# PREDICTING ACTUAL CONSUMER BEHAVIOUR IN RETAIL BANKING

*Chris Baumann, Graduate Accounting and Commerce Centre, Macquarie University, NSW 2109, Australia, cbaumann@efs.mq.edu.au*
*Suzan Burton, Graduate School of Management, Macquarie University, suzan.burton@mgsm.edu.au*
*Greg Elliott, Graduate School of Management, Macquarie University, greg.elliott@mgsm.edu.au*

## ABSTRACT

A critical measure largely neglected in previous loyalty studies is the customer's 'share of wallet' (SOW). This study, based on 1,924 retail banking customers, suggests that about 25-65% of the variance in customer loyalty in terms of actual behaviour can be predicted, in particular by demographic factors such as age, income and a customer's residential location. In recognition of the fact that banks generate different profits from savings/investment products and loans, the study develops separate models predicting SOW in terms of deposits, debts/loans; and percentages of accounts, loans and credit cards used from a customer's main bank. While satisfaction and attitude are strong predictors of behavioural intentions, they were, together with service quality, found not to be significantly associated with SOW.

## INTRODUCTION

The competitive battle in retail banking at the present time is said to be around "share of wallet" (SOW), which is essentially the proportion of a consumer's business allotted to a single bank [1]. The target is to attract customers to conduct an increased percentage of their banking business with one institution. Banks realise that they need to retain profitable customers by at least maintaining or, better still, increasing customer loyalty. The US *Marketing Science Institute* has listed customer loyalty measurement and valuation as a "Top Tier Priority Topic" of "greatest interest" [2, p. 4 & 5]. Many studies provide the context for the research discussed in this paper. The bulk of studies concur that satisfaction is a leading factor in customer loyalty. Based on Day's notion [3] that loyalty has two dimensions, behavioural and attitudinal, this study extends previous research and explores the extent to which specific customer characteristics can predict actual behaviour. A model was developed based on Ajzen and Fishbein's work [4], incorporating customer attitudes, satisfaction, the customer's environment such as family and friends (social norms) and situational factors (competing offers). The service quality in banking was also included, based on the five SERVQUAL dimensions [5]. Importantly, this study develops different SOW models for savings/investments and loans in retail banking. This distinction relies on the proposition that the magnitude and determinants of loyalty in terms of investments and deposits may be different from those of debts/loans.

*This paper is an abridged version only. The full paper and references are available from the first author.*

## METHODOLOGY

The current study is based on results of a survey of 5,000 individuals obtained from a commercial mailing list in Australia. A total of 1,924 usable responses were received, which represents a 39% response rate (after returned mail). Females (61%) are over-weighted in the sample, reflecting the higher proportion in the sample frame (63% females). Principal components analyses were used for data reduction [6], providing a single value for the multi-item constructs. These variables were then used in regression analyses to model behavioural loyalty in terms of share of wallet (SOW) regarding financial deposits and debts/loans held with the main bank. Given the categorical nature of the dependent variables, ordinal logistic regressions were performed applying the backward deletion method. The models were selected based on their goodness of fit (Pearson method) and explanatory power (Goodman-Kruskal Gamma).

## RESULTS

The major focus of this study was the extent to which *actual* behaviour in retail banking can be predicted. Table 1 shows the predictors of SOW Deposits, i.e. the percentage of the total financial deposits such as savings accounts, shares and bonds a client holds with her/his bank.

**Table 1: Predicting SOW Deposits: Ordinal logistic regression**

| **Independent Variables** | $\beta$ | *SE* $\beta$ | *P* | *Odds Ratio* |
|---|---|---|---|---|
| Number of current suppliers | 0.476 | 0.055 | <0.001 | 1.61 |
| Age | 0.130 | 0.030 | <0.001 | 1.14 |
| Gender | 0.271 | 0.098 | 0.006 | 1.31 |
| Income | 0.073 | 0.031 | 0.018 | 1.08 |
| Education | 0.189 | 0.102 | 0.063 | 1.21 |
| Meet expectations | -0.006 | 0.028 | 0.842 | 0.99 |

Similar models were developed for other behavioural variables and are summarised in the Appendix that also incorporates the key predictors of behavioural intentions such as word of mouth, short- (within the next six months) and long-term (within the next five years) intentions to remain with the main bank.

