Theory of Due Repurchase

Gaining More from Using Less

A thesis presented in partial fulfilment of the requirements for the degree of

Master of Business Studies
in
Marketing

at Massey University, Albany
New Zealand

Hussam Abdulrahman H. Aldolaigan

2016

STATEMENT OF ACADEMIC INTEGRITY

I declare that this research study is entirely the product of my own work and that it has not been taken from the work of others. When the work and ideas of others have been used in the study, the work has been properly cited in the text.

Hussam A. H. Aldolaigan

June 2016

Abstract

The aim of the thesis is to enhance the current knowledge on repurchase behaviour and provide a model that enables marketing practitioners to ‘gain more from using less’ through reallocating their resources and investing more in underutilised customer data. This is because producing the desired customer response using the least costly marketing actions is the key to success in today’s increasingly competitive marketplace. Although models predicting repurchase behaviour in non-contractual settings exist, their predictive and explanatory performances are poor. None of these existing models considers the roles of purchase quantity (PQ) and homogeneity of interpurchase times (IPTs) in predicting repurchase behaviour. Hence, Theory of Due Repurchase is developed in this thesis and suggests that the customer’s next purchase is highly expected under three repurchase conditions, which are that the customer is 1) a frequent shopper; 2) has upward-trending PQs; and 3) has homogeneous IPTs. These three variables are not only expected to be strong predictors of repurchase behaviour, but also correctly classify more customers than existing behavioural models, including recency, frequency and monetary value (RFM). Using a transaction dataset available in the literature, six studies were conducted to empirically test the Theory of Due Repurchase, examine its predictive accuracy and replicate the findings. The results support all of the hypotheses, developed as part of the conceptual model, and replicate the findings. Theory of Due Repurchase correctly classifies over 88% of customers across four samples, improving the current level of accuracy in predicting repurchase behaviour by approximately 19 percentage points. The thesis provides a number of academic and managerial insights on effective targeting.

ACKNOWLEDGEMENTS

I would like to sincerely thank Dr Andrew Murphy for his supervision of this thesis and support as well as Associate Professor Jonathan Elms for his co-supervision of this thesis and support. I would also like to thank Al-Watania Poultry and Saudi Telecom Company (STC) for their interest in this research and willingness to participate. Finally, I would like to thank my friend Faheem Zaidi from Massey's Institute of Mathematical Sciences for his feedback on the purchase quantity measure.

Contents

LIST OF EQUATIONS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	*Explanation*
C	Clumpiness
F	Frequency
IPT	Interpurchase Time
IPT_h	Interpurchase Time homogeneity
LPQ	Last Purchase Quantity
MV	Monetary Value
PQ	Purchase Quantity
R	Recency
RB	Repurchase Behaviour
RF	Repurchase Frequency
T	Relationship length

1 Introduction

1.1 Background to the Thesis

The aim of this thesis is to enhance knowledge on repurchase behaviour and provide marketing practitioners with a model which has the potential to enable them to ‘gain more for less’ through reallocating, and investing in, internal resources. This is because survival in today’s increasingly-competitive markets largely depends on understanding the behaviours of existing customers (Grewal, Levy & Kumar, 2009). More companies are now leaning towards defensive marketing; a strategy that focuses on managing the company’s existing customers (Zineldin, 2006). Focusing on and maintaining good relationships with current customers, instead of attracting new ones, is key to business growth (Buchanan & Gillies, 1990) and profitability (Payne, 1994). A little effort put into retaining existing customers can substantially reduce the marketing costs of acquiring new customers (Zineldin, 2006) and potentially double profits (Buchanan & Gillies, 1990).

Effective communication with existing customers has been foreseen to be “the key strategic source of business” (Webster, 1992, p.1). Indeed, an increase of only 1% in predicting the actions of existing customers can raise profits substantially (Baesens, Viaene, Van den Poel, Vanthienen & Dedene, 2002). Such is underscored by Van den Poel (2003), who found that companies could add significantly to their profits through improving customer predictability. Profit margins widen as a result of effective targeting, which reduces non-response and cost figures in marketing campaigns. This is why improvement in targeting is often on the top of marketers’ priority lists (Viaene et al., 2001; Van den Poel, 2003).

The vast majority of retailers currently maintain customer databases (Ghani, Probst, Liu, Krema & Fano, 2006) at low costs (Blattberg, Kim, & Neslin, 2008). With technology allowing for the collecting and storing of richer consumer-level data, more businesses have been encouraged to invest in their internal resources, including *customer-base analysis* (Fader & Hardie, 2009). Having existing customers repurchase is inexpensive and less difficult compared to new customers (Schoenbachler, Gordon, Foley, & Spellman, 1997). Consumer data, including purchase history, are underutilised marketing resources, which, once used to learn and predict the customer’s value and actions, could well maximise business gains.

Success in the current retail environment requires reallocating marketing resources in a way that allows the retailer to gain more from using less (Radjou & Jaideep, 2015). While increasingly acknowledging the importance of understanding the behaviours of existing consumers (Puccinelli et al., 2009; Fader & Hardie, 2009), retailers seem to underinvest in their current resources when learning about their customers. In the past few years, many retailers have allocated significant amounts of resources to research into understanding and predicting the actions of consumers (Puccinelli et al., 2009). Due to this, marketing costs are rapidly increasing, while production and general management costs are decreasing; the marketing budget, in particular, has been under close scrutiny by top-level management (Weber, 2002).

Given the continuously increasing competition (Van den Poel, 2003), “marketers face rising pressure to become more efficient and productive” (Weber, 2002, p.705). Thus there is a need for *efficient marketing,* defined as producing the desired response using the least costly marketing actions (Kotler, 1972). However, because the customer’s purchase decision is influenced by marketing, economic, environmental and/or situational factors, predicting their next purchase is not a simple task (Ajzen, 1991;

Wójcik & Doligalski, 2014). Producing the desired consumer response, or repurchase decision, requires an accurate prediction of consumer behaviour (Jebarajakirthy & Thaichon, 2016).

1.2 Academic Relevance of the Thesis

While a number of theories and models predicting repurchase behaviour in non-contractual settings already exist in the marketing literature (Fader & Hardie, 2009), the predictive and explanatory performances of these theories and models are dissatisfying (Day, Gan, Gendall & Esslemont, 1991; Sutton, 1998). Researchers are still proposing extensions to these models to improve their poor predictive and explanatory performances (Al-Shayea & Al-Shayea, 2014; Han & Ryu, 2012). One reason why existing theories and models perform poorly when applied in a consumer context is that these are initially developed and tested in non-business contexts, such as health and charity contexts (Ajzen, 1991; Al-Shayea & Al-Shayea, 2014; Bagozzi & Warshaw, 1990; Drossaert, Boer & Seydel, 2003; Perugini & Bagozzi, 2001; Schifter & Ajzen as cited in Bagozzi & Warsaw, 1990; Sejwacz et al. as cited in Bagozzi & Warshaw, 1990). Moreover, along with the complex nature of humans, environmental and situational factors intervening during purchasing activities make it more difficult to explain and/or accurately predict repurchase behaviour (Ajzen, 1991; Wójcik & Doligalski, 2014).

Explaining more of the repurchase behaviour and accurately predicting it are two different problems approached by two different schools of thought[1]. First, researchers attempting to increase the explained variance in repurchase behaviour appear to be

[1] A school of thought refers to a prominent group of studies conducted for the purpose of, in this context, predicting purchase behaviour using similar research methods.

inspired by the attitudinal school of thought. Here, consumer behaviour is predicted by consumers' feelings and emotions towards a brand. The attitudinal school relies on self-reported measures of attitude, such as satisfaction, commitment, preference and trust (East, Gendall, Hammond & Lomax, 2005). Attitudinal studies focusing on explaining more variance in repeat behaviour are cross-sectional and measure the effect on a continuous dependent variable. Both advocates and critics of the attitudinal school agree that there is room for improvement in attitude-behaviour models (Sheppard, Hartwick & Warshaw, 1988; Sutton, 1998). Second, researchers focusing on improving the accuracy of predicting repurchase behaviour are inspired by the behavioural school of thought, wherein consumer behaviour is predicted by consumers' past behaviours. Examples of behavioural measures include the well-known measures of recency, frequency and monetary value (RFM) of purchasing behaviour. Behavioural studies focusing on improving accuracy in predicting repeat behaviour are longitudinal and measure the effect on a dichotomous dependent variable (repurchased or not). Neither school, however, provides a comprehensive model that satisfactorily explains much of the variance in repeat behaviour and/or accurately predicts it in various business contexts. This, therefore, provides the focus and rationale for this thesis.

1.3 Thesis Objectives and Structure

Given the limitations of the extant literature, as briefly described above, this thesis is designed to introduce and then subsequently build upon the Theory of Due Repurchase. As such, the objectives of this thesis are two-fold. First, to construct a conceptual model based upon the extant literature in order to predict repurchase behaviour. Second, to empirically test the conceptual model in order to examine its accuracy in predicting repurchase behaviour. In terms of structure, the next chapter reviews the literature on predicting repurchase behaviour. The attitudinal and behavioural schools of thought are reviewed and critiqued, and the justification why the behavioural school is adopted in this research is presented. Based on this discussion, a conceptual model and the hypotheses are developed. In Chapter 3, the research methodology adopted in this research is described and discussed. This is followed by the presentation of six studies in Chapter 4 that were conducted in order to test the hypotheses and replicate the findings. The main findings of these six studies are reviewed, put together and discussed in detail in Chapter 5. Chapter 6 concludes the thesis, presents managerial implications, and outlines the limitations of the research, as well as signalling areas for future research.

2 Literature Review

2.0 Introduction

The previous chapter provided the background to this thesis, and briefly discussed the managerial and academic rationale for the current research. The aim of the thesis is to enhance the current knowledge on repurchase behaviour and provide marketing practitioners with a model which has the potential to enable them to 'gain more for less' through reallocating, and investing, in internal resources. Breaking it down, the objectives of this thesis are: first, to construct a conceptual model which predicts repurchase behaviour, and; second, to subsequently empirically test the conceptual model to examine its accuracy. The purpose of this chapter is therefore to review and synthesise relevant literature from marketing and retail research in order to construct a comprehensive conceptual model which predicts repurchase behaviour. Specifically the attitudinal and behavioural schools of thought are each reviewed in turn, and their relative limitations highlighted. The discussion also justifies why the behavioural school is adopted in this thesis. This is followed by the presentation of the conceptual model, and discussion which develops the research hypotheses.

2.1 Attitudinal School of Thought

The poor predicative ability of repurchase-behaviour models, built on demographic and socioeconomic variables, led to the development of theories and models consisting of intention and attitudinal constructs (Day et al., 1991). A distinguishing feature of the attitudinal school of thought is the use of cross-sectional data and reliance on self-reported measures captured by survey methods. Generally, attitudinal studies examine the effects of consumers' feelings and emotions including satisfaction, commitment, preference, and trust (East et al., 2005) on repeat behaviour measured as a continuous dependent variable. Both advocates and critics of attitude-behaviour models agree that there is room for improvement in these models (Sheppard et al., 1988; Sutton, 1998). Figure 2.1 illustrates visually how well existing attitude-behaviour models perform.

Fishbein and Ajzen (1975; Ajzen & Fishbein 1980) developed the Theory of Reasoned Action (TRA) to predict human behaviour. The TRA suggests that behaviour is determined by the intention to perform that behaviour which mediates the effects of behavioural beliefs (attitude) and normative beliefs (subjective norms) on behaviour (Fishbein & Ajzan, 1975; Madden, Ellen & Ajzen, 1992; Sheppard et al., 1988; Sutton, 1998). Ajzen (1988, 1991) extended the TRA and developed the well-known Theory of Planned Behaviour (TPB) through adding perception of behavioural control as a predictor of intention. Both the TRA and TPB fail to explain more than 50% of the variation in intention and 38% of the variation in behaviour (Sutton, 1998).

Bagozzi and Warshaw (1990) extended the TPB and developed the Theory of Trying (TT). The TT takes into account recency and frequency of past actions. Recency is added to the TT model as a predictor of behaviour, while frequency of past actions is added to predict both intention and behaviour. Bagozzi and Warshaw (1990) conducted a study on weight loss to test the TT model, which explained 59% of the variance in the intention to lose weight and 45% of the variance in attempting to lose weight (Bagozzi & Warshaw, 1990).

An extension to the TT was proposed by Perugini and Bagozzi (2001), who suggest that a) anticipated emotions affect the human desire to perform a task; and b) that *desire* is antecedent to intention and mediates the effects of attitude, subjective norms, perception of behavioural control, and anticipated emotions on intention. This extension is known as the Model of Directed-Goal Behaviour (MDB). Again using studies on weight loss, the MDB explained a maximum of 72% of the variation in desire to lose weight, 78% of the variation in intention to lose wright and 46% of the variation in acting to lose weight (Perugini & Bagozzi, 2001).

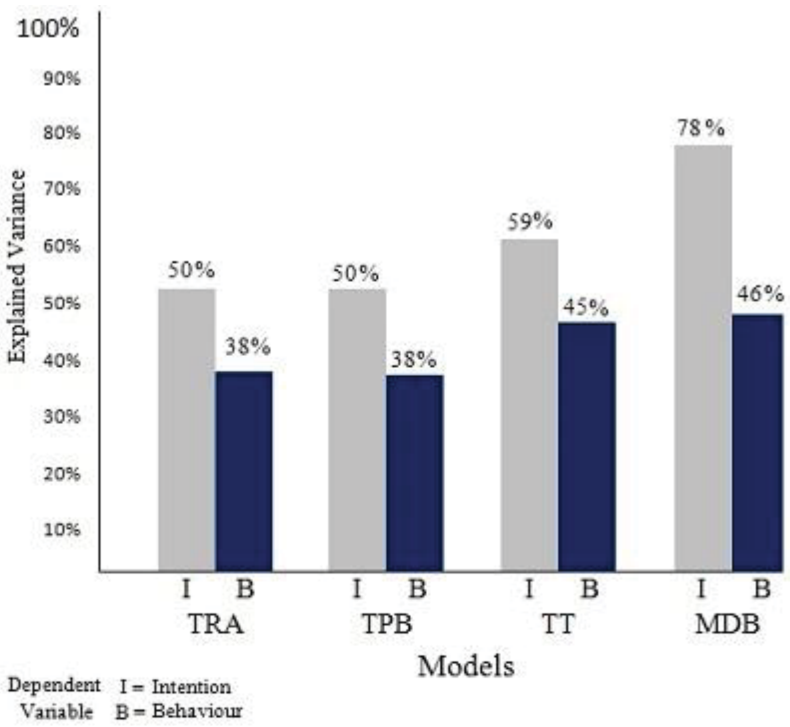

Figure 2.1: Summary of the Performance of Attitude-behaviour Models

Han and Ryu (2012) proposed the Theory of Repurchase Decision-Making (TRD), which is a modification of the MDB. Unlike other attitude-based models, intension is the outcome in the TRD. Their modification of the original MDB included rearranging and/or removing the effects of beliefs, overall image, customer satisfaction, commitment, switching cost, and desire to predict intention. Whereas intention to repurchase is the dependent variable in the TRD model, switching cost, desire and commitment play mediating roles in the model (Han & Ryu, 2012). The amount of variance in rebuying intention explained by the TRD is very similar to the amount of variance explained by the MDB. Even though the TRD does not predict repeat behaviour, it is important to acknowledge this work to recognise that, even with the addition of new attitudinal variables and introducing mediators, the variance explained is not much improved.

Along with being costly (Van den Poel, 2003), attitude-behaviour models are increasingly criticised on a) their inability to explain more variance in repeat behaviour (Sutton, 1998); and, b) their limited applicability in varying contexts (Ajzen, 1991). Firstly, the validity of the link between attitude and behaviour is still questionable (Park & Maclnnis, as cited in Grewal et al., 2009). Critics of attitude-based models stress that attitudinal measures and metrics lack accuracy and fail to predict, and encourage, behaviours, such as repeat purchase (Anderson, Fornell & Lehmann, 1994; Lowenstein, as cited in Sharma, 2007; Peterson & Wilson, 1992; Puccinelli et al., 2009; Reese, as cited in Sharma, 2007; Reichheld, 1996). Secondly, these models are applicable to specific contexts only (Ajzen, 1991). The majority of studies use weight-loss data (Ajzen, 1991; Bagozzi & Warshaw, 1990; Perugini & Bagozzi, 2001; Schifter & Ajzen as cited in Bagozzi & Warsaw, 1990; Sejwacz et al. as cited in Bagozzi & Warshaw, 1990). In a health context, a study on identifying the predictors of repeat attendance at breast cancer screening found that TPB's predictors explain only 17% of the variation in intention to attend breast screening and only 6% of the variation in repeat attendance (Drossaert et al., 2003). In a retailing context, TPB's predictors are found to explain 52% of the variance in intention to repurchase apparel, which in turn explains 19% of the variance in purchase incidence (De Cannière, De Pelsmacker & Geuens, 2009).

Regardless of the context, however, attitude-behaviour models fail in explaining more than 46% of the variance in repeat behaviour.

Disappointed at the predicative performance of attitude-based models, Sutton (1998) points out that although the vast majority of previous studies measured intentions and its antecedents at the same time, using the same questionnaires and scale items, no more than 50% of the variance in intention has been explained. Even though De Cannière et al. (2009) could explain 52% of the variance in behavioural intention, Sutton's point is still valid and has not been addressed in the extant literature. Sutton (1998) ascribes this poor predictive performance of attitude-behaviour models to a number of reasons, including intentions being a changing, provisional, insufficient cause of repeat behaviour, and that they are mostly measured using a single-item scale. This criticism of attitude-behaviour models is valid and raises concerns about the robustness of these models. De Cannière et al. (2009) show that the effects of attitudinal variables on behaviour become insignificant when behavioural variables are added to the model. They found that attitudinal predictors fail to predict repeat purchase when combined with behavioural predictors, and concluded that the RFM predictors have a much better predictive performance than attitudinal predictors.

2.2 Behavioural School of Thought

The need for accurate predictions of repeat purchase encouraged researchers to adopt the behavioural school of thought. In this school, data are longitudinal and the measures are obtained using the consumer's purchase history. Behaviour-behaviour models are developed on the basis that past actions predict future ones (Bagozzi, Bentler & Speckart, and Witten-braker, Gibbs & Kahle, both as cited in Bagozzi & Warshaw, 1990; Ouellette & Wood, 1998). Behavioural studies focusing on improving accuracy in predicting repurchase behaviour measure the effects of consumers' previous actions and decisions on repeat behaviour commonly measured as a dichotomous dependent variable. This school of thought is relatively younger than the attitudinal school, and its models seem to originate in the segmentation stream of literature (Van den Poel, 2003).

Having been reliable segmentation tools for years (Marcus, 1998), the RFM variables are found useful for predicting future behaviour. Currently, there is no single behaviour-behaviour model that does not include at least one of the RFM variables. In fact, the addition of one or more of the RFM variables improved the performance of attitude-behaviour models (Bagozzi & Warshaw, 1990). Ample evidence shows that RFM variables are strong predictors of repurchase behaviour (De Cannière et al., 2009; Buckinx & Van den Poel, 2005).

