What can Monitoring our Bank Account Cash Flows say about our Loyalty Cards?

Journal:	*Journal of Marketing Theory and Practice*
Manuscript ID	MMTP-20-04-1656.R6
Manuscript Type:	Original Article
Keywords:	Loyalty cards, Loyalty schemes, Bank balance, Prospect theory
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Introduction

Looking into the retail sector in the UK (Figure A1), it becomes evident that the FTSE Retail UK[1] (red line) has remained stationary since 1995, but this is not the same for FTSE Retail World[2] (green line), which excludes the UK. It can be assumed that the FTSE Index Price (Data on Figures A1 and A2 are from Thompson Reuters) will keep displaying a non-stationary trend towards 2020 and onwards. Similar results are depicted for the Food and Drug retailers, where the FTSE UK in 2014 turned back its stationary trend towards a steady decline. The FTSE UK Index of Food and Drug Retailers had a downward trend before 2015, and it can be assumed

[1] Capitalisation-weighted index consisting of listed retailer companies in UK.
[2] Capitalisation-weighted index consisting of listed retailer companies outside in UK.

that it will continue as such until 2020. However, this is not happening when the reader inspects the FTSE World for Food and Drug, excluding UK (green line), showing a rising trend without a sign of reversing its trend till 2020. It cannot be assumed that the retail sector's shrinkage is an outcome of overstoring or a preference for online purchasing because these strategies add value, as depicted in Figure A1 in the Appendix. The graphs in the appendix aim to provide a context for the declining indexes, which might have to do with a customer's inability to make ends meet, and retailers must consider these parameters.

Figure A1 implies that retailers in the UK need to follow different strategies if they want to avoid a future shrinkage of the sector and possible mergers and acquisitions from foreign competitors. This paper is written amid fears of a potential offloading of 460 stores upon a merger between Sainsbury's and Asda in the UK.

It is critical to explore why the UK's retail FTSE index (on both general retail and the food and retail drug sector) is falling behind the World FTSE index, excluding the UK. It requires considering the rising trend for credit card outstanding amounts in the UK to tackle this question. If this rising trend, depicted in Figure A2, is neglected, that would equate with making any marketing approach secluded from what is happening in the economy. Back in the 90s, when households' debt began to rise, Lea et al. (1993) named this phenomenon a 'growing indebtedness culture'. Should firms continue to invest in customer satisfaction in the traditional sense, hoping that customer loyalty and profits will follow suit? Should firms continue to search for links in isolation to what is happening in the economy without examining their broader context? The answer is no.

Customer loyalty is increasingly viewed as a prime determinant of achieving long-term financial performance in a competitive environment (Jones and Sasser, 1995). The literature's attitude is that members of loyalty programmes (such as loyalty cards) weigh intentions for frequent use more seriously than non-members, thus indicating a direct relationship between reward-programme membership and behavioural loyalty (Bolton et al., 2000). The literature favours the links between brand and loyalty programme members. This paper aims to extend this argument further and claim that there is more than the eye can see. Hence, are individuals who micromanage their bank transactions (by checking them frequently) keener on also micromanaging[3] their purchases with a loyalty card? Note that insecurity (from the frequency of checking the banking accounts) is separated from income insecurity[4]. The two key concepts explored are firstly, how frequently individuals monitor their bank account balance and secondly, their ownership of loyalty cards. The research objective is to investigate the relationship between these two concepts.

Recent research from Cendrola and Memmo (2010) on loyalty card programmes and Kumar et al. (2013) cast doubt on the long belief of a strong connection between customer satisfaction and loyalty. This motivates the present work to question the satisfaction-loyalty link's present efficacy and admit a somewhat nuanced behaviour on what leads individuals into using loyalty cards (loyalty). Rust et al. (1995) question firms' narrow focus only on customer satisfaction, hoping that this predictor alone will only suffice. Seiders et al. (2005) articulate that what matters is the repurchase behaviour per se and not the repurchase intention. The approach implemented in this work is behavioural because it captures the actual behaviour (not the intentions) from both directions. In this study, the predictor behaviour (representing the actual behaviour) is the frequency of checking the bank account balance, whilst loyalty card ownership is the outcome behaviour. Both the predictor and the outcome behaviours will help validate Prospect Theory in the loyalty card context.

[3] Possibly due to internet banking adoption (Giovanis et al., 2012).
[4] Somebody may have a source of income, but equally a rising outstanding amount getting bigger as way of living remains, e.g. fixed costs from utility bills, rents, substance costs, loans.

The remaining part of the paper presents the following. A literature review on the existing links that have dominated marketing literature concerning loyalty cards. The derived data section and the associated analysis are conducted separately. The data section will cover where the data have been obtained and which main variables will be used for the estimation process. In the modelling section, a series of steps are followed to develop the methodological approach gradually. The investigation of the appropriate tool will help us in the results section to draw empirical generalisations that offer a consistent explanation of the complicated relationship of brand loyalty. The conclusion briefly highlights the main findings reported, covers the theoretical and managerial implications, as well as the endogenous limitations of this research.

Literature review

Loyalty cards

Loyalty cards are encompassed under loyalty programs and are designed to engage customers in long-lasting relationships by offering economic discounts in addition to financial incentives. These are often entailed by social aspects, e.g. status, customised newsletters and price coupons and often rely on personal customisation to build a more intimate relationship.

Research from Gomez et al. (2012) reports that customers displaying shopping enjoyment were concerned with privacy, and had a favourable attitude toward loyalty programmes. They argue that shopping enjoyment emerges as a barrier to consumer participation in loyalty programmes, which require customer participation and commitment. However, if individuals view these programmes as overly beneficial to the firm, customers develop an unfavourable opinion of such loyalty programmes, especially when cautious about their privacy. A study on Korean consumers reports that brand images, perceived quality, and switching costs perception better determine loyalty (Kim et al., 2004). The service quality, causing satisfaction, receives considerable support (Brady and Robertson, 2001). Subsequently, the more cognitive oriented service quality and value appraisals gained influence emotive satisfaction, which drives loyalty (Ennew and Binks, 1999).

Historically, loyalty card literature has investigated the perceived quality or image postulated by brands. Under specific perceived characteristics or qualities, they will positively influence value, while prices (or costs) will negatively influence values (Hellier et al., 2003). Corporate image is a perception of an organisation held in consumer memory and works as a filter, which filters out external perceptions about the firm (Keller, 1993). The attitude theory suggests that evaluations form perceptions, and their predictive validity is based on how accessible or strongly depicted in memory they are (Fazio and Zanna, 1978). Ultimately, a direct experience makes attitudes more accessible and predictive to future satisfaction (Oliver, 1980). Hence, the perception of service quality directly impacts the perceived perception of the firm's image (Aydin and Ozer, 2005). Andreassen and Lindestad (1998) posit that a firm's image, through a filtering effect, impacts customers' evaluation and changes the quality of services and their derived satisfaction from the product value. Service quality influences customer loyalty only through value and satisfaction (Gotlieb et al., 1994). Others, such as Bloemer and Ruyter (1998), report that satisfaction acts as a mediator between image and loyalty. It is important to remember that the memory of a positive experience might decay over time (Mittal et al., 1999). According to Magi (2003), customer satisfaction has a positive, albeit modest, effect on shares, while consumer economic shopping orientation negatively impacts those shares. Oliva et al. (1992) provide evidence that when transaction costs are sufficiently high, a consumer may remain loyal even under mild dissatisfaction, leaving the customer entangled in an unsatisfactory relationship. Mittal and Kamakura (2001) find that females can be more faithful (as depicted by repurchase behaviour) to the brand than males. Customers divide their spending among different brands in a category and are continually influenced by the competition in their choices (Yim and Kannan, 1999). Besides, when customers' income is high, it is less likely to reduce their spending levels with the same firm (Cooil et al., 2007). Participation in loyalty programmes is meaningful because it positively affects wallet shares (Bowman and Narayandas, 2001; Verhoef, 2003; Perkins-Munn et al., 2005).

Frequency of checking the bank account

According to Massoud et al. (2011), the reason behind individuals frequently monitoring their bank account flows is either due to late credit card payments or due to charging an amount over their preauthorized limit (or both). That being the case, over the limit fees are applied. These penalty fees are charged to consumers as a punishment for being late or over the limit and should not be confused with the fixed annual fees paid up-front by all holders of specific cards or certain services. Essentially, penalty fees are associated with consumer default risks. In general, consumers' costs on credit card accounts include interest charges, annual or monthly fees, late or over the limit fees, cash advance fees, and balance transfer fees (Stango and Zinman, 2009). An early indication of why customers begin frequently checking their bank accounts may explain this upon looking at Figure 2 and the increasing outstanding amounts on consumers' balances.

