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When do changes in consumer preferences make forecasts from choice-based conjoint models unreliable?

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ABSTRACT

Forecasting the sales or market share of new products is a major challenge as there is little or no sales history with which to estimate levels and trends. Choice-based conjoint (CBC) is one of the most common approaches used to forecast new products' sales. However, the accuracy of forecasts based on CBC models may be reduced when consumers' preferences for the attributes of products are labile. Despite this, there is a lack of research on the extent to which lability can impair accuracy when the coefficients estimated in CBC models are assumed to be constant over time. This paper aims to address this research gap by investigating the prevalence of lability for consumer durable products and its potential impact on the accuracy of forecasts. There are reasons to expect that lability may be particularly evident where a product is subject to rapid technological change and has a short product life-cycle. We carried out a longitudinal survey of the preferences of 161 potential consumers relating to four different types of products. We established that for both functional and innovative products: (i) the CBC models vary significantly over time, indicating changes in consumer preferences and (ii) such changes may cause large differences in forecasts of the probabilities that consumers will purchase particular brands of products. Hence employing models where coefficients do not change over time can potentially lead to inaccurate market share forecasts for high-tech, short life-cycle products that are launched even a short time after the choice-based modelling has been conducted.

Key words: Forecasting, New product forecasting, Choice based conjoint, Attribute coefficient change, Longitudinal study

Introduction

Forecasting the sales or market share of new, or nearly new, products is a major challenge for companies, as there is little or no sales history with which to estimate levels and trends. Yet, profitability depends on the reliability of these forecasts (Goodwin et al, 2014). One approach that has been used to forecast new products' sales is choice-based conjoint (CBC) analysis. CBC uses data collected at the individual customer level to investigate how different characteristics of products affect consumers' choice (Greene, 2009; Karniouchina et al. 2009). Potential consumers are invited to choose amongst products with different combinations of attributes. From the resulting data, methods such as multi-nominal logit (MNL) analysis are used to determine how the probability of a given product being chosen is related to these attributes. When a forecast for a new product is required, its particular set of attributes can be used as inputs for the CBC model to determine the probability that consumers will select it. With that information, forecasts of market share and sales can be obtained.

The conceptual basis that underpins a CBC model is the assumption that consumers choose products that maximise their utilities. However, for a given set of product attributes and a set of identical consumers, unmeasured psychological factors may lead to variations in individuals' subjective utility. This is assumed to lead to a random component of utility. Maximisation of utilities that contain a random element is referred to as random utility maximisation (RUM) (see Jun and Park, 1999; Lee et al. 2008). In RUM, participant n's utility for a given product j, U_{nj} is decomposed into two components: a deterministic utility (systematic component) that can be measured as V_{nj}, and a stochastic utility (random component) that cannot be measured as ε_{nj}. The resulting participant n's utility for product j can be presented as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta X_{nj} + \varepsilon_{nj} \tag{1}$$

with X_{nj} the vector of attribute levels for product j presented to participant n; and β the vector of model coefficients (It is worth noting that RUM is not the only method used to estimate utility functions. For a review on other existing methods, we refer the reader to Halme and Kallio (2011, 2014)). Participants choose the product j that maximises their utility. Although researchers cannot observe the consumer's utility directly, they do observe the choice consumers have made based on the attributes of the available products.

The coefficients of the regression, i.e. the βs, measure the effect on the utility due to changes in the attribute values, e.g. a change in the battery life of a laptop by one unit or the presence, as opposed to the absence, of a high-resolution camera in a mobile phone. The probability of a participant choosing a product that has a particular combination of attribute values can be estimated by using Equation 2, where P_{ni} is the probability participant n will choose product i from J, a set of products. V_{nj} is usually specified to be linear as $V_{nj} = \beta X_{nj}$, where X_{nj} is the vector of the observed variables.

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} = \frac{e^{\beta x_{ni}}}{\sum_j e^{\beta x_{nj}}} \quad (2)$$

These probabilities can be used to forecast market share and sales. However, there is a potential limitation of using CBC models for these purposes. If consumers' preferences for the attributes are labile, the relative importance of attributes, and hence the probabilities of choosing particular products can change over time. If that is the case, this could have a deleterious effect on the accuracy of forecasts that are made for even a few periods ahead based on the assumption of constant preferences. Despite this there is a lack of research on the extent to which lability can impair accuracy when, as is usually the case, the coefficients estimated in CBC models are assumed to be constant over time. Some researchers have referred to dynamic random utility models (Lee et al., 2006) but the dynamic element of the model is designed to reflect changes in a product's attribute levels (e.g. an increase in its price) rather than changes in the preferences that consumers may have for the attributes even if they remain constant. The current paper is innovative in that it focuses on the latter, by examining the collective effect of changes in the β on forecast accuracy. There are reasons to expect that lability may be particularly evident where a product is subject to rapid technological change and has a short product life cycle. A second innovation of the paper is that it compares the effects of lability on forecast accuracy for four different types of consumer durable products by reporting the results of a longitudinal survey of the preferences of 161 potential consumers.

The paper is structured as follows. Following a review of the relevant literature in Section 2, the research process and data collection are outlined in Section 3. Section 4 reports the results of the data analysis for the change in consumer preferences, followed by an analysis of how that affects product forecasting, in Section 5. We conclude the paper and point to new potential areas of research in Section 6.

2. Literature Review

2.1 Changes in consumer preferences over time

There are numerous potential explanations as to why consumers' relative preferences for the attributes of products may change over time. These relate to (i) cognitive biases, (ii) product familiarity, and (iii) external factors.

Simon's (1955) bounded rationality theory asserts that human beings are subject to computational and informational limitations when taking decisions. Consumers may evaluate or recall, for instance, only a subset of the available attributes during the process of choosing a product. If the subset changes over time, perhaps because some attributes have become more or less salient due to changes in external or internal stimuli, the relative importance of the attributes in the decision making process may also change. This is particularly relevant for consumer electronic products, as the number of attributes has increased substantially in recent years partly because there is huge pressure to differentiate products from competitors (Hledik, 2012). In addition, products with a wide range of features can satisfy different segments of the market while reaping the cost savings of mass production - a concept known as the 'mass customised product' (Davis, 1989; Cox and Alm, 1998). Increases in the number of features have been made to such an extent that it is difficult for consumers to consider all of them when making a decision.

The notion of bounded rationality is consistent with the growing belief among decision researchers that preferences for options involving complex and novel situations are often constructed, not merely revealed, when making a decision (Bettman et al., 1998). People often do not have well-defined preferences; instead, they may construct them when faced with a choice. If they face identical choices at different times or in different contexts, different preferences may be constructed.

A second cognitive factor that might lead to changing preferences over time is a tendency for people to seek variety in product choice. Kahn (1995) suggested that consumers seek variety to satisfy a need for stimulation. Once consumers are used to the products there is a danger that they will become bored with their original choice and hence opt for alternatives. They may also seek variety to produce a portfolio of options as a hedge against future uncertainty.

Coupey et al. (1998) suggested that consumers' prior knowledge of a product (i.e. familiarity) might also affect the stability of their preferences. With familiar products, choice is likely to be an easily performed task, as consumers are likely to know which attributes are most important to them, whereas for unfamiliar products they have less information to guide them. Consequently, for the latter there will be more changes in their preferences for different attributes as consumers learn more about them. Unfamiliarity of consumers with a product is to be expected when it is new, or has had new features added or is a high tech product with many complex features. This is particularly likely to be the case with many short life-cycle electronic products.

Finally, changes in preferences may result from external factors such as changes in the economic circumstances of a household (Pollak, 1978) or changes in lifestyle or social status (Anderson, 1984) or they may be stimulated by fashion and advertising (Fader and Lattin, 1993). Some of these changes may only occur over relatively long periods. However, advances in communication and information technology have not only changed the nature of products but they have also changed the way that consumers become informed about them. As a result, some attributes have become more or less important over relatively short periods of time (Jahanbin et al., 2013).