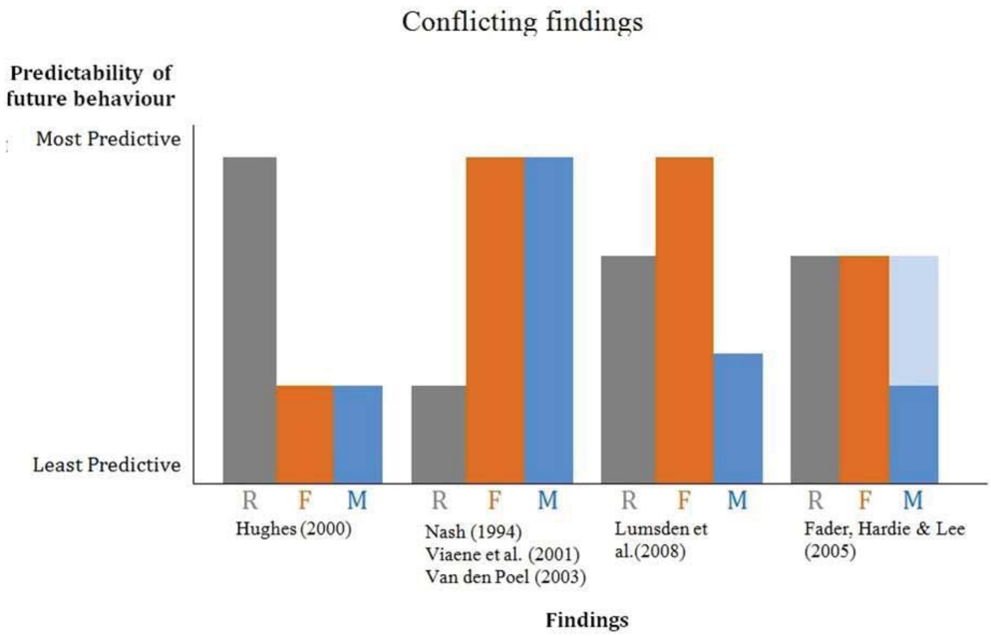

Figure 2.2: Predictive Performance of RFM Variables

However, there has been some ambiguity regarding the predictive power of each of the RFM variables. Figure 2.2 illustrates the conflicting findings regarding the predictive performance of RFM. Hughes (2000) asserts that frequency and monetary value are much less predictive of consumer response than recency. Other researchers disagree and found recency to be less important in predicting future purchases than frequency and monetary value (Nash, 1994; Viaene et al., 2001; Van den Poel; 2003). Lumsden, Beldona and Morrison (2008) find that recency and monetary value are weaker predictors than frequency. Fader, Hardie and Lee (hereafter denoted to as FHL) (2005a) assume that frequency and recency are independent of monetary value, while further analysis revealed that monetary value and frequency are connected more tightly than expected. Bagozzi and Warshaw (1990, p.137) concluded their research with a call for "better definitions and measures of both recency and frequency".

Due to the absence of a behavioural conceptual framework (Van den Poel, 2003), repurchase behaviour is modelled differently across studies. Van den Poel (2003) investigated the predictive performance of combinations of behavioural predictors that could make up a conceptual model to predict repeat behaviour. He found that the best combination of behavioural predictors[2] correctly classifies 69% of buyers (Nagelkerke R^2 is not reported). Buckinx and Van den Poel (2005) focus only on loyal customers of a FMCG retailer to predict whether they partially defect, using RFM of past purchases; this set of behavioural variables correctly classified 80% of consumers who are temporarily non-loyal (Nagelkerke R^2 is not reported) (Buckinx & Van den Poel, 2005). Although this classification accuracy is high, it is important to bear in mind that this is a classification of a specific segment (loyal consumers) with similar shopping behaviours.

Recently, Al-Shayea and Al-Shayea (2014) extended the RFM model by adding relationship time to predict the choice of donating blood using the Neural Network method, which correctly classified 89% of blood donors. There are a number of reasons for obtaining such a high percentage of correct classification. First, Neural Network has a tendency to overfit models. Second, the reliability of the result might be questionable,

[2] Recency, Frequency, Monetary Value, Relationship Age and Credit Usage.

as Neural Network has a limited ability in establishing causal relationship and is considered inappropriate for analysing linear models with dichotomous dependent variables (Tu, 1996), such as donating blood or not. Third, the context of donating blood is incomparable to the context of repurchasing where factors such as price, competition and product alternatives play crucial roles in repurchase behaviour.

In-between the two ends of the spectrum are researchers who have investigated the combined effects of behavioural, attitudinal, socioeconomic and/or demographic variables on repeat purchase. Bult (1993) used demographic, socioeconomic and behavioural variables to predict holders of credit-cards; this combination correctly classifies 62.9% of credit-card holders. Viaene et al. (2001) tested the effects of 25 behavioural and non-behavioural predictors on repeat purchase and then dropped 16 of them to correctly classify 72.20% of buyers. The remaining 9 predictors include frequency of past behaviour, monetary value and other non-RFM predictors such as seeking information and complaining. Baesens et al. (2002) combined the RFM variables with other behavioural and non-behavioural variables to model repurchase behaviour; this resulted in a percentage of correct classification of 72.4%. Table 2.1 is a literature review of the work on behaviour-behaviour modelling.

Table 2.1: Literature Review and Research Gap

		Independent variables								
Contribution by:	**Year**	R	F	M	Oth_Bhv	Non_Bhv	H_IPT	PQ	PCC	R^2
Bult	1993			•	•	•			62.90%	-
Viaene et al.	2001	•	•	•	•	•			72.20%	-
Baesens et al.	2002	•	•	•	•	•			72.40%	-
De Cannière et al	2009	•	•	•					Not reported	Not reported
Van den Poel	2003	•	•	•	•				69.00%	-
Buckinx and Van den Poel	2005	•	•	•		•			80.00%	-
Q. Al-Shayea and T. Al-Shayea	2014	•	•	•	•				89.00%	-
Zhang, Bradlow and Small	2015	•	•	•	•				Not reported	Not reported
This paper	2016		•				•	•	-	-

Keys:

- R = Recency
- F = Frequency
- M = Monetary value
- Oth_Bhv = Other behavioural variables
- Non_Bhv = Non-Behavioural variables
- H_IPT = Homogeneity of Interpurchase Time
- PQ = Purchase Quantity
- PCC = Percentage Correctly Classified

While many behavioural variables have been modelled to predict repurchase behaviour, no single model has considered the roles of purchase quantity (PQ) and homogeneity of inter-purchase times (IPTs) in predicting repurchase behaviour at the consumer level (see Table 2.1). The future monetary value of customers appears to be linked to the variability of the times and quantities of their purchases (Jen, Chou & Allenby, 2009). Abe (2009, p.552) concluded that “a model that can capture behavioural differences in dynamic purchase pattern could provide valuable insights into CRM”. In behavioural research, much more attention is paid to *when* a purchase is made and *what* brand/category is purchased, while very little attention is given to *how much/many* is purchased (Wansink, Kent & Hoch, 1998). PQ decisions are thought of as indicators of the purchaser’s consumption ability and plans (Beasley, 1998). IPT is considered one of the best indicators of customer activity and behavioural commitment (Buckinx & Van den Poel, 2005).

Summary

Attitude-behaviour models are costly (Van den Poel, 2003) and fail to explain a satisfactory amount of the variation in repeat purchase (Sutton, 1998). Although these models, as well as their extensions, measure the outcome, dependent and antecedent variables simultaneously using same questionnaires and scale items, these models show a poor predictive performance (Sutton, 1998). Critics of the attitudinal school of thought ascribe the poor explanatory performance of attitudinal models to the lack of accuracy from which attitudinal measures and metrics suffer (Anderson, Fornell & Lehmann, 1994; Fornell, 1992; Lowenstein, as cited in Sharma, 2007; Peterson & Wilson, 1992; Puccinelli et al., 2009; Reese, as cited in Sharma, 2007; Reichheld, 1996). Moreover, attitude-behaviour models seem context-dependent and are more applicable in health contexts (Ajzen, 1991) than in business contexts. Furthermore, the robustness of attitude-behaviour models is questionable especially when behavioural variables, such as RFM, are added (De Cannière et al., 2009; Park & Maclnnis, as cited in Grewal et al., 2009).

Behaviour-behaviour models perform better in business contexts as behavioural predictors are found to explain more variance in repurchase behaviour and predict it more accurately than attitudinal predictors do (De Cannière et al., 2009; Buckinx & Van den Poel, 2005). However, the marketing and retail research literature does not offer one behavioural conceptual framework to predict repurchase behaviour (Van den Poel, 2003). Moreover, the predictive performances of behavioural predictors appear inconsistent across studies. Additionally, the highest accuracy level was obtained using five behavioural variables that accurately predicted 69% of future purchasers (Van den Poel, 2003).

While the literature offers a number of behaviour-based models, none of them took into consideration the effects of purchase quantity and the homogeneity of the customer's IPTs on repurchase behaviour (refer to Table 2.1). These two variables seem to play more critical roles in predicting repurchase behaviour that one would expect. The quantity and time variability of purchases are linked to the future value of a customer (Jen et al., 2009).

2.3 Conceptual Model

A large body of literature suggests that on a shopping trip consumers ask and answer three questions related to 1) whether to purchase product X now or later; 2) whether to purchase brand A, B, C, or D; and 3) what quantity of brand A, B, C, or D should be bought (Wansink et al., 1998). Consumers' answers to these three questions on each shopping trip make up their purchase history, including purchase frequency, purchase quantities and the time between purchases. These three behavioural variables have been found strong predictors of customer future values (Buckinx & Van den Poel, 2005; Jen et al., 2009; Ouellette & Wood, 1998).

Theory of Due Repurchase is built on three behavioural dimensions that are vital to the generation of a reaction; these dimensions are frequency, quantity, and time. Variations in each of the three dimensions are reflected in the potential to repurchase. In a non-contractual setting, the consumer’s purchase decision is influenced more by routine and opportunity than by attitude or a preference (East et al., 2005). The theory suggests that what people say, feel, prefer, or even believe, is not necessarily what they actually do. Whether it is accessibility, effortlessness, quickness, convenience, environmental pressure, or just a habit, there is usually a behavioural reason behind most purchases. For example, a vegetarian could be loyal to a butcher shop just because their spouse, children, or roommates are non-vegetarians. Although vegetarians’ attitude towards meat consumption does not suggest that they would be regular buyers of meat, they may not act on this attitude.

Theory of Due Repurchase suggests that the customer’s next purchase is due (highly expected) when the following three conditions are met:

1. The consumer is a frequent shopper;
2. The consumer’s LPQ builds on an existing trend of increasing PQs; and
3. The consumer’s IPTs are homogeneous.

Figure 2.3 depicts the conceptual model. Repurchase behaviour is believed to be determined by the frequency of past purchases (F), last purchase quantity (LPQ), and the homogeneity of the consumer’s inter-purchase times (IPTs). Given the importance of the three variables in decision making, these are expected to predict repurchase behaviour more accurately than the best performing behaviour-behaviour model, which combined RFM, relationship age and credit card usage to correctly classify 69% of consumers (Van den Poel, 2003). The conceptual reasoning for the expected relationships and effects that Theory of Due Repurchase proposes is discussed next, followed by a set of hypotheses.

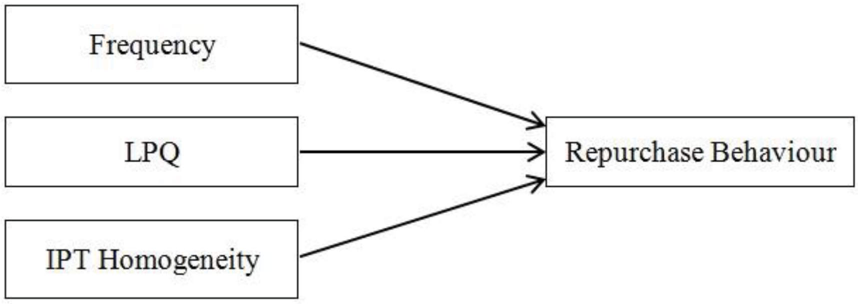

Figure 2.3: Theory of Due Repurchase

Past frequency of behaviour plays a critical role in forming future decisions (Bagozzi & Dholakia, Lee et al., Perugini & Bagozzi, Poels & Dewitte, Ryu & Jang, and Taylor et al., all as cited in Han & Ryu, 2012; Fader et al., 2005a). A number of studies found that the frequency of performing a behaviour is positively associated with the frequency of performing that particular behaviour in the future (Lemon et al., as cited in Buckinx & Van den Poel, 2005). Triandis (as cited in Ouellette & Wood, 1998) found that the frequency of exercising a habit indicates its strength. Frequency of past actions is considered the best predictor of future behaviour, especially under conditions in which the behaviour is learnt very well and the context is a stable one (Ouellette & Wood, 1998). Therefore, there would be more potential to repurchase when the consumer is a frequent shopper.

Purchase quantity has generally been studied in relation to price and promotion (Beasley, 1998; Beasley & Shank, 1994; Chintagunta, 1993; Gupta, 1988;

Krishnamurthi & Raj, 1988; Neslin, Henderson, & Quelch, 1985; Pauwels, Hanssens & Siddarth, 2002; Van Heerde, Leeflang & Wittink, 2000). Studies in these fields often investigate the effects of marketing mix and/or fluctuations in lifestyle on the consumer's PQ decisions. Helsen and Schmittlein (1992) found that the heavier the promotion of a product, the higher the consumer's inventory becomes; Beasley (1998) found that higher inventory in a household leads to longer periods of customer inactivity. Laroche, Pons, Zgolli and Kim (2001) found that when people become busier, they purchase in larger quantities. Research in the direct marketing literature suggests that heavy purchasers are likely to be loyal (Jacoby & Kyner and Reichheld, Markey & Hopton, both as cited in Jen et al., 2009; Van den Poel, 2003). To the best of the author's knowledge, no single study has examined how the consumer's LPQ decision is associated with, or affects, repurchase behaviour. Consumers have different consumption abilities and plans, which are reflected in the quantity they purchase on each purchase incidence (Beasley, 1998).

Along with the fact that purchase-quantity decisions vary in response to marketing stimuli and lifestyle changes (Beasley, 1998; Helsen & Schmittlein, 1992; Laroche et. al., 2001), consumers' needs and purchasing powers are not the same. For example, a consumer who is currently going through a period of unemployment would be unable to make the same PQ decision as s/he would when employed, especially if no monetary incentive was offered. This introduces the problem of what classifies the consumer as a heavy or light purchaser at a particular point of time. Instead of classifying consumers as heavy or light purchasers, the classification in this paper is based on whether the individual consumer's overall PQ is increasing or decreasing.

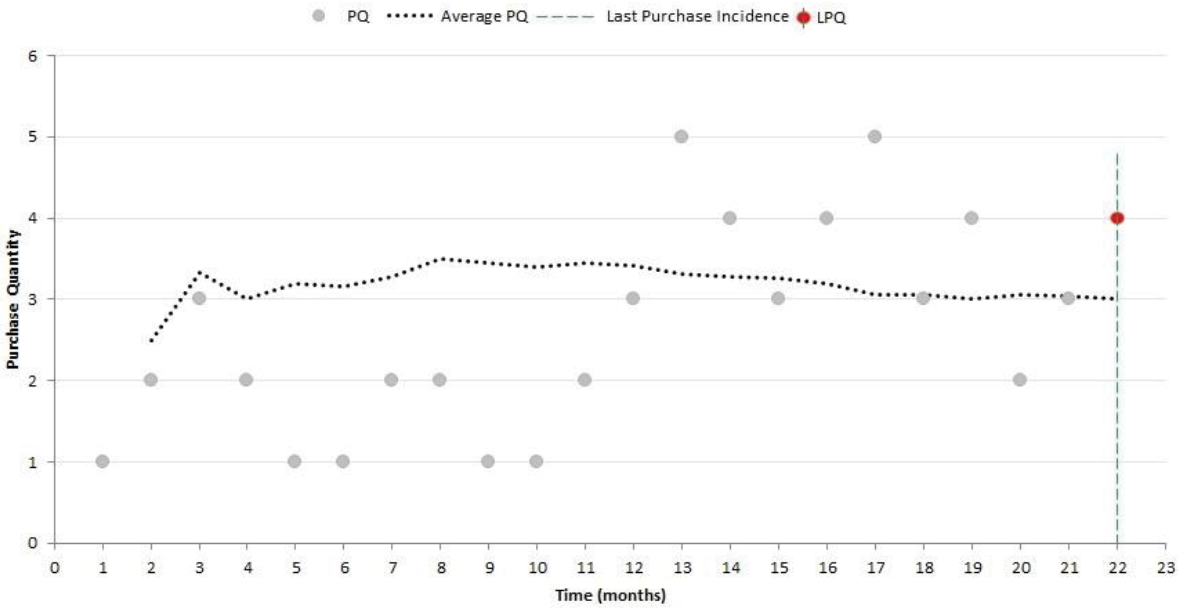

Figure 2.4: Increasing PQ

Theory of Due Repurchase suggests that the trend of the customer's PQ indicates their current behavioural commitment to buying a brand or buying from a given retailer. Figure 2.4 and 2.5 display the PQ histories of two customers; one has (Figure 2.4) an increasing PQ and the other (Figure 2.5) has a decreasing PQ. If the customer's LPQ builds on an existing trend of increasing/decreasing PQs, reflecting an increasing/decreasing behavioural attachment to the brand/retailer, then the customer at this point of time is a heavy/light purchaser. A repurchase is expected when the customer is behaviourally attached to the brand/retailer. The developed theory suggests that the customer's next purchase is due when their LPQ continues an increasing trend of PQs; the lower the LPQ, the more potential there is to repurchase unless the low LPQ is following a period of decreasing purchase quantities.

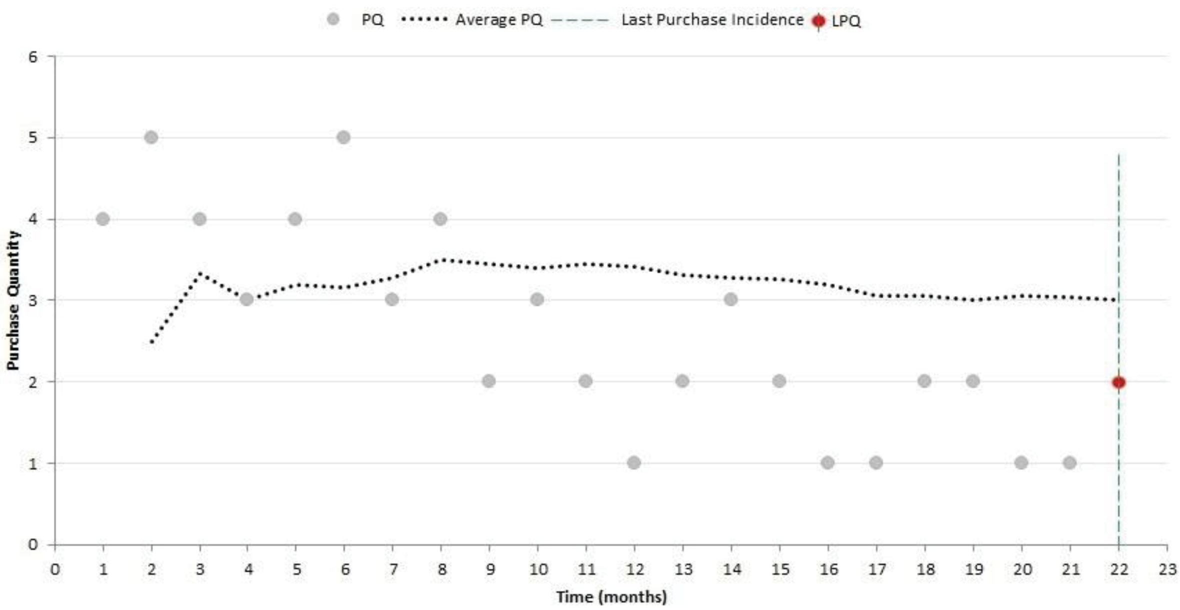

Figure 2.5: Decreasing PQ

The customer's IPT is a key behavioural variable that has been used for the purposes of segmenting the market and predicting customer value (Buckinx & Van den Poel, 2005). The existence of customer relationship management (CRM) systems, focusing on providing a customised product/service to each consumer, have made it important to consider behavioural homogeneity/heterogeneity in marketing models (Jen et al., 2009). In a consumer context, behavioural homogeneity is defined as similarities in decision-making that lead to a repurchase decision (Moskowitz & Rabino, as cited in Broderick, Greenley & Mueller, 2007). Disloyal consumers are found to purchase at random times while loyal consumers purchase at more consistent time intervals (Abe, 2009). Regardless of how long or short IPTs are, similar time intervals between purchases reflect purchasing patterns that could well be automatically repeated in the future (Ouellette & Wood, 1998).

FHL (2005a) find that consumers who buy more recently and frequently are less valuable than others who buy less frequently but more recently; this phenomenon has been identified as the "increasing frequency paradox" (2005a, pp.422-423). FHL (2005a) explain this paradox by showing that consumers become inactive, although their purchase histories suggest the opposite. They (2005a) emphasise the importance of capturing this phenomenon.