Additionally, participating in a loyalty program might motivate people to obtain economic benefits, such as discounts. Income insecurity may lead to participation in loyalty programs not because a consumer is genuinely loyal, but instead forced to take advantage of such programs' gains, due to limited resources.

Theoretical underpinnings

What theoretical underpinnings relate to consumers' habit of checking their balances in their bank account? The logic rests on consumers' information search theory. Understanding consumers' information search behaviour is crucial to firms' strategic decision-making (Punj and Staelin, 1983; Urbany et al., 1989; Maity et al., 2014). This directly contrasts to research where consumers exhibit very little pre-purchase information activity (Beatty and Smith, 1987). The information search theory is standard in marketing (Schmidt and Spreng, 1996; Mortimer and Pressey, 2013) and builds on search's economic theory (Stigler, 1961; Rothchild, 1973). The ramifications of this theory extend to include consumers' prior beliefs in shaping their search strategies. Consumers frame their problems and incorporate them into their environment (Payne, 1982); they carefully relate those to delineate alternatives (Weitzman, 1979). Current work has focused on whether consumer searches depend on search costs rather than involvement or brand uncertainty. The allocation of resources outlined here speaks to the search costs induced by the uncertainty derived from limited resources at consumers' disposal. According to Murray's (1991) tradition, the perceived risk is information distinctive to the products or services. This approach is often associated with preferences (Mitra et al., 1999). Hence, research has moved into motivations for keeping consumers searching for alternative product or service options (Sharma et al., 2014), knowledge (Awasthy et al., 2012) often derived from self-confidence (Loibl et al., 2009). Even though many loyalty card theories align with information search theory, this work makes a turn towards Prospect Theory to capture not intentions or difficulties in market search, but the willingness to engage or not in a loyalty scheme.

The theoretical approach implemented here is Prospect Theory. According to the theory, individuals tend to behave riskily when faced with massive losses and small gains. At the same time, individuals are risk avoiders in small losses and large gains (Kahneman and Tversky, 1984; Tversky and Kahneman, 1992). Dowling (1986) argues that apart from product and respondent, the purchase situation and capacity is equally salient in consumer decisions. King and Devasagayam (2017) favour the idea that consumers exhibit hoarding behaviour in the presence of product scarcity. However, research has focused on product scarcity rather than disposable income scarcity. Consumers value their deposits as another hoarded product, which they will exchange for consumer products. This scarcity elicits an aversive reaction to risk due to the prospect of losing their items of value. Due to the endowment effect, individuals place a higher value on objects they own than objects they do not own (Thaler, 1980). However, the reader might be tempted to view the frequency of checking the bank balance through the lens of the expected utility theory. Our argument here is that Prospect Theory is more relevant due to the framing effects. The framing is enhanced repeatedly over the frequency; the individuals decide to check their balance account. This approach violates expected utility theory and points us towards Prospect Theory since it explains the decision making under uncertainty. To argue further on, the validity of our framing effect has been studied very early by researchers and it has been argued that decisions are heavily influenced by framing (Tversky and Kahneman, 1981; Diamond, 1988; Elliott and Archibald, 1989; Van Schie and Van Der Pligt, 1995). Under the lighting of the research question posed in the introduction and implementing the theoretical underpinning, the work is ready to present its **first hypothesis**:

H_1: People who check their bank account frequently are more likely to own loyalty cards.

The effort exerted by consumers is determined by the time spent on information searching before taking the decision. Individual consumers who worry extensively about their account balance have an extra reason to direct their efforts in spending their time productively rather than searching for alternatives. However, as Srinivasan and Ratchford (1991) put it, information search should include efforts to acquire information from the external environment. Since the time devoted to searching very often on a personal bank account is a measure of efforts to direct decisions on targeted behaviours, such as loyalty cards, this paper contributes to the literature by incorporating the frequency (efforts) of checking the balance account as an essential determinant for loyalty card adoption. The opportunity cost of time is the wage rate (Marvel, 1976). Usually, the literature income is a proxy for the opportunity cost of search (Alcaly, 1976). My approach is to use the frequency of checking the bank account balances. Since the 80s, Furse et al. (1984) have suggested that income is negatively related to search, implying that those in lower rewarding occupations (occupations low in objective career success) will search more for alternatives. Since time scarcity has been consistently found to be negatively related to external product information search (Kolodinsky, 1990), consumers' income is a determinant of their buying behaviour (Ramya and Ali, 2016).

Gender sensitivity

The marketing literature posits that men and women respond differently to various product characteristics (Fournier, 1998; Evanschitzky and Wunderlich, 2006; Babin et al., 2013; Vilches-Montero et al., 2018). Several studies report mixed results for loyalty program participation between genders. Kivets and Simonson (2002) report that loyalty programs are pronounced among women compared to men, while Audrain-Pontevia and Vanhuele (2016) suggest the contrary – men are the ones who are more positively oriented toward loyalty programs. On the other hand, Melnyk and Van Osselaer (2012) bring mixed results with men selecting a loyalty card based on status. Women are more positively oriented towards personal settings when choosing a loyalty scheme. Thus, the **second hypothesis** is proposed as:

H_2: Women are more likely to own loyalty cards than men when they frequently check their bank account.

Data

Two datasets have motivated this research. The first one is Thompson Reuters Datastream, which enhances the article's motivation and allows moving onto the argument without breaking the logical process. Loyalty card equal to nonzero and non-missing indicates a positive outcome. The individual has selected the specific loyalty card during shopping, whereas equal to zero predicts a negative outcome. The second dataset, which will be the centre of my analysis, is obtained from the Understanding Society Innovation Panel. The Innovation Panel contains a sample of 1,500 households used by researchers as a testbed for developing new research areas[5]. Only the 9th wave of the Innovation Panel has been included in the present study since this is the only wave with available data for loyalty cards.

The respondents were asked the following question during the questionnaire: "Which of the following store loyalty cards do you have?" (The reader should not confuse this question with choosing between different loyalty cards but with participation in various programs). Please select all that apply: (1) Tesco Clubcard, (2) Nectar Card, (3) myWaitrose Card, (4) Morrisons Match & More Card, (5) The Co-operative Card, (6) my John Lewis Card, (7) Ikea family Card, (8) Boots Advantage Card, (9) Nando's Card, (10) Costa Coffee Club Card, (11) Starbucks Card, (12) British Airways Executive Club Card, (13) Virgin Atlantic Flying Club Card, and (96) No store loyalty cards". Nandos is a fast-food retailer; Starbucks provides coffee and relaxation, British Airways and Virgin Atlantic are airlines. Having a mix of firms using loyalty programmes offers the opportunity to generalise, which is not possible with only one brand. This one will be the primary dependent variable. In the data management process, the analysis generates dichotomous variables. Value one corresponds to an individual's specific loyalty card and zeroes when the particular individual has not applied for that loyalty card. The primary independent variable is encountered in the questionnaire with the following question: "How often do you check your bank balance". The respondent has to select one option from (1) Most days, (2) At least once a week, (3) A couple of times a month, (4) At least once a

[5] Notice that a household can have many members, and this is translated in up to 2227 observations reported for the variables (see Table A1)

month, (5) Less than once a month and (6) Never. A detailed description of the variable statistics is reported in Table A1 in Appendix I. It becomes evident that the higher the number of the independent variable, the lower the frequency of an individual checking her bank balance. The question chosen allows to separate any safety strategies. The question posited does not leave room to assume that this happened at some point in a person's life, which might be situational, e.g. a lost wallet. The question refers to the respondents' general habit of checking their bank account.

By methodologically considering one card at a time, this study investigates whether participants are willing to stay loyal and be part in a loyalty program. By testing the same model for every store, the study tests the findings' robustness. The reader might notice and argue that the same person can be in several models and be the card owner. This could raise a question about the independence of observations across models. This is not a problem since this work does not study why people own a single card or multiple cards. Instead, to tackle any issue or concern of population representativeness from the innovation panel, this work performs the estimation process as many times as the loyalty cards plus no card for robustness.

