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Bank controlling with a marketing attitude – applied statistics in the service of controlling*

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In this study, the authors present the analysis of 14 regression models (implemented in business practice as well) which examine willingness to buy and were prepared in the past 5 years at three market-leading retail banks in the United Kingdom, as well as the analysis of the output / explanatory variables of these models. The models aimed primarily at existing customers' willingness related to the buying and repeated buying of instant access, fixed term and ISA-type savings products. The models prepared jointly by the authors and the banks' own analysts fundamentally served a double purpose. The ultimate business objective was to use the models in real sales campaigns with the intention to elaborate, in addition to the selection criteria of the existing direct marketing system, a selection procedure that gives a more precise estimate of willingness to buy. With the help of the more precise estimation, the new procedure proposes the involvement of only those customers in direct marketing whose willingness to buy is higher than in the case of random selection. This boosts cost efficiency, reduces the number of customer complaints and increases customer satisfaction. The scientific goal of the study is to explore the factors that affect the purchase of bank products, the weight of these factors and the direction of influencing, as well as to call attention to a potential development possibility of the methodology of controlling. The methodological processes described in the study can be applied in the preparation of more accurate product sales forecasts, may serve as a basis for campaign cost optimisation processes and may be part of customer value calculation methods as well. The findings can be utilised in other areas of science and business as well. Firstly, they provide information for controlling specialists responsible for the area of marketing that allows more precise planning, and provide timely insight for business analysts into the area of customer behaviour. Secondly, with this study the authors wish to call attention to the necessity of using up-to-date statistical methods and the results of social science in the field of banking and other services sectors.

Journal of Economic Literature (JEL) Classifications: C35, G14, G21, M31

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1. Introduction

The impact of the banking sector on the economy and society is indisputably significant. The changing macroeconomic environment of the past decade and the financial crisis that took place threw light upon the need for banks to be able to quickly react to changes in the external environment. Changes to the banking operations methods applied by West European banks have been seen in recent years. These modifications are implemented according to the bank business policy concept developed depending on the given economic environment and, of course, take place depending on the changes in macroeconomic factors, as a necessity. The reasons include the general deceleration in the demand for banking services, the strengthening competition aiming at private savings, now not only among banks, but, inter alia, among insurance companies as well, and also the growth in banks' operating costs, while there is a decline in transactions that ensure a rapid increase in business volumes and that used to be able to offset this rise in costs.

Following the crisis, the industry started to focus on reregulation, profitability, increasing efficiency and processes that create value for customers and investors. The achievement of these targets requires a logically designed, wide-ranging information system, the implementation and content background of which is provided by a well-designed controlling structure and system. At the same time, in addition to compiling an information basis that is tuned to various decision-making alternatives and contains relevant data, for decision-makers it has become necessary to redesign the planning system in a way to be able to follow the rapid changes in market conditions and thus to ensure the achievement of banks' strategic and operational objectives (*Zéman 2013*). Nevertheless, controlling cannot be considered a 'cure-all' method that is able to automatically guarantee the effectiveness of financial management. It is only conducive to decision-makers' awareness of responsibility and profitability, consequently resulting in consistent, purposeful and systematic decision-making at all levels of banking activity.

In order for financial institutions to be able to meet the new market and regulatory challenges, continuous development and innovation[1] are needed. This may mean the introduction of new products as well as the development of new methods and banking operations methods which increase cost efficiency and allow for more precise planning, in addition to increasing customer satisfaction and loyalty. We believe that the potential development possibility of the current controlling systems lies in the mapping and integration of the applied procedures of the various banking activities. The development of information technology allows

[1] 'An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations.' Source: OECD Oslo Manual, 3rd Edition, http://nkfih.gov.hu/szakpolitika-strategia/archivum/oecd-oslo-kezikonyv

the running of complex algorithms on extensive databases, which, in addition to a number of other benefits, facilitates more accurate forecasting, income and cost planning as well as cost management. Take, for example, the scoring models, which examine the risk of customers becoming insolvent. Although the primary objective of these methods is related to the given banking function (to the reduction of bank risks in this example), both the methodology and the results may improve the planning and analysis functions of the management controlling system via more accurate forecasting; in addition, they contribute to banks' more efficient cost management (e.g. with the help of more accurate forecasts of collection charges) (*Oravecz 2007*).