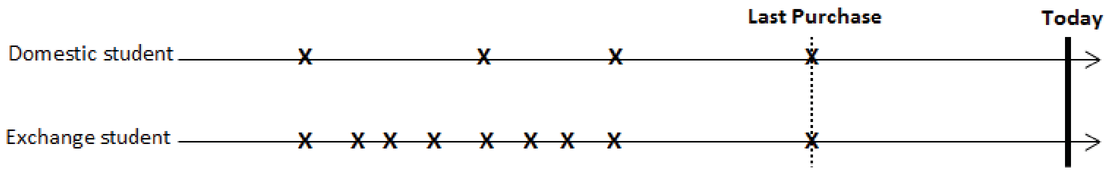

Figure 2.6: Improved version of the paradox illustration first developed by FHL (2005a, p.422).

The current research uses FHL's (2005a) example to illustrate how homogeneity of IPTs could capture the phenomenon of increasing frequency-decreasing recency. Figure 2.6 is a modified version of the "increasing frequency paradox" illustration developed by FHL (2005a, p. 422). Consider two university students; one is domestic, and the other is an exchange student who went back to his home country at the end of the academic semester. In Figure 5, the buying pattern of the exchange student strongly suggests that he will repurchase. However, by looking at and comparing the time from *Last Purchase* until *Today* (or recency), the purchasing pattern of the domestic student is more homogeneous. Considering the similar IPTs of the two students, the domestic student is more likely to repurchase today than the exchange student is. Homogeneity of IPTs solves the paradox and controls for the exaggerated effect of low recency and high frequency. Therefore, it is expected that the more homogenous the customer's IPTs, the more likely the customer is to repurchase and be behaviourally loyal in the future. Hence, the five hypotheses below are developed.

2.4 Hypotheses

H_1: ***There is more potential to repurchase when the consumer:***

- *H_1_A: is a frequent purchaser (vs. infrequent);*
- *H_1_B: 's LPQ continues an existing trend of increasing purchase quantities; and*
- *H_1_C: has homogeneous (vs. heterogeneous) IPTs.*

H_2: ***The consumer's next purchase is due*** **(highly expected)** ***when the following conditions are met:***

- *The consumer is a frequent purchaser;*
- *The consumer's LPQ continues an existing trend of increasing purchase quantities; and*
- *The consumer has homogeneous IPTs.*

H_3: ***The absence of one, or any combination, of the following conditions is associated with the consumer's choice not to repurchase:***

- *The consumer is a frequent purchaser;*
- *The consumer's LPQ continues an existing trend of increasing purchase quantities; and*
- *The consumer has homogeneous IPTs.*

H_4: ***The potential to repurchase varies depending on the combination of repurchase conditions; repurchase potential is highest when all repurchase conditions are satisfied.***

H_5: ***Purchase frequency, LPQ and IPT homogeneity:***

- *H_5_A : are predictors of repurchase behaviour; and*
- *H_5_B: correctly classify more than 69% of future purchasers.*

2.5 Chapter Summary

This chapter reviewed the literature on predicting repurchase behaviour and developed the conceptual model for the Theory of Due Repurchase as well as five hypotheses. It began with introducing, highlighting the differences between, and discussing the attitudinal and behavioural schools of thought researchers adopt to predict repurchase behaviour. The choice of adopting the behavioural school of thought was justified. Then, the conceptual rationale for the expected relationships and effects were discussed. This was followed with the formulation of a set of hypotheses. The next chapter will introduce and discuss the methodological approach adopted in this research and elaborate on the data, samples, measurement and procedures.

3 Methodology

3.0 Introduction

The previous chapter reviewed and synthesised the literature on predicting repurchase behaviour. This review of literature led to identifying the research gap which is the absence of research on the roles of purchase quantity (PQ) and homogeneity of interpurchase times (IPTs) in predicting repurchase behaviour. The chapter then introduced the Theory of Due Repurchase, discussed its conceptual rationale, and developed five hypotheses to test it and examine its predictive accuracy. The purpose of this chapter is to introduce and discuss the methodological approach adopted in this research, including descriptions and discussions of the data used and the drawn samples, as well as descriptions and discussions of the measurements and procedures.

3.1 Methodological Approach

The objectives of this thesis are to empirically test the Theory of Due Repurchase and subsequently examine its accuracy in predicting repurchase behaviour. To meet these objectives, this thesis adopts a quantitative longitudinal research approach. This approach is deemed appropriate because the objectives of this research including testing associations and causal relationships between variables. The data used to test the conceptual model and hypotheses are secondary data collected by a commercial entity over some period of time. Given that the data used here are secondary, approval to conduct this research was not required[3]. Transaction data are used here because these are suitable for the purpose of this research and offer a number of advantages. First,

[3] However, because Massey University Human Ethics Committee (MUHEC) encourages new researchers to be familiar with the Code of Ethical Conduct for Research, a Low-risk Notification Application was submitted to MUHEC. A copy of the low-risk notification issued by MUHEC can be found in Appendix 1.

transaction data provide rich information that is critical to understanding relationships between choice alternatives (Rao & Sabavala, 1981). Second, purchase-behaviour measures provided by transaction data are more accurate than purchase-behaviour measures provided by other data-collection methods. Third, the chance of omitting purchase-behaviour measures is lower with transaction data (Frank & Strain, 1972).

3.2 Data

Over 26 companies based in 7 different countries and operating in 8 different industries were invited to participate in this research through providing transaction data. Only two companies, Al-Watania Poultry and Saudi Telecom Company (STC), showed willingness to share data. Unfortunately, the only data the two companies could share were distributor-level and store-level data; this research, however, requires consumer-level data. Although most of the companies showed interest in the research objectives, they declined the invitation to participate; usually because of one of two reasons. Either this type of data is considered too confidential to be shared or the decision-making process within the company is long and highly bureaucratic. Luckily, the marketing literature provides researchers in this field with transaction data.

3.2.1 Dataset

The present paper utilises a purchase-history dataset, known in the literature as CDNOW, which was first used by Fader and Hardie (2001), and who kindly made it available to other researchers. The CDNOW dataset contains purchase transactions made at CDNow.com, a giant North American e-tailer operating in the music industry. A total of 69,659 transactions made by 23,570 customers were recorded over 18 months (78 weeks), starting from the 1st of January 1997 to the 30th of June 1998. The types of data recorded in each transaction include a unique purchaser ID, the transaction date, the quantity of purchased CDs and the monetary value of the transaction in U.S. dollars. All customers had made their first-ever purchase at CDNow.com within the first three months of 1997, a period during which 23,570 purchasers were attracted to try CDNow.com (Fader & Hardie, 2001). Although the dataset might be considered outdated, it is still a popular dataset among scholars and has been used in the literature to develop and test theories, models and measures (Abe, 2009; Fader & Hardie, 2001; FHL, 2005a, 2005b; Ma & Büschken, 2011; Zhang et al., 2015).

3.2.2 Samples

Because no new transaction dataset was obtained from currently operating businesses, four samples, drawn from the full CDNOW dataset, are used to test the research hypotheses and replicate the findings. The first sample is the 1/10th systematic sample, which Fader, Hardie and Lee (hereafter denoted as FHL) (2005b) took to test the performance of the BG/NBD model. This sample is used to test the research hypotheses. In addition, this thesis draws three large samples from the entire CDNOW dataset and labels them Samples A, B and C. This is because "testing additional samples of the target population with the same methods provides supporting or contradictory evidence regarding the existence of a phenomenon" (Mackey, 2012, p.21). Drawing more samples, which are larger than FHL's 1/10th Sample, was the only available option to overcome the lack of data, bring more variation into the analysis, and increase certainty in the findings. These three samples are used in this research to replicate and increase the external validity of the findings (Lucas, 2003; Mackey, 2012).

Drawing Samples A, B and C

Samples A, B and C are taken from the full CDNow.com dataset using systematic random sampling without replacement; this ensures that the sampling unit in each of the three samples is distinct (Thompson, 1990). Firstly, observations in the full dataset are randomised using the randomisation function in Excel. Secondly, using Customer ID, an observation is selected at random to be the starting point for the systematic-random sampling procedure; then, every third case is selected, resulting in Samples A, B and C. Each sample contains a distinct group of purchasers. For example, Customer #509, who is in Sample B, has no information at all in Samples A or C.

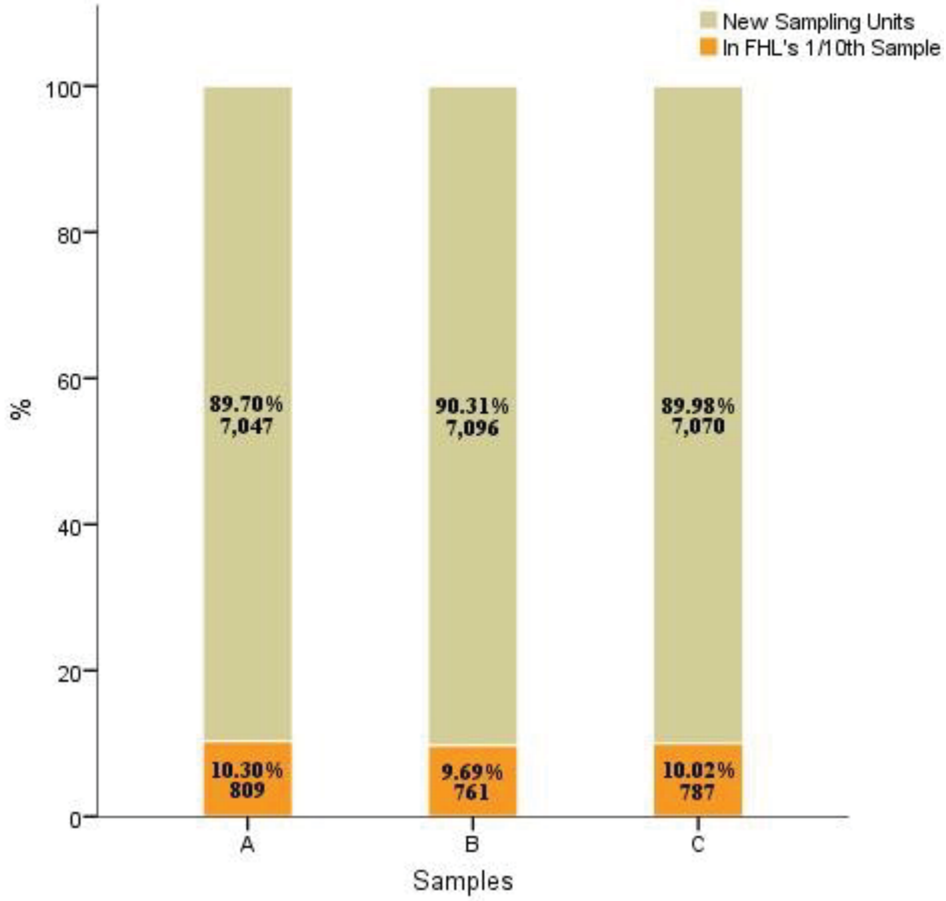

Figure 3.1: Distribution of FHL's Sampling Units across Samples A, B and C

It is noteworthy that sampling units (purchasers) in FHL's 1/10th Sample are spread across Samples A, B and C. These sampling units are, almost, evenly distributed across the three samples. Figure 3.1 displays the distribution of FHL's sampling units across Samples A, B and C. Purchasers who are sampled in FHL's sample make up no more than 11% of each of the three samples. New sampling units, however, constitute 89.70%, 90.31% and 89.98% of Sample A, B and C, respectively. This should make variations in each of the four samples unique enough to increase confidence in the results.

Table 3.1 provides the descriptive statistics of the 4 samples. The sizes of Samples A, B and C are fairly similar and are three times larger than FHL's 1/10th Sample. Purchasers in Sample C made more transactions (23,774) than purchasers in other samples. Compared to the other samples, there is less variability in the frequency of purchases in Sample A. The average CD consumption, across the 4 samples, is 1 CD. More heterogeneity of purchase quantity exists in FHL's 1/10th Sample and Sample B. Purchasers in the 1/10th Sample have shorter IPTs than purchasers in other samples; there seems to be groups of purchasers who wait much longer to repurchase, and have not been selected in the 1/10th Sample. All these variations, with and across samples, should help increase confidence in the research findings.

Table 3.1: Descriptive Statistics of the Four Samples

		FHL Sample	Sample A	Sample B	Sample C	Full Dataset
	Consumers =	*2,357*	*7,856*	*7,857*	*7,857*	**23,570**
	Transactions =	*6,918*	*23,068*	*22,817*	*23,774*	**69,659**
Frequency	$\overline{F}$=	*2.66*	*2.60*	*2.56*	*2.65*	
	σ =	*2.96*	*2.72*	*2.89*	*3.16*	
Purchase Quantity:	$\overline{PQ}$=	*1.16*	*1.16*	*1.16*	*1.16*	
	σ =	*1.04*	*1.12*	*1.03*	*1.11*	
Interpurchase Time:	$\overline{IPT}$=	*28.00*	*66.67*	*70.64*	*67.31*	
	σ =	*22.90*	*38.81*	*38.98*	*38.53*	

3.3 Data Preparation

3.3.1 Outliers

Preparing the 1/10th Sample dataset for analysis, FHL (2005a) identified and removed the purchase history of 10 purchasers who represent potential outliers. Throughout the observation period, the monetary contribution of these 10 purchasers exceeded $4,000.00, leading to the existence of major outliers. CDNow.com advised FHL (2005a) to exclude these 10 purchasers from any consumer-level analysis because, according to representatives at CDNow.com, "these people are probably unauthorised resellers" (FHL, 2005a, p.416).

Table 3.2: Purchase Data Forming Potential Outliers

Sample:		$4000+	On average	$2000-$3999	On average	$1000-$1999	On average
FHL 1/10th	*N =*	*1*		*0*		*6*	
	Transactions =	*56*		---		*82*	
	Quantity=	*378*	10 CDs per week	---		*412*	2 CDs per week
Sample A	*N =*	*0*		*2*		*16*	
	Transactions =	---		*71*		*199*	
	Quantity=	---		*437*	6 CDs per week	*1241*	2 CDs per week
Sample B	*N =*	*2*		*2*		*14*	
	Transactions =	*226*		*90*		*275*	
	Quantity=	*656*	8 CDs per week	*325*	4 CDs per week	*1191*	2 CDs per week
Sample C	*N =*	*1*		*4*		*20*	
	Transactions =	*107*		*146*		*380*	
	Quantity=	*548*	14 CDs per week	*933*	6 CDs per week	*1714*	2 CDs per week

- Observations over the calibration period (39 weeks).

To ensure that no outliers affect the results, the four samples have been scanned for abnormal observations. Table 3.2 identifies and analyses the purchase history of customers who bought $4,000.00+, $2,000.00-$3,999.00 and $1,000.00-$1,999.00 worth of CDs over the calibration period (39 weeks). Records show that, across the four samples, 4 people spent $4000.00+, 8 people spent $2,000.00-$3,999.00 and 56 purchasers spent $1,000.00-$1,999.00 on CDs. Although FHL (2005a) kindly cleaned the 1/10th Sample dataset and removed the outliers, one person who purchased $6,552.7 worth of CDs appears to have been overlooked. The purchase history of this unauthorised reseller is removed from FHL's 1/10th Sample prior to it being used in this research. Assuming that FHL (2005b) overlooked and tested their BG/NBD model without removing this potential outlier, their findings do not seem affected by the existence of this outlier. Appendix 8.2 replicates FHL's (2005b) study using FHL's 1/10th Sample, Sample A and Sample B.

To determine which group/s of spenders could be potential outliers (along with the $4000.00+ group), the mean average of quantity purchased every week is derived and assessed. Because each customer in the three groups bought a large number of CDs anyway, it has been assumed that customers, within each group, have purchased equal quantities. Hence, purchasers in FHL's 1/10th Sample, Sample B and Sample C who spent $4000.00+ with CDNow.com buy, on average, 10, 8 and 14 CDs per week, respectively. Similarly, people in Samples A, B and C who spent totals of $2,000.00-$3,999.00 on CDs buy, on average, 6, 4 and 6 CDs per week, respectively. Because heavy music consumers in the U.S. spend, on average, $402.00 per annum (Nielsen, as cited in Peoples, 2013), the purchase-history data of these two groups of abnormal spenders ($4000.00+ & $2,000.00-$3,999.00) could well constitute potential outliers and are, therefore, excluded from the analysis. It is implausible for an ordinary music consumer to buy more than 4 CDs weekly for 39 consecutive weeks.

However, purchase data for the group of purchasers who bought $1,000.00-$1,999.00 worth of CDs over 39 weeks have not been removed because of two reasons. First, the number of purchasers in this group across the four samples is large enough to be considered and included in the analysis. Second, the Nielsen report (as cited in Peoples, 2013) is recent, while the data were collected in the late 1990s, during which period digital music and online purchasing were not as popular as they are today. Thus, it is plausible to assume that a heavy music consumer buys weekly, on average, 2 CDs for

39 consecutive weeks. Therefore, purchase data for this group of purchasers are kept and included in the analysis.

3.3.2 Trial Purchases (1st Purchase)

All customers' first purchases (trials) are excluded from the analysis. This is not only because frequency is defined here as repeat purchases (FHL, 2005a, 2005b), but also to control for the effect of promotion. CDNow.com succeeded in marketing its product and persuading 23,570 people to make a trial purchase within the first three months of the observation period. Despite the type of promotion (i.e. a price deal or an anchor-based promotion), future purchase decisions are influenced by the offered incentives (Beasley, 1998; Krishnamurthi & Raj, 1988; Wansink et al.,1998). This implies that promotion has an effect that should be taken into consideration. A large number of CDNow.com's customers were incentivised by the trial purchase only, so they did not make a subsequent purchase. Figure 3.2 shows the distribution of transactions, including trial purchases, by year quarter across the four samples. Figure 3.3 displays the distribution of transactions across the 4 samples after excluding trial purchases. Excluding trial purchases normalises the distribution of transactions in each sample. To control for the promotion effect and ensure that any subsequent purchase is a genuine one, all trial transactions (1st purchases) have been excluded from the analysis.