Modelling

The present research fits a logit model for a binary response[6] through a maximum likelihood process (Berkson, 1944). It models the probability of a positive loyalty card participation given the frequency individuals check their bank account balances, plus an additional set of regressors for accounting for any potential sample selection error. The logit model is employed due to its convenience of coefficient interpretation[7]. More specifically, the model used in the analysis is:

[6] Stata statistical software is used for applying the statistical methodology and generating results.
[7] Reports coefficients over odds.

$$\Pr\,(Loyalty\ Card = 1) = F\big(\beta_0 + \beta_1 frequencycheck + \beta_2 Z\big) \quad (1)$$

where $F(c) = \frac{e^c}{(1+e^c)}$ is the cumulative logistic regression, and the likelihood function to be maximised is:

$$lnL = \sum_{j\in S} lnF(c) + \sum_{j\notin S} \ln\{1 - F(c)\} \quad (2)$$

and

$$c = \beta_0 + \beta_1 frequencycheck + \beta_2 Z \quad (3)$$

where S is the set for all observations j, such that $y_j \neq 0$ and Z is the vector of additional control variables. The model is specified so that the standard errors reported are robust to some kinds of misspecification. Valid, robust estimates of the standard errors are needed in case the error term is not identically distributed. Thus, if data are not identically distributed, valid statistical inferences are made about the estimated coefficients. Our independent variable, the frequency of checking bank accounts, is an ordinal (categorical) variable, ordered from 1 (most days) to 6 (never). Despite being impossible to say that going from 1 (most days) to 2 (at least once a week) as having the same marginal probability from 5 (less than once a month) to 6 (never), the advantage of this approach is that it offers a more straightforward interpretation. The intervals between scales may seem unequal; thus, rendering the standard deviation unbiased, which is why the Huber/White/Sandwich estimator was used and tested consistency with the goodness of fit tests below.

To check for the goodness of fit, the analysis tests the Pearson goodness-of-fit χ^2 test (Pearson, 1900). Let us define M as the total number of covariate patterns across N observations and define m_j as the total number of observations having a covariate pattern j. Moreover, y_j is defined as the total number of positive responses across observations with covariate pattern j

and p_j is the predicted probability of a positive outcome in a covariate pattern j. The Pearson χ^2 goodness-of-fit statistic is:

$$\chi^2 = \sum_{j=1}^{M} \frac{(y_j - m_j p_j)^2}{m_j p_j (1 - p_j)} \tag{4}$$

which has $M - k$ degrees of freedom for the estimation sample, where k is the number of independent variables, including the constant term. For selecting models, the present work implements the Akaike's (1974) Information Criterion defined as:

$$AIC = -2lnL + 2k \tag{5}$$

where lnL is the maximised log-likelihood of the model, and k is the number of parameters estimated. Additionally, Schwarz's (1978) Bayesian Information Criterion is another measure of fit defined as:

$$BIC = -2lnL + klnN \tag{6}$$

with N being the sample size. Information criteria are used for benchmarking, and the lowest values reported, the better the model.

Following the AIC and BIC, the Receiver Operating Characteristic (ROC) curve are calculated. This approach calculates the area under the curve, which equals the probability that a classifier will rank a randomly chosen positive outcome higher than a randomly chosen negative outcome (Peterson et al., 1954; Metz, 1978). This is a sensitivity curve versus one minus specificity as the cut-off c is varied, while it calculates the area below the curve. Sensitivity is the fraction from observed positive-outcome cases, which had been correctly classified, while specificity is the fraction from observed negative-outcome cases that are correctly classified. More specifically, suppose that a positive outcome is when "loyalty card != 0" to predict failure perfectly and when loyalty card is not zero, then zero probability of success should be anticipated. If it were not zero, then this would be a negative outcome. The curve begins at (0,0), corresponding to $c = 1$, and continues to (1,1), corresponding to $c = 0$. A model with zero predictive power would be a 45^o line and the higher the predictive power, the more bowed will be the curve and, hence, the area below the curve is the measure of predictive power. Generally, an area of 0.5 (the benchmark) has no diagnostic power, while an area of one is an excellent diagnostic ability.

Assume that X refers to the value of the criterion variable in the negative population, and Y refers to the value of the criterion variable from the positive population. The binormal model assumes that both X and Y are normally distributed with different means and variances, that is:

$$X \sim N\left(\mu_x, \sigma_x^2\right), Y \sim N\left(\mu_y, \sigma_y^2\right) \tag{7}$$

The function identifies the ROC curve:

$$\{FP(z), TP(z)\} = \left\{\Phi\left(\frac{\mu_x - z}{\sigma_x}\right), \Phi\left(\frac{\mu_y - z}{\sigma_y}\right)\right\}, -\infty < z < \infty \tag{8}$$

where $\Phi(\delta)$ is the cumulative normal distribution function. The partial area under the curve (AUC) is calculated as:

$$A = \int_{z_1}^{z_2} TP(z)FP(z)dz = \frac{1}{\sigma_x}\int_{z_2}^{z_2} \Phi\left(\frac{\mu_y - z}{\sigma_y}\right)\Phi\left(\frac{\mu_x - z}{\sigma_x}\right)dz \tag{9}$$

where:

$$z_i = \mu_x + \sigma_x \Phi^{-1}(FP_i) \tag{10}$$

In the end, the margins of responses for probabilities and linear predictions are estimated and are plotted. The predicted probability of a positive outcome is calculated and then graphed into the margins plot. The margins are plotted on the y axis and all the discrete covariates specified are placed in the x axis. The following section explains in depth the outcomes of the Figures. At the output tables, the Pseudo R^2 and the χ^2 are reported. However, the logit framework does not have an equivalent to R^2 encountered in OLS regression, which reports the proportion of variance explained by the predictors (McFadden, 1977). The χ^2 per se does not have an interpretation meaning, but what is interesting is the probability of obtaining a χ^2. This is the joint null hypothesis test that all independent variables included in the model jointly or altogether have a coefficient zero. A zero probability will help reject this hypothesis and assume that our independent variables can identify any effect. Notice here that in Table 2, only two independent variables are included compared to Table 3, where 33 independent variables are considered.

Empirical results

For Sainsbury's Nectar loyalty card, the Pearson statistic and both AIC and BIC favour the advanced model. However, for the case of Waitrose, the BIC criterion seems to favour a simple model instead of what the AIC and Pearson criteria would suggest. The same inconsistency is encountered with Morrisons, Coop, John lewis, Ikea, Boots, Costa, Starbucks, British Airways and Virgin Atlantic. The criteria seem to support the advanced model over the simple one for Nando's and No card.

[Table 1 near here]

Since the identification measures in Table 1 could not provide a definitive answer to the model specification, the present investigation proceeds and uses the Receiver Operating Characteristic (ROC) curve, a graphical plot illustrating a binary model's diagnostic ability when its discrimination threshold is changing. Notice that in Table 1, Tesco's Pearson goodness-of-fit seems to favour the simple model, while both AIC and BIC identification criteria favour the advanced model.

In the simple model reported in Table 2, data come from all the thirteen loyalty programmes from Tesco, Nectar, Waitrose, Morrisons, Coop, John Lewis, Ikea, Boots, Nando's, Costa, Starbucks, British Airways and Virgin Atlantic, plus the option for individuals who conscientiously select of opting out from any loyalty card programme. The simple model uses the variables mentioned above, with an additional gender variable as a covariate. According to the overview report derived from Table 2, it is found that the higher the frequency of individuals checking their bank accounts, the higher is the probability for opting in for loyalty cards, thus accepting **hypothesis one** (H_1). On top of that, the probability for females is higher than the probability for males to opt-in, which comes in accordance with **hypothesis two** (H_2). For Tesco stores, the coefficient is -0.118 (odds ratio: 0.889, p-value < 0.01), for Sainsbury's (the Nectar card) the coefficient is -0.113 (odds ratio: 0.893, p-value < 0.01), for Waitrose this is -0.094 (odds ratio: 0.910, p-value < 0.05), for Morrisons -0.090 (odds ratio: 1.094, p-value < 0.05), while for Ikea this stands for -0.171 (odds ratio: 0.843, p-value < 0.01). As for Boots, the robust logit coefficient reports the value of -0.135 (odds ratio: 0.874, p-value < 0.01), for Nando's this is -0.546 (odds ratio: 0.579, p-value < 0.01), and for Costa cafeterias the coefficient is -0.178 (odds ratio: 0.836, p-value < 0.01). Starbucks report a -0.307 (odds ratio: 0.735, p-value < 0.01) coefficient, -0.287 (odds ratio: 0.751, p-value < 0.01) for the former national air carrier, and -0.267 (odds ratio: 0.766, p-value < 0.05) for Virgin Atlantic. For those who have opted out from loyalty card programmes, the coefficient has a positive sign 0.219 (odds ratio: 1.245, p-value < 0.01).

[Table 2 near here]

The ROC curves in Figure 1 indicate that the simple logit estimation models should be taken with a grain of salt, as they do not meet the standards of a very good identification model. Instead, Figure 2 suggests that an advanced model with more variables for controls would allow getting a higher identification model, and it seems robust to report the findings of Table 3.