The deviation of bank controlling from the standard controlling methodology is determined by the individual tasks of banks' value creation processes and their products as well as by the banking transactions (payment transactions, lending, capital investment etc.). Accordingly, in view of its nature, bank controlling performs its management tasks for the bank as a whole by integrating two well-defined partial areas, i.e. the controlling tasks of the bank's internal operation and the services (*Zéman 2013*). This integration can only be achieved by connecting the planning, plan–fact deviation analysis and information provision functions of the controlling subsystems functioning with the bank's organisation (cost controlling, profit controlling and financial controlling). Consequently, the stance of bank controlling is twofold: controlling tasks that guarantee the bank's internal operational security and customer controlling tasks between the bank and its clientele.

This study examines a potential connection point of the simultaneous application of the performance-oriented controlling approach and efficient market-oriented marketing. The starting point of the analysis is constituted by the customer relationship management ('propensity') models, which are applied in Western banking practice in an increasingly widespread manner and examine customers' buying potential. Unlike before, instead of all customers or a group of customers selected on the basis of only a simple system of criteria, in the various marketing campaigns these models target only the really potential customers. This is advantageous for both the customer, who receives only the advertisements and publicity materials that are relevant for him, and for the bank, because the use of the models allows the attainment of a higher cost efficiency level. Major enterprises and financial institutions, which have large staff of analysts and data of adequate quantity and quality, set up the models that examine customers' willingness to buy within the framework of their regular risk analysis and customer relationship management (CRM) activities. Although these methods are used by the major credit institutions in Hungary as well, the organisations operating in

Western countries typically apply higher-standard statistical methods in a wider range, in several areas of business activity. The regression models that examine estimated willingness to buy estimate the probability of a certain activity (for example, in the case of a bank, the probability of applying for an account, loan, etc.) to be carried out by those subject to the study on the basis of earlier (often several years old) data. This allows banks to attain a similar level of sales by the targeted involvement of a narrower range of customers, compared to involving all existing customers in the given campaign. As a result, it becomes possible not only to reduce a part of the marketing costs, but also to reduce them to an optimum level from an economic point of view, depending on the sales and customer strategy. In addition to the direct economic benefit, these regression models may provide valuable information for the annual strategic planning. Banks and credit institutions both in Hungary and abroad are starting to realise that identifying and quantifying the factors that influence customers' willingness to buy as well as the utilisation of the results of regression models, for example with the help of linear programming, allows marketing controllers to prepare more accurate sales projections as well as optimised cost planning. From a scientific point of view, the examination of the factors affecting willingness to buy on the basis of an extensive sample and the valuable insight into the current trends of the behaviour of bank customers can be considered significant.

As part of a comprehensive research examining the marketing controlling phenomenon, in this study the authors present the analysis of 14 regression models (implemented in business practice as well) which examine willingness to buy and were prepared at three market-leading retail banks in the United Kingdom, as well as the analysis of the output/explanatory variables of these models. The models were prepared during the past 5 years, using the data of nearly 25 million customers. The models primarily aimed at existing customers' willingness related to the buying and repeated buying of instant access,[2] fixed term[3] and ISA (tax-free, fixed term 'individual savings account')[4] type savings products.

In order to understand the factors that affect customers' willingness to buy, it is important to examine the level and background of the interaction between customers and financial institutions. In the services sector, especially in the case of confidential services, such as financial services, it is essential for all organisations to maintain the standard of customer relations, to handle the services and

[2] Equivalents of instant access type products in Hungary: short-term deposits; savings accounts with higher sight interest rates; and investment accounts (usually current accounts tied to money market mutual fund shares).

[3] Fixed term type products are primarily known in Hungary as long-term bank deposits.

[4] ISA type products can be compared to the long-term investment accounts.

complaints as well as to operate customer-oriented, value-creating processes and marketing. The various organisations establish relations with their customers primarily through their products/services and relationship marketing activity. *Berry (1983)* identifies relationship marketing as a course of actions of crucial importance, whose aim is to *'establish, maintain and develop customer relations'*.

In their comprehensive study, *Neto et al. (2011)* examine the three levels of relationship marketing: *(i) Retention Marketing*': with the help of financial incentives; *(ii)* '*Personalised Services'*: social and financial relations; *(iii)* '*Relationship consolidation with structural links'*: by making the services valuable for the customer.