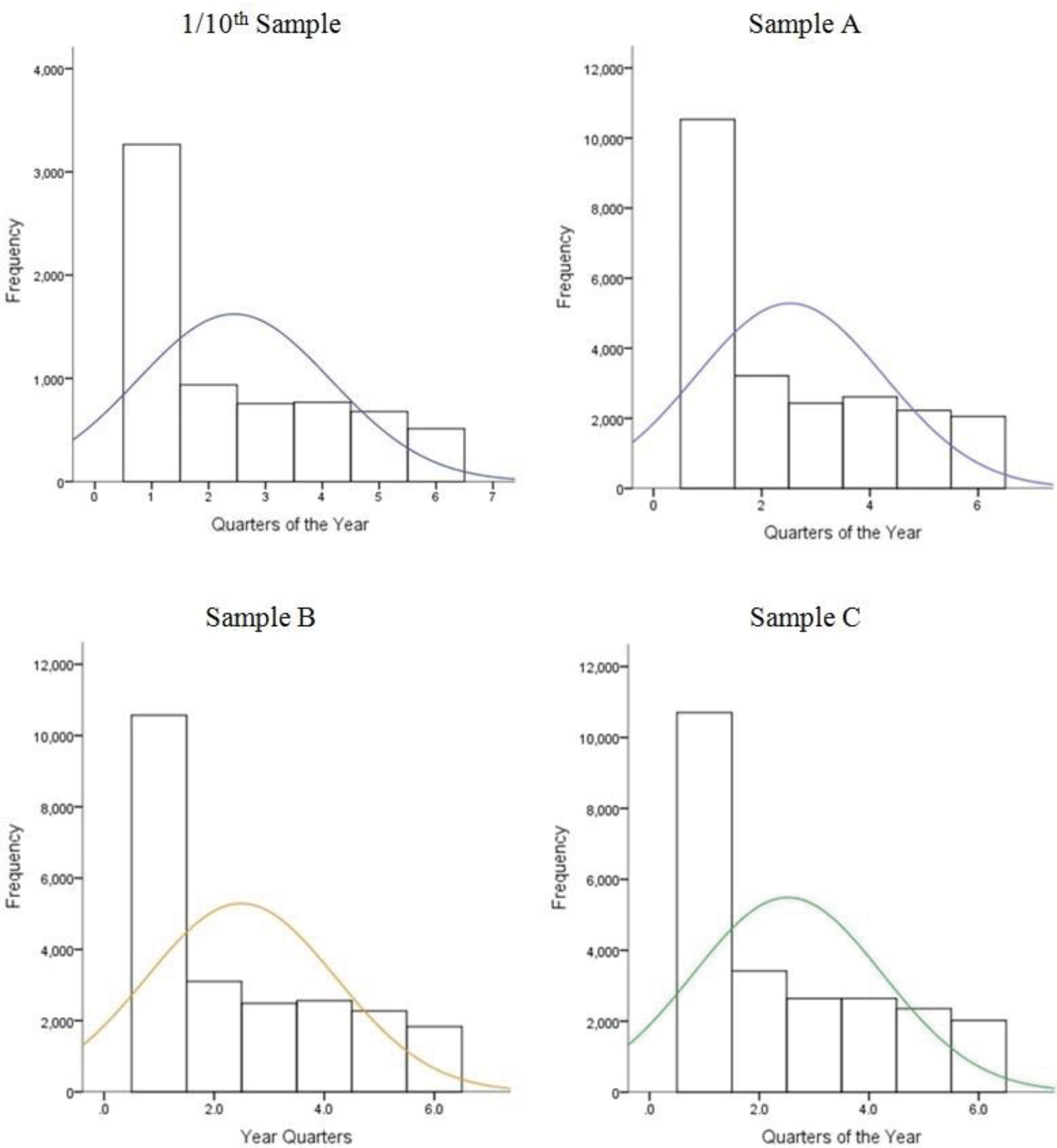

Figure 3.2: Distribution of Purchase Transactions over Six Quarters across Four Samples (Trial Purchase Included)

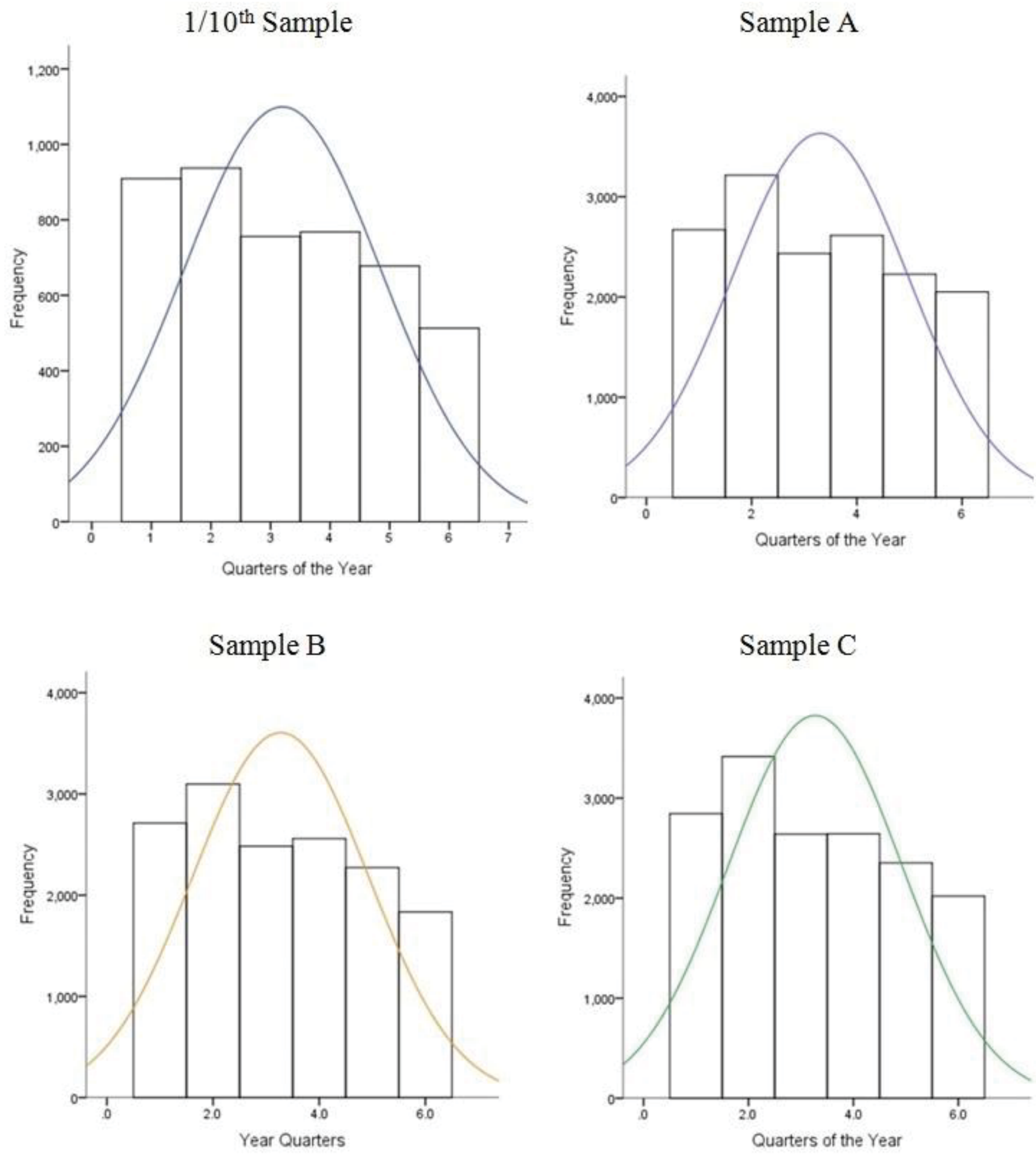

Figure 3.3: Distribution of Purchase Transactions over Six Quarters across Four Samples (Trial Purchase Excluded)

3.4 Measurement

The thesis objectives are to build the Theory of Due Repurchase and to subsequently empirically test it to examine its accuracy in predicting repurchase behaviour. The measures used to accomplish the research objectives are presented and discussed in this section. Table 3.3 summarises, and lists the sources of, the measures used in this research.

Table 3.3: Summary of Measures

	Model Variables				
	Frequency (F)	**Last Purchase Quantity (LPQ)**	**IPT Homogeneity (IPT_h)**	**Repurchase Behaviour (RB)**	**Repurchase Frequency (RF)**
Definition	The number of repeat transactions in the calibration period.	The weight of the number of items purchased in the last purchase incidence relative to the total number of purchased items.	Behavioural similarities between the consumers' IPTs.	A repurchase made by the consumer in the validation period.	The number of purchase transactions in the validation period.
Unit	Transactions	CDs	Days	Transactions	Transactions
Operationalisation	Average	$\frac{LPQ_i}{\sum_{i=1}^{n} PQ_i}$	HHI $= \sum_{i=1}^{n} (\frac{IPT}{T})^2$	$1 = Repurchased$ $0 = Skipped$	Count
Source/s	Buckinx & Van den Poel (2005)	This paper	Rhoades (1993) Simonson & Winer (1992)	Van den Poel (2003)	Zhang, Bradlow & Small (2015)
Condition	Frequent if $F > \overline{F}$	Increasing if $LPQ > \frac{\sum_{i=1}^{n} PQ_i}{n-1}$	Homogeneous if $\geq (\frac{R}{T})^2$	$1 = Repurchased$	----
	Infrequent if $F \leq \overline{F}$	Decreasing if $LPQ \leq \frac{\sum_{i=1}^{n} PQ_i}{n-1}$	Heterogeneous if $< (\frac{R}{T})^2$	$0 = Skipped$	
Applied in	Buckinx & Van den Poel (2005)	This paper	This paper	Van den Poel (2003)	Zhang, Bradlow & Small (2015)

		Control Variables		
		Monetary Value (MV)	**Clumpiness (C)**	**Relationship Length (T)**
Unit		Currency	Days	Days
Operationalisation		Sum	$= 1 + \frac{\sum_{i=1}^{n+1} \log(x_i) \cdot x_i}{\log(n+1)}$	(Today – 1st purchase)
Source/s		Viaene et al. (2001) Van den Poel (2003)	Zhang, Bradlow & Small, (2013, 2015)	FHL (2005b)

3.4.1 Frequency (F)

Frequency of past purchases has been defined and operationalised in a variety of ways in the literature. For example, Viaene et al. (2001) classically measure frequency using the number of purchase incidences in the calibration period, while Bauer (as cited in Viaene et al., 2001) measures it through dividing the number of purchases by the length in time of the customer's relationship. This research uses FHL's (2005a, 2005b) definition of frequency, which is the number of repeat transactions. Buckinx and Van den Poel (2005) use the average frequency of transactions to differentiate between shoppers who are behaviourally loyal and potentially profitable, and those who are not. Because frequency is considered an indicator of behavioural loyalty (Wu & Chen, as cited in Buckinx & Van den Poel, 2005) and shows whether or not a shopper is a frequent shopper, it is measured by a dichotomous variable. Therefore, customers are classified in this research as frequent shoppers, and coded as 1, if their purchase frequency is greater than average; otherwise they are infrequent shoppers and coded as 0.

3.4.2 Last Purchase Quantity (LPQ)

The consumer's PQ decisions reflect their consumption abilities and plans (Neslin et al., 1985; Helsen & Schmittlein, 1992; Beasley, 1998; Laroche et al., 2001). A number of different measures of PQ were used in previous studies. These measures are used to test effects on PQ decisions. PQ, in most previous studies, is often measured as a dependent variable, which does not seem to suit the purpose of the current research. For example, Helsen and Schmittlein (1992) measure PQ using time periods, while Boatwright, Borle and Kadane (2003) measure it using dollar amounts. Neither of these measures can be used in this research. This is because of two reasons.

First, the measurement units are different from what this research intends to measure. For example, using the monetary value does not capture the quantity effect. One music album containing 10 songs by Adele will probably cost more than a music album also containing 10 songs by a less popular music artist; although the quantity is the same, the dollar amount is different. The reverse could also be the case. For example, two packets of national brand and private label toilet paper are sold at the same price, although the private label packet contains 10 paper rolls more than the national brand packet of toilet paper. Second, the Theory of Due Repurchase acknowledges the effect of LPQ and specifies its relevance to the customer's consumption plans. Therefore, this phenomenon cannot be captured by measures other than the actual number of items purchased. Items, such as CDs, are an appropriate measurement unit of PQ (Beasley, 1998), suit the purpose of this research, and should reduce the chance of making measurement errors.

Theory of Due Repurchase acknowledges the link between the customer LPQ and their choice to repurchase. Equation 3.1 is a mathematical expression of this link. Simplifying Equation 1 results in obtaining Equation 3.2; the two equations are, indeed, the same. The only difference is that Equation 1 presents the outcomes in percentages, whereas Equation 2 yields absolute values. In this research in particular, the number of observations in the denominator is subtracted by 1(n – 1) to exclude the trial purchase and control for promotion. Failing to do so reduces the accuracy of predicting non-purchasers by about 77%. If controlling for the trial purchase is not required, then there is no need for the subtraction and, instead, only the number of observations in the sample is used.

Equation 3.1: Condition for LPQ in percentages

$$\frac{LPQ_i}{\sum_{i=1}^{n} PQ_i} > \frac{\overline{PQ_i}}{\sum_{i=1}^{n} PQ_i - \overline{PQ_i}} \tag{3.1}$$

$$\rightarrow \quad LPQ_i > \frac{\overline{PQ_i} \times n(\overline{PQ_i})}{n(\overline{PQ_i}) \times \overline{PQ_i}}$$

$$\rightarrow \quad LPQ_i > \frac{\overline{PQ_i} \times n(\overline{PQ_i})}{\overline{PQ_i}(n-1)}$$

$$\rightarrow \quad LPQ_i > \frac{\overline{PQ_i} \times n(\cancel{\overline{PQ_i}})}{\cancel{\overline{PQ_i}}(n-1)}$$

$$\rightarrow \quad LPQ_i > \frac{n(\overline{PQ_i})}{(n-1)}$$

$$\rightarrow \quad LPQ_i > \frac{\cancel{n}}{(n-1)} \times \frac{\sum_{i=1}^{n} PQ_i}{\cancel{n}}$$

Equation 3.2: Condition for LPQ in absolute values

$$LPQ > \frac{\sum_{i=1}^{n} PQ_i}{n-1} \tag{3.2}$$

Where;

LPQ = Last Purchase Quantity,
PQ = Purchase Quantity,
$\overline{PQ}$ = Average Purchase Quantity,
n = Number of observations, and
n – 1 = Degree of freedom.

LPQ is operationalised as a dichotomous variable and measured through comparing each customer's LPQ to their cumulative average PQ, as expressed in Equation 3.2. The customer's PQs are considered increasing, and coded as 1, when $> \frac{\sum_{i=1}^{n} PQ_i}{n-1}$; and considered decreasing, and coded as 0, when $LPQ \leq \frac{\sum_{i=1}^{n} PQ_i}{n-1}$. Figure 3.4 graphically compares the two scenarios of increasing and decreasing PQs and visually illustrates the difference between them. In Figure 3.4A, the customer's LPQ (month = 22) is greater than the cumulative average and has built on an existing trend of increasing PQs (as the upward-sloping line shows); hence, it is expected to be associated with the choice to repurchase. Figure 3.4B, on the other hand, shows that the customer's LPQ (month =

22) is lower than the cumulative average and has built on an existing trend of decreasing PQs (as the downward-sloping line shows); thus, it is expected to be related to the choice to skip.

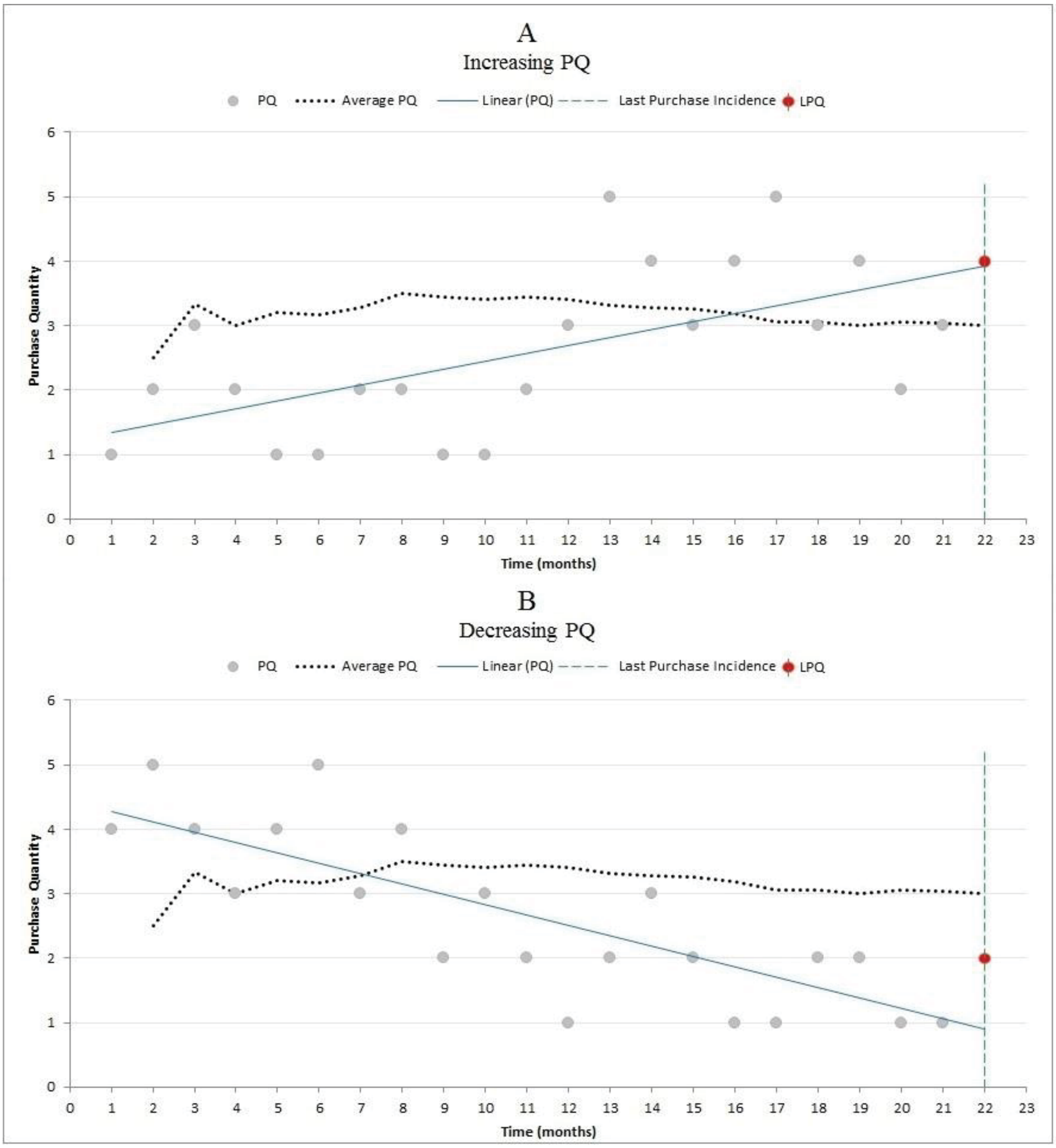

Figure 3.4: Increasing vs. Decreasing Purchase Quantity

3.4.3 IPT Homogeneity (IPT_h)

In non-contractual settings, IPT can be the most important indicator of active and inactive customers (Reinartz & Kumar, as cited in Buckinx & Van den Poel, 2005). The focus here is on measuring the homogeneity of IPTs within each customer's purchase transactions. Existing marketing measures of IPT are context-dependent and do not suit the purpose of this research. Buckinx and Van den Poel (2005), for example, studied the effects of RFM of past behaviour on the customer's decision to switch and be temporary inactive. For this purpose, their research (2005, p.255) focuses only on one segment of the customer base, which is "the best customers of the company". They measure the regularity of each customer's purchase visits by, first, dividing the standard deviation of the customer's IPT by the mean average of the customer's IPT; the result is, then, compared it to the population's average IPT. A result below average indicates regularity of purchase transactions and is, subsequently, coded as 1 (Buckinx & Van den Poel, 2005). Given the context of their research, simply dividing the standard deviation of IPT by the mean of IPT might be appropriate to measure the regularity of visits. However, the present research focuses on the entire customer base.

Zhang et al. (2013) developed and tested a measure of irregularity, which they call the clumpiness measure. It measures non-stationary behaviour and seeks to answer the question of whether a consumer's purchases, over a given period of time, are meaningfully clustered. To avoid any confusion, it is important to emphasise that the clumpiness measure cannot be used to measure IPT homogeneity because of two reasons. First, it focuses on the number of customer activities/transactions, while the focus here is on time intervals. Second, the lowest value of the clumpiness measure is obtained when IPTs are equal (Zhang et al., 2013), whereas this could mean an absolute homogeneity of IPTs.

The Herfindahl-Hirschman Index (HHI) appears optimal for measuring IPT homogeneity within cases and has been successfully used in marketing and retail contexts (Simonson & Winer, 1992; Bergès & Orozco, 2010). The HHI measures concentration in various contexts (Rhoades, 1993) through summing the squares of object shares (i.e. market shares or brand shares) (Simonson & Winer, 1992). Higher HHI values indicate higher concentration (Hyman & Kovacic, 2004) and higher homogeneity (Simonson & Winer, 1992). In economics, the highest HHI value (100%) means perfect monopoly (Calkins, 1983; Hyman & Kovacic, 2004). In the context of this research, an HHI value of 100% means that the customer has made only two purchase transactions, so the time between the first and second transactions is equal to the length of the customer relationship ($\mathrm{HHI} = \sum_{i=1}^{1} (\frac{IPT}{T})^2 = (\frac{1}{1})^2 = 100\%$); hence, the customer's IPT is perfectly homogeneous.

There are two advantages of using the HHI to measure IPT homogeneity. The first is HHI's sensitivity to skewness (Calkins, 1983). Regardless of whether the consumer's IPTs are shorter/longer in the beginning/end of the relationship, HHI takes into account the asymmetry of the consumer's IPT distribution. The second advantage is that the HHI measure deals with the "increasing frequency paradox", a problem identified and illustrated by FHL (2005a, pp.422-423). Figure 3.5 is an edited version of the paradox illustration FHL (2005a, p.422) used.