[Figures 1 and 2 about here]

For Tesco supermarkets, the simple model ROC area is 0.5998. Instead, the advanced model comes with a region of 0.7145. For Sainsbury's, the area under the ROC curve for the simple model is 0.5902, when for the advanced model is 0.7168. The Waitrose simple model reports values of 0.5608. Instead, the more advanced logit model gives back an area of 0.7225, which is significantly better. For Morrisons and Cooperative supermarkets, the simple model areas are 0.5670 and 0.5650, respectively, when on the other hand, their advanced models report areas of 0.6509 and 0.6915. For John Lewis, the model does not go more than 0.5641, when for the advanced model, this area is 0.7557. The values for the simple model of Ikea and Boots are 0.6053 and 0.7596, respectively. The simple models for Boots are explained satisfactorily. Thus, the areas for the advanced models stand for 0.7196 and 0.8122, respectively. The Boots advanced model ROC area is even higher than the simple one, and this is a good indication of choosing the advanced version over the simple one. For Nando's, Costa and Starbucks, the simple model ROC areas are 0.6834, 0.6250 and 0.6238, respectively. For their advanced models, these areas rise to 0.8337, 0.7122 and 0.7735, respectively. For the simple models of UK's airways, the area values are 0.6319 and 0.5799, respectively. In contrast, the advanced model areas are 0.7944 and 0.8074, respectively.

The advanced model represents a better fit with a 0.7942 ROC value over the simple model for those who have opted out from loyalty card programmes, reporting a value of 0.6788. Contrary to Pearson's statistic for goodness-of-fit, AIC and BIC identification models, which reports mixed results about the appropriate models (simple or advanced) to select for our final estimation strategy, the ROC specification provides a more consistent model selection strategy in favour of the advanced models. As a result, the reader should be confident of the advanced model's specification to proceed and interpret the empirical findings safely.

[Table 3 near here]

Preliminary results from Table 2 illustrate an early indication of what should be expected from Table 3. The suspicion is that the coefficient signs will not fall far off, thus accepting both **hypotheses** (H_1) and (H_2). Following the overview from Table 3, the analysis shows a negative correlation between selecting over the Tesco loyalty card and frequently checking the bank balance account with a beta equal to -0.112 (odds ratio: 0.894, p-value < 0.01). The next correlate for Sainsbury's is -0.142 (odds ratio: 0.868, p-value < 0.01), while the coefficient for Waitrose is -0.119 (odds ratio: 0.888, p-value 0.01). For Morrisons the correlate is -0.124 (odds ratio: 0.883, p-value < 0.01), while for Coop the negative signs remains, but the strength of the coefficient drops to -0.086 (odds ratio: 0.918, p-value < 0.1). For John Lewis, Starbucks, Costa, Virgin Atlantic and Ikea, there are no statistically significant results; thus, they are left out from the analysis. Boots and Nando's report findings of -0.128 (odds ratio: 0.880, p-value < 0.01) and -0.377 (odds ratio: 0.686, p-value < 0.01), respectively. For the final loyalty card, British Airways also reports a negative coefficient of -0.296 (odds ratio: 0.744, p-value < 0.01), which is not very far off from what encountered in the simple model. As far as those who have not participated in the loyalty card programme, the correlation is 0.263 (odds ratio: 1.301, p-value < 0.01). As a result, Table 3 results support both H_1 and H_2 hypotheses.

At this point, it is essential to look at the marginal probabilities for every loyalty card programme that has been statistically significant in Table 3. For Tesco, the predictive margins with 95% confidence intervals are different for both genders. For females, those checking their bank balance account most days report a 0.67 probability of selecting the loyalty card. For females who never bother to check their bank account, that likelihood drops to 0.55. As for males, those who check their balance account at least once a week report a probability of 0.48 when those who check it less than once a month report a probability of 0.40. These results are illustrated in Figure 3. For Sainsbury's, females report a 58% probability of selecting the Nectar loyalty card when checking their bank account frequently, while males have a probability of 43%. For those females that never check their balance, the likelihood of using Nectar's is 0.42, while for males, this is only 28%. Going to check the Waitrose probabilities, females report a probability of 16% when they check their balance a couple of times per month when for males, the same probability is a little less than 11%. For Morrisons, the predictive probability is 27% when checking at least a month for females and 19% for males. For the same frequencies when checking the likelihood of selecting the Coop loyalty card, females' probability remains steady at 17%, while 11% for males. As far as Boots is concerned, the likelihood of selecting a Boots loyalty card programme is 67% for females checking their account very frequently.

In comparison, males report only a very low 17% probability for the same frequency checks level. For Nando's, the probabilities of self-selecting into the loyalty programme are very low. They are 12% for females and 7% for males when both genders very often check their balance. Similarly, the probabilities for British Airways are 0.04 for females and 0.06 for males, when both are very often checking their accounts. Finally, when males have selected to be excluded from any loyalty programme, they have a 44% probability not to opt-in when they rarely check their accounts. In comparison, for females, the likelihood of actually not selecting any loyalty program turns out to be 19%.

[Figure 3 near here]

In most figures, males fail to catch up to females. It becomes evident that the marginal effect is higher for females than for males. Besides, the marginal plotted probability depicted in Figure 3 shows that the marginal likelihood of having a loyalty card is higher for the individuals who are frequent checkers of their bank accounts.

In light of how the ordinal structure of the variable is structured and what might be seam as inconsistent[8], negative relationships indicate that individuals who rarely check their accounts have a lesser likelihood of self-selecting a loyalty card program.

Discussion

Theoretical implications

The present investigation tested the Prospect Theory (Kahneman and Tversky, 1984; Tversky and Kahneman, 1992) on losses during uncertainty and found out that individuals are more likely to own a loyalty card when checking frequently their individual bank accounts. The first hypothesis has been accepted, which leads us to believe that consumers in an uncertain environment (e.g. similar caused by the pandemic of COVID-19) can be forced to stick to their habits and use royalty cards more often. The second theoretical implication supports the gender differences in marketing decisions (Fournier, 1998; Evanschitzky and Wunderlich, 2006; Babin et al., 2013; Vilches-Montero et al., 2018). In specific, this work identifies that women are more inclined to own a loyalty card, thus supporting Kivets and Simonson (2002) over Audrain-Pontevia and Vanhuele (2016) and others with mixed results, such as Melnyk and Van Osselaer (2012). Consumer loyalty is a complex topic given that discussion can refer to loyalty in a firm, brand or shopping location. Consumer loyalty may differ based upon the type of product, service, or store. The current research draws away from loyalty cards' attitudinal

[8] Meaning that higher values of the frequency of checking the bank balance variable is reported as low for higher values.

approach and approaches the subject from a market perspective. On the same page, the study at hand walks away from the utilitarian perspective, demanding more customers to use the same loyalty card to receive benefits and discounts. Implications exist on the share of wallet, or else customers dividing their purchases across competing firms and how retailers can increase their share of their customers' total category expenditure. Customers are indeed heterogeneous, which is depicted on the predictive margins reported in Figure 3 – where despite the downward trend in probabilities, as the frequency of checking the bank account balance became scarce, the probability followed in decline. Individuals checking their bank account frequently were used as a proxy variable of income insecurity (rising debt outstanding to consumer credit card). A common alternative would be to use income insecurity as the primary independent variable, which could be a good alternative variable for future research. The present work does not follow this approach as it tends to walk away from individual behaviours with her or his bank account and generalises with income insecurity, which covers a vast area related to income sources. When individuals do not have many sources of secure income, they may never check simply because they might not have much to look at. Instead, insecurity is arisen when they want to monitor their account transactions and micromanage them.

Managerial implications

The study should help marketing practitioners better understand the interrelationship between income insecurity and following a customer-oriented marketing programme[9]. The present research looks beyond the long tradition of service quality, customer satisfaction, perceived values, and the role of the corporate image that had dominated before the crisis in helping retailers, banks, pharmaceuticals or telecommunications and more to gain a more extensive market share, thus, drawing the attention on the population needs and how retailers can deliver

[9] Such as loyalty cards and the underpinnings of the mechanism for enhancing brand loyalty.

a better service. It becomes essential to question whether brand managers should focus their marketing attention only on consumers who are more likely to purchase in a specific store or focus on customer income security needs.