Based on these is the highest level of relationship marketing, where *'the switching cost is high and senseless'* for the customer. The study also points out that this level may primarily be reached with the help of information technology. The spreading of information technology allows banks to get to know and understand their clients better, which may even lead to the creation of services meeting customers' individual demands. This contributes to customer loyalty, which is essential for *'strong customer relations [...] and repeated product purchase'* (*Dick–Basu 1994*). And strong relations are vital in the present consumer environment (*Alnsour 2013*).

Nowadays, one of the most efficient and most valuable business and relationship marketing 'tool' is customer relationship management (CRM), (*Kaur 2013*). Certain authors consider customer relationship management as a *'key to organisation survival and customer loyalty'* (*Anabila 2013*). In any case, the loyalty-increasing effect of CRM and its impact on profit are indisputable. At the same time, the most optimal result can be achieved if organisations implement the results and procedures of marketing and CRM in the goal-oriented controlling (*Gaál 2007*) practice as well that focuses on cost and income statement, thus creating cost-effective procedures that have scientific bases (for example in the areas of planning and plan–fact analyses).

The literature also contains numerous efforts aimed at the scientific examination of customer profiles and the identification of key factors that affect customers' purchasing decisions concerning a given product, such as Gilberto's conventional mortgage refinancing model from 1989 or the regression model of *Neto et al. (2011)* that estimates the propensity to end accounts. In this study, the authors wish to examine the factors that affect the willingness to buy bank savings products following the methodological rules of the aforementioned models.

In this study, in the course of constructing the models, the primary ultimate business objective was to use the models in real sales campaigns with the intention to elaborate, in addition to the selection criteria of the existing direct marketing system, a selection procedure that gives a more precise estimate of willingness to buy. With the help of the more precise estimation, the new procedure proposes the involvement of only those customers in direct marketing whose willingness to buy is higher than in the case of random selection.[5] The secondary business objective was the streamlining of existing product sales forecasts and annual financial planning. Credit institutions intended to use the results of the models and the estimation function of the models for the preparation of more accurate sales projections and related cost projections within the framework of annual financial planning. The scientific goal of the study is to explore the factors that affect the purchase of bank products, the weight of these factors and the direction of influencing, as well as to call attention to a potential development possibility of the methodology of controlling. Earlier data series as well as the subsequent evaluation of campaigns were used for the verification of the models.

2. Material and methodology

This study is based on the 14 regression models that examine willingness to buy and were prepared by the authors at three market-leading[6] retail banks in the United Kingdom. The models were prepared during the past 5 years, using the data of nearly 25 million[7] customers. The models aimed primarily at existing customers' willingness related to the buying and repeated buying of instant access, fixed term and ISA ('tax free, fixed-term' Individual Savings Account[8]) type savings products.

Data: For a model, the current holdings of an average 7.5 million customers were used.[9] The variables that constitute the basis for the models were compiled on the basis of the data of the 12 months preceding the campaign period. These variables can be classified into 8 main categories: *(i)* demographic variables (age, gender, marital status, geographical location, etc.), *(ii)* relationship with the credit institution (length of the relationship, number of products, marketing segmentation, etc.), *(iii)* products possessed (products possessed earlier and at present, active product categories, etc.), *(iv)* behaviour (product use, transaction patterns, balance categories, etc.), *(v)* channel use (preferred channels, account-opening, transaction channels, etc.), *(vi)* external customer segmentation (e.g.

[5] As no similar method existed before, all sales within the given decile that are additional compared to the random selection can be considered advantageous from the bank's point of view.

[6] The three banks accounted for nearly 17% of the estimated total household savings market in 2014. (Source: https://www.bba.org.uk/wp-ontent/uploads/2014/06/BBA_Competition_Report_23.06_WEB_2.0.pdf)

[7] By the 25 million customers the authors mean the total clientele of the three banks.