## CONCLUSION

This current study finds that models predicting 25-65% of actual behaviour in banking can be developed. Prediction of actual behaviour can be reliably predicted predominantly by demographics. Another important finding from this study is that satisfaction, attitude and service quality do not seem to reliably predict actual behaviour in retail banking (while they do, however, predict behavioural intentions). The key conclusion of this study is that bankers need to profile customers with potential for growth in terms of SOW and then target them specifically with tailor-made products and services. A profiling example for deposits is that the typical client with potential is male, aged 35-65, has a high income and a university degree. The results also indicate that researchers should not only focus on satisfaction, attitude and service quality when attempting to predict actual consumer behaviour, but rather on socio-demographic characteristics. A key contribution of this study is its focus on actual behaviour rather than behavioural intentions. Prediction of intentions is only of relevance to practitioners if intentions lead to actual behaviour, a link that has been questioned in the literature. Further, the results of this study also indicate that the two constructs are fundamentally different, since they can be explained by different variables. Hence, focusing directly on actual behaviour as the dependent variable should be a timely addition to the consumer behaviour literature. One could conclude that customers are loyal as a result of their current life situations (e.g. age and income) rather than resulting from a positive attitude towards their bank. Researchers are encouraged to explore the unexplained proportions of variation in actual behaviour, e.g. 35% in the variation of percentage of accounts used from the main bank.

## Appendix: Overview of key predictors of behavioural intentions and actual behaviour

| **Dependent Variables (% of variation explained)** ⇘ | ***Behavioural Intentions*** | | | ***Behaviour (Deposits)*** | | ***Behaviour (Loans)*** | | |
|---|---|---|---|---|---|---|---|---|
| **Predictors** ⇩ | ***Word of mouth 72%*** | ***Short-term BI 47%*** | ***Long-term BI 55%*** | ***SOW deposits 25%*** | ***% accounts 65%*** | ***SOW debts/loans 25%*** | ***% loans 27%*** | ***% credit cards 50%*** |
| ***Key predictors of intentions and behaviour*** | | | | | | | | |
| Number of current suppliers | * | | | * | * | * | | * |
| Length of relationship (LRS) | *** | | * | | * | | | * |
| Confidence in judgement | * | | * | | * | | | |
| Meet expectations | | * | | *** | | | | |
| ***Key predictors of intentions*** | | | | | | | | |
| Overall satisfaction | * | * | * | | | | | |
| Fees and interest rates | * | * | * | | | | | |
| Switching costs (SC) | *** | * | * | | | | | |
| Affective attitude towards bank | * | | * | | | | | |
| Role requirements | * | | * | | | | | |
| Interaction: Satisfaction * SC | *** | * | | | | | | |
| Attitude squared | * | | | | | | | |
| Interaction: Satisfaction * LRS | * | | | | | | | |
| Tangibles | | * | | | | | | |
| Motivation to comply | | * | | | | | | |
| Banking knowledge | | | * | | | | | |
| Interaction: Attitude * LRS | | | * | | | | | |
| ***Key predictors of behaviour*** | | | | | | | | |
| Age | | | | * | | * | * | |
| Income | | | | * | | * | | * |
| Number of suppliers in 10 years | | | | | * | | | * |
| Residential location | | | | | * | ** | | |
| Recently opened account with competitor | | | | | | | * | *** |
| Gender | | | | * | | | | |
| Culture | | | | | | | | * |
| Education | | | | ** | | | | |
| Switching benefits | | | | | ** | | | |
| Empathy | | | | | | ** | | |

* Significant ($p \leq 0.05$)
** Trend ($p > 0.05$ and $p \leq 0.10$)
*** Not significant, but contributes to power of overall model (i.e. explanatory power and/or model fit)

References available from the authors