2.2 Incorporating changing consumer preferences in forecasting models

Diffusion models (Bass, 1969; Mahajan, et al., 2000; Meade and Islam, 2006) have traditionally dealt with changes in consumers' propensity to purchase new products over time. Diffusion models work on the principle that many consumer products have a generic pattern of penetration into consumer base. The most well-known diffusion model was proposed by Bass (1969). The model has been subject to a number of extensions but the basic model assumes that there are two main drivers of demand: external factors such as advertising, which particularly drive early adoption of the product, and word of mouth. Bass (1969) identified these two drivers as the innovation and imitation factors respectively. Experiences of using a new product that are shared by word of mouth can reduce the perceived risk a new consumer associates with a decision to adopt it. Both drivers can lead to changes in preferences for the product by individual consumers over time and hence determine the nature of its diffusion pattern. However, diffusion models do not specify how these changes are related to the specific attributes of the product. In contrast, choice models do link consumer preferences to product attributes but they usually assume that the preferences remain unchanged (Greene, 2009). A number of studies have attempted to bridge this gap by combining diffusion and choice models to forecast new product demand (Jun and Park, 1999; Kumar and Krishnan, 2002; Jun et al., 2002; Lee et al., 2006; Lee et al., 2008; Eager and Eager, 2011).

Jun and Park (1999) combined a diffusion model and a multi-nominal logit (MNL) choice model to forecast multi-generation sales/demand of DRAM (dynamic random access memory). Jun et al. (2002) used the same modelling approach to forecast sales of analogue and digital mobile phones and PCs in Korea. The models allowed the utilities for a given generation of a product to change over time to reflect the effects of diffusion. As a product becomes more popular, consumers will acquire more information about it, which may lead them to re-evaluate their initial preferences for the product. For example, if the product succeeds consumers may place increased valuations on it. However, for a given generation of a product, the preferences relating to the specified attributes are assumed to remain unchanged during the lifetime of that generation, so that changes in preferences for specific attributes not related to advertising or word of mouth, are not accounted for in these models.

Lee et al. (2006) also combined choice and diffusion models for forecasting the adoption of flat screen TVs in Korea. The diffusion model was used to forecast the size of the market for all TVs at given time t. The choice modelling was involved in the derivation of what they referred to as a dynamic random utility function for specific products. However, the dynamic element of the model was generated by forecasts of price changes, not by changes in the coefficients, β, that were attached to price and the other attributes. Hence, as the prices of TVs fell as a result of technological changes, the relative importance of price was assumed to remain unchanged. Similarly, when making forecasts for the home networking market in South Korea, Lee at al. (2008) assumed in their dynamic random utility model that 'the degree of preference (β) of construction companies for technology attributes is constant over time'. Eggers and Eggers (2011) also assumed constant preferences for attributes in their forecasts of the demand for electric vehicles.

Clearly, in situations where consumers' preferences for attributes tend to change over relatively short periods, forecasts based on the assumption of constant preferences are likely to be inaccurate, particularly when the preferences have been measured well ahead of the forecast period. As indicated above, this may especially be the case in the consumer electronic goods market as it involves complex products with short life-cycles and a high level of technology. (Lee, 2002)

In this work, we investigate the seriousness of the problem of changing attribute-preferences over time and the extent to which it depends on the nature of the product. We first assess the change in potential consumers' preferences for four different categories of products (and hence their implied preferences for different attributes) over three rounds of a longitudinal survey when CBC models were fitted to their responses. Subsequently, we examine how sensitive forecasts of the probabilities that consumers will purchase particular brands are to any changes that are observed in the model's coefficients and identify the type of products where CBC-based forecasts are likely to be unreliable. Based on the literature review we test the following research questions.

R_{1a}: Do consumer preferences change significantly for products with short life-cycles over a three and six months' period?

R_{1b}: Do consumer preferences change significantly for products with long life-cycles over a three and six months' period?

R_2: Are forecasts of the probabilities that consumers will purchase particular brands based on CBC analysis likely to be less accurate for products with short life-cycles when compared to products with longer life-cycles?

3. Research process and data collection

We tracked the preferences of potential consumers for different brands of four products over a six months' period in three rounds of data gathering, which took place in March 2014, June 2014, and September 2014 (henceforth referred, respectively, as R1, R2 and R3). The four product categories were chosen to include a mixture of high-technology short life-cycle products that are subject to rapid technological change (mobile phones and laptops), a long–established product that is subject to some technological changes (televisions) and a relatively low-technology product that is subject to few changes (fan heaters) and has relatively long life-cycles. Qualitative research was conducted to establish the key features and the levels that were likely to influence customers' choice of the products. This involved two stages: desktop research and focus groups. Information collected from major retailers and manufactures in the UK was used to identify features and levels for all products[1]. This was augmented by three focus groups that were conducted for mobile phones using both consumer and sales representatives. Table 1 shows the attributes and levels for the four products.

[1] Offerings from the following shops were used to create the list of features and levels: Vodaphone, EverythingEverywhere (EE), Comet, PC World, Argos and Curry's.

The total number of possible attributes and their levels is too large for a practical experiment if one is considering all possible combinations of characteristics and levels. As a result, a fractional factorial design (orthogonal design) was used, consisting of selected subsets of the designs based on a sample of the total possible combinations (Raghavarao et al., 2011). This approach resulted in 32 alternative profiles for mobile phones, 24 for fan heaters, 32 for laptops, and 28 for TVs. The number of alternatives is still quite large to be presented in one choice set. Therefore, the decision was taken to follow a suggestion by Kuhfeld (2010) to divide the choice design into smaller sets. Other researchers have adopted a similar approach (Hansen, 1987; Friedman et al., 1992 and Woodward, 1992). Further, we included a 'non-choice' option in each choice set, based on a suggestion by Dhar (1997), so as to reflect the reality that a given consumer may not choose any of the available options. From the orthogonal design for the mobile phones and laptops (32 profiles for each product), a random combination of profiles was presented to the participants in eight sets, with each set including five choices (four profile choices and one non-choice option). Similarly, for the fan heaters (24 profiles) and TVs (28 profiles), a random combination of profiles was presented to the participants in six sets and seven sets, respectively. The aggregation of the chosen alternatives for each participant was collected in a dataset, which was then used to identify the parameters of the CBC model for a given product.