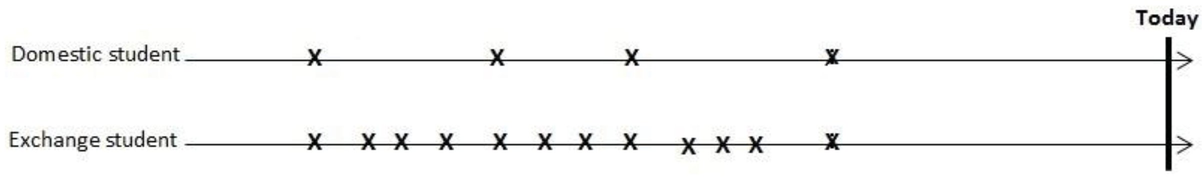

Figure 3.5: Illustration of the "Increasing Frequency Paradox" (FHL, 2005a, p.422)

Figure 3.5 shows the purchase history of two university students at an on-campus convenience store; one student is domestic (living off-campus) and the other is an exchange student (living on-campus). Their first and last purchases occurred on the same days so they have identical relationship lengths ($T_{Domestic} = T_{Exchange}$), IPT periods ($\sum IPT_{Domestic} = \sum IPT_{Exchange}$) and recency periods ($R_{Domestic} = R_{Exchange}$). The difference is that the exchange student shopped more frequently than the domestic student did at this convenience store. Given their frequencies of purchase, it is tempting to conclude that the exchange student is more likely to shop again than the domestic student is. However, the purchasing patterns of the two students suggest the opposite (FHL, 2005a).

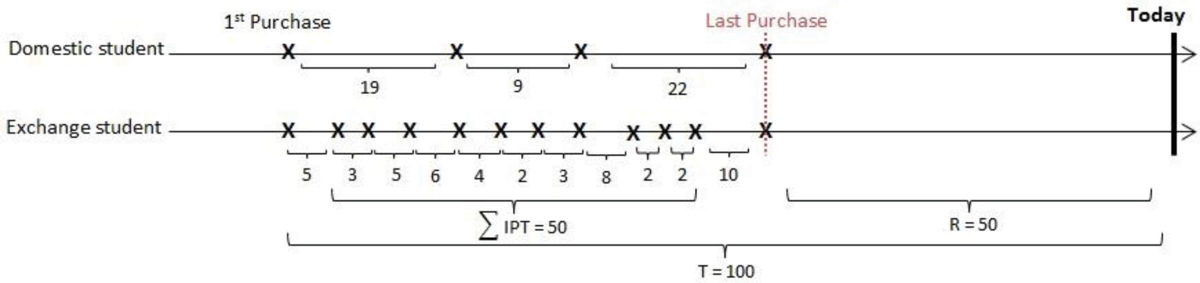

Figure 3.6: Measuring IPT Homogeneity Using HHI

Figure 3.6 illustrates how HHI is measured and how it deals with the paradox of increasing frequency. Note that the domestic and exchange students have the same relationship lengths (T = 100), IPT periods ($\sum IPT = 50$) and recency periods (R = 50). The only difference is that the exchange student purchased 11 times during the 100 days, resulting in shorter IPTs, while the domestic student shopped only 4 times during the same time period, resulting in longer IPTs. Thus:

Equation 3.3: Measure of IPT Homogeneity

$$\text{HHI} = \sum_{i=1}^{n} \left(\frac{IPT}{T}\right)^2 \tag{3.3}$$

Where;

IPT = Interpurchase Time, and

T = the length of the customer relationship.

Using Equation 3.3, the HHI values for the domestic and exchange students are 37% and 12%, respectively. According to the scale values of HHI, the domestic student's IPTs are more homogeneous (HHI= 37%) than the exchange student's IPTs (HHI= 12%). These degrees of IPT homogeneity imply that the domestic student is more likely to return to the shop and repurchase, which is what FHL (2005a) suggest. In theory, the exchange student's last purchase was probably made at the end of the academic semester at which s/he left the university campus. Hence, the phenomenon of unfavourably high frequency is captured by HHI.

The remaining question is how to distinguish customers with homogeneous IPTs from others with heterogeneous IPTs? In economics, a market is classified as concentrated when the value of the HHI is greater than 18%, moderately concentrated when HHI value ranges from 10%-18%, and unconcentrated when HHI is smaller than 10% (Hyman & Kovacic, 2004). However, these cut-off values are identified to specifically assess merger proposals (Calkins, 1983; Hyman & Kovacic, 2004) and may not be applicable when classifying the consumer's IPTs as either homogeneous or heterogeneous.

Equation 3.4: Condition for Homogenous vs. Heterogeneous IPTs

$$\mathrm{HHI} = \sum_{i=1}^{n} \left(\frac{IPT}{T}\right)^2 \geq \left(\frac{R_i}{T_i}\right)^2 \tag{3.4}$$

Where;
IPT = Interpurchase Time,
T = The length of the customer relationship, and
R = The recency period (time from last purchase).

Therefore, the present thesis suggests that to distinguish consumers with homogeneous IPTs from others with heterogeneous IPTs, the value of HHI should be compared with the squared weight of the recency period. An HHI value greater than, or equal to, $(\frac{R_i}{T_i})^2$ indicates that the consumer's IPTs are homogeneous and still within a familiar time zone. On the other hand, an HHI value smaller than $(\frac{R_i}{T_i})^2$ means that the consumer's IPTs are heterogeneous and that their past behaviour does not match their current behaviour.

Going back to the example of university students, each of the two students falls under a different IPT classification. Applying the condition in Equation 3.4, the domestic student is classified as a consumer with homogenous IPTs because their HHI (37%) is greater than their $(\frac{R_i}{T_i})^2$, which is 25%; hence, s/he is expected to repurchase. The exchange student's IPTs, on the other hand, are classified as heterogeneous because the HHI value (12%) is lower than their$(\frac{R_i}{T_i})^2$, which is also 25%; thus, s/he is not expected to repurchase. Hence, purchasers whose HHI values are greater than, or equal to, $(\frac{R_i}{T_i})^2$ have homogenous IPTs and are therefore coded as 1; otherwise coded as 0.

Validity and Reliability: Variations in IPTs between those with homogeneous IPTs and others with heterogeneous IPTs are examined to determine whether there are significant variance differences between the groups. Levene's Test of Homogeneity of Variances, run using FHL's 1/10th Sample, indicates that the two groups have significantly different variances (p<0.001; Levene's statistics = 191.12). Welch and Brown-Forsythe tests confirm that result (P<0.001; F = 383). Table 3.4 presents the significantly different variances of homogeneous and heterogeneous IPT groups across the four samples.

Table 3.4: Variances of Homogeneous and Heterogeneous IPT Groups across the Four Samples

Sample:	Levene's Test	Welch Test	Brown-Forsythe Test
	Levene's statistics =	*F =*	*F =*
FHL 1/10th	191.12***	383***	383***
A	27.4***	1029.26***	1029.26***
B	20.25***	1274.75***	1274.75***
C	19.08***	911.14***	911.14***

*** P<0.001

3.4.4 Repurchase Behaviour (RB)

Repurchase Behaviour measures whether the customer made a purchase transaction in the validation period and is operationalised as a binary variable. Any customer who made one or more repeat transactions in the validation period is coded as 1 and labelled *Repurchaser*; otherwise they are coded as 0 and labelled *Skipper*. One important reason for using a binary variable as a measure of future behaviour is to improve the robustness of the results (Van den Poel, 2003).

3.4.5 Repurchase Frequency (RF)

Repurchase Frequency refers to the total number of repeat purchase transactions made by the customer in the validation period. In other words, the number of times the consumer repurchased. It is a discrete variable measured using purchase transactions and operationalised by counting the number of transactions made in the validation period for each consumer (Zhang et al., 2015). The lowest value in the scale (zero) indicates that no single purchase transaction was made by the customer in the validation period; the higher the value, the higher the frequency of repurchasing.

The effects of the consumer's monetary value, relationship length and clumpiness of data are controlled for.

3.4.6 Control Variables

Monetary value refers to the total amount of money the consumer spent on purchases (Hughes, 2000; Van den Poel, 2003; Viaene et al., 2001; Wang, as cited in Wei, Lin & Wu, 2010). The effect of monetary value is controlled for because the more money the consumer spends, the more likely s/he is to repurchase (Levin & Zahavi, as cited in Van den Poel, 2003; Lumsden et al., 2008). Relationship length refers to the length of time from the first purchase until today (Al-Shayea & Al-Ahayea, 2014; FHL, 2005b; Van den Poel, 2003). It is controlled for because longer consumer-business relationships are more likely to continue (Van den Poel, 2003). Clumpiness of purchase transactions is defined as irregular clusters of activities (Zhang et al., 2013). It is controlled for because customers' repurchase frequency increases as purchase transactions become more meaningfully clustered (Zhang et al., 2015). These three control variables will be discussed further in the next chapter.

3.5 Procedures

3.5.1 Analytics

Each of the four datasets/samples is split into calibration and validation periods of equal lengths. Similar to FHL (2005a), the calibration period is a nine-month (weeks 1-39) period starting from the very first day in 1997 and ending on the 30th of September 1997; the time period from October 1997 through to the end of the observation period (weeks 40-78) is used as the validation period. This approach has been successfully applied in the literature by a number of researchers for different purposes, including model extension (Abe, 2009), model development (Ma & Büschken, 2011) and measure development (Zhang et al., 2015).

3.5.2 Studies

To empirically test and examine the predictive accuracy of the Theory of Due Repurchase, the thesis conducts six studies. These studies will be conducted to test research hypotheses and replicate the findings. Three studies are run to test the research hypotheses using FHL's 1/10th Sample, while the other three are run to replicate the findings using Samples A, B and C. Replication studies are crucial for theory testing as they increase the external validity of research findings (Lucas, 2003) and increase confidence in the proposed theory (Raman, as cited in Lucas, 2003).

3.6 Chapter Summary

This chapter presented, and justified the choice of, the methodological approach adopted to test the Theory of Due Repurchase and the hypotheses formulated in Chapter 2. After describing and discussing the data used in this research the chapter drew and described three samples, which were then compared to an existing, well-known sample provided in the literature. This was followed by the presentation and discussions of measurements and procedures. The next chapter will conduct, present the results, and discuss the findings of six studies.

4 Findings

4.0 Introduction

Chapter 3 selected, and justified the use of, longitudinal quantitative research as the methodology adopted in this research. It also discussed the appropriateness of using transaction data and described the dataset, CDNOW, which will be used in this research. From the full CDNOW dataset, the chapter drew and described three large samples; these were then compared to the dataset provided by Fader, Hardie and Lee (hereafter denoted as FHL) (2005b). This was then followed by the presentation and discussions of measurements and procedures. The purpose of this chapter is to empirically test and examine the predictive accuracy of Theory of Due Repurchase. This chapter conducts, presents the results, and discusses the findings of six studies.

Table 4.1: Summary of the Conducted Studies

Study	Objective:
1	Test H_1 and H_2
2	Replicate Study 1
3	Test H_3 and H_4
4	Replicate Study 3
5	Test H_5
6	Replicate Study 5

Table 4.1 presents the six studies in the order they are conducted and summarises their objectives. The studies are conducted for the purposes of testing the research hypotheses and replicating the findings. Studies 1, 3 and 5 are run to test Hypotheses 1-2, 3-4 and 5, respectively, using FHL's 1/10th Sample. Each of these studies is followed by a replication study run using Samples A, B and C. Using different larger samples to replicate studies in social sciences is required to reduce the probability of error.

Replication studies are necessary for theory testing as they increase the external validity of research findings (Lucas, 2003) and increase confidence in the proposed theory (Raman, as cited in Lucas, 2003).

4.1 Study 1: The Foundation of Theory of Due Repurchase

4.1.0 Introduction

Study 1 focuses on establishing the foundation of Theory of Due Repurchase. In this study, FHL's 1/10th Sample is used to test Hypotheses 1 and 2. The sample consists of 2,357 customers, who made 6,918 transactions over an 18-month period. FHL's 1/10th Sample has been used a number of times in the literature and is, scientifically, an acceptable sample (Abe, 2009; FHL, 2005a, 2005b; Ma & Büschken, 2011; Zhang et al., 2015). Hypothesis 1 is tested using an independent sample t-test. This test is conducted to learn whether the repurchase frequency differs significantly when the customer is a frequent shopper (vs. infrequent), having an increasing PQ (vs. decreasing PQ), and having homogeneous IPTs (vs. heterogeneous IPTs). To understand the association between satisfying the three repurchase conditions and the customer's choice to repurchase (H_2), a chi-square analysis is run. Study 1's results should indicate whether the two hypotheses should be accepted or rejected.

4.1.1 Results

Figure 4.1 presents the results of the independent-sample t-tests. As expected, the results provide evidence supporting H_1_A, H_1_B, and H_1_C (P<0.001). First, frequent shoppers ($\overline{x} = 2.53$) repurchase more frequently than infrequent shoppers ($\overline{x} = 0.70$). Second, customers whose LPQs build on an existing trend of increasing PQs ($\overline{x} = 3.01$) have a higher repurchase frequency than others ($\overline{x} = 0.36$). Finally, repurchase frequency is higher when the customer's IPT is homogeneous ($\overline{x} = 2.60$) than when it is heterogeneous ($\overline{x} = 0.82$).

FHL 1/10th Sample

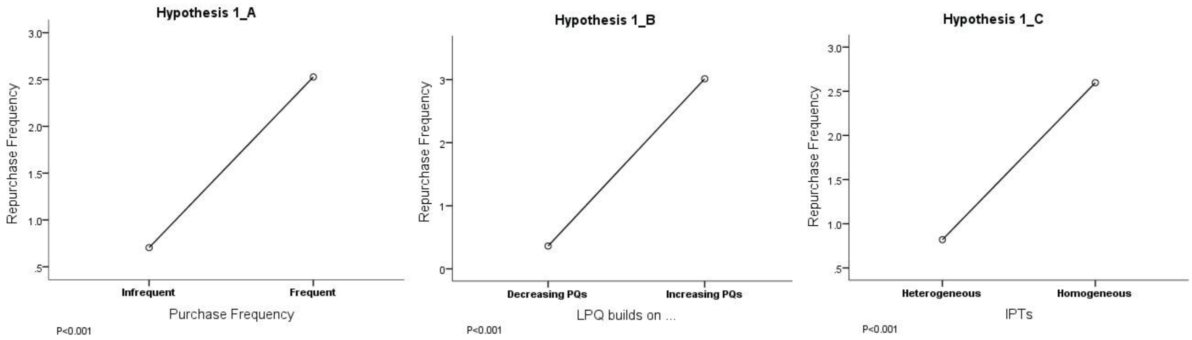

Figure 4.1: Mean Differences in RF between Behavioural Groups (Hypothesis 1)

Analyses of associations between repurchase behaviour (RB) and each of the three behavioural dimensions reveal the followings:

a) about 69% of re-purchasers (RB= 1) are frequent shoppers and 61% of skippers (RB= 0) are infrequent shoppers;
b) about 88% of re-purchasers made LPQ decisions that built on an existing trend of increasing PQs, whereas nearly 90% of skippers made LPQ decisions that built on an existing trend of decreasing PQs; and
c) around 63% of re-purchasers have homogeneous IPTs, while 65% of skippers have heterogeneous IPTs.

These relationships are not only significant, but also strong (Actual Count > Expected Count; *p*<0.001). The question is, then, whether the customer's next purchase is due (expected) when all the three aforementioned conditions are simultaneously satisfied.

Table 4.2 presents the result of a chi-square analysis run to test Hypothesis 2. The association between repurchase behaviour and satisfying all repurchase conditions is tested and is found to be significant ($p<0.001$). The result reveals that, of the 226 (24%) customers who have satisfied all three conditions, 91% (205) have repurchased. Customers who satisfied all three conditions but did not repurchase make up only 2% (21) of the sample. There are 732 customers who have not met all three conditions and about 61% of them (446) skipped their next purchases. There are strong relationships between repurchasing and meeting all three conditions (Actual Count = 205 > Expected Count = 115.8), and between skipping the purchase and not satisfying the three conditions (Actual Count = 446 > Expected Count = 356.8).

Therefore, H_2 is supported and the likelihood of the customer's purchase is high when all three conditions are satisfied. For further insights into the results, Bayes' Theorem[4] is applied using the information presented in Table 4.2. According to Bayes' Theorem, customers satisfying all the repurchase conditions have a 91% repurchase probability, whereas others not satisfying these conditions have a repurchase probability of 39%.

Table 4.2: Relationship between RB and Satisfying Repurchase Conditions

			Conditions are		
			Unsatisfied	Satisfied	*Total*
Repurchase Behaviour	Skipped	N=	446*	21	*467*
	Repurchased	N=	286	205*	*491*
	Total	*N=*	*732*	*226*	**958**

P<0.001
*Actual Count > Expected Count

[4] $P(Repurchase \mid met\ conditions) = \frac{\mathrm{P(met\ conditions|repurchase)\times P(repurchase)}}{\mathrm{P(\ met\ conditions|repurchase\ )\times P(repurchase)+P(\ met\ conditions|skipped\ )\times\ P(Skpped)}}$

4.1.2 Discussion

Study 1 is run to establish the foundation of Theory of Due Repurchase. Study 1 investigates differences in repurchase frequency under three conditions of repurchase and tests associations between repurchase behaviour and satisfying all these conditions. What Study 1 does not do is investigate causal relationships. An independent-samples t-test and chi-square analysis are conducted to test Hypotheses 1 and 2. The results are significant and support the two hypotheses.

Repurchase frequency differs significantly under each of the three repurchase conditions. First, customers whose past frequency of purchase is greater than average are deemed to be behaviourally loyal (Buckinx & Van den Poel, 2005) and, therefore, repurchase more frequently. Second, customers whose LPQs built on existing trends of increasing PQs have higher repurchase frequency. The customer's LPQ decision reflects how behaviourally committed s/he is to buying the brand or shopping at the retailer. Third, repurchase frequency is higher when the customer's IPTs are homogeneous. This finding appears to be consistent with Abe's (2009) finding that loyal consumers have regular IPTs, whereas others purchase at random times.

The results show an interesting association between satisfying all repurchase conditions and the decision to repurchase. Of those whose purchase histories satisfy the repurchase conditions, 91% made at least one repeat purchase in the validation period. This relationship is not only statistically significant but is also strong. This finding supports and strengthens the idea that the customer's next purchase is likely when all repurchase conditions are satisfied. Meeting all three repurchase conditions means that the customer is a frequent shopper, has increasing PQs and has homogeneous IPTs. Study 1's findings are new to the literature as, to the author's best knowledge, no single study has tested the relationship between purchase frequency, purchase quantity and IPTs combined with repurchase behaviour.

4.1.3 Conclusion

Study 1 is run for the purpose of establishing the foundation of Theory of Due Repurchase. Using FHL's 1/10th Sample, an independent-samples t-test and chi-square analysis were conducted to test Hypotheses 1 and 2, respectively; the two hypotheses are supported. Repurchase frequency is significantly higher when the customer is a frequent shopper (vs. infrequent), has an upward-trending PQ (vs. downward), and has homogeneous IPTs (vs. heterogeneous). As the Theory of Due Repurchase suggests, the customer's next purchase is due (highly expected) when the three repurchase conditions are satisfied. The customer's decision to repurchase is significantly and strongly associated with satisfying the three repurchases conditions. Of the 24% customers who have satisfied all three conditions, 91% repurchased. According to Bayes' Theorem, customers satisfying all the repurchase conditions have a 91% repurchase probability, whereas those who did not satisfy all these conditions have a repurchase probability of 39%. However, how confident can one be in these findings? We now replicate Study 1's findings to address this question.

4.2 Study 2: A Replication of Study 1

4.2.0 Introduction

Study 2 is conducted with the goal of replicating Study 1's findings to enhance the reliability and generalisability of the findings. Study 2 applies the same method, procedures, and analytical tools as in Study 1 to retest H_1 and H_2 using Samples A, B and C. Recall that Study 1 uses FHL's 1/10th Sample, which consists of 2,357 customers who made 6,918 transactions. In this study, Sample A consists of 7,856 customers who made 23,068 transactions, Sample B consists of 7,857 customers who made 22,817 transactions, and Sample C consists of 7,857 customers who made 23,774 transactions. Each of Samples A, B and C contain a distinct group of customers. Each consumer is represented once only in either Sample A, B or C and there are many customers who are excluded from the analysis (see § 3.3). This should capture any evidence of Type I and II errors if they exist. It is expected that the results are significant and resemble those found in Study 1.

