * \left(\#cases - (PCC * \#cases)\right)}{\#cases}}}$$

$$z = \frac{(0.33 * 108) - (0.26 * 108)}{\sqrt{(\frac{(0.26 * 108) * \left(108 - (0.26 * 108)\right)}{108}}}$$

$$z = 1.73$$

The accompanying p-value with z-value of 1.73 from a right sided z-table at a 95% confidence interval is **0.0418**. This is smaller than 0.05, therefore the predictions made by the multinomial logistic regression model for the preference of the mobile app are regarded as internally **valid**.

Table 33: Classification table mobile app model with hold-out sample. 1=not preferred at all, 5=very much preferred.

		predicted					
		1	2	3	4	5	Recall
observed	1	25	0	0	0	7	78%
	2	9	0	0	0	0	0%
	3	23	0	0	0	12	0%
	4	8	1	0	4	7	20%
	5	4	0	1	0	7	58%
Precision		36%	0%	0%	100%	21%	*33%* Total accuracy

Mobile

In the training sample 58.7% scored a 1, 14.7% scored a 2, 11.5% scored a 3, 8.0% scored a 4 and 6.9% scored a 5. The PCC is therefore $0.587^2 + 0.147^2 + 0.115^2 + 0.08^2 + 0.069^2 = 0.39$. As can be seen in Table 34 the overall accuracy rate of the predictions for preference for mobile was 35%. This rate is lower than the PCC, meaning that the model performs worse than randomly classifying cases to groups in proportion to group sizes. The predictions made by the multinomial logistic regression model for the preference of mobile are therefore regarded as internally **invalid**.

Table 34:Classification table mobile model with hold-out sample. 1=not preferred at all, 5=very much preferred.

		predicted					
		1	2	3	4	5	Recall
observed	1	38	0	0	0	0	100%
	2	23	0	1	0	0	0%
	3	28	0	0	0	0	0%
	4	11	0	0	0	0	0%
	5	7	0	0	0	0	0%
Precision		36%	0%	0%	0%	0%	*35%* Total accuracy

Landline

In the training sample 44.1% scored a 1, 11.5% scored a 2, 13.9% scored a 3, 16.5% scored a 4 and 14.0% scored a 5. The PCC is therefore $0.441^2 + 0.115^2 + 0.139^2 + 0.165^2 + 0.140^2 = 0.27$. As can be seen in Table 35 the overall accuracy rate of the predictions for preference for mobile was 19%. This rate is lower than the PCC, meaning that the model performs worse than randomly classifying cases to groups in proportion to group sizes. The predictions made by the multinomial logistic regression model for the preference of landline are therefore regarded as internally **invalid**.

Table 35: Classification table of Landline model with hold-out sample. 1=not preferred at all, 5=very much preferred.

		predicted					
		1	2	3	4	5	Recall
observed	1	11	0	2	2	4	58%
	2	6	0	0	0	7	0%
	3	30	0	0	3	11	0%
	4	12	0	1	3	0	19%
	5	3	0	5	2	6	38%
Precision		18%	0%	0%	30%	21%	*19%* Total accuracy

E-mail

In the training sample 7.6% scored a 1, 3.9% scored a 2, 12.8% scored a 3, 21.9% scored a 4 and 53.7% scored a 5. The PCC is therefore $0.076^2 + 0.039^2 + 0.128^2 + 0.219^2 + 0.537^2 = 0.36$. As can be seen in Table 36 the overall accuracy rate of the predictions for preference for mobile was 23%. This rate is lower than the PCC, meaning that the model performs worse than randomly classifying cases to groups in proportion to group sizes. The predictions made by the multinomial logistic regression model for the preference of e-mail are therefore regarded as internally **invalid**.

Table 36: Classification table of E-mail model with hold-out sample. 1=not preferred at all, 5=very much preferred.

		predicted					
		1	2	3	4	5	Recall
observed	1	0	0	2	2	7	0%
	2	1	0	2	0	2	0%
	3	6	0	1	1	15	4%
	4	0	0	0	2	39	5%
	5	0	0	5	1	22	79%
	Precision	0%	0%	10%	33%	26%	*23%* Total accuracy

Internet banking

In the training sample 22.9% scored a 1, 6.5% scored a 2, 18.5% scored a 3, 21.7% scored a 4 and 30.4% scored a 5. The PCC is therefore $0.229^2 + 0.065^2 + 0.185^2 + 0.217^2 + 0.304^2 = 0.23$. As can be seen in Table 37 the overall accuracy rate of the predictions for preference internet banking was 31%. The accompanying z-value with this score is 1.85.

Table 37: Classification table of internet banking model with hold-out sample. 1=not preferred at all, 5=very much preferred.

		predicted					
		1	2	3	4	5	Recall
observed	1	6	0	2	0	8	38%
	2	2	0	0	0	3	0%
	3	11	0	11	3	19	25%
	4	2	0	4	5	13	21%
	5	4	0	4	0	11	58%
	Precision	24%	0%	52%	63%	20%	*31%* Total accuracy

The corresponding p-value with z-value of 1.85 from a right sided z-table at a 95% confidence interval is **0.0322**. This is smaller than 0.05, therefore the predictions made by the multinomial logistic regression model for the preference of internet banking are regarded as internally **valid**.

XVII. Appendix: Validation for MLR model with 3 level dependent variable

This appendix provides the calculations for the internal validation op channel preference predictions made by the MLR model for Mobile app. This model is based on the dependent variable *preference for mobile app* that has 3 levels (1=negative, 2=neutral, 3=positive) instead of 5 levels.

In the training sample 29.4% scored a 1, 18.5% scored a 2, 52.1% scored a 3. The PCC is therefore $0.294^2 + 0.185^2 + 0.521^2 = 0.39$. As can be seen in Table 38 the overall accuracy rate of the predictions for preference for Mobile app was 49%. The accompanying z-value with this score is 2.43. The corresponding p-value with z-value of 2.43 from a right sided z-table at a 95% confidence interval is **0.0075**. This is smaller than 0.05, therefore the predictions made by the multinomial logistic regression model for the preference of the mobile app, based on a 3 level scale of preference, are regarded as internally **valid**.

Table 38: Classification table of Mobile app model with hold-out sample. 1=negative, 2=neutral, 3=positive.

		predicted				
		1	2	3	Recall	
observed	1	34	0	7	83%	
	2	23	0	12	0%	
	3	12	1	19	59%	
	Precision	49%	0%	50%	*49%*	Total accuracy