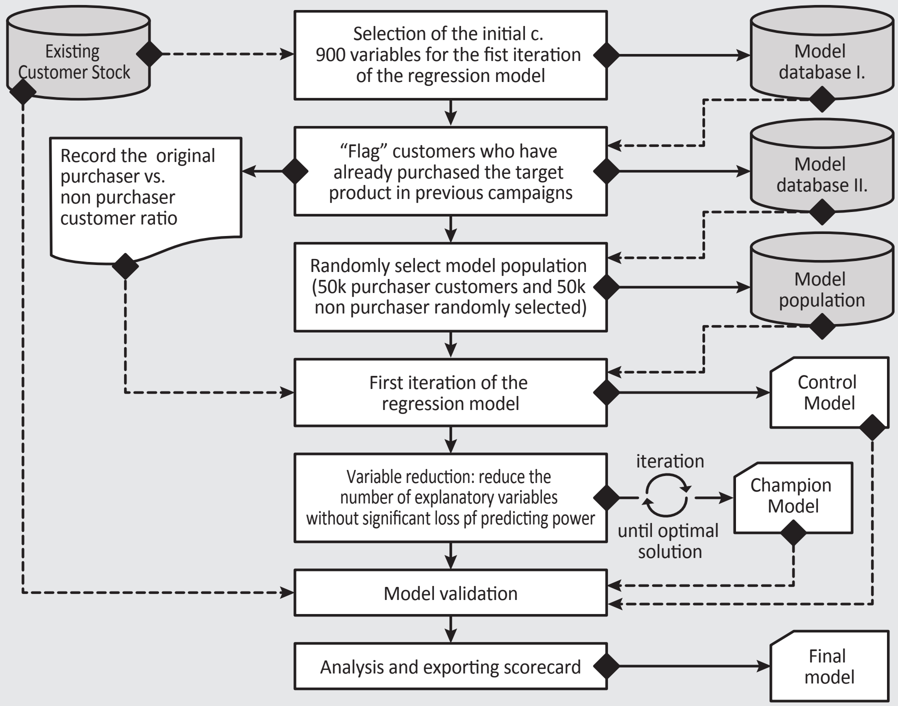
[8] For more information on the ISA – Individual Savings Account – see the site of HM Revenue & Customs. (http://www.hmrc.gov.uk/isa/index.htm)

[9] Examining 5 years, in the case of the 3 products and 14 models it means nearly 25 million different customers.

ACORN[10] or MOSAIC,[11] category system), *(vii)* risk segmentation (standardised information provided by external service provider, etc.), *(viii)* current and future customer value (customer profitability, NPV, buying potential, etc.).

Statistical methodology applied: For the individual models, the methodology of logistic regression was used,[12] as the models basically examine the likelihood of occurrence of a dual outcome event (in this case the purchase of a given product). *Figure 1* details the standardised process of preparing the model designed for the study. As a first step, the nearly 900 variables (which is the average number of variables on the basis of the 14 models) needed for the regression model

Figure 1.
The "start to end" process of predictive propensity model building at the assessed banks



Source: Own composition

[10] For more information on the ACORN type customer segmentation see the official website of the organisation called CACI. (*http://acorn.caci.co.uk/*)

[11] For more information on the MOSAIC type customer segmentation see the official website of the organisation called EXPERIAN. (*http://www.experian.co.uk/business-strategies/mosaic-uk.html*)

[12] As the dependent variable is dichotom, in the course of preparing the model the authors presumed that the explanatory variables have an effect on the likelihood of occurrence of the result.

are formulated with simple data mining methods. There are several possible approaches in this step. For mapping the latent structure among the variables, the authors propose the application of data-reduction multivariate methods (such as main component analysis or factor analysis). These methods help in exploring latent factors that can be formed from groups of variables that are in closer correlation with one another. The new variables created in this way can be used in the model. Another possibility is the involvement in the initial model of all the available variables that are logically relevant in terms of the given subject, which, depending on the number of elements, may require significant calculation and IT capacity. For the interpretability of the results of regression models, it is important to rationalise the number of variables. At the same time, upon forming the variables it is important to take into account that in the case of logistic regression, if we wish to involve in the analysis a categorial explanatory variable that contains more than 2 categories, we have to form different categorial groups from that variable with the help of so-called 'dummy' variables. In many cases (e.g. in the cases of variables that examine the value of transactions, income and asset portfolio) the authors formed several binary variables that examine each category separately, which resulted in a relatively high number of initial variables.