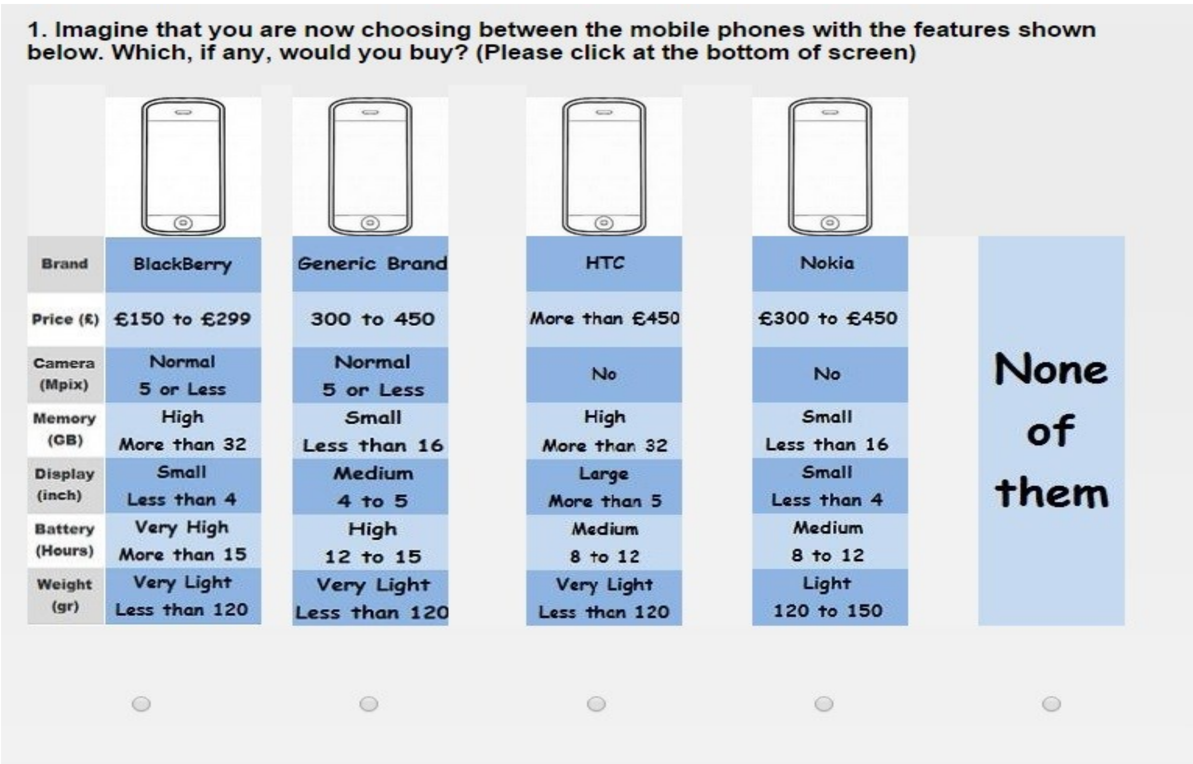
Table 1. Product characteristics

Fan Heater	
Brand	Challenge, Dimplex, DeLonghi, Dyson
Price (£)	<25, 25 to 49, 50 to 75, >75
Power (kwh)	<2, 2 to 2.9, 3 or more
Type	Upright, Flat, Down Flow
Oscillating	Yes, No
Laptop	
Brand	Apple, Samsung, HP, Sony, Dell, Lenovo, Toshiba, Generic
Price (£)	<400, 400 to 699, 700 to 1000, >1000
Display size (inches)	Small (<12.9), Medium (13 to 16), Large (>16)
Processor	Normal, Fast, High Performance
Memory size (GB)	Small (<4), Medium (4 to 8), Large (>8)
Hard Drive (GB)	Medium (<499), High (500 to 1000), Very High (>1000)
Weight (kg)	Ultra-light (<2), Light (>2)
Mobile phone	
Brand	Apple, Samsung, Nokia, HTC, Sony, BlackBerry, Generic
Price (£)	<150, 150 to 299, 300 to 450, >500
Camera resolution (Mpix)	No camera, Normal (5 or less), High (>5)
Memory size (GB)	Small (<16), Medium (16 to 32), High (>32)
Display size(inches)	Small (<4), Medium (4 to 5), High (>5)
Battery life (hours)	Short (<8), Medium (8 to 12), High (12 to 15), Very High (>15)

Weight (g)	Very light (<120), Light (120 to 150), Medium (>150)
TV	
Brand	JVC, Sony, Panasonic, Samsung, LG, Toshiba, Generic
Price (£)	<200, 200 to 400, >450
Screen size (inches)	Medium (<25), Large (25 to 42), Very Large(>42)
Smart TV?	Yes, No
3D?	Active, Passive, No
Freeview?	Yes, No

Four different approaches to presenting the experiment to the participants were tested in a pilot study by using eight participants. This resulted in using black and white sketches for all products as a visual aid (in order to minimise biases) as well as descriptions of each choice as can be seen in Figure 1.

Figure 1. Examples of presentations used in experiments



9. Imagine that you are now choosing between the Fan Heaters with the features shown below. Which, if any, would you buy?

Brand	Dimplex	Dimplex	Dyson	DeLonghi	None of them
Price (£)	Less than £25	£50 to £75	£25 to £49	£25 to £49	
Power (KW)	Very High 3 or more	High 2 to 2.9	Very High 3 or more	Medium Less than 2	
Type	Upright	Flat	Down Flow	Flat	
Oscillating	No	Yes	Yes	No	

The choice experiment was based on convenience sampling, in line with and Yu and Cooper (1983), Chiu et al. (2005) and Maringe (2006). Although convenience sampling might be subject to some biases, the aim of our study was to uncover variation in preferences. Hence, it was critically important that as many as of the same participants took part in all three rounds of the experiment. In an effort to retain participants, we set up an incentive scheme involving charity donations as well as Amazon vouchers as potential rewards for participations. In the first round of online experiments, there were 327 participants. Of these, 215 people completed the second round, while 161 participated in all the three rounds. Only data from participants who completed all rounds were used in the analysis. Details of these participants are presented in Table 2.

Table 2. Demographic detail of participants.

Demographics	Categories	Frequency	Percent
Gender	Male	82	50.9
	Female	79	49.1
Age	18-30	81	50.3
	31-45	50	31.1
	46-60	27	16.8
	Over 60	3	1.9
Education	Secondary School	13	8.1
	Undergraduate	41	25.5
	Postgraduate	107	66.5
Occupation	Unemployed	3	1.9
	Student	59	36.6
	Full-time employee	83	51.6
	Part-time employee	4	2.5
	Self-employed	11	6.8
	Retired	1	0.6

The data from the profile and response tables were merged into one table and dummy variables were used to represent the product attributes. Subsequently, a binary logistic regression model was estimated for each product category for each round of data collection. The dependent variable took on a value of one if a product was chosen and zero if it was not.

4. Data Analyses and discussion

In this section, we examine Research Question 1 to see whether there is a significant difference between the models constructed in rounds one and two and also in rounds one and three.

4.1. Attribute coefficients of different product categories – products with long life-cycle.

For each product category repeated measures logistic regression was applied to the choices made in each round using the method of generalized estimating equations. The coefficients of the models are shown in tables 3 to 6. Log-likelihood estimates were derived from the corrected quasi likelihood under independence model criterion (QICC) (IBM Knowledge Center, 2011) which approximates to 2k-2log-likelihood, where k is the number of parameters estimated in a model. In order to test whether there were significant differences between the results obtained in rounds one and two, and one and three, we used the Chow Test Analogue for logistic regressions. The Chow Test Analogue allows one to test whether coefficients in two logistic regression models fitted to two different data sets are significantly different (DeMaris, 2004). The test statistic is given by:

$$\chi 2 = -2Ln(Lc)-(-2ln(L_1)-2ln(L_2))$$

Where Lc is the log-likelihood for the model fitted to the combined datasets and L_1 and L_2 are the log-likelihoods for the models fitted to datasets 1 and 2, respectively. The number of degrees of freedom equals the total number of parameters estimated in the two models fitted to the separate datasets minus the number of parameters estimated for the model fitted to the combined dataset. For televisions, the results of the test indicate that there are significant changes in the models' coefficients between the R1 and R2 models ($\chi^2(15) = 42.54, p < 0.000$) but not between the R1 and R3 models (given the small p-values the difference between R1 and R2 is also significant after applying a Bonferroni correction for multiple comparisons). The regression results for TVs are summarised in Table 3.

Table 3. Regression coefficients for the logit model for televisions estimated for the combined samples as well as separately for R1, R2 and R3.

	combined sample (R1+R2)	combined sample (R1+R3)	Sample R1	Sample R2	Sample R3
Brand JVC	.64 (.12)	.61 (.13)	.51 (.17)	.79 (.18)	.72 (.18)
Brand Sony	1.02 (.15)	1.12 (.15)	.84 (.20)	1.20 (.22)	1.38 (.21)
Brand Panasonic	1.61 (.15)	1.61 (.14)	1.54 (.19)	1.69 (.22)	1.69 (.21)
Brand Samsung	1.16 (.16)	1.18 (.16)	1.02 (.22)	1.31 (.23)	1.35 (.22)
Brand LG	1.02 (.15)	1.01 (.15)	1.00 (.20)	1.05 (.24)	1.03 (.21)
Brand Toshiba	.89 (.16)	.72 (.15)	.54 (.22)	1.22 (.22)	.90 (.21)
Price_Low	0.96 (.12)	.96 (.11)	.95 (.16)	.97 (.17)	.97 (.17)
Price_Medium	1.19 (.10)	1.15 (.09)	1.21 (.12)	1.17 (.15)	1.10 (.13)
Screen_Size_Medium	-.87 (.10)	-.74 (.10)	-.80 (.14)	-.93 (.15)	-.69 (.14)
Screen_Size_ Large	.32 (.08)	.36 (.08)	.39 (.11)	.25 (.13)	.33 (.12)
Smart_Yes	.98 (.08)	.86 (.08)	.94 (.12)	1.04 (.11)	.79 (.10)
ThreeD_Active	0.08 (.08)	.04 (.08)	.12 (.12)	0.05 (.12)	-.04 (.10)
ThreeD_Passive	-.10 (.09)	-.12 (.08)	-.17 (.12)	-.02 (.12)	-.06 (.11)
Freeview_Yes	.51 (.08)	.49 (.08)	.56 (.12)	.46 (.11)	.45 (.12)
Constant	-4.12 (.20)	-4.03 (.19)	-4.02 (.26)	-4.25 (.31)	-4.06 (.28)
Log Likelihood	-3709.10	-3740.63	-1855.85	-1831.98	-1878.35
McFadden pseudo R-squared	0.106	0.099	0.130	0.134	0.114

This table provides the results of repeated-measures logistic regression analyses testing the effect of product-specific determinants on purchasing intention. The dependent variable assumes binary values: 0 corresponds to a given product specification not being chosen, while 1 indicates otherwise. Standard errors are shown between brackets. On Wald Chi-squared tests all attributes had a significant effect at p<0.001 except ThreeD. The Chow-test-analogue indicated a signifcant difference between the R1 and R2 models (p<0.001) but not between the R1 and R3 models.