4.2.1 Results

Figure 4.2 shows the results of the independent-samples t-tests run to retest H_1 using Samples A, B and C. Evidence supporting H_1 is found across all samples and the results, obtained using FHL' 1/10th Sample, are similar to those found using the three other samples. Repurchase frequency differs significantly between customers with different purchase histories across the four samples. Frequent shoppers have a higher repurchase frequency than infrequent shoppers; the frequency of repurchasing is higher when LPQ builds on an existing trend of increasing PQs; and customers who have homogeneous IPTs have a higher repurchase frequency than others with heterogeneous IPTs.

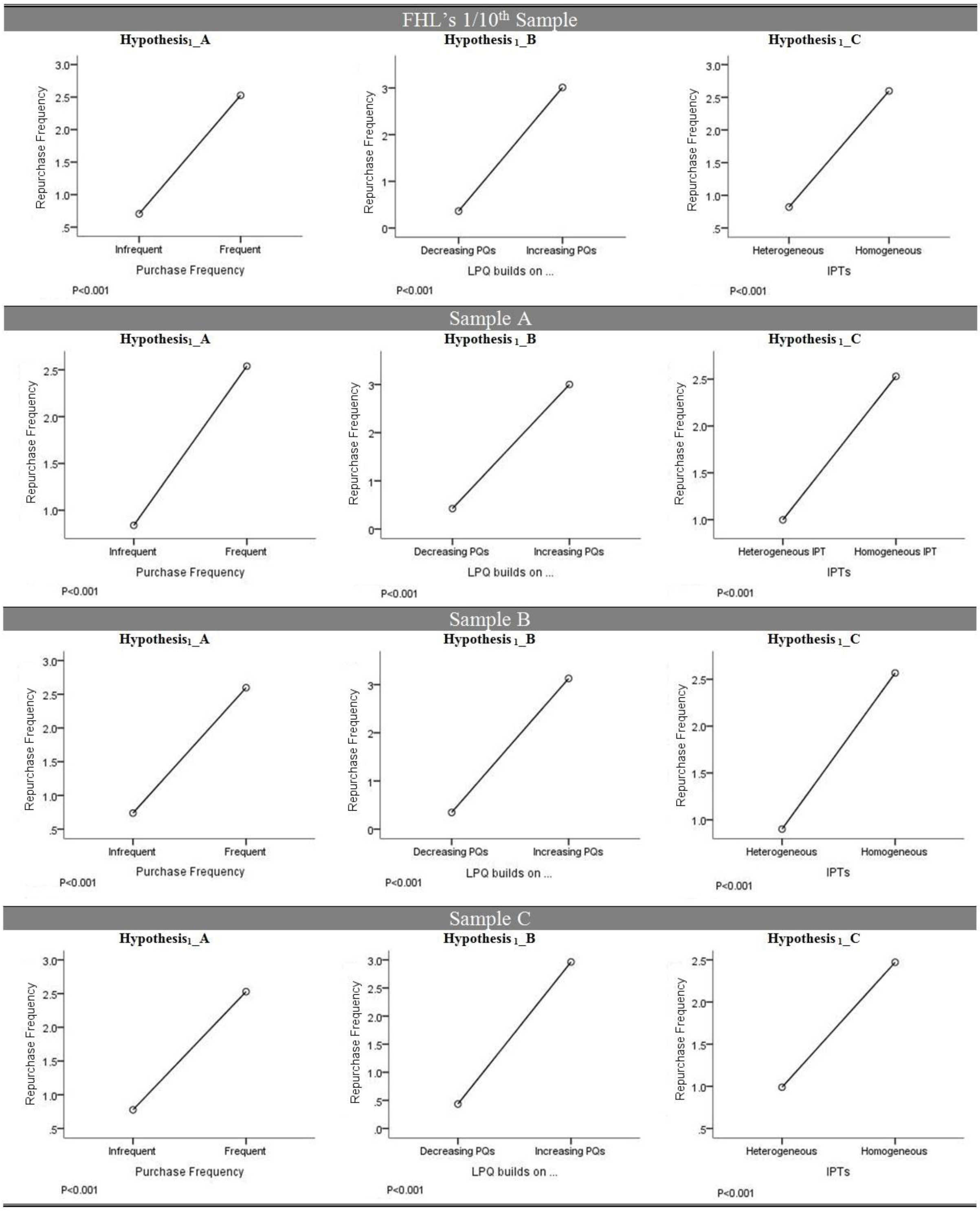

Figure 4.2: Mean Differences in RF between Behavioural Groups across Samples

Figure 4.3 presents the results of the chi-square analyses conducted to retest H_2 using Samples A, B and C. The results obtained from the three replication samples support

H_2. The bar chart, titled FHL's 1/10th Sample, is a visual presentation of Study 1's finding shown earlier in Table 4.2. All chi-square tests have *p*-values below 0.1%. Across Samples A, B and C there is a strong relationship between satisfying all repurchase conditions and the choice to repurchase (Actual Count > Expected Count; $p<0.001$). Additionally, the association between not satisfying all repurchase conditions and skipping the repurchase is also strong across all samples (Actual Count > Expected Count; $p<0.001$). Of those who satisfied all repurchase conditions in:

- FHL's 1/10th Sample, 91% of them repurchased;
- Sample A, 90% of them repurchased;
- Sample B, 89% of them repurchased; and
- Sample C, 89% of them repurchased.

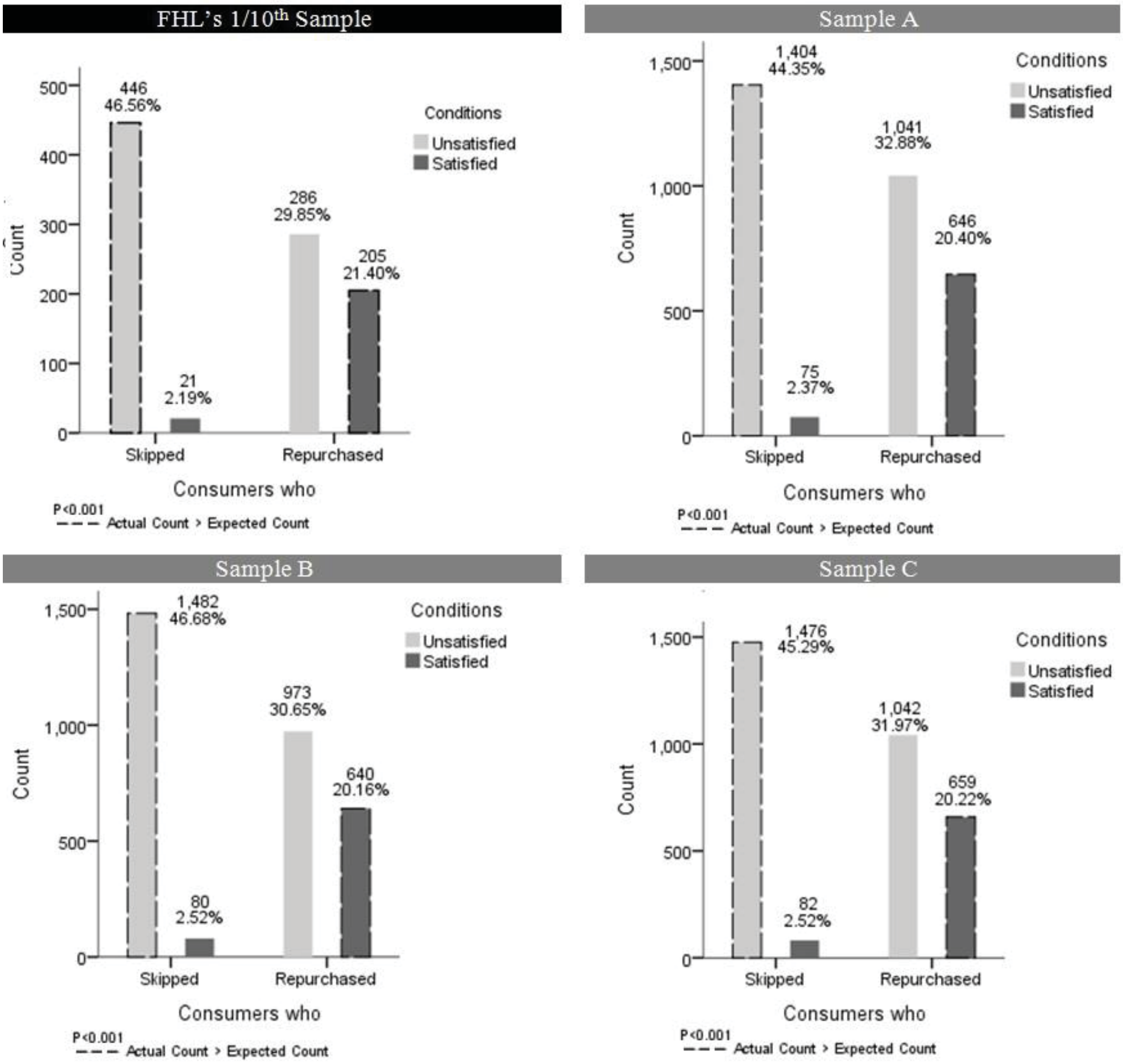

Figure 4.3: Repurchase Decision vs. Satisfying All Repurchase Conditions (across Samples)

4.2.2 Discussion

Study 2 is run to replicate Study 1's findings and enhance the reliability and generalisability of findings. The method, procedures and statistical packages used in the two studies are the same; the only difference is that Study 1 uses FHL's 1/10th Sample, whereas Study 2 uses Samples A, B and C. The samples used in Study 2 are three times larger than the sample used in Study 1. Using larger samples to replicate studies in social sciences is required, as it reduces the probability of error. In addition, testing more than one sample of the population under study gives confidence in the findings as it provides supporting evidence of the in/existence of an event or phenomenon (Mackey, 2012).

Figures 4.2 and 4.3 compare Study 2's results with those found in Study 1. Figure 4.2 presents the results obtained from testing H_1, which is supported in all four samples. The results replicate Study 1's finding that repurchase frequency is higher when the customer is a frequent shopper, has increasing PQs, and has homogeneous IPTs. Figure 4.3 depicts the results of testing H_2, which is also supported across the four samples. The results replicate Study 1's finding, and emphasise the interesting relationship, between the customer's choice to repurchase and meeting the three repurchase conditions. This relationship is not only significant but also strong.

Study 2's results reduce the error probability and increase confidence in Study 1's findings. No evidence of Type I error is found, as the *p*-value is consistently very low (0.1%) across the four samples. Even though the sample sizes are large and different, the results are both statistically significant and consistent across the four samples. Therefore, Study 2's results replicate Study 1's findings and enhance the reliability and generalisability of the findings. Together, all these findings constitute the foundation of the Theory of Due Repurchase.

4.2.3 Conclusion

Study 2 is conducted to replicate Study 1's findings. Study 2 retests H_1 and H_2 using the same method, procedures, analytical tools and statistical packages as Study 1. The difference, however, is that Study 2 uses Samples A, B and C instead of FHL's 1/10th Sample. Hypotheses 1 and 2 are supported across the three samples. The findings are replicated, increasing the external validity of Study 1. So it is confirmed that, a) repurchase frequency differs depending on whether each repurchase condition has been satisfied; and b) there is a strong relationship between repurchase decision and satisfying all repurchase conditions. This makes one wonder whether different combinations of the three repurchase conditions associate differently with repurchase behaviour and whether repurchase frequency becomes higher, or lower, under each combination.

4.3 Study 3: Furnishing Perspective into the Theory of Due Repurchase

4.3.0 Introduction

Whereas Study 1 focuses on the '*what*' question and shows that the three behavioural dimensions combined make up the foundation of the Theory of Due Repurchase, Study 3 focuses on the '*what-if*' question and examines all possible combinations of repurchase conditions. The objectives of conducting Study 3 include challenging, and increasing the understanding of, Theory of Due Repurchase. This is achieved through examining repurchase behaviour and repurchase frequency under various combinations of the three behavioural variables (repurchase conditions).

Chi-square and ANOVA analyses are run to test H_3 and H_4, respectively. The chi-square investigates associations between repurchase behaviour and combinations of repurchase conditions. ANOVA is run to investigate differences in repurchase frequency across these combinations of repurchase conditions. This study uses FHL's 1/10th Sample because it has been previously used in scientific research and is known to researchers (Abe, 2009; FHL, 2005a, 2005b; Ma & Büschken, 2011; Zhang et al., 2015). The sample consists of 2,357 purchasers who made 6,918 transactions over a period of 18 months.

Table 4.3: Scenarios of Repurchase Conditions (2×2×2 Block Design)

IPT	Purchase Quantity	Frequency: Frequent	Frequency: Infrequent
Homogeneous	Increasing	1	5
	Decreasing	2	6
Heterogeneous	Increasing	3	7
	Decreasing	4	8

Scenarios	Hypothesis
1	$H_{2 \text{ and } 3}$
2	H_3
3	H_3
4	H_3
5	H_3
6	H_3
7	H_3
8	$H_{3 \text{ and } 4}$

Table 4.3 shows all the possible combinations, along with the absence, of the three repurchase conditions suggested by Theory of Due Repurchase. As a 2×2×2 block design, there are eight possible scenarios under which a repurchase could be made or skipped. Customers are expected to have different responses under each scenario (H_3). Also, repurchase frequency is expected to vary under each of these scenarios (H_4). As shown in Table 4.3, in Scenario 1, the customer is a frequent shopper, has homogeneous IPTs, and their LPQ is built on an existing trend of increasing PQs; this is the scenario under which the customer's next purchase is due (highly expected) according to Theory of Due Repurchase. In Scenario 8, however, the customer is an infrequent shopper, has a heterogeneous IPTs and their LPQ is built on an existing trend of decreasing PQs; this is the scenario under which the customer's next purchase is not due (highly unexpected) according to the Theory of Due Repurchase. While it is hard to predict the order of

repurchase likelihood in Scenarios 2-7, these are unique and interesting combinations of repurchase conditions. Therefore, the results of these combinations are expected to be of value to both practitioners and researchers.

4.3.1 Results

Table 4.4: Repurchase Behaviour vs. Scenarios of Repurchase Conditions

FHL's 1/10th Sample

		Scenarios								
		1	2	3	4	5	6	7	8	***Total***
Skipped	N=	21	28	61*	71*	0	80*	0	206*	***467***
	%	2.19%	2.92%	6.37%	7.41%	0%	8.35%	0%	21.50%	***48.74%***
Repurchased	N=	205*	77*	37	18	65*	0	84*	5	***491***
	%	21.40%	8.04%	3.86%	1.88%	6.78%	0%	8.77%	0.52%	***51.25%***
Total		***226*** ***24%***	***105*** ***11%***	***98*** ***10%***	***89*** ***9%***	***65*** ***7%***	***80*** ***8%***	***84*** ***9%***	***211*** ***22%***	***958*** ***100%***

P<0.001
*Actual Count > Expected Count

Table 4.4 presents the results of a chi-square analysis run to test H_3. The customer's choice to skip the next purchase is expected to be associated with the absence of the three repurchase conditions. That is, the customer is an infrequent shopper, has heterogeneous IPTs and has decreasing PQs; hence, this customer falls within Scenario 8 (refer to Table 4.3 to see what combination of repurchase conditions is represented in each scenario). The results provide evidence supporting H_3, and show a significant and strong association between skipping a purchase and not satisfying all the three repurchase conditions ($p<0.001$; Actual Count > Expected Count). About 98% of customers who have not satisfied any of the repurchase conditions (Scenario 8) did not repurchase. On the other hand, 91% of customers who satisfied all the repurchase conditions did repurchase (Scenario 1). Customers in Scenario 1 and Scenario 8 make up 24% and 22% (=46% combined) of the sample, respectively. Customers falling under any other scenario (2-7) constitute no more than 11% of the sample in any one scenario and 54% collectively. The associations between repurchase behaviour and Scenarios 5, 6 and 7 are particularity interesting, as these three scenarios are completely

(100%) associated with repurchase behaviour. Either 100% repurchased (Scenarios 5 and 7) or not at all (Scenario 6).

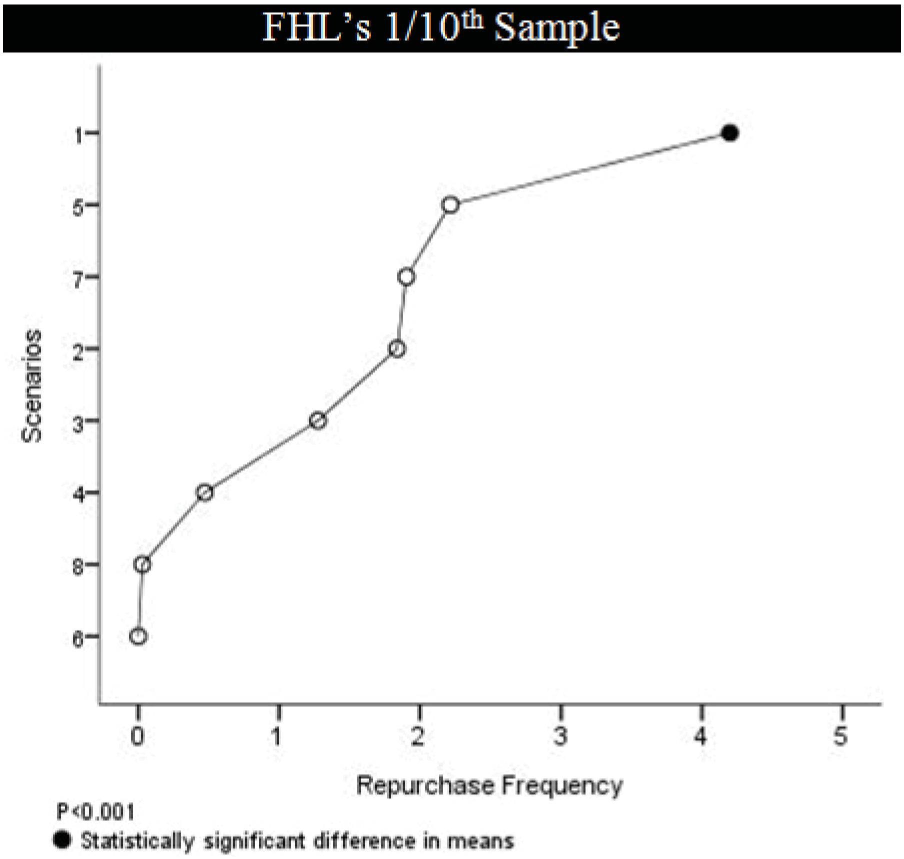

Figure 4.4: Mean Differences in RF across 8 Scenarios of Repurchase Conditions

Figure 4.4 displays the results of the ANOVA analysis run to test H_4. Repurchase frequency is expected to vary across the eight scenarios of repurchase conditions and to reach its highest in Scenario 1, in which all repurchase conditions are satisfied. The results are statistically significant and support H_4 (P<0.001). As displayed in Figure 11, repurchase frequency differs significantly, and is much higher when all repurchase conditions are satisfied (Scenario 1) (Scheffe: p<0.001; $\overline{RP_1} = 4.20$). In addition to the very interesting associations with repurchase behaviour, shown in Table 4.4, customers in Scenarios 5 and 7 have a much higher repurchase frequency than customers in Scenarios 6 and 8 (Scheffe: p<0.01; $\overline{RP_5} = 2.22$ and $\overline{RP_7} = 1.90$).

4.3.2 Discussion

Study 3 challenges, and furnishes insight into, the Theory of Due Repurchase through examining repurchase behaviour and frequency using eight *what-if* scenarios. Utilising FHL's 1/10th Sample, chi-square and ANOVA analyses are run to test H_3 and H_4. The results provide evidence supporting both H_3 and H_4.

Building on Study's 1 findings, Study 3 finds that the decision not to repurchase (skipping) is significantly and strongly associated with satisfying none of the three repurchase conditions. In other words, customers who are infrequent shoppers, have heterogeneous IPTs and decreasing PQs did not repurchase. On the other hand, the choice to repurchase is significantly and strongly associated with satisfying all the repurchase conditions. The reasons for repurchase behaviour being negatively associated with not satisfying repurchase conditions but positively associated with satisfying all of them include:

1. performing a behaviour in the past is associated with re-performing it in the future (Lemon et al., as cited in Buckinx & Van den Poel, 2005);
2. similar IPTs form a purchasing pattern that is likely to be repeated in the future (Ouellette & Wood, 1998); and
3. behavioural loyalty is found to be linked to buying in larger quantities (Jacoby & Kyner; Reichheld, Markey & Hopton as cited in Jen et al., 2009; Van den Poel, 2003).