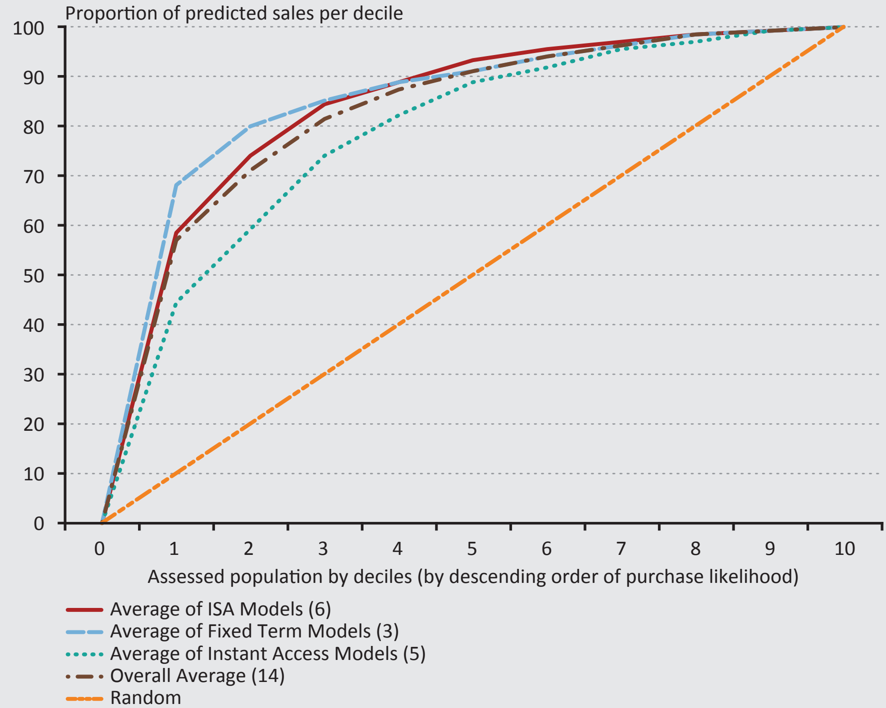
The second phase of model construction begins with forming a randomly selected population. It was primarily necessary in order to reduce the time of processing (the authors used the SAS® Enterprise Miner™ 5.1 version for constructing the models). For most of the models they randomly selected 50,000 customers who had already bought similar products in an earlier campaign and 50,000 customers who had not. Then, taking account of the original distribution and with the involvement of the whole stock of variables, the control model is formed by using a range of CHAID (Chi^2 Automatic Interaction Detector – multivariate recursive classification method) decision trees and logistic (logit) regression models. The following mathematical base model is used during the calculations (*Campbell 2004*):

$$\ln\frac{P\left(Y=1|x_i\right)}{1-P\left(Y=1|x_i\right)}=\ln\frac{P\left(Y=1|x_i\right)}{P\left(Y=0|x_i\right)}=a+\sum_{j=1}^{m}b_j*x_{i,j} \tag{1}$$

where Y = target variable; a = constant value, taken when Y=0; b_j = the j^{th} the vector of the independent variable; $x_{i,j}$ = the value of the j^{th} attribute of the i^{th} individual; m = number of attributes

The third phase of model construction comprises the reduction (optimisation) of the number of variables and the verification of the estimating power of the models. In the first step, the verification of the created model within software is carried out. For the verification, the control model is taken as a basis, because it is the one that is able to explain the target variable to the greatest extent. During the various iterations, the number of variables[13] is reduced (using a 'stepwise' method) in a way that cumulative profit should not decline significantly.[14] Although the models are constructed with the help of the statistical software, subsequent tuning by analysts is indispensable so that the result of the produced model can be interpreted along the strategic objective. The model often involves more variables in the analysis than necessary, and thus it may be necessary to combine certain variables or ignore some of them based on analysts' decision, if this does not significantly affect the cumulative likelihood of purchase.[14]

Figure 2.
The predicting power of propensity models (ROC15)
Comparison of logit regressions models (average by product type) with the random selection.



Source: Own composition

[13] A condition of variables' remaining in the model is that the value of the F-proof must not exceed the level of 0.05.

[14] During the analysis, the authors took into account that the primary objective of the models is to increase the efficiency of sales and thus to optimise costs; accordingly, the manageability and interpretability of the final model were also important aspects. The authors set the minimising of explanatory variables as an aim, in addition to determining that, compared to the initial model, the decline in profit attained in the first decile of the final model may not exceed 5%. A further criterion was that the performance of the initial model (AUC – Area under curve) may not be less than 70%.