To make matters worse, online stores have created less loyal customers. Rather than having consumers repurchase a product repeatedly over time, internet users are more likely to use price comparison websites, counting on the impressive quantity of information and choices available online. Often, firms are more interested in observing customers' behaviour than intentions since they are directly linked to revenues and profitability (Chandon et al., 2005). But how about the introduction of no cashier retailers? Mobile payments provide substantial benefits for both customers and merchants because they are immediately available and increase time efficiency at the point of sale. In mobile technology, Meyll and Walter (2019) argue that mobile payments (such as those without cashier) might be related to costly credit card behaviours, which may depict an early stage where individuals with high income attempted the technology first. As this technology becomes widespread and the population becomes heterogeneous, more individuals who are frequent checkers of their bank account will join them, and retailers should be ready to include those people. This comes to support a strand of literature assuming that loyalty is guided by elements other than the loyalty programme, in particular, the competitive position, proximity, inertia, comfort, product variety, store size, sales promotions and the store's relative isolation. The findings should not encourage firms to abandon loyalty programmes since that will disadvantage them vis-a-vis their competitors. Instead, they should reform their loyalty programmes and include those who are in need. Assuming that the frequency of checking the bank balance account is associated with debt, then the debt is more common among those with lower incomes (Cameron and Golby, 1991).

A question remains: How will firms know who is checking their bank balance often and who is not? A possible solution might be to ask individuals directly. This work opens up a new avenue of direction, calling researchers to find proxies of this behaviour. Instead of firms asking individuals directly and getting no for an answer, they can extrapolate their frequency of checking their account balance from other implicit responses. Possibly, risks, job satisfaction, and life satisfaction, which might connect to their career success.

Because consumers tend to exhibit an emotional attachment to possessing an item, a feeling of loss aversion prompts a decision to measure the level of deposits before proceeding with the purchase. Our findings have severe managerial implications under the light of the new pandemic. Helson (1964) postulates that people have an adaptation level based on their past experiences and environmental factors. In a virtual environment, when consumers do not have the flexibility to visit the store and evaluate the product closely, their past experience or reference would be the deposit stimulus before purchasing, if any and consumers may adapt to that level. What is additionally identified here is that women are more likely to adopt a royalty card than men when faced with financial constraints. The results of this present study indicate that women are keener to selecting a loyalty card scheme when under an income-stressed scenario.

Limitations and future directions

Further research can analyse the variation of the shape of the relationship based on individuals' industry characteristics to pinpoint the probability of adopting a specific loyalty card, depending on how well the industry is performing. A further limitation lies in the research's cross-sectional nature — the present research-derived data from the final wave of the Understanding Society Innovation Panel. A future direction could be incorporating time series into the analysis, where researchers can expand the current analysis's scope to include the time variable, and implement longitudinal methodologies. Additional limitations lie in the causality direction. Although it might be difficult to intuitively assume that a specific loyalty card causes individuals to check their account balance, a more robust methodology such as structural equation modelling would be ideal for robustness check. Finally, even though the reader can appreciate the inclusion of some covariates in the form of Z variables, there may be endogeneity issues. Low incomes cause people to own loyalty cards and check balances frequently. The deeper relationships have to be estimated using more variables and a more complex model.

During the pandemic, retail chains realised their sales were contingent on customers going to where the product is being sold. Consumers swifter towards electronic methods for purchasing goods ranging from food delivery to cloth and electronic devices during the worldwide lockdown period. Loyalty cards are losing their subsistence, and their notion needs to move into the virtual realm. In specific, loyalty cards can be translated to virtual accounts in e-retailers, where discounts are offered based on the quantity or amount purchased in a single spell. In the future, we are expecting to see more consumers be conscious of their available income, and understanding this can help e-retailers understand the duration a product remains in a customer's wishlist. Wishlist could be evolved into the new norm for loyalty cards, where customers stay loyal but unable to fulfil the purchase unless engaged. Investigating the attitudinal elements and wishlist product retention could be beneficial and enlightening for future researchers and managers.

Conclusion

With a large proportion of the marketing battle being carried out in the reward programme arena (Noordhoff et al., 2004), this study provided empirical early evidence of the probability of joining a reward programme when that influence is relative to the income insecurity felt by individuals. The analysis employed a probit methodology and examined the frequency of checking the bank account balance on the willingness to use a loyalty card among 13 corporate brands, plus the willingness not to use any loyalty cards at all. The findings reported that for some brands, the probability of self-selecting into a loyalty card programme was very low for both genders. The predictive margins indicated that the higher the frequency of individuals checking their bank balance accounts, the higher the probability of participating in a loyalty programme. Note here that the research is far from conclusive. Further research is required to explore the mechanisms behind it. It would be nice to see in the future how other variables such as demographics or psychographics moderate the relationship.

Acknowledgements

I would like to thank three anonymous referees for their valuable comments and suggestions. Their support was immense to polish a final version of this work.

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Appendix

Table A1. Descriptive statistics

	Observations	Mean	Standard Deviation	Minimum	Maximum
Loyalty Cards					
Tesco	2157	-	-	0	1
Nectar	2157	-	-	0	1
Waitrose	2157	-	-	0	1
Morrisons	2157	-	-	0	1
Coop	2157	-	-	0	1
John Lewis	2157	-	-	0	1
Ikea	2157	-	-	0	1
Boots	2157	-	-	0	1
Nando's	2157	-	-	0	1
Costa	2157	-	-	0	1
Starbucks	2157	-	-	0	1

British Airways	2157	-	-	0	1
Virgin Atlantic	2157	-	-	0	1
No card	2157	-	-	0	1
Age Groups					
10 – 19	2236	-	-	0	1
20 – 29	2236	-	-	0	1
30 – 39	2236	-	-	0	1
40 – 49	2236	-	-	0	1
50 – 59	2236	-	-	0	1
60 – 69	2236	-	-	0	1
70 and more	2236	-	-	0	1
Career Success					
Satisfaction with income	2109	4.8430	1.5812	1	7
Gross personal income	2174	1827.9	1667.2	0	15000
Education					
University degree	2220	-	-	0	1
Other higher degree	2220	-	-	0	1
A level	2220	-	-	0	1
GCSE	2220	-	-	0	1
Other qualification	2220	-	-	0	1
No qualification	2220	-	-	0	1
Demographics					
If male	2237	-	-	0	1
Single	2226	-	-	0	1
Married	2226	-	-	0	1
Same-sex relationship	2226	-	-	0	1
Separated but married	2226	-	-	0	1
Divorced	2226	-	-	0	1
Widowed	2226	-	-	0	1
Separated from partnership	2226	-	-	0	1

Number of children	2237	-	-	0	7
Self-employed	2227	-	-	0	1
Paid employed	2227	-	-	0	1
Unemployed	2227	-	-	0	1
Retired	2227	-	-	0	1
Maternity leave	2227	-	-	0	1
Family care	2227	-	-	0	1
Student	2227	-	-	0	1
Disabled	2227	-	-	0	1
Apprenticeship	2227	-	-	0	1
Doing something else	2227	-	-	0	1
Family business	2227	-	-	0	1

Table 1. Pearson Goodness-of-fit, Akaike's and Bayes information criteria on model specification

Simple model	Tesco	Nectar	Waitrose	Morrisons	Coop	John Lewis	Ikea	Boots	Nando's	Costa	Starbucks	British Airways	Virgin Atlantic	No card
Pearson goodness-of-fit	0.6026	0.0036	0.3970	0.2349	0.0037	0.2505	0.2503	0.0790	0.8713	0.0009	0.6396	0.1576	0.0969	0.0039
AIC	2886.247	2917.874	1665.044	2381.806	1804.527	1054.875	1551.055	2386.488	1006.574	1812.762	622.1721	629.4194	475.3556	1869.428
BIC	2903.268	2934.895	1682.065	2398.827	1821.548	1071.896	1568.076	2403.509	1023.595	1829.783	639.1932	646.4404	492.3766	1886.449
Advanced Model														
Pearson goodness-of-fit	0.2085	0.4688	0.4326	0.3265	0.3617	0.0432	0.341	0.3399	0.9176	0.8208	0.9979	0.0039	0.5501	0.3219
AIC	2571.632	2580.006	1540.366	2251.593	1694.75	968.1078	1424.185	2228.704	863.6832	1713.176	596.0942	554.2989	411.5887	1607.57
BIC	2757.629	2765.891	1709.002	2431.783	1874.956	1135.909	1602.604	2420.387	1018.672	1893.49	750.7819	685.1844	538.2426	1793.566

When the number of covariate patterns is close to the number of observations, it makes the applicability of the Pearson χ^2 test questionable but not necessarily inappropriate. As for Akaike's and Schwarz's Bayesian information criteria, for model comparison "smaller is better" rule is applied here.