One interesting finding is that customers who met all repurchase conditions (Scenario 1) and others who met none of them (Scenarios 8) make up 24% and 22% of the sample, respectively. These two groups of customers represent the largest and second largest groups in the sample. This is practically important because focusing only on these two groups of customers mean targeting 46% of existing customers, 24% of them have 91% repurchase probability and the rest (22%) have a skipping probability of 98%.

The results for Scenarios 2-7 are not only interesting but are also of value to both practitioners and researchers. Three interesting associations are found between repurchase behaviour and the combinations of repurchase conditions represented in Scenarios 5, 6 and 7. As shown in Table 4.4, repurchase behaviour is 100% associated with these combinations. Scenarios 5 and 7 are strongly associated with the decision to repurchase, whereas Scenario 6 is strongly associated with the choice to skip. What customers in these scenarios have in common is that they are all infrequent purchasers.

In Scenarios 5 and 7, no single customer skipped their next repurchase. This is very interesting, not only because of the high repurchase probability, but also because a) they are infrequent purchasers; and b) homogeneity of IPTs plays no direct role in these associations. FHL (2005a) found that customers with low frequency values and shorter recency periods have higher repurchase frequency. To check whether this is the case, an ANOVA analysis is run with recency (time from last purchase) as the dependent variable and the eight scenarios as the factors. Interestingly, the results show that customers in Scenario 7 have significantly longer recency periods than customers in Scenario 5 (Scheffe: p<0.001; $\overline{X_5} = 58.43$ and $\overline{X_7} = 176.86$). Hence, the phenomenon of low frequency and short recency is not the case here.

One repurchase condition that is satisfied in both Scenarios 5 and 7 is increasing PQs. Customers in these two scenarios made LPQ decisions that built on existing trends of increasing PQs. An ANOVA analysis of customers' average PQs reveals that, compared to other customers, those in Scenarios 5 and 7 have the lowest average PQs (Scheffe: p<0.001; $\overline{PQ_5} = 0.53$ and $\overline{PQ_7} = 0.64$). Possibly, those customers are being increasingly behaviourally committed to buying CDs from the e-tailer so that their purchase frequency will be higher and their purchasing patterns will be clearly formed. Regardless of IPT homogeneity, lower frequency values are good news as long as the customer's PQs are increasing over time. In addition, customers in these two groups have significantly higher repurchase frequency (see Figure 4.4). This indicates that they are not only likely to repurchase in the future but also more likely to make many more repeat purchases.

In Scenario 6, 100% of customers skipped their next purchases. These customers are infrequent shoppers, have homogeneous IPTs and downward trending PQs. This is plausible because of three reasons. First, past frequency of behaviour is positively associated with the future frequency of that behaviour. Second, purchasing fewer quantities increasingly suggests a lack of behavioural commitment. Third, homogenous IPTs form purchasing patterns, featuring infrequency of purchase and decreasing PQs, which are likely to be repeated in the future which, in this case, result in the choice to skip the purchase. Although all customers in Scenario 6 did not purchase, this group should not be dropped out of the customer relationship with the business.

FHL (2005a) pointed out that even though light buyers are assumed to be inactive and treated as defected customers after 18 months, these customers account for a significant proportion of customers' future value to the business. The fact that the customers' IPTs are homogeneous suggests that these customers are still active but it just takes them longer than others to repurchase (Abe, 2009). To show that this is the case, an ANOVA analysis is run with the average IPT as the dependent variable and the eight scenarios as factors. The result is significant and shows that customers in Scenario 6 have, by far, the highest average IPT compared to all other scenarios (Scheffe: p<0.001; $\overline{IPT_6} = 80.18$). This is evidence that this group of customers represents long-term purchasers who wait longer than others to repurchase. Hence, these customers are expected not to repurchase in the validation period only, but should be taken into account in the future.

4.3.3 Conclusion

Study 3 challenges, and furnishes insights into, the Theory of Due Repurchase through asking '*what-if*' questions. The study examines repurchase behaviour and frequency under eight scenarios, or combinations of repurchase conditions (refer to Table 4.3). Hypotheses 3 and 4 are tested using chi-square and ANOVA analyses, respectively. The results support the two hypotheses. First, the choice to skip a repurchase is significantly and strongly associated with satisfying none of the repurchase conditions suggested by the Theory of Due Repurchase. As a matter of fact, of those (22%) who satisfied none of the repurchase conditions, 98% did not repurchase. Second, repurchase frequency varies across the eight scenarios and reaches its highest when all repurchase conditions are satisfied. Consumers who are frequent shoppers, have homogenous IPTs and their PQs are trending upward (Scenario 1) have a higher repurchase frequency than all other consumers (Scheffe: p<0.001; $\overline{RP_1} = 4.20$). Satisfying the three repurchase conditions is not only associated with the choice to repurchase but also related to making more repeat purchases in the future.

Study 3's key findings include:

- The repurchase decision is strongly associated with satisfying repurchase conditions;
- Skipping the next purchase is strongly associated with satisfying none of the conditions to repurchase;

- Customers who satisfied all repurchase conditions and others who satisfied none of them make up, on average, 45% of the customer database; on average, 20.5% of them have a repurchase probability of 89.75% whereas 21.61% of them have a skipping probability of 99%;
- The decision to repurchase is completely (100%) associated with being an infrequent purchaser and having upward-trending PQs;
- The decision to skip a repurchase is completely (100%) associated with being an infrequent purchaser, having homogeneous IPTs and downward-trending PQs; and
- The highest frequency of repurchase exists when the consumer is a frequent shopper, has homogeneous IPTs and has increasing PQs.

Study 3 built on Study 1's findings and provided insights into the Theory of Due Repurchase. Study 3's findings are significant and are of value to both practitioners and researchers. However, how reliable and generalisable are these findings? Next, Study 3's findings arereplicated.

4.4 Study 4: A Replication of Study 3

4.4.0 Introduction

Before moving to the next step of theory building, it is crucial to test the validity of Study 3's findings. To ensure that the results are not influenced by any systematic, procedural and/or human errors, Study 4 is run. Hypotheses 3 and 4 are retested in this study using the same method, procedures, and analytical tools as in Study 3. Instead of using FHL's 1/10th Sample, however, Study 4 uses Samples A, B and C as in Study 2. Each of these samples is about three times larger than FHL's 1/10th Sample. The purchase history of each CDNOW customer is analysed once only in either Sample A, B or C, which collectively account for 41% $(= \frac{9{,}600}{23{,}570})$ of all CDNOW customers sampled. This should provide for good scrutiny of errors.

4.4.1 Results

Table 4.5: Repurchase Behaviour vs. Scenarios of Repurchase Conditions across Samples

FHL's 1/10th Sample

		Scenarios 1	2	3	4	5	6	7	8	*Total*
Skipped	N=	21	28	61*	71*	0	80*	0	206*	***467***
	%	2.19%	2.92%	6.37%	7.41%	0%	8.35%	0%	21.50%	***48.74%***
Repurchased	N=	205*	77*	37	18	65*	0	84*	5	***491***
	%	21.40%	8.04%	3.86%	1.88%	6.78%	0%	8.77%	0.52%	***51.25%***
Total		***226***	***105***	***98***	***89***	***65***	***80***	***84***	***211***	***958***
		24%	***11%***	***10%***	***9%***	***7%***	***8%***	***9%***	***22%***	***100%***

Sample A

		Scenarios 1	2	3	4	5	6	7	8	*Total*
Skipped	N=	75	184*	93	231*	0	229*	0	667*	***1479***
	%	2.37%	5.81%	2.94%	7.30%	0%	7.23%	0%	21.07%	***46.72%***
Repurchased	N=	646*	146	237*	80	269*	0	306*	3	***1687***
	%	20.40%	4.61%	7.49%	2.53%	8.50%	0%	9.67%	0.09%	***53.28%***
Total		***721***	***330***	***330***	***311***	***269***	***229***	***306***	***670***	***3166***
		22.8%	***10.4%***	***10.4%***	***9.8%***	***8.5%***	***7.2%***	***9.7%***	***21.2%***	***100%***

Sample B

		Scenarios 1	2	3	4	5	6	7	8	*Total*
Skipped	N=	80	184*	87	229*	0	265*	0	717*	***1562***
	%	2.52%	5.80%	2.74%	7.21%	0%	8.35%	0%	22.58%	***49.20%***
Repurchased	N=	640*	149	239*	62	235*	0	282*	6	***1613***
	%	20.16%	4.69%	7.53%	1.95%	7.40%	0%	8.88%	0.1%	***50.80%***
Total		***720***	***333***	***326***	***291***	***235***	***265***	***282***	***723***	***3175***
		22.7%	***10.5%***	***10.3%***	***9.2%***	***7.4%***	***8.3%***	***8.9%***	***22.8%***	***100%***

Sample C

		Scenarios 1	2	3	4	5	6	7	8	*Total*
Skipped	N=	82	193*	97	233*	0	259*	0	694*	***1558***
	%	2.52%	5.92%	2.98%	7.15%	0%	7.95%	0%	21.29%	***47.81%***
Repurchased	N=	659*	151	254*	76	251*	0	307*	3	***1701***
	%	20.22%	4.63%	7.79%	2.33%	7.70%	0%	9.42%	0.09%	***52.19%***
Total		***741***	***344***	***351***	***309***	***251***	***259***	***307***	***697***	***3259***
		22.7%	***10.6%***	***10.8%***	***9.5%***	***7.7%***	***7.9%***	***9.4%***	***21.4%***	***100%***

All $P<0.001$
*****Actual Count > Expected Count

Table 4.5 presents and compares the results of chi-square analyses run to retest H_3 across the three samples. The results obtained in Samples A, B, and C provide evidence to support H_3 (p<0.001). The decision to skip the repurchase is associated with not satisfying the three repurchase conditions (Scenario 8). Across the four samples, the association between skipping the repurchase and not satisfying the three repurchase conditions is significant and strong (p<0.001; Actual Count > Expected Count).

Customers in Scenario 1 constitute 22.8%, 22.7% and 22.7% of Samples A, B and C, respectively, whereas customers in Scenario 8 make up 21.2%, 22.8%, and 21.4% of Samples A, B and C, respectively. Combined, customers in Scenarios 1 and 8 combined make up 44%, 45.5% and 44.1% of Sample A, B, and C, respectively. Across the four samples, customers falling under any other scenario (2-7) constitute no more than 11% of the sample. Additionally, repurchase behaviour is 100% associated with each combination of the repurchase conditions in Scenarios 5, 6 and 7 across the four samples.

Figure 4.5 below depicts the results of the ANOVA analyses conducted to retest H_4 across the three samples. The results provide evidence supporting H_4 (p<0.001). Across the three samples, repurchase frequency varies and is significantly higher when all repurchase conditions are satisfied (Scenario 1). In addition, customers falling under Scenarios 5 and 7 have a significantly high repurchase frequency across the three samples. On the other hand, customers represented in Scenarios 6 and 8 have the lowest repurchase frequency across all samples. All results are consistent with those found in Study 3.

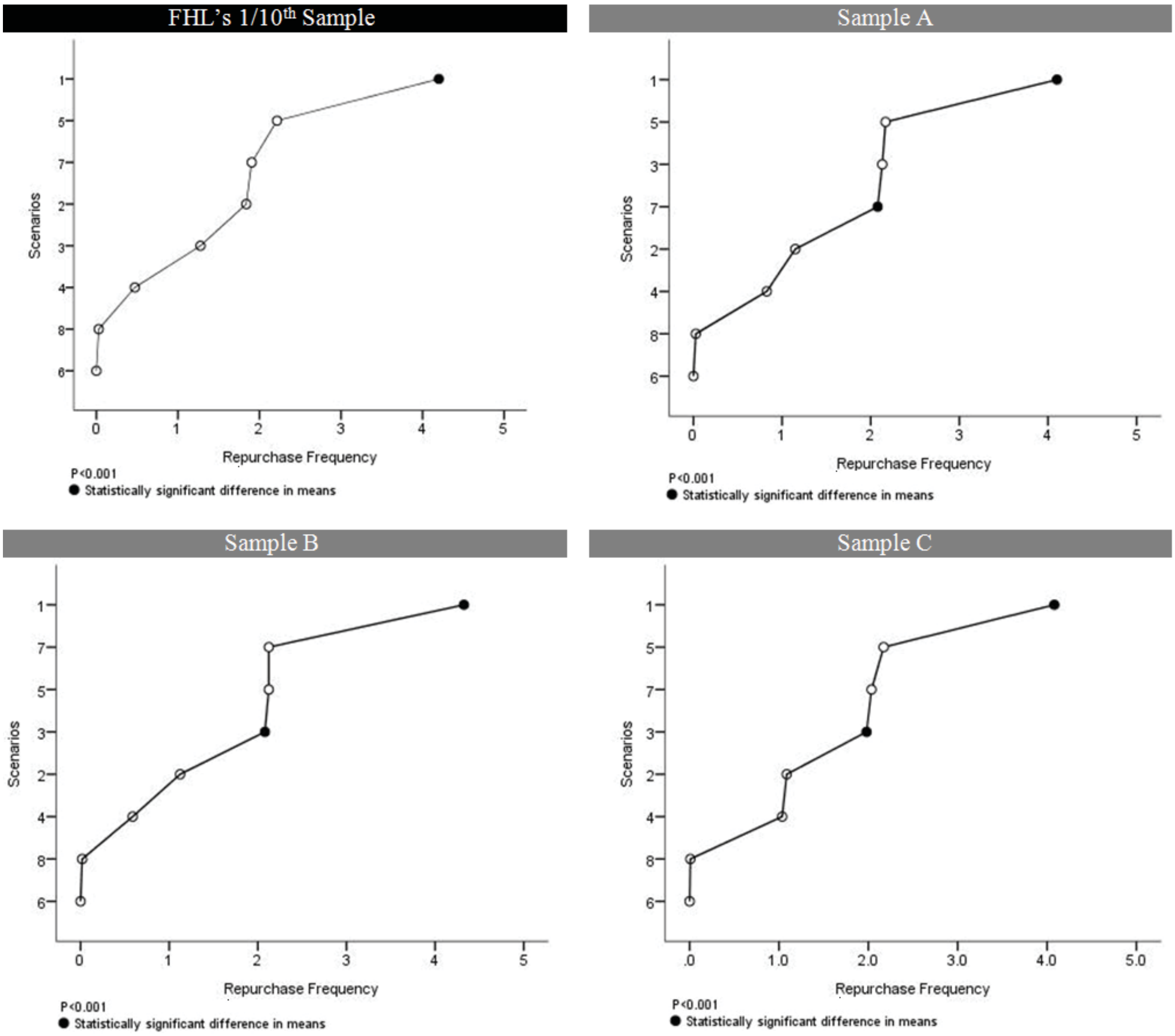

Figure 4.5: Mean Differences in RF across Eight Scenarios of Repurchase Conditions (Across Samples)

4.4.2 Discussion

Study 4 applies the same method, procedures, analytical tools and statistical packages as in Study 3 to replicate its findings. The difference is that Study 4 uses Samples A, B and C to retest H_3 and H_4.

Firstly, the results of this study provide evidence in favour of H_3. This replicates Study 3's finding that the decision to skip the repurchase is significantly and strongly associated with satisfying none of the three repurchase conditions. Customers who are infrequent shoppers, have heterogeneous IPTs and have decreasing PQs did not repurchase. Also consistent with Study 3 is that the choice to repurchase is significantly and strongly associated with satisfying all the repurchase conditions. These findings are consistent with other papers that found existing associations between future behaviour and 1) past frequency (Lemon et al., as cited in Buckinx & Van den Poel, 2005); 2) similar IPTs (Ouellette & Wood, 1998); and 3) purchasing in small/large quantities (Jacoby & Kyner and Reichheld, Markey & Hopton, both as cited in Jen et al., 2009; Van den Poel, 2003). This further increases one's confidence in the validity of this finding. Secondly, the results of this study also provide evidence supporting H_4. This replicates Study's 3 finding that repurchase frequency varies across the eight scenarios and is at its highest when all repurchase conditions are satisfied (Scenario 1). This indicates that customers in Scenario 1 are not only very likely to repurchase in the near future but also to make more repeat purchases.

Study 4 also replicates other findings which could be of value to both researchers and practitioners. First, customers who met all repurchase conditions (Scenario 1) and others who met none of them (Scenarios 8) represent the largest and second largest groups in Samples A, B and C. Communicating with these two groups means targeting almost half of existing customers, whose probability of either repurchasing or skipping is very high. Second, the decision to repurchase is entirely associated with Scenarios 5 and 7, in which customers are infrequent shoppers with increasing PQs, whereas the decision to skip is completely associated with Scenario 6, in which customers are infrequent shoppers, have downward-trending PQs, and homogenous IPTs. This emphasises that a) past frequency of behaviour is positively associated with the future frequency of that behaviour; b) PQ is linked to behavioural commitment; and c) similar IPTs form a purchasing pattern, featuring infrequency of purchase and decreasing PQs, that is likely to be repeated in the future or, in this case, result in the choice to skip/postpone the purchase. Third, customers in Scenario 6 have, by far, the highest average IPT compared to all other scenarios (Scheffe: $p<0.001$; $\overline{IPT_6} = 80.18$). Given this statistic, it is evident that this group of customers are active but it takes them longer than others to repurchase. Therefore, one should not conclude that customers in Scenario 6 are behaviourally disloyal.

Study 4 provides evidence supporting H_3 and H_4 and replicates Study 3's findings. The results of this study are consistent with those found in Study 3 and in the literature. The probability for these relationships and differences to occur by chance is low and consistent across all samples ($p<0.001$); thus there is no evidence of Type I error. Additionally, the results are consistent, although the four samples are of different sizes and have distinct units of analysis. This increases confidence in the existence of the studied phenomenon (Mackey, 2012) and in a Type II error not being present. Given the significance and consistency of the results across all samples, Study 4 replicates Study 3's findings and enhances the reliability and generalisability of the findings.

4.4.3 Conclusion

For the purpose of replicating Study 3's findings, Study 4 applies Study 3's method, procedures and analytical tools. The difference, however, is that Study 4 uses Samples A, B and C instead of FHL's 1/10th Sample, which is about three times smaller than the other three samples. Evidence supporting H_3 and H_4 is found, and all of Study 3's findings have been replicated. Key findings that have been replicated include:

- the repurchase decision is significantly strongly associated with satisfying repurchase conditions;
- the choice to skip a purchase is significantly and strongly associated with satisfying none of the three conditions to repurchase;

- customers who satisfied all repurchase conditions (Scenario 1) and others who satisfied none of them (Scenario 8) make up, on average, 45%, 44%, 45.5% and 44.1% of FHL's 1/10th Sample, Samples A, B and C, respectively;
- across samples, customers in Scenario 1 have a 89.75% repurchase probability, while customers in Scenario 8 have a 99% skipping probability;
- the decision to repurchase is completely (100%) associated with being an infrequent purchaser and having upward-trending PQs (Scenarios 5 and 7);
- the decision to skip a repurchase is completely (100%) associated with being an infrequent purchaser, having homogeneous IPTs and downward-trending PQs (Scenario 6); and
- the highest frequency of repurchase exists when the consumer is a frequent shopper, has homogeneous IPTs and has increasing PQs.

No evidence of any systematic, procedural and/or human errors was found. Study 4 confirms that satisfying the three repurchase conditions is not only strongly associated with the choice to repurchase but also relates to making more repeat purchases in the near future. While associations between repurchase behaviour and the three variables are significant and strong, do these variables determine repurchase behaviour and, if so, how accurately do these variables predict it?