For fan heaters the Chow Test Analogue also indicates significant changes in the model coefficients over time, with $p<0.05$ for the differences between R1 and R2 but not between R1 and R3 after Bonferroni correction (see Table 4).

Table 4. Regression coefficients for the logit model for fan heaters estimated for the combined samples as well as separately for R1, R2 and R3.

	combined sample (R1+R2)	combined sample (R1+R3)	Sample R1	Sample R2	Sample R3
Brand_Challenger	-1.02 (.13)	-.94 (.13)	-.95 (.17)	-1.10 (.21)	-.92 (.20)
Brand_Dimplex	0.11 (.08)	.17 (0.07)	.03 (.10)	.20 (.11)	.33 (.10)
Brand_DeLonghi	0.17 (.08)	.14 (.09)	-.02 (.12)	.35 (.11)	.30 (.12)
Brand_Dyson	0.41 (.09)	.44 (.10)	.30 (.13)	.52 (.14)	.59 (.14)
Price <25	2.09 (.14)	2.09 (.14)	2.05 (.20)	2.16 (.19)	2.16 (.20)
Price 25 to 49	1.69 (.14)	1.68 (.14)	1.66 (.19)	1.73 (.20)	-1.71 (.21)
Price 50 to 75	0.47 (.12)	.38 (.12)	.576 (.17)	.37 (.18)	-.18 (.18)
Power <2	-0.69 (.11)	-.55 (.10)	-.549 (.15)	-.81 (.16)	-.55 (.14)
Power 2 to 2.9	0.05 (.08)	.18 (.08)	.218 (.10)	-.10 (.12)	.16 (.12)
Type_Upright	0.58 (.10)	.60 (.10)	.635 (.15)	.53 (.15)	.57 (.14)
TypeFlat	0.14 (.08)	.12 (.09)	.21 (.13)	.08 (.10)	.03 (.12)
Oscillating_Yes	0.78 (.08)	.83 (.08)	.61 (.11)	.95 (.11)	1.05 (.11)
Constant	3.37 (.15)	-3.52 (.16)	-3.39 (.21)	-3.39 (.22)	-3.70 (.23)
Log Likelihood	-3437.49	-3417.48	-1713.27	-1711.67	-1692.79
McFadden's pseudo R-squared	0.136	0.137	0.121	0.157	0.160

On Wald Chi-squared tests all attributes had a significant effect in all models at $p<0.001$. The Chow-test-analogue test indicated a significant difference between the R1 and R2 models ($p=0.02$) but not between the R1 and R3 models after Bonferroni correction ($p=0.04$ and would need to be below 0.025 at the 5% level of significance).

4.2.1. Attribute coefficients of different product categories – products with short life-cycle.

The Chow Test Analogue applied to laptops did not indicate a significant difference between the coefficients of the R1 and R2 models. However, the difference between the R1 and R3 models was highly significant (p<0.000 after Bonferroni correction). For mobile phones, the Chow Test Analogue indicated that the model coefficients were significantly different between R1 and R2 (p<0.000) as well as between R1 and R3 (p<0.000). Tables 5 and 6 present the main results of the regressions.

Table 5. Regression coefficients for the logit model for laptops estimated for the combined samples as well as separately for R1, R2 and R3.

	combined sample (R1+R2)	combined sample (R1+R3)	Sample R1	Sample R2	Sample R3
Brand_Apple	2.00 (.15)	1.91 (.15)	1.79 (.19)	2.26 (.23)	2.12 (.25)
Bran_Samsung	.52 (.13)	.51 (.14)	.32 (.19)	.75 (.19)	.76 (.22)
Brand_HP	.62 (.12)	.70 (,12)	.45 (.16)	85 (.19)	1.04 (.19)
Brand_Sony	.67 (.13)	.65 (13)	.46 (.18)	.93 (.19)	.91 (.21)
Brand_Dell	.62 (.12)	.68 (.13)	.37 (.17)	.89 (.20)	1.03 (.22)
Brand_Lenovo	.23 (.13)	.29 (.13)	-.04 (.18)	.55 (.19)	.70 (.19)
Brand_Toshiba	.70 (.14)	.72 (.14)	.39 (.19)	1.06 (.21)	1.12 (.22)
Price_Low	1.03 (0.09)	1.00 (.10)	1.06 (.13)	1.02 (.13)	.93 (.15)
Price_Medium	.63 (0.09)	.63 (,10)	.71 (.15)	.57 (.13)	.57 (.15)
Price_High	.52 (.09)	.47 (.09)	.59 (.13)	.47 (.11)	.35 (.13)
Display_Small	-.42 (.09)	.41 (.09)	-.35 (.13)	-.48 (.13)	-.46 (.130
Display_Medium	.132 (.08)	.12 (.08)	.08 (.11)	.18 (.12)	.16 (.11)
Processor_Normal	-.61 (.07)	-.63 (.07)	-.76 (.10)	-.45 (.10)	-.50 (.10)
Processor_Fast	-.13 (.07)	-.10 (.07)	-.16 (.10)	-.10 (.10)	-.03 (.11)
Memory_Small	-.78 (.08)	-.77 (.08)	-.71 (.11)	-.86 (.13)	-.83 (.12)
Memory_Medium	-.23 (.070	-.19 (.07)	-.23 (.09)	-.23 (.10)	-.15 (.08)
Hard_Drive_Medium	-.18 (.07)	-.21 (.070	-.22 (.09)	-.13 (.10)	-.21 (.11)
Hard_Drive_High	.30 (.06)	.18 (.07)	.33 (.09)	.28 (.09)	.03 (.10)
Weight_Ultra_Light	.55 (.06)	.55 (.06)	.63 (.09)	.46 (.09)	.45 (.09)
Constant	-2.31 (.16)	-2.28 (.16)	-2.13 (.21)	-2.57 (0.22)	-2.51 (.24)
Log Likelihood	-4,174.11	-4,167.46	-2,112.38	-2,048.59	-2,035.92
McFadden's pseudo R-squared	0.124	0.117	0.126	0.127	0.116

On Wald Chi-squared tests all attributes had a significant effect in all models at p<0.05. The Chow-test-analogue test indicated a significant difference between the R1 and R3 models (p=0.008) but not between the R1 and R2 models (p=0.16).

Table 6. Regression coefficients for the logit model for mobile phones estimated for the combined samples as well as separately for R1, R2 and R3.