Table 2. Loyalty cards (Simple Logit Model) with Huber/White/sandwich estimator

	Tesco	Nectar	Waitrose	Morrisons	Coop	John Lewis	Ikea	Boots	Nando's	Costa	Starbucks	British Airways	Virgin Atlantic	No card
Account frequency check	-0.118***	-0.113***	-0.094**	-0.090**	0.006	-0.068	-0.171***	-0.135***	-0.546***	-0.178***	-0.307***	-0.287***	-0.267**	0.219***
	(0.032)	(0.032)	(0.045)	(0.037)	(0.040)	(0.062)	(0.054)	(0.036)	(0.080)	(0.047)	(0.102)	(0.086)	(0.119)	(0.042)
If male	-0.651***	-0.598***	-0.369***	-0.399***	-0.468***	-0.461**	-0.568***	-2.245***	-0.496***	-0.766***	-0.500**	0.534**	-0.032	1.212***
	(0.089)	(0.088)	(0.132)	(0.103)	(0.126)	(0.181)	(0.141)	(0.107)	(0.184)	(0.129)	(0.255)	(0.243)	(0.289)	(0.122)
R2_P	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.19	0.06	0.03	0.02	0.02	0.01	0.07
chi2	67.58	58.63	12.94	21.08	13.82	9.07	25.95	448.48	51.32	51.61	14.40	13.03	5.64	119.12
p	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00

Ll	-1,440.12	-1,455.94	-829.52	-1,187.90	-899.26	-524.44	-772.53	-1,190.24	-500.29	-903.38	-308.09	-311.71	-234.68	-931.71
N	2,151	2,151	2,151	2,151	2,151	2,151	2,151	2,151	2,151	2,151	2,151	2,151	2,151	2,151

* p<0.1; ** p<0.05; *** p<0.01. Reports of the estimated coefficients have not been transformed into odds ratios, that is, e^{β} rather than β.

Table 3. Loyalty cards (Advanced Logit Model) with Huber/White/sandwich estimator

	Tesco	Nectar	Waitrose	Morrisons	Coop	John Lewis	Ikea	Boots	Nando's	Costa	Starbucks	British Airways	Virgin Atlantic	No card
Account frequency check	-0.112***	-0.142***	-0.119**	-0.124***	-0.086*	-0.077	-0.090	-0.128***	-0.377***	-0.057	-0.164	-0.296***	-0.188	0.263***
	(0.037)	(0.037)	(0.055)	(0.043)	(0.049)	(0.076)	(0.061)	(0.040)	(0.087)	(0.051)	(0.103)	(0.111)	(0.125)	(0.050)
Age groups														
10 – 19	-2.202***	-2.556***	-2.092***	-0.804	-1.707**	-1.857*		-0.661	3.881***	1.559***	1.684		1.191	1.696***
	(0.477)	(0.492)	(0.799)	(0.547)	(0.663)	(1.116)		(0.466)	(1.336)	(0.559)	(1.123)		(1.218)	(0.489)
20 – 29	-0.384	-1.050***	-1.187***	0.019	-1.176**	-0.936	0.312	-0.370	3.637***	1.744***	1.514	0.576	0.587	0.967**
	(0.319)	(0.316)	(0.439)	(0.361)	(0.482)	(0.613)	(0.545)	(0.382)	(1.101)	(0.475)	(1.009)	(0.887)	(0.813)	(0.414)
30 – 39	-0.055	-0.573**	-0.519	0.095	-1.052***	-0.247	0.727	0.001	3.327***	1.137***	1.203	1.769**	0.617	0.159
	(0.294)	(0.291)	(0.393)	(0.321)	(0.391)	(0.522)	(0.452)	(0.342)	(1.074)	(0.453)	(0.979)	(0.770)	(0.639)	(0.400)
40 – 49	0.080	-0.541**	-0.465	0.308	-0.686**	-0.515	0.543	0.131	2.128**	1.261***	0.190	1.484**	0.947	0.129
	(0.272)	(0.269)	(0.362)	(0.295)	(0.344)	(0.494)	(0.433)	(0.317)	(1.064)	(0.436)	(0.999)	(0.692)	(0.621)	(0.375)
50 – 59	0.110	-0.149	-0.218	-0.078	-0.537*	-0.161	0.122	-0.208	1.851*	0.773*	0.609	0.900	0.221	-0.018
	(0.248)	(0.244)	(0.327)	(0.264)	(0.291)	(0.444)	(0.403)	(0.294)	(1.021)	(0.409)	(0.916)	(0.627)	(0.502)	(0.342)
60 – 69	0.026	-0.148	0.017	0.123	-0.170	0.164	0.134	-0.165	0.155	0.517	-0.974	0.324		0.334
	(0.177)	(0.180)	(0.241)	(0.190)	(0.211)	(0.334)	(0.312)	(0.211)	(1.310)	(0.334)	(0.903)	(0.458)		(0.258)
Career Success														
Satisfaction with income	0.026	0.043	0.120**	-0.047	-0.022	0.101	-0.050	0.073**	0.083	0.042	0.095	0.171*	0.349***	-0.058
	(0.033)	(0.033)	(0.048)	(0.036)	(0.042)	(0.067)	(0.047)	(0.036)	(0.064)	(0.043)	(0.097)	(0.098)	(0.131)	(0.045)
Gross personal income	0.000*	0.000	0.000*	-0.000	-0.000	0.000***	0.000	0.000	0.000	0.000**	0.000***	0.000***	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education														
University degree	0.320	1.233***	1.670***	0.002	0.350	1.771***	1.717***	1.033***	0.285	1.408***	0.300	1.944*	1.427	-0.825***
	(0.214)	(0.217)	(0.373)	(0.232)	(0.276)	(0.540)	(0.540)	(0.248)	(0.524)	(0.409)	(0.685)	(1.041)	(0.895)	(0.290)
Other higher degree	-0.092	0.860***	1.315***	-0.082	0.404	0.807	1.735***	0.735***	-0.359	1.266***	0.319	1.611	1.061	-0.340
	(0.222)	(0.225)	(0.388)	(0.244)	(0.290)	(0.583)	(0.547)	(0.251)	(0.586)	(0.426)	(0.727)	(1.059)	(0.936)	(0.287)
A level	0.022	0.512**	0.929**	0.361	0.457*	0.452	1.478***	0.903***	0.320	1.278***	0.060	1.628	0.603	-0.565**
	(0.211)	(0.215)	(0.385)	(0.228)	(0.275)	(0.586)	(0.545)	(0.247)	(0.508)	(0.412)	(0.676)	(1.059)	(0.932)	(0.259)
GCSE	-0.191	0.487**	0.626	0.025	0.071	1.009*	1.039*	0.691***	0.032	1.168***	-0.320	0.625	0.731	-0.166
	(0.204)	(0.207)	(0.381)	(0.223)	(0.271)	(0.555)	(0.544)	(0.236)	(0.523)	(0.409)	(0.710)	(1.091)	(0.910)	(0.250)
Other qualification	-0.306	0.067	0.567	0.096	0.111	-1.293	0.333	0.409	0.316	-0.095	-0.234			0.003
	(0.256)	(0.262)	(0.461)	(0.278)	(0.325)	(1.153)	(0.718)	(0.295)	(0.903)	(0.655)	(1.190)			(0.318)
Demographics														
Female	-0.832***	-0.818***	-0.629***	-0.413***	-0.530***	-0.788***	-0.694***	-2.500***	-0.608***	-0.909***	-0.702**	0.229	-0.412	1.503***
	(0.104)	(0.103)	(0.145)	(0.115)	(0.141)	(0.203)	(0.157)	(0.124)	(0.203)	(0.141)	(0.275)	(0.266)	(0.299)	(0.145)
Single	-0.566***	-0.766***	-0.104	-0.946***	-1.166***	-0.200	-0.474	-0.284	0.984***	-0.204	0.292	1.002	1.718*	0.871***
	(0.203)	(0.199)	(0.284)	(0.238)	(0.327)	(0.365)	(0.330)	(0.233)	(0.404)	(0.261)	(0.519)	(0.643)	(0.956)	(0.262)
Married	0.229	-0.215	-0.211	-0.300*	-0.282	-0.323	0.442*	0.250	1.009***	0.102	0.201	0.490	1.184	-0.178
	(0.174)	(0.172)	(0.237)	(0.174)	(0.219)	(0.299)	(0.250)	(0.191)	(0.433)	(0.221)	(0.441)	(0.572)	(0.925)	(0.247)
Same sex relationship	-0.170	1.058	1.719*	-0.854	0.042	-0.140	0.585	-1.404*		-0.912			2.212	0.110
	(0.660)	(0.786)	(0.924)	(0.791)	(0.879)	(1.215)	(0.797)	(0.776)		(1.165)			(1.353)	(0.894)
Separated but married	-0.397	-0.833**	0.155	-0.464	-0.944	-0.571	-0.808	-0.238	-0.212	-0.240				0.485