As a result of the model, the estimated additional sales are stated by deciles, in a cumulative manner. In the analysis, the authors used the ROC[15] curves to depict the differential ability of the models. *Figure 2* shows to what extent (averaging by product type) the individual models are able to estimate the likelihood of the occurrence of a given event compared to random selection. It becomes possible to compare model performances on the basis of the size of the area below the graph (AUC – Area Under Curve).

If the number of variables is optimal (minimal number of variables without a significant[14] decline in profit), the regression equation (model scores/scorecard) is exported and further verified. As a second step, the model data are tested on the basis of earlier campaign data not used for the construction. Typically the data of 6, 12 and 18 months are included, because older data cannot be considered relevant as a result of significant differences in market conditions. If the data of the model are stable, the final verification of the model is conducted with the help of the estimation of the willingness to buy of the current clientele on the basis of the regression equation, using statistical software (the authors used the SAS® Enterprise Guide™ 4.1 version). If there is no significant[16] deviation between the distribution measured at the beginning of the model from the new, dotted distribution originating from the current stock, it is possible to use the model for business purposes. The models prepared can be used in new campaigns, although it is always necessary to check how the explanatory power of the models changes, and a new model has to be constructed if necessary.

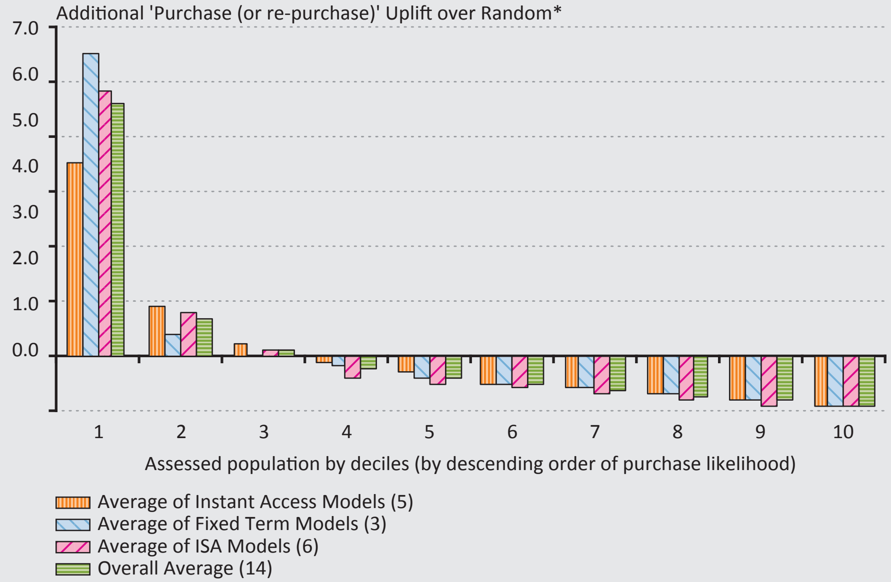
3. Results

In the current banking practice, campaign budgets are prepared at the beginning of the year on the basis of previous years' experience and data, the strategic objectives and inflation. In the case of the banks under review, the practice was that in each campaign they targeted only 30–40% of a given product's clientele with direct marketing tools (e.g. letter, e-mail, phone call, etc.). The models helped this selection process by ranking the customers on the basis of their willingness to buy related to the given product compared to the random selection. As a result, banks can inform that 30–40% where the probability of purchase is the highest, thus attaining a higher level of cost efficiency. *Figure 3* shows that in terms of the primary ultimate business objective, 11 of the 14 models prepared by the authors

[15] Receiver Operating Characteristic

[16] In the case of the models used for the study, the distribution of the population under review and of the original population have to reach an at least 0.7 correlation level in any case, depending on the likelihood of purchase and the explanatory factors. In the event that the correlation of distributions had not reached the given level as a function of a factor, further examination of the given explanatory variable was necessary.

Figure 3.
Cumulative Gains from the 14 assessed models
(average by product type)



**Az ábra azt mutatja meg, hogy a becslő modell használata esetén mekkora várható többletértékesítés érhető el az adott decilisbes amennyiben a véletlenszerű kiválasztás által elérhető értékesítést egységnyinek vesszük.*
Source: Own composition

resulted in significant[17] additional sales in the first three deciles, while the other 3 models in the first four deciles.