	combined sample (R1+R2)	combined sample (R1+R3)	Sample R1	Sample R2	Sample R3
Brand_Apple	1.06 (.11)	1.16 (.12)	.77 (.15)	1.46 (.19)	1.73 (.23)
Brand_Samsung	.59 (.13)	.67 (.14)	.46 (.16)	.82 (.23)	1.04 (.25)
Brand_Nokia	.19 (.17)	.17 (.19)	-.12 (.24)	.57 (.25)	.62 (.30)
Brand_HTC	.20 (.16)	.41 (.18)	.01 (.22)	.48 (.24)	.98 (.30)
Brand_Sony	.00 (.15)	.14 (.17)	-.40 (.22)	.46 (.21)	.84 (.28)
Brand_BlackBerry	-.05 (.19)	.02 (.20)	-.56 (.28)	.53 (.28)	.76 (.30)
Price <150	1.06 (.16)	1.08 (.16)	1.02 (.23)	1.11 (.22)	1.14 (.22)
Price 150 to 299	.83 (.13)	.81 (.14)	.82 (.20)	.85 (.17)	.82 (.19)
Price 300 to 450	.45 (.10)	.39 (.10)	.44 (.15)	.40 (.14)	.28 (.15)
Camera_Resolution_None	-2.08 (.11)	-2.17 (,12)	-2.21 (.17)	-1.96 (.16)	-2.14 (.18)
Camera_ResolutionNormal	-.64 (.06)	-.63 (0.06)	-0.66 (.08)	-.68 (0.09)	.66 (.09)
Memory_Small	-.53 (.10)	-.52 (.10)	-.41 (.13)	-.64 (.15)	-.63 (.16)
Memory_Medium	-.03 (.08)	-.04 (.09)	-.01 (.12)	-.04 (.10)	-.06 (.12)
Display_Size_Small'	-.30 (.09)	-.44 (.10)	-.45 (.13)	-.20 (.11)	-.48 (.14)
Display_Size_Medium	.13 (.08)	.14 (.09)	.22 (.12)	-.00 (.12)	.01 (.14)
Battery_Life_Short	-1.29 (.11)	-1.13 (.11)	-1.18 (.16)	-1.40 (.16)	-1.07 (.16)
Battery_Life_Medium	-.58 (.10)	-.55 (.11)	-.63 (.15)	-.54 (.13)	-.46 (.16)
Battery_Life_High	-.21 (.09)	-.18 (.09)	-.12 (.13)	-.34 (.11)	-.27 (.14)
Weight_Very_Light	.34 (.11)	.42 (.11)	.43 (.16)	.22 (.14)	.40 (.17)
Weight_Light	.18 (.11)	.21 (.12)	.35 (.17)	.01 (.15)	-.06 (.17)
Constant	-1.08 (.19)	-1.22 (.20)	-.92 (.28)	-1.26 (.27)	-1.64 (0.32)
Log Likelihood	-3,916.38	-3,835.07	-1,939.16	-1,946.33	-1,866.89
McFadden pseudo R-squared	0.184	0.184	0.188	0.193	0.192

On Wald Chi-squared tests all attributes had a significant effect in all models at $p<0.05$ except Display Size and Weight in the R2 model. The Chow-test-analogue test indicated highly significant differences between the R1 and R2 models and the R1 and R3 models ($p<0.001$).

5. Sensitivity of forecasts to changes in model coefficients

5.1. The forecasting of short life-cycle products.

In this Section, we examine Research Question 2. To test the sensitivity of forecasts of purchase probabilities to changes in the coefficients of the models, forecasts for a group of mobile phones and laptops were calculated using the models estimated from different rounds. The specifications for six mobile phones were selected from mobile phone offerings found in the UK market in January 2015 at a major mobile phone provider's website (http://www.three.co.uk), as shown in Table 7. Equation 2 was used to calculate the probability that a product with a given set of features and level of specifications would be chosen by a consumer. It was assumed in the simulations that a manufacturer or retailer needed to forecast the probabilities of purchase in January 2015. We first consider the probabilities of purchase based on data collected nine, six and three months prior to the launch of the product, i.e. in R1, R2 and R3. We refer to these scenarios as scenarios 1, 2 and 3 respectively. We also examine the effect of averaging the probabilities estimated in R1 and R2 (scenario 4), R2 and R3 (scenario 5), R1 and R3 (scenario 6) and R1, R2 and R3 (scenario 7).

The main results are shown in Figure 2. They demonstrate that probability forecasts based on the R1 data for mobile phones are very different from those based on the R2 and R3 Data. Therefore, a retailer or manufacturer who bases the forecasts for these products just on the R1 survey would find these to be very different from forecasts based on just the R2 survey. These results suggest that forecasts of purchase probabilities are highly sensitive to the timing of the data collection.

Table 7. Specification of chosen mobile phones.

Model	iPhone 6 plus	Galaxy S4 mini	Curve 9320	Acer Liquid E3	Desire 610	Z2 Xperia
Brand	Apple	Samsung	BlackBerry	Generic Brand	HTC	Sony
Price (£)	699.99	199.99	109.99	134.99	164.99	509.99
Camera Resolution (Mpix)	8	8	3.2	13	8	20.7
Memory Size (GB)	64	8	0.5	4	8	16
Display Size (inch)	5.5	4.3	2.44	4.7	4.7	5.2
Battery Life (Talking hours)	14	10.75	7	5	15.8	15
Weight (g)	172	107	103	135	143.5	158

Table 8. Specification of chosen laptops.

Model	MacBook Pro	Inspiron 5000	Acer Aspire-V3	Samsung	Yoga 2 Pro	HP 15j-143
Brand	Apple	Dell	Generic Brand	Samsung	Lenovo	HP
Price (£)	1199	329	499.99	217.99	1049	799
Display Size (inch)	13	17	15.6	10.1	13.3	15.6
Processor	Fast	Normal	High Performance	Normal	High Performance	High Performance
Memory Size (GB)	8	4	8	2	4	12
Hard Drive (GB)	256	500	1000	256	500	1000
Weight (g)	1570	3000	2550	1400	1390	2560

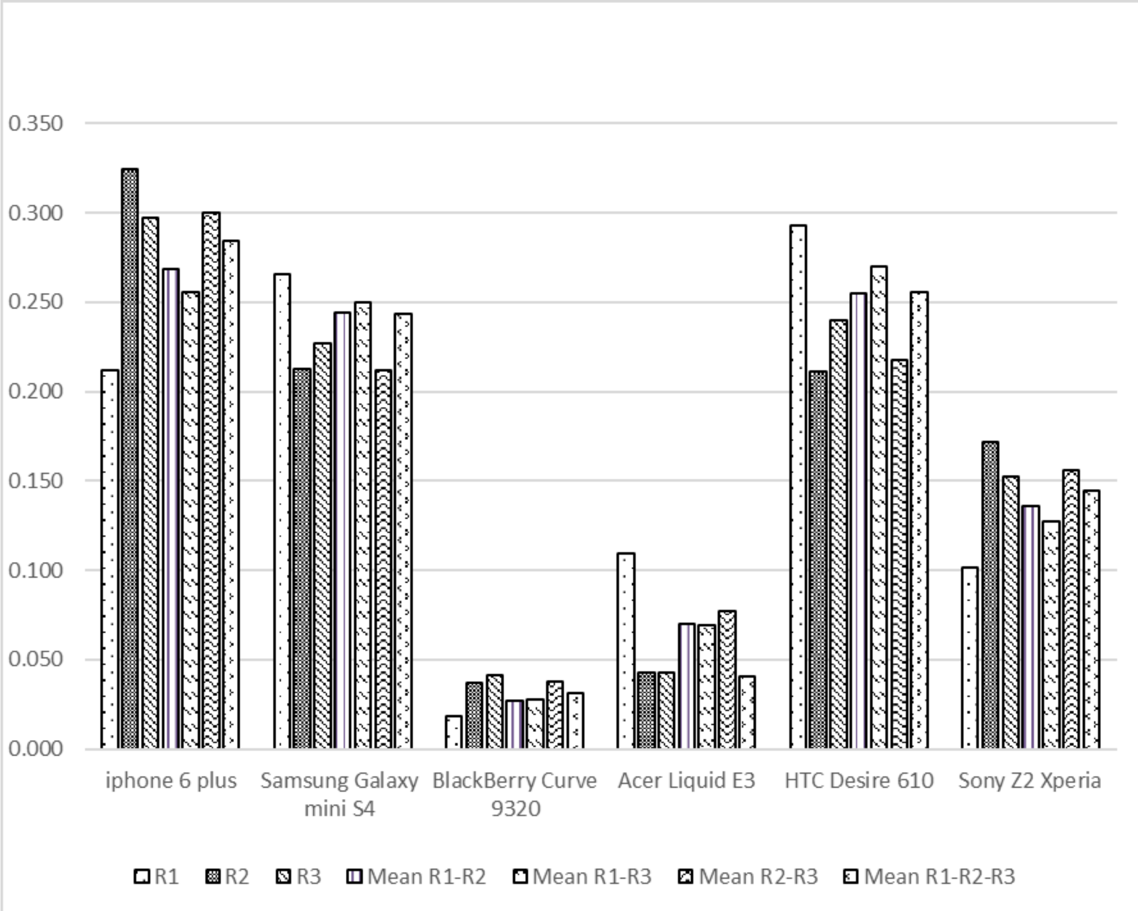
Table 9. Specification of chosen fan heaters.