	(0.388)	(0.396)	(0.516)	(0.456)	(0.650)	(0.816)	(0.778)	(0.464)	(1.172)	(0.546)				(0.547)
Divorced	0.074	-0.529**	-0.355	-0.721***	-0.190	-0.825*	0.090	0.165	1.030*	-0.586*	-0.025	-0.444	0.787	0.291
	(0.240)	(0.236)	(0.337)	(0.269)	(0.290)	(0.482)	(0.355)	(0.268)	(0.594)	(0.350)	(0.699)	(0.857)	(1.169)	(0.335)
Widowed	-0.827***	-0.649**	-0.914**	-0.489*	-0.879**	-1.087*	-0.045	-0.578*		-0.474		0.122	1.335	0.734**
	(0.269)	(0.276)	(0.429)	(0.287)	(0.345)	(0.582)	(0.505)	(0.305)		(0.508)		(0.924)	(1.388)	(0.367)
Separated from partnership	-1.482	-0.905						-0.874						1.858*
	(1.220)	(1.289)						(1.246)						(0.993)
Number of children	-0.003	0.013	-0.119	-0.165**	-0.120	-0.275*	0.021	0.015	-0.016	-0.140	0.048	-0.435*	-0.040	0.019
	(0.073)	(0.075)	(0.103)	(0.083)	(0.116)	(0.159)	(0.087)	(0.084)	(0.115)	(0.102)	(0.214)	(0.222)	(0.235)	(0.103)
Self-employed	-0.817	1.232	-0.800	-0.176	-0.493	-2.699***	0.612	0.754	0.457	-1.595**	-0.587	-1.699	0.247	0.000
	(0.692)	(0.853)	(1.051)	(1.044)	(0.994)	(0.983)	(1.008)	(0.717)	(0.946)	(0.717)	(1.083)	(1.402)	(1.277)	(0.925)
Paid employed	-0.576	1.163	-1.053	0.262	-0.763	-2.489***	0.100	1.078	0.213	-1.563**	-0.806	-0.462	-0.785	-0.355
	(0.692)	(0.839)	(1.029)	(1.021)	(0.973)	(0.906)	(0.992)	(0.695)	(0.873)	(0.679)	(0.998)	(1.105)	(1.173)	(0.905)
Unemployed	-0.694	0.547	-1.394	-0.967	-0.814	-3.209**	-0.932	0.641	-0.243	-2.082***	-1.530	0.579		0.388
	(0.720)	(0.901)	(1.182)	(1.114)	(1.082)	(1.353)	(1.202)	(0.750)	(1.000)	(0.801)	(1.351)	(1.288)		(0.935)
Retired	-0.746	1.128	-0.857	0.484	-0.547	-2.387**	0.162	1.315*	-0.061	-1.505**	-0.917	1.328	1.057	-0.487
	(0.700)	(0.860)	(1.047)	(1.043)	(0.997)	(0.927)	(1.029)	(0.729)	(1.001)	(0.732)	(1.270)	(1.328)	(1.211)	(0.943)
Maternity leave	-1.367	1.029		0.990	-0.719	-2.024	0.570	1.575	0.129	-2.004**	-0.617			-0.115
	(0.987)	(1.039)		(1.158)	(1.464)	(1.411)	(1.252)	(1.068)	(1.214)	(1.008)	(1.448)			(1.297)
Family care	-0.790	0.565	-1.436	0.296	-0.461	-3.329***	0.041	0.608	-0.162	-1.766**	-2.070	0.499	-1.078	0.416
	(0.719)	(0.878)	(1.107)	(1.062)	(1.028)	(1.163)	(1.130)	(0.738)	(1.022)	(0.748)	(1.514)	(1.374)	(1.846)	(0.974)
Student	-0.720	1.579*	-1.125	-0.338	-1.479	-2.653**	-0.531	0.724	0.038	-1.901***	-0.826			-0.808
	(0.735)	(0.900)	(1.162)	(1.014)	(1.143)	(1.178)	(1.202)	(0.750)	(0.897)	(0.736)	(1.039)			(0.939)
Disabled	-1.314*	0.576	-1.764	-0.410	-0.405		-1.843	0.249		-1.415*				0.288
	(0.717)	(0.884)	(1.174)	(1.076)	(1.038)		(1.404)	(0.763)		(0.763)				(0.949)
Apprenticeship	-0.419						1.631	0.638		-1.007	0.378			-0.411
	(1.205)						(1.434)	(0.955)		(1.042)	(1.300)			(1.125)
Family business		1.429		0.340	-0.011		2.918*	0.0345						
		(1.582)		(1.639)	(1.593)		(1.555)	(1.707)						
R2_P	0.12	0.12	0.09	0.05	0.07	0.12	0.09	0.24	0.20	0.09	0.11	0.15	0.16	0.19
Chi2	231.88	270.52	138.92	103.77	111.60	107.67	127.47	500.17	215.16	153.60	77.53	81.75	81.07	282.09
P	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ll	-1,258.82	-1,257.00	-740.18	-1,093.80	-815.37	-454.05	-680.09	-1,080.35	-403.16	-824.59	-270.25	-253.15	-181.79	-770.78
N	2,070	2,065	2,041	2,061	2,062	1,985	1,950	2,075	1,873	2,069	1,853	1,726	1,447	2,072

* p<0.1; ** p<0.05; *** p<0.01. Reports of the estimated coefficients have not been transformed into odds ratios, that is, e^{β} rather than β. Collinear variables have been omitted because doing so usually causes estimation to fail because of the matrix singularity caused by collinearity. On top of that identification, issues would have risen.

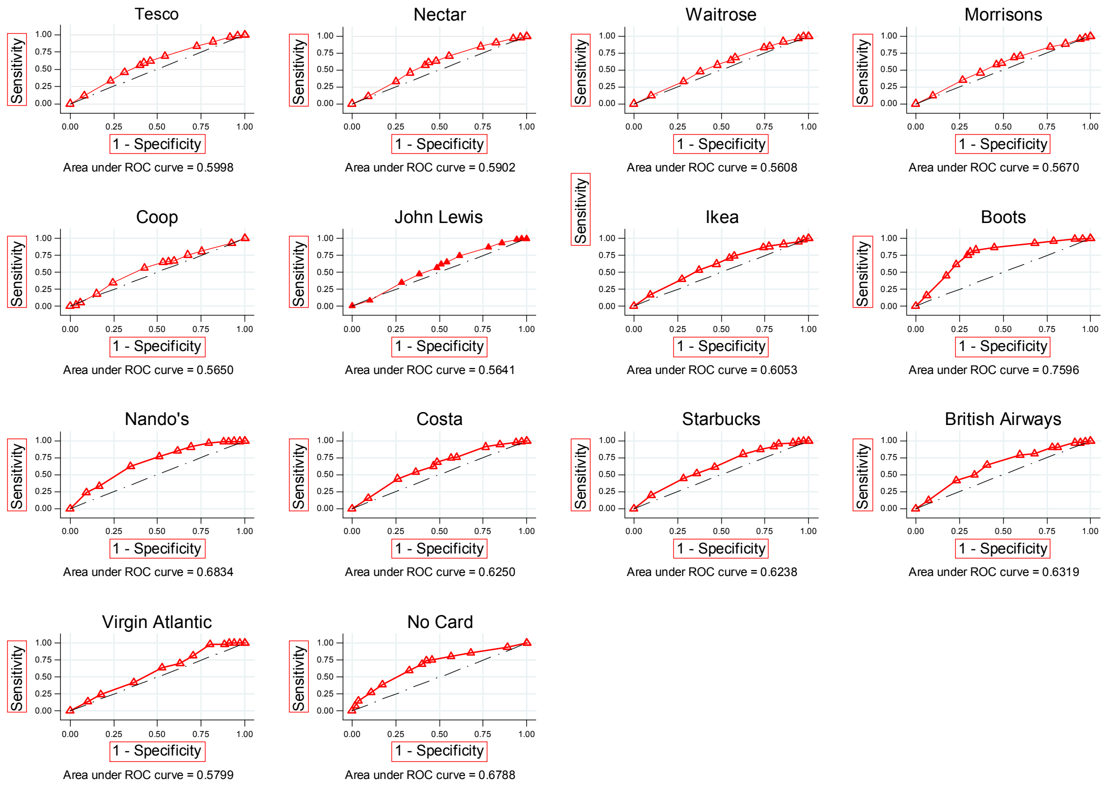

Figure 1. ROC curves for the simple model.