On the basis of the models prepared, instead of a pre-determined appropriation, for banks it is worthwhile to involve new customers in the case of each additional spending until they are able to involve a customer whose likelihood of purchase at least corresponds to the likelihood upon random selection (assuming that the selection of customers is carried out in a declining order of likelihood of purchase).

In addition to the primary business objective, based on the variables included in the model it becomes possible to formulate the profile of the potential customer regarding the various products. This is especially important during product planning and the planning of annual product sales. *Figure 4* presents the variables of the 14 models summed up by product types and their average impact on the models.

[17] All additional sales potential identified compared to the random selection has to be recorded as positive result in the given decile. In the case of the credit institutions under review, product managers classified all additional likelihood of sales as significant that resulted, compared to random selection, in an at least double likelihood of purchase in the case of 30% or 40% of all customers.

Based on their occurrence in the various models, the variables can be divided into two groups: *(i)* common factors that are present as explanatory variables in at least two types of products; *(ii)* savings product specific factors that belong only to one given product model.

Table 1.
Key factors of product purchase / re-purchase propensity
(average by product type)

	Weight and direction of impact in: Instant Access Models	Fixed Term Models	ISA Models	
Lifestage category / External consumer segment	40%	28%	23%	Common Variables
Customer Age	8%	15%	41%	
Number of other savings products	5%	4%	7%	
Average Savings Balance (3months)	2%	24%		
Average Current Account balance (3months)		5%	4%	
Online Banking Usage	22%		18%	
Customer tenure	3%			Savings Product Type specific variables
Current Account Direct Debit volume			3%	
Credit product held	(–)14%			
Average BACS Transaction value	4%			
Number of Dependants		(–)2%		
Risk Grade		4%		
Marital Status		12%		
Current Account credit interest earned		3%		

** Variables with less than 2% explanatory power have not been added to the table above.*
Source: Own composition

Common factors: The factor with the greatest explanatory power is the Stage of life / External customer segmentation. This variable is the result of the regular questionnaire survey of an independent market research firm (CACI, Ebenchmarkers) and of the national census. The data show the various segments of the whole population of the United Kingdom broken down by postal districts, based on an in-depth analysis of demographic, geographical and lifestyle characteristics as well as consumption habits. The real strength of the variable is given by the depth of the insight into consumer segments, which information is not available for banks in any other way.[18]

[18] For example, the population is divided into five main categories from 'wealthy achievers' to 'hard pressed'. These variables were created from the data originating from the census and as a result of questionnaire surveys analysing lifestyle and consumption habits, also strengthening the estimation ability of models.

The second strongest explanatory factor in the models that examine willingness to buy savings products and willingness to buy them again is the age of the customer. This variable accounts for nearly 41% of the explained portion of the ISA ('tax free, fixed-term' Individual Savings Account) models. The age variable is essential in savings models because it represents the amount of time available for the customer to obtain sufficient funds for living and saving. The preliminary analysis of the models shows that the amount of average savings per customer has a strong correlation with the age of the customer. This is especially perceptible in the case of the ISA models. The essence of the ISA products is that the customer can place new savings on a tax free account up to an annual limit determined by the state. Cumulative savings of previous years can be taken on to this new tax free account upon maturity (for this, it is necessary to buy a new ISA product that is in line with the current conditions and interest rates), or the customer may decide not to buy a new ISA product, but in this case he receives only an annual 0.5% interest premium. Consequently, the more money the customer saved during the years in a cumulative manner, the more interested he is in continuing to keep the tax free savings on a new tax free account that offers the highest yield under the current circumstances and in adding new savings to the account up to the annual limit. Another predisposing factor is the number of other active savings possessed. Although this variable is less relevant, it is able to describe the earlier relationship of the customer with the bank and the extent of market presence.

The savings and current account balance of the three months preceding the purchase of the product is also one of the factors. These variables are good indicators of the existence of the amount intended to be placed on the savings account and of the evolving conscious willingness to save. The last common factor (on the basis of this study) is the use of the Internetbank. This factor has influencing power in the case of the instant access and ISA models, but is not present in the case of fixed term products. The underlying reason is the age profile. While mainly people over the age of 55 (69% of all those who have fixed term products) look for fixed term products, in the case of instant access products the customers most probably (38%) fall in the age group of 25–44 and in the case of ISA products in the age group of 35–64 (83%). Internet use also correlates with the age of customers, but in an inverse proportion.