Model	Challenge	De Longhi	Dyson	Stanely	Dimplex	De Longhi
Brand	Challenge	De Longhi	Dyson	Generic Brand	Dimplex	Challenge
Price (£)	19.99	29.99	369.99	27.99	35.99	44.99
Power (KW)	2.4	2.5	2.8	1.8	1.8	2.5
Type	Flat	Upright	Upright	Upright	Upright	Upright
Oscillating	Yes	No	Yes	Yes	No	No

Table 10. Specifications of chosen TVs.

Name	Toshiba	Samsung	LG	Sony	Panasonic	JVC
Brand	Toshiba	Samsung	LG	Sony	Panasonic	JVC
Price (£)	189	129	629	499	599	280
Screen Size (inch)	32	22	47	42	45	32
Smart	No	No	Yes	Yes	Yes	No
3D	No	No	No	Active	Active	No
Freeview	No	Yes	Yes	Yes	Yes	Yes

Figure 2. Comparison of forecasts of mobile phone purchase probabilities

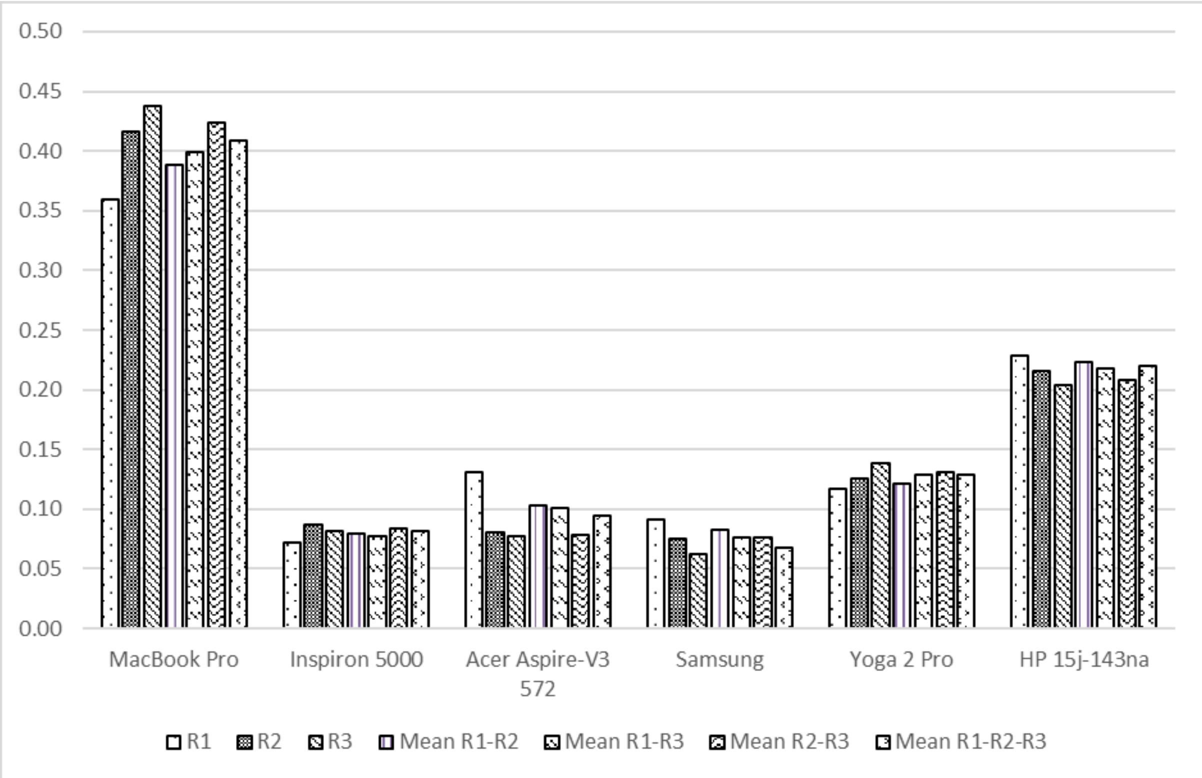


Analysis of the forecasting of purchase probabilities for mobile phones. R1, R2 and R3 are the forecasts, based on the data collected, respectively, in time 1, 2 and 3. Mean R1-R2 is the probability forecast based on the mean of the R1 and R2 forecasts. Mean R1-R3 and R2-R3 are defined similarly. The y-axis shows the estimated probability of a typical consumer in the surveys purchasing the brand.

A similar analysis was conducted for six laptops that were selected from the UK market in January 2015 from major manufacturers' websites in the UK, as shown in table 8.

The sensitivity of the forecasts to the models estimated in the different rounds is shown Figure 3. As with mobile phones the forecasts are sensitive to the changes in the models though less so than for mobile phones.

Figure 3. Comparison of forecasts of laptop purchase probabilities



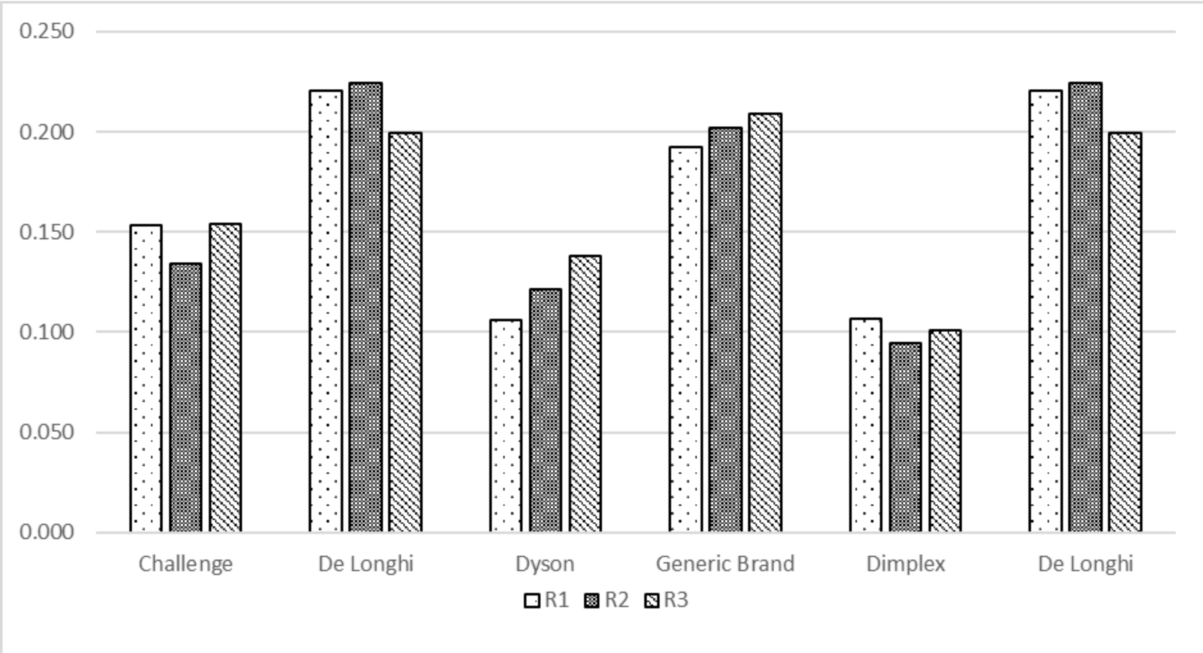
Analysis of the forecasting of purchase probabilities for laptops. R1, R2 and R3 are the forecasts, based on the data collected, respectively, in rounds 1, 2 and 3. Mean R1-R2 is the probability forecast based on the mean of the R1 and R2 forecasts. Mean R1-R3 and R2-R3 are defined similarly. The y-axis shows the estimated probability of a typical consumer in the surveys purchasing the brand.

5.2. The forecasting of long life-cycle products.

In this section, we present the purchase probability forecasts for fan heaters and TVs based on the data collected in the different rounds. The specifications of six fan heaters and six TVs were obtained from the websites of two major UK retailers (Argos website, 2015; Currys website, 2015), as shown in Tables 9 and 10.