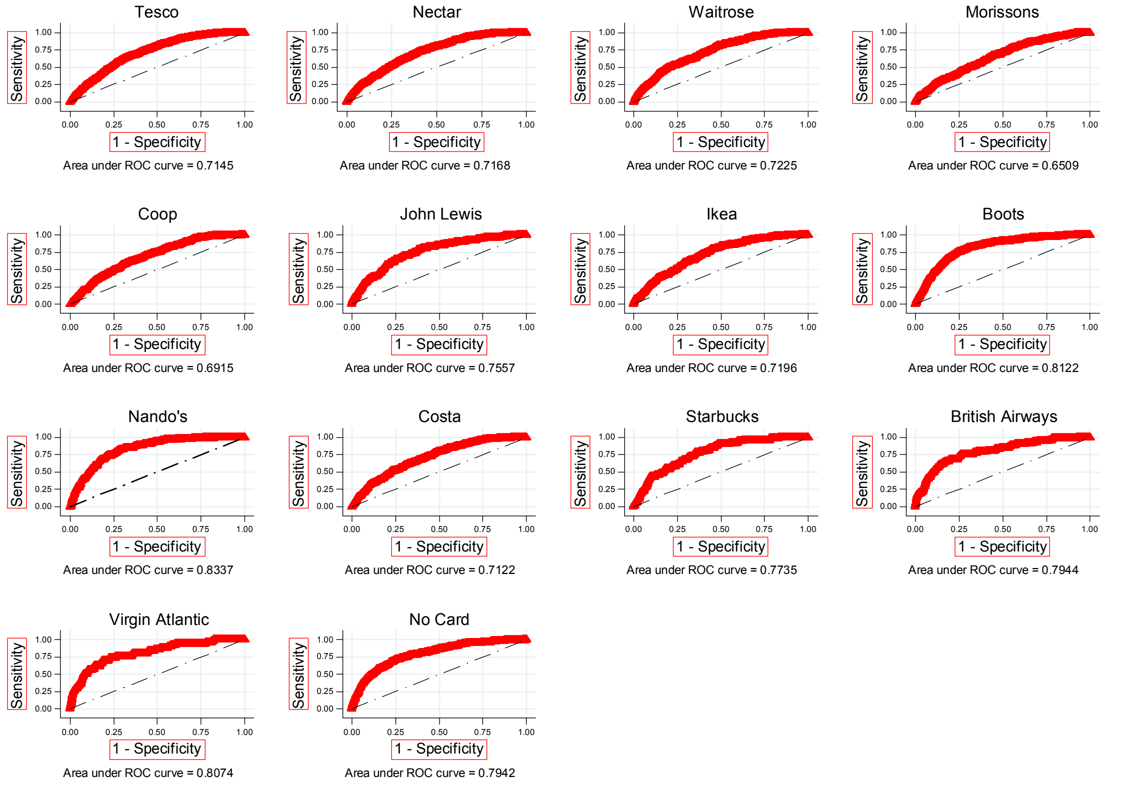

Figure 2. ROC curves for the advanced model.

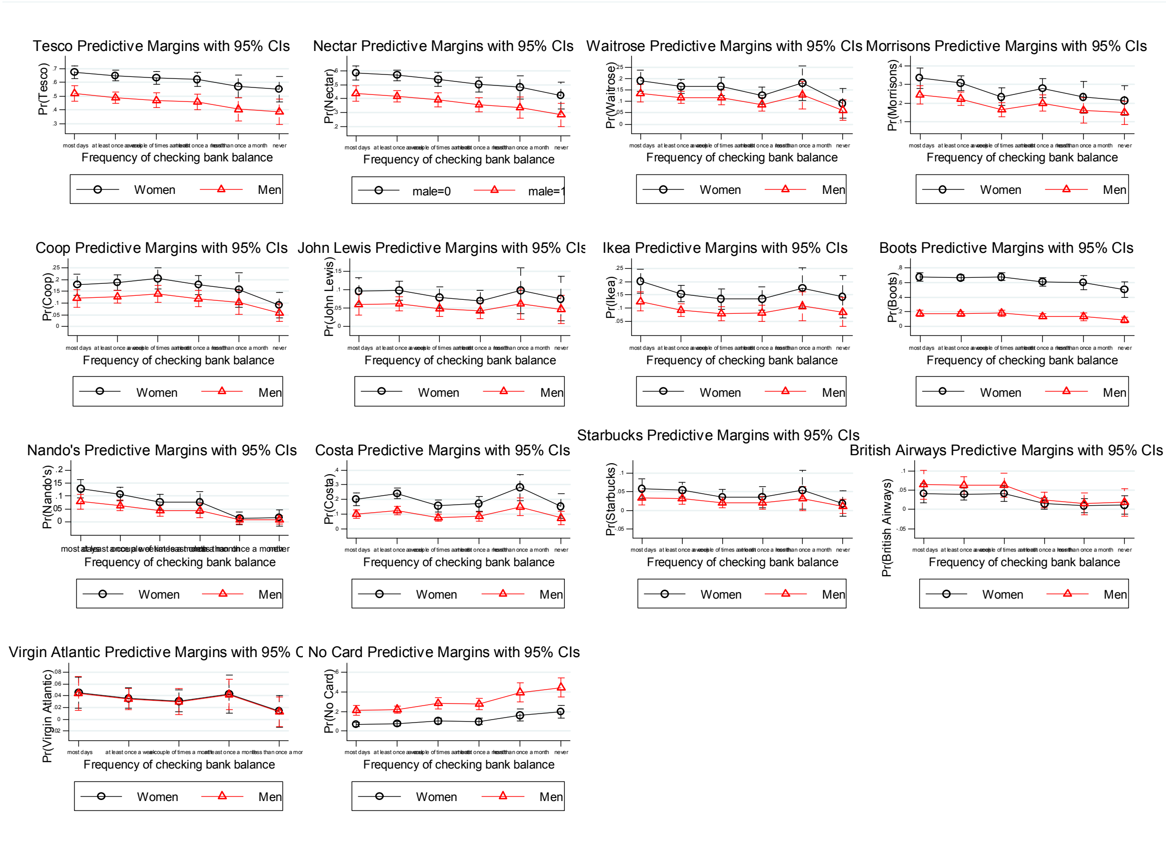

Figure 3. Predictive margins with 95% for both genders and every brand.

Appendix

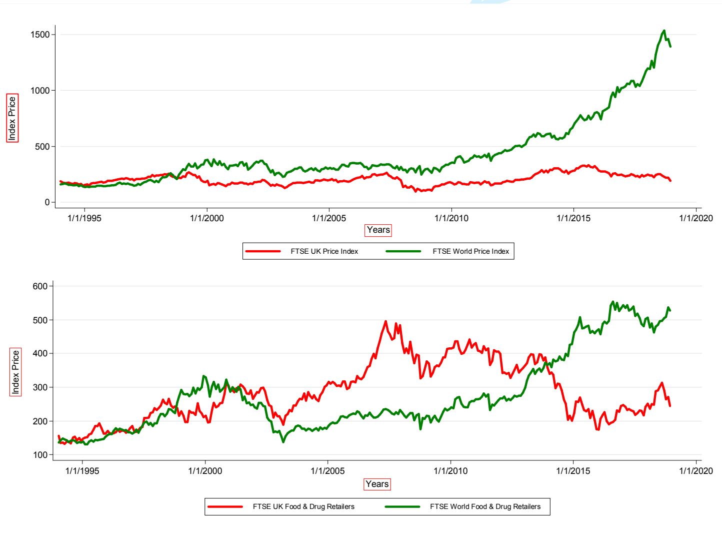

Figure A1. Evolution of time series for FTSE world and UK food and drug retailers

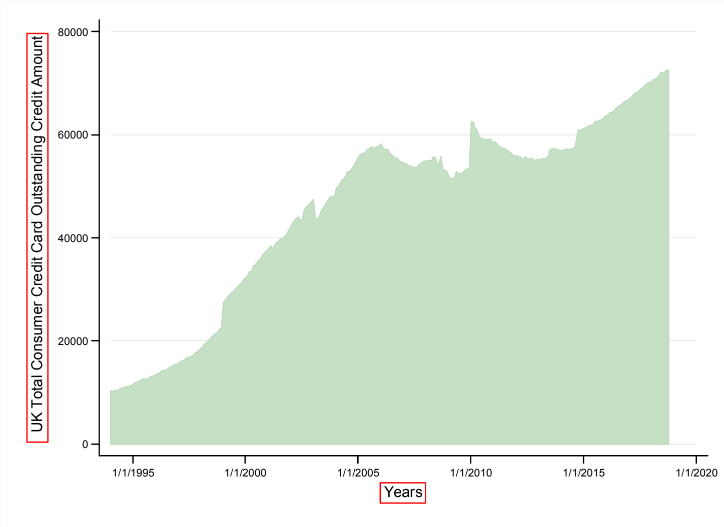

Figure A2. Evolution of credit card outstanding time series in the UK