Savings product-specific factors: instant access product models: in these models, customer relationship lifespan and average current account transactions as explanatory factors play a significant role. Nevertheless, of the product-specific factors, loan product possession had the most significant impact. Particularly strong correlation is shown by the presence and magnitude of the overdraft facility and the size of credit card debt. The negative impact on the model clearly shows that the magnitude of the loan is inversely proportional to the customer's willingness to save (perhaps in this case it is more appropriate to use the term ‘ability to save’). This factor is significant in instant access models because the target age group of this product and of the loan products is basically the same.

Fixed term product models: fixed term products are basically related to a given stage of life, thus the factors with the greatest impact are the ones that characterise the profile of the stage of life, such as the number of dependants, marital status, risk rating, etc. The models reveal that these products will most probably be purchased by older couples who do not live in the same household with their children any longer, the customer does not have active loans and belongs to a good debtor risk category. Due to the basically low current reference interest rates, the choice of bank interest rates is relatively narrow for customers. The interest rate dispersion of demand deposit products offered at present in the UK market is low. Accordingly, it is clearly visible from the models as well that price sensitivity (interest rate sensitivity) is not strongly represented in the models. The only product type is the fixed term product where this size of interest rate appears among the explanatory variables. Depending on the maturity, the dispersion of reference interest rates is greater here, which clearly indicates stronger competition. The interest rate sensitivity that appears in the fixed term model corroborates that the customers who look for this product are also aware of the aforementioned competitive situation and their bargaining position.

ISA product models: for these models (based on the average of the analysed 6 models), 93% of the explained proportion can be explained with the common factors that influence the willingness to buy savings products. Another variable, albeit with a low explanatory power, is the number of direct debit orders. The number of direct debit orders is basically a transaction behaviour profile related to a stage of life, showing similarities with customers that buy ISA products in terms of age and customer segment. The following figure summarises the various factors as well as their impact on the models and their direction.

4. Conclusions and proposals

In our opinion, the analytical processes created during the preparation of the model and their results can be utilised at several levels: *(i)* In a direct manner, as parts of sales campaigns, they can be cost-effective and efficient tools for compiling the target group of customers. *(ii)* At the same time, in addition to the marketing function, in their present form the models are able to prepare more accurate product sales forecasts as well. This may improve the efficiency of the planning function of controlling to a great extent. In our opinion, the degree of efficiency of forecasting can be increased with the inclusion of further, mainly non-bank factors/

variables.[19] *(iii)* The models prepared and mathematical and statistical methods in general allow the determination of the optimum level of certain cost categories. For example, instead of the aforementioned simple campaign cost planning process, it becomes possible to determine the optimum number of customers who can be involved in the campaign, which ensures the maximum expected profit for the bank at a given unit cost.[20] *(iv)* In an indirect manner, the models may also serve strategic planning functions. Firstly, the results help decision-makers to better understand the target segment of a product. Secondly, an indispensable condition of determining customer value, which is used increasingly frequently in the banking industry, is the presence of future-oriented indicators that examine willingness to buy, i.e. the potential future value.

In our opinion, the results and the methodological approach can be utilised not only in the banking industry but also in other areas of science and business. Firstly, for controlling specialists responsible for the area of marketing they provide information that allows more accurate planning (*for example they can be parts of the indicators that can be built around the aforementioned variables, reports or the annual sales planning model*), and provide up-to-date insight for business analysts into the area of customer behaviour. Secondly, with this study the authors wish to call attention to the necessity of using up-to-date statistical methods and the results of social science in fields of banking and other services sectors.

The authors propose further analysis of the subject. Firstly, the research can be extended to the data on other countries (e.g. Hungary), and secondly, to other product types (loan products, current account products, insurance products). A possible direction of research is the examination of cultural and social differences as well as of the differences between the customer profiles of the pre-crisis and post-crisis periods.

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[19] For example, the given credit institution's market share in the given range of products, customer satisfaction, the dispersion of the product range that is in the market, the relative size of branch use, etc.

[20] The number of customers where the unit cost of additional direct marketing coincides with the marginal additional income that can be expected from the additional direct marketing.

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