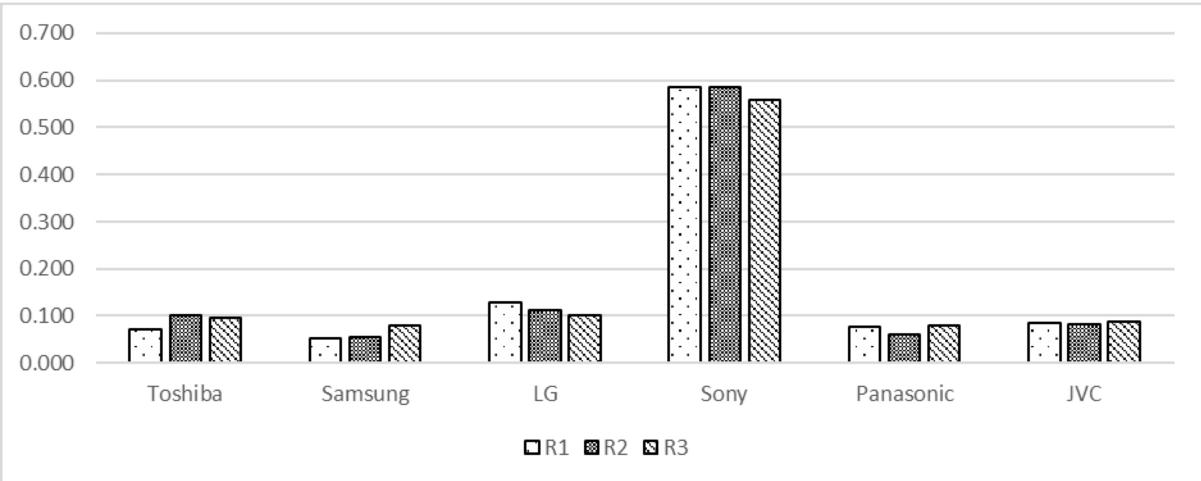
In this case, for brevity, we exclude the forecasts based on the averaging of probabilities from different rounds. Figures 4 and 5 show the results. As expected, for these products the forecasts are less sensitive to the timing of the data collection

Figure 4. Comparison of forecasts of fan heater purchase probabilities



Analysis of the forecasting of purchase probabilities for fan heaters. R1, R2 and R3 are the forecasts, based on the data collected, respectively, in time 1, 2 and 3. The y-axis shows the estimated probability of a typical consumer in the surveys purchasing the brand.

Figure 5. Comparison of forecasts of TV purchase probabilities

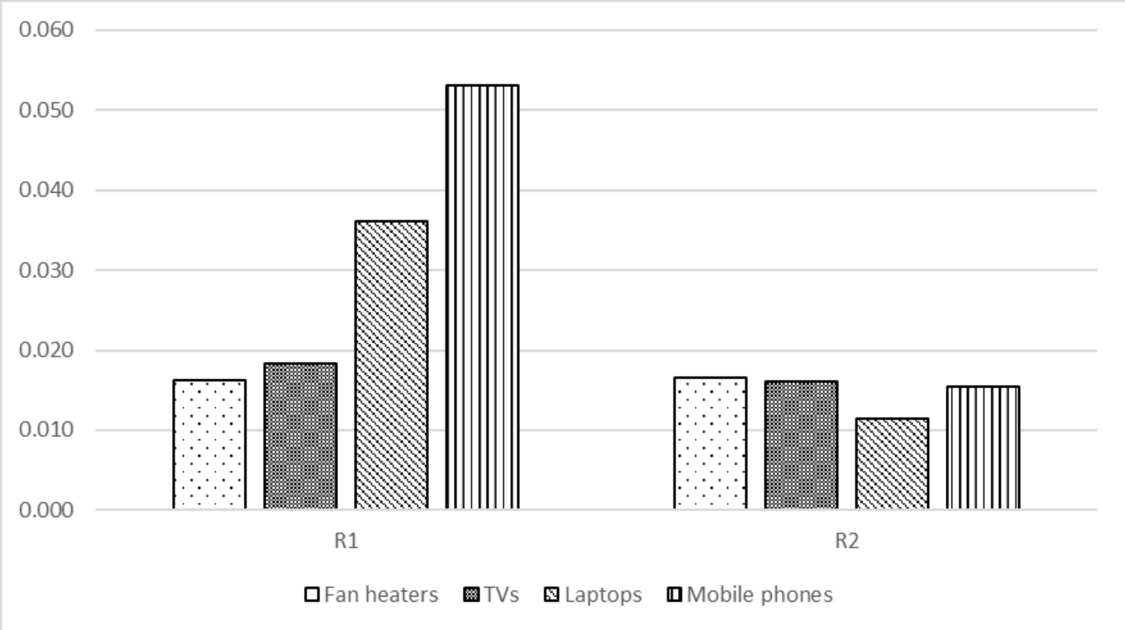


Analysis of the forecasting of purchase probabilities for TVs. R1, R2 and R3 are the forecasts, based on the data collected, respectively, in time 1, 2 and 3. The y-axis shows the estimated probability of a typical consumer in the surveys purchasing the brand.

5.3. Comparing forecasts for long vs. short life cycle products

To provide a further assessment of the potential effect of changing model coefficients on forecast accuracy we treated the R3 purchase probabilities as a proxy for the true purchase probabilities and measured how accurate forecasts of these probabilities were, when they were based on the R1 and R2 data. For each product, group accuracy was measured using the mean absolute error (MAE). For laptops and for the data collected in R1, for instance, MAE is the sum of the absolute differences between the probability forecasts made in R1 and the estimated purchase probability in R3 for each of the six products shown in Table 8. The MAE was chosen because the forecasted probabilities are most likely to be translated into forecasts of market share. In this case, a discrepancy between a forecast of 10% and outcome of 20% is likely to be as serious as a discrepancy between 50% and 60%. Both errors represent 10% of the potential market. If the market size is one million units the error in both cases is 100,000 sales units, representing the same lost sales or surplus stocks. In addition, recent research suggests that relative error measures, such as the mean absolute percentage error (MAPE) and its variants do not accurately reflect the loss functions of forecasts (Davydenko and Fildes, 2013). The results for all product types are shown in Figure 6. The findings suggest that purchase probability forecasts for short life-cycle, high tech products is less reliable because of changing consumer preferences. Hence forecasts for 'stable' products can be relatively reliable and can probably be performed by carrying out just one survey, which can be undertaken well in advance of a product's launch. In contrast, for short life-cycle high tech products forecasts based on surveys that take place well in advance of a product's launch can lead to highly inaccurate forecasts of purchase probabilities. Also, the mean absolute errors for R1 are much larger than those for R2, suggesting that the greater the time interval between the survey and the product's launch, the greater will be the error in forecasting the product's purchase probability.

Figure 6. Mean absolute error (MAE) based on R3 data as proxy for actual purchase probability.



The y-axis shows the MAE.

Overall, forecast accuracy was negatively associated with life-cycle length. Mobile phones are the products with the shortest life-cycle among the ones surveyed. TVs have lower technological complexity than mobile phones and laptops and hence, unsurprisingly, came third in terms of forecast accuracy over time. Finally, fan heaters have the longest life-cycle and are relatively simple products with little technological sophistication, and therefore very long life-cycles. Some of the identified instability for complex and high tech products with short life-cycles in comparison to simple ones with a long life-cycle could be due to cognitive factors as discussed in the literature review, bounded rationality (Simon, 1955) being one of these cognitive factors. For example, Bettman et al., (1998) argue that consumer preferences become more unstable in the face of complex or unfamiliar decisions. In particular, the task of making trade-offs between different attributes becomes more difficult the greater the number of attributes so that consumers are likely to resort to simplified heuristics when making their choice (Payne et al., 1993). Some of these heuristics, such as the lexicographic strategy, involve choosing on the basis of a highly restricted subset of attributes. The contents of this subset may vary over time as the relative salience of the attributes changes in response to stimuli such as product innovations, familiarity with different features and advertising. The technological advances that are associated with hi-tech short-life cycle products have led to increasingly complex combinations of product features (Kurawarawala and Matsuop, 1996; 1998) and greater numbers of these features. Moreover, initially some of these new features are likely to be unfamiliar to potential consumers, but familiarity is likely to increase over time leading to the use of alternative heuristics and revised choices (Park and Lessig, 1981). All of these factors will be associated with changeable preferences. Their presence therefore suggests that forecasters should have reservations about using CBC models to forecast the purchase probabilities, sales and market share of innovative products that are likely to have short life-cycles. For these products, the results suggest that there is a need to develop models that can reflect changes in the preferences for product attributes and hence make forecasts of future changes.

Figure 6 also shows that for laptops and mobile phones the R1 forecasts of the R3 probabilities were substantially less accurate than the R2 forecasts. This suggests that because of changing preferences for these products the lead-time of their forecasts should be kept as short as possible. This could be related to familiarity with these products, which tend to have more rapidly evolving features. Participants may change their preferences as they became more knowledgeable about these features over time. Another cause could be due to the construction of consumer preferences during the experimental process. This can be explained by the results of Amir and Levav's (2008) study on how people learn to become more consistent in their choices through repetition. More specifically, making repeated choices is likely to reveal peoples' subjective attribute values, which enables them to learn how they prefer to resolve trade-offs between conflicting attributes in a choice set. If participants make more choices in a domain, they become more confident in their subjective value for the levels of each attribute and more internally consistent in their choices. However, further research would be needed to confirm these possibilities.

5.4. Attributes most associated with changes in preferences

To further investigate which type of product attributes were most associated with changes in consumer preferences we carried out a detailed comparison of the models estimated in rounds 1 and 3. For each attribute we measured the mean effect of the change in its coefficient, β, on the log of the odds favouring the purchase of a product ($\ln(P_{ni}/1- P_{ni})$), averaged over all other possible combinations of attributes. For example for TVs if Brand_Sony was combined, in turn with each possible combination of levels for Price, Screen size, Smart, ThreeD and Freeview on average its log-odds would change from -1.87 in R1 to -1.45 in R3: an absolute difference of 0.43 (after rounding). This was the maximum absolute difference for the different brands. Table 11 shows the maxima of these mean absolute changes in the log-odds between rounds 1 and 3 for the attributes of each of the four products. The log-odds were analysed as they are linearly related to the coefficients, unlike the probabilities. The maximum is displayed to show which attribute had the greatest potential for contributing to forecasting errors.

Table 11. Effect of changes in model coefficients between R1 and R3 on changes in log-odds of product purchase.

TVs	Max change	Mobiles	Max change	Fan heaters	Max change	Laptops	Max change
Brand	0.43	Brand	0.68	Brand	0.25	Brand	0.59
Price	0.18	Price	0.27	Price	0.40	Price	0.21
Screen	0.36	Camera	0.13	Power	0.10	Display	0.19
Smart	0.10	Memory	0.24	Type	0.16	Processor	0.23
ThreeD	0.23	Display	0.24	Oscillating	0.29	Memory	0.20
Freeview	0.20	Battery	0.29			Hard drive	0.30
		Weight	0.29			Weight	0.19

It can be seen that for all products except fan heaters changes in preferences for brands had the greatest potential to contribute to forecast errors. Several studies on the effects of brand on consumer choices were published between 1980 and 1995 (e.g. see Guadagni and Little, 1983; Fader and Lattin, 1993). These studies showed the relative importance of product brand in determining consumer preferences but they did not investigate changes in preferences for brand over time. The existence of stronger inter-temporal changes in consumer preferences with regards to brand when compared to other features may be due to the superficiality of consumers' perceptions of brand. The importance of this attribute is driven by perceptions that are shaped by marketers' adeptness in using advertisements, brand identity, news, and lifestyle to promote their brand. According to Erdem and Keane's (1996) study, advertising can affect consumer choices in the short term, which might explain these brand preference variations across the different rounds of the experiment. Table 11 suggests that changes in brand preferences would not be a major potential source of forecast errors for fan heaters. While further research would be needed to establish the reason for this, it seems likely that consumers will be less aware of brands of fan heater than they are of brands of (say) mobile phones. This may reflect both lower levels of interest in fan heaters (Park and Lessig, 1981) and less experience of competing advertisements for these products, which might otherwise motivate them to make frequent changes in their preferences. For this product, changing preferences for price could pose the largest threat to forecast accuracy. It is unclear why preference changes for this attribute should occur over the relatively short period covered by the surveys.

6. Conclusions, limitations and further research

Our results show that consumer preferences for different attributes of products may vary significantly over time. Variation was found to create the largest impact on forecasts of purchase probabilities for high technology products with short life-cycles. For these products, long lead time market share forecasts that are based on single applications of choice based models are likely to be relatively inaccurate. The results also suggest that lability in preferences is particularly likely to be associated with products where branding is a key attribute.

These results have potentially important implications for new product development where forecasts of future demand often have been made well in advance of the product launch date in order to plan production and distribution capacity. They suggest that point forecasts based on CBC that are made even a few months before launch may be highly unreliable for high technology short life cycle products. Ironically, it is the manufacturers of these products, who are most likely to have the greatest need for reliable new product demand forecasts, given the frequency of their launches of innovative products. For these manufacturers, making the forecast as close as possible to the launch date and being prepared to make frequent updates to forecasts, when this is feasible, would be likely to improve accuracy. More fundamentally, our results suggest that they would be unwise to base their decisions entirely, if at all, on point forecasts and that an emphasis should be placed on assessing the risk associated with these forecasts by estimating probability distributions of future demand or market share. Where there is scant availability of data to support these estimates management judgment may have a valuable contribution to make, as long as it is elicited through structured procedures such as credence decomposition (Goodwin and Wright, 2014).

This study is subject to a number of limitations. The first limitation refers to the impossibility of comparing the same product-characteristics over the four products. Take brand, for instance. Whereas brands like Blackberry have featured in the news considerably over the past year or so as a result of falling demand, much less was heard about brands of fan-heaters. In other words, perhaps attribute salience, as well as life-cycle length may help to explain why preferences for the attributes of mobile phones and laptops vary considerably more. Similarly, Table 11 suggests that price level may have an influence on the changeability of consumer preferences. Price level was the attribute that was potentially most inimical to forecast accuracy for fan-heaters, which were also the lowest priced products. That issue is also not addressed in this paper.

In particular, no out-of-sample data on purchase probability or market share was available to assess forecasting accuracy directly. Also the study only involved examining three consumer electronics product categories and a consumer durable as a fourth product category. Future work could examine other consumer electronics products with different specifications as well as products from different categories or in different countries covering a range of cultural backgrounds or socioeconomic factors.

In addition, the stimuli for the participants' choices, namely the available products, were displayed on a computer screen. Hence, unlike purchasing experiences in brick-and-mortar environments, consumers were unable to physically see or handle the products or read reviews about them. In addition, the choices were simulated, rather than real so consumers did not have to actually buy any of the products they had chosen. It is possible that fatigue resulting from the number of choices required may itself have induced inconsistency. Nevertheless, many of these limitations are inherent in applications of CBC in practice. If ways could be developed to overcome these problems (e.g. the use of virtual reality to provide a more faithful simulation of product choice) or more efficient experiments could be designed to restrict the number of choices required, this would be likely to reduce inconsistency and thus lead to CBC being a more reliable forecasting tool.

In this study, because of limited resources and time constraints convenience sampling was used, based on volunteers who might have different characteristics to people who chose not to volunteer. Quota sampling would have been an alternative and would have allowed the participants to represent the demographic structure of a given market, thereby allowing the results to be generalised for that market. From a statistical perspective the use of a probability sample, such as a stratified sample, would have been ideal, but this would have been impractical given the unavailability of a sampling frame and the costs involved in accessing a large geographically disparate population. Additionally, the research lost some of the participants each time a new survey was conducted, which was inevitable. Hence, we cannot know whether those who left the process were more or less changeable in their preferences than those who stayed.

Future work could test the validity of the outcomes from this research in real-time forecasting. Prior research has shown that declared preference models can be poor predictors of real purchase and other behaviours (Ozer, 2011). Also, if surveys were carried out on a greater number of points in time, then time series analysis could be applied to the model coefficients in order to forecast their future values. For example, the coefficients could be exponentially smoothed over time, allowing more recent values to have a greater influence on the subsequent forecasts. When sufficient data is available, more sophisticated possibilities include experimenting with time-varying parameter models. In addition, the development of models that allow for the assessments of risks associated with demand forecasts would allow manufacturers of new products to make decisions with greater realism and insight.

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