4.5 Study 5: Predictive Performance of Theory of Due Repurchase

4.5.0 Introduction

Study 5 is conducted to test whether purchase frequency, LPQ and IPT homogeneity are predictors of repurchase behaviour, and learn how accurately they predict it (refer Figure 2.3). Studies 1-4 examined the associations between the three behavioural variables and repurchase behaviour, as well as differences in repurchase frequency across combinations of these variables. This study examines a) causality in the relationship between repurchase behaviour and the three behavioural variables; and b) the predictive accuracy of the model. As the Theory of Due Repurchase suggests, the probability to repurchase is dependent on frequency of purchase, LPQ and the homogeneity of the customer's IPTs (H_{5_A}), which together correctly classify more than 69% of future purchasers (H_{5_B}). As in Studies 1 and 3, to test H_5, Study 5 uses FHL's 1/10th Sample, which consists of 2,357 purchasers who made 6,918 transactions over one and a half year. This sample has been previously utilised for testing hypotheses and building models (Abe, 2009; FHL, 2005a, 2005b; Ma & Büschken, 2011; Zhang et al., 2015).

Table 4.6: Summary of Model's Measures

	Variables						
	Dependent	Independent			Control		
	Repurchase Behaviour (RB)	Frequency (F)	Last Purchase Quantity (LPQ)	IPT Homogeneity (IPT_h)	Monetary Value (MV)	Relationship Length (T)	Clumpiness (C)
Unit	Transaction	Transactions	CDs	Days	Currency	Days	Days
Operationalization	$1 = Repurchased$ $0 = Skipped$	Count	$LPQ = \frac{\sum_{i=1}^{n} PQ_i}{n-1}$	$\text{HHI} = \sum_{i=1}^{n} (\frac{IPT}{T})^2$	Sum	(Today – 1st purchase)	$= 1 + \frac{\sum_{i=1}^{n+1} \log(x_i) \cdot x_i}{\log(n+1)}$
Source/s	Van den Poel (2003)	FHL (2005a,b)	This paper	Rhoades (1993) Simonson & Winer (1992)	Viaene et al. (2001) Van den Poel (2003)	FHL (2005b)	Zhang, Bradlow, & Small (2013, 2015)
Condition			Increasing if $LPQ > \frac{\sum_{i=1}^{n} PQ_i}{n-1}$				
			Decreasing if $LPQ \leq \frac{\sum_{i=1}^{n} PQ_i}{n-1}$				
Applied in			This paper				

4.5.1 Model Variables

Table 4.6 provides a summary of the model's dependant, independent and controlled variables. Using a logit model, repurchase behaviour (RB) is regressed on three predictors and three control variables. It is operationalised as a binary variable, in which the value 1 is assigned to repurchasers and 0 is assigned to skippers. The model's predictors are frequency of past purchases (F), LPQ and IPT homogeneity (IPT_h). The model's control variables are monetary value (MV), relationship length (T) and clumpiness (C).

Frequency of past purchases is defined as the number of repurchase transactions made in the calibration period (FHL, 2005a, 2005b). To be consistent with other studies in the field, frequency of past purchases is not operationalised as a binary variable. Instead, purchase frequency is measured as a continuous variable using the count of purchase transactions (FHL, 2005a, 2005b; Van den Poel, 2003; Viaene et al., 2001; Zhang et al., 2015). LPQ is defined in this paper as the weight of the number of items the consumer purchased in the last purchase incidence relative to the total number of the consumer's purchased items. LPQ is operationalised as a dummy variable and considered to be increasing, and coded as 1, if the consumer's LPQ is higher than their average PQ; otherwise it is coded as 0. IPT homogeneity refers to the similarities in time intervals between purchase transactions. In this study, IPT homogeneity is measured using the HHI index and operationalised as a continuous variable. Higher HHI values indicate higher concentration (Hyman & Kovacic, 2004) and higher homogeneity (Simonson & Winer, 1992).

The model controls for the effects of the customer's monetary value, relationship length and clumpiness of data. The effect of monetary value has been unclear (FHL, 2005a) and justified by the fact that the more money the customer spends, the more likely s/he is to repurchase (Levin & Zahavi, as cited in Van den Poel, 2003; Lumsden et al., 2008). Similar to other studies in the field, monetary value is defined as the total amount of money the customer spent on purchases (Hughes, 2000; Van den Poel, 2003; Viaene et al., 2001; Wang, as cited in Wei et al., 2010). Including monetary value in the logit model controls for a) the different purchasing powers customers have; and b) extreme loyalty, Buckinx and Van den Poel (2005) found that the average spend of customers who are behaviourally loyal is twice as much as typical customers. Monetary value is expected to have a positive relationship with repurchase behaviour.

The relationship length refers to the time since the first purchase (Al-Shayea & Al-Shayea, 2014; FHL, 2005b; Van den Poel, 2003). Compared to newcomers with shorter customer-business relationships, longer customer-business relationships are more likely to continue (Van den Poel, 2003), as these reflect a higher behavioural commitment to buying from the retailer. Van den Poel (2003) found that the predictive performance of RFM models improves when relationship length is added. Hence, controlling for the effect of relationship length on repurchase behaviour ensures that the odds of repurchasing are neither overestimated nor underestimated.

The present model also controls for clumpiness of purchase transactions, referred to as irregular clusters of activities, such as purchases (Zhang et al., 2013). Because the customer’s purchases, over a given period of time, could be clustered in a meaningful way, the clumpiness measure is developed to capture this phenomenon. The measure yields values between 0 and 1; the closer the clumpiness value is to 1, the clumpier (more clustered) the customer’s purchases are (Zhang et al., 2013). The non-stationarity of purchase behaviour, or clumpiness, has previously been found to have a significant, strong and positive effect on future frequency of purchasing (Zhang et al., 2015). Thus, controlling for non-stationarity of purchase behaviour helps in obtaining more accurate odds of repurchasing. However, clumpiness is expected here to have a negative relationship with repurchase behaviour. This is because the regularity of performing a behaviour is, in various contexts, found to be linked to behavioural loyalty (Abe, 2009; Buckinx & Van den Poel, 2005).

4.5.2 Regression Model

A logistic regression analysis is run to test the effects of six metric and nonmetric variables on a binary dependent variable. Logistic regression has been successfully used in previous predictive-modelling studies (Bult, 1993; Van den Poel, 2003; Buckinx & Van den Poel, 2005; Cannière et al., 2009). This technique is "at the forefront of predictive modelling in" database marketing (Levin & Zahavi, 1998, p.9), well-known (Buckinx & Van den Poel, 2005; Coussement, Van den Bossche & De Bock, 2014) and used frequently in marketing (Bucklin & Gupta, as cited in Van den Poel, 2003; D'Haen, Van den Poel & Thorleuchter, 2012). The reasons that make running logistic regression appropriate for this study include yielding "consistent, efficient and asymmetrically normally distributed estimators" (Bult, 1993, p.382). Other advantages of using logistic regression include the ease of use and interpretation, quickness of obtaining results and robustness of the results (Buckinx & Van den Poel, 2005; Van den Poel, 2003).

Equation 4.1: Logit Regression Model

$$P(RB_i = 1) = \frac{e_i(\alpha + \beta_1 F_{1i} + \beta_2 LPQ_{2i} + \beta_3 IPT_{3i} + \beta_4 MV_{4i} + \beta_5 T_{5i} - \beta_6 C_{6i})}{1 + e_i(\alpha + \beta_1 F_{1i} + \beta_2 LPQ_{2i} + \beta_3 IPT_{3i} + \beta_4 MV_{4i} + \beta_5 T_{5i} - \beta_6 C_{6i})}$$

Where;

RB =	Repurchase Behaviour,	*MV* =	Monetary Value,
F =	Frequency,	***T*** =	Relationship Length, and
LPQ =	Last Purchase Quantity,	*C* =	Clumpiness.
IPT =	Interpurchase Time Homogeneity,		

The logit model above suggests that the probability of making a repurchase is determined by frequency of past purchases, LPQ and IPT homogeneity (H_{5_A}= β_1, β_2, and β_3). The model controls for monetary value (β_4), relationship length (β_5) and clumpiness (- β_6). To assess the predictive validity of the model, customers are split into estimation and validation samples using their IDs. The estimation sample consists of the first 70% of customer IDs, while the rest (30%) are used as a validation sample.

4.5.3 Results

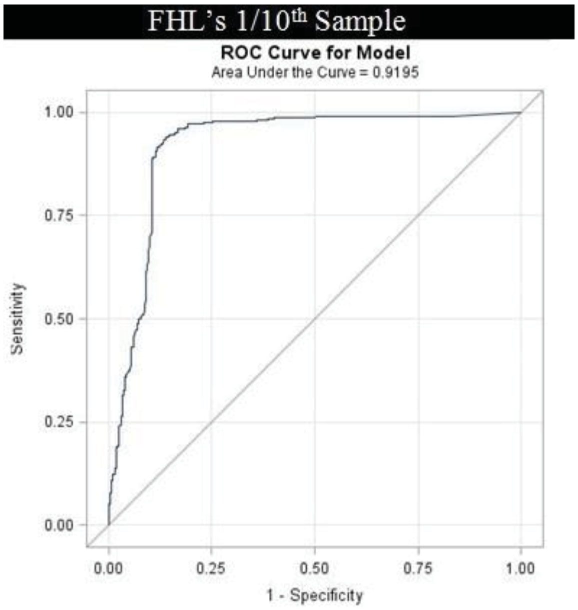

Figure 4.6: ROC Curve for the Model

Figure 4.6 is a received operating characteristic (ROC) curve plot showing how the model performs; differently put, it shows the extent to which the model's predictions and data agree (Peng & So, 2002). Figure 4.6 shows the trade off the model makes; for the model to correctly classify, say 88%, of re-purchasers, it has to misclassify about 25% of skippers. The area below the ROC curve is very large and the model is associated more with sensitivity than with 1-specificity. In other words, more customers can be correctly classified, while misclassifying fewer customers because the proportion of customers that has to be misclassified is very small. This is a sign of a good model (Peng & So, 2002).

Table 4.7: Full Model's Estimates and Statistics

	Full Model		
	β	S.E.	Exp(β)
α	-1.481	1.953	0.227
Variables			
F	0.619***	0.128	1.858
LPQ	-4.211***	0.272	0.015
$H_{\_IPTs}$	1.429**	0.548	4.173
MV	-0.004**	0.001	0.996
T	-0.006	0.008	1.006
C	1.625	1.105	5.079

Nagelkerke R^2= 70.7%

	Samples	
	Estimation	Validation
% correct =	88.8%	90.3%

*p<0.05
** *p*<0.01
*** *p*<0.001

Table 4.7 presents the results. The model is significant (p<0.001) and is a good fit (70.7%). The results support H_{5_A}; the probability to repurchase changes in response to changes in frequency of purchase (p<0.001; β_1=0.619), LPQ (p<0.001; β_2= -4.211) and homogeneity of IPTs (p<0.01; β_3=1.429). The model correctly classifies 88.8% of re-purchasers in the estimation sample and 90.3% of re-purchasers in the validation sample. Therefore, H_{5_B} is supported.

Not all of the control variables significantly affect the probability to repurchase. Relationship length and clumpiness of data do not significantly affect the probability to repurchase. On the other hand, monetary value significantly affects repurchase probability (p<0.01; β_4=-0.004). An increase in the customer's spend decreases the probability to repurchase by a factor of 0.996 (-0.004%).

4.5.4 Robustness Checks

Table 4.8 shows the model's performance with the control variables excluded. The model remains statistically significant and well fit (p<0.001; Nagelkerke R^2= 70.1%). Frequency, LPQ and IPT homogeneity still have significant effects on the probability to repurchase. The directions of the effects did not change. Whereas the magnitude of the IPT homogeneity effect remained unchanged, the frequency and LPQ effects changed slightly. Excluding the control variables results in 1) the intercept increasing from -1.481 to 0.819; and 2) the probability to repurchase becoming affected slightly less by frequency of past purchasing (p<0.001; β_1=0.346), LPQ (p<0.001; β_2= -4.041) and IPT homogeneity (p<0.01; β_3= 1.403). But, would the model remain robust when put into practice?

Table 4.8: Robustness Check – Variables Dropped Out

	Model		
	β	S.E.	Exp(β)
α	0.819^{**}	0.245	2.267
Variables			
F	0.346^{***}	0.057	1.413
LPQ	-4.041^{***}	0.257	0.018
H_{IPTs}	1.403^{**}	0.538	4.067
MV	---	---	---
T	---	---	---
C	---	---	---

Nagelkerke R^2= 70.1%

	Samples	
	Estimation	Validation
% correct =	88.7%	90.3%

$^{*}p$<0.05
$^{**}p$<0.01
$^{***}p$<0.001

To answer the question, the probability to repurchase is calculated and checked for each customer in FHL's 1/10th Sample. The significant estimates of the full model are plugged into the logistic regression model, as shown in Equation 4.2. Table 4.9 reports how the model performs and provides empirical evidence on the robustness of the model. The vast majority (85%) of customers who have 90% or more probability of repurchasing did, indeed, repurchase, whilst 79% of customers who have 50% or more probability of repurchasing did repurchase. It seems that as the predicted probability of repurchasing increases, the model's predicative accuracy improves.

Equation 4.2: Plugging Parameters into the Regression Model

$$P(RB_i = 1) = \frac{e_i(-1.481 + 0.619(F_{1i}) - 4.211(LPQ_{2i}) + 1.429(IPT_{3i}) - 0.004(MV_{4i}))}{1 + e_i(-1.481 + 0.619(F_{1i}) - 4.211(LPQ_{2i}) + 1.429(IPT_{3i}) - 0.004(MV_{4i}))}$$

Table 4.9: Robustness Check - Model's Actual Performance

		Repurchased		Skipped	
$P(RB_i = 1)$	Total	N	%	N	%
90%+	40	34	85.00	6	15.00
80%+	68	56	82.00	12	18.00
70%+	92	76	83.00	16	17.00
60%+	127	100	79.00	27	21.00
50%+	158	125	79.00	33	21.00

Sample Size = 958

4.5.5 Discussion

Study 5 is run to test Hypothesis 5. The study utilises FHL's 1/10th Sample, which has been used in the marketing literature for testing hypotheses and building models (Abe, 2009; FHL, 2005a, 2005b; Ma & Büschken, 2011; Zhang et al., 2015). A logistic regression analysis is run to test a) whether purchase frequency, LPQ and IPT homogeneity are predictors of repurchase behaviour; and b) whether the three variables correctly classify more than 69% of customers. The results provide evidence supporting both H_{5_A} and H_{5_B}.

Building on previous studies in this thesis, the three behavioural variables are predictors of repurchase behaviour. The probability of repurchasing increases when frequency increases, IPT homogeneity increases and LPQ is lower than average. Consistent with other studies (FHL, 2005a; Lumsden et al., 2008; Nash, 1994; Ouellette & Wood, 1998; Van den Poel, 2003), frequency of past purchase is predictive of repurchase behaviour. While the positive effect of past frequency on repurchase behaviour is not surprising, its magnitude is. This is because frequency of past actions is consistently found to be one of the strongest predictors of future behaviour (Buckinx & Van den Poel, 2005; Cannière et al., 2009; Jen et al., 2009; Lumsden et al., 2008; Ouellette & Wood, 1998; Van den Poel, 2003). The model reveals that a one unit increase in frequency increases the odds to repurchase by a factor of 1.858 (85.8%). This relatively weak frequency effect can be attributed to the addition of two strong predictors of repurchase behaviour, namely LPQ and IPT homogeneity.

LPQ is not only a determinant of repurchase behaviour but also affects it strongly. When the customer's LPQ is greater than their average PQ, the odds of repurchasing decreases by a factor of 0.015 (-98.5%). The negative effect of LPQ on repurchase behaviour furnishes insight into the previous findings. Beasley (1998) found a positive relationship between the quantity of items held at home and the length of customer inactivity. Purchasing a quantity that is more than usually purchased increases the stock at home and reduces the need to repurchase, resulting in the customer being temporarily inactive.

Repurchase behaviour is also determined by the homogeneity of the customer's IPTs. It has been established that IPT is a key segmentation variable and is predictive of customer value (Buckinx & Van den Poel, 2005). This thesis adds that the homogeneity of IPT is a key predictor of repurchase behaviour. An increase in IPT homogeneity increases the odds of repurchase by a factor of 4.173 (317.3%). The strong effect of IPT-homogeneity may not be surprising, as time measures tend to explain phenomena quite well (Zhang et al., 2015). Similar time intervals between purchases are associated with behavioural loyalty (Abe, 2009) and reflect purchasing patterns that could well be automatically repeated in the future (Ouellette & Wood, 1998).

Of the three control variables added to the model, only one that has a significant effect on repurchase behaviour. Monetary value negatively affects repurchase probability (p<0.01; β_4=-0.004). An increase in the customer's spend decreases the odds of repurchase by a factor of 0.996 (-0.004%). This relationship is interesting because customers who are spending more money with the business are more likely to repurchase (Levin & Zahavi, as cited in Van den Poel, 2003; Lumsden et al., 2008). Repurchase behaviour is not affected by either relationship length or clumpiness. However, clumpiness (p>0.05; β_6= 1.467) carries much more weight than relationship length (p>0.05; β_5=-0.006). Zhang et al. (2015) found that clumpiness has a significant and strong effect on repurchase frequency.

Theory of Due Repurchase hypothesises that the three behavioural variables (F, LPQ and IPT_h) correctly classify more than 69% of repurchasers and skippers. This hypothesis (H_{5_B}) is supported, as the developed model correctly classifies 88.7% of customers. The model's predictive validity is also tested. The percentages of correctly classified customers in the estimation (88.7%) and validation (90.3%) samples are high and consistent. In fact, the Theory of Due Repurchase correctly classifies more customers than existing theories and models do, using only the three behavioural variables. Among behaviour-behaviour models, the highest percentage of correct classification (69%) is obtained using five behavioural variables (Van den Poel, 2003), including RFM, which are considered the best predictors of future behaviour (Buckinx & Van den Poel, 2005; De Cannière et al., 2009). Other models based on RFM combined with other behavioural and non-behavioural predictors correctly classify no more than 72.4% of customers (Viaene et al., 2001; Baesens et al., 2002). Viaene et al. (2001) emphasise that models built on fewer variables improve computational performance and the human understanding of phenomena. They (2001) added that the predictive power of algorithms improves when irrelevant and/or redundant variables are dropped from models.

However, one may question the reliability and precision of the results obtained by logistic regression as logistic regression models have received criticism in the literature. First, these models do not capture all the behavioural information when analysing longitudinal data. As technology now allows for collecting more precise consumer-level data, such as the exact purchase time, binary models are blamed for missing critical information that could impact the quality of results (Gupta, 1991). Wheat and Morrison (1990, p.168), however, studied this claim and concluded that logistic regression models predicting the occurrence of an event are "preferable because they are unaffected by discrete shopping behaviour and right censored data". This is quite reassuring, as what the present model predicts is the occurrence of a repurchase regardless of when, where and/or how many times this repurchase occurs. Second, logistic regression models are criticised for their disregard of unobserved heterogeneity (Gupta, 1991). Defined as non-random differences across customers (Berg & Mansley, 2004), unobserved heterogeneity is equivalent to omitting a variable, and biases coefficient estimates (Heckman & Singer, as cited in Gupta, 1991; Vilcassim & Jain, 1991; Mood, 2010). Omitting variables results in depressing the model's coefficient estimates towards zero (Cramer, 2007). Although this has been observed in the present model, the difference in coefficient estimates after removing the control variable is very small (refer to Tables 4.7 and 4.8). While “unobserved heterogeneity is almost always present”, the seriousness of its effect depends on the amount of heterogeneity that has not been observed (Mood, 2010, p.72). Perhaps checking the model’s robustness addresses one’s doubts and provides further assurance about the reliability and precision of the present logit model and its estimates.

The robustness checks provide further assurance about the stability of the model. Dropping the control variables from the model does not majorly change the estimates of the covariates. Doing so does not change the significance or direction of the effects of the remaining predictors on the dependent variable. The intercept slightly increases (α = 0.819), and the magnitudes of the frequency, LPQ and IPT homogeneity effects slightly decrease (p<0.001; β_1=-0.346, β_2= -4.041, and β_3= 1.403). Although 50% of the model’s variables are excluded, the model remains stable and its estimates resemble the full model.

To further increase confidence in the robustness of the present logit model and its estimates, the probability of repurchasing by each customer in FHL’s 1/10th Sample is calculated and assessed. A pattern emerges; the higher the calculated probability of repurchasing, the better the predictive accuracy becomes. Customers with high probabilities of repurchasing are much more likely to repurchase. In fact, 85% of customers who have repurchase probability of 90% or more did repurchase. This is practical evidence of the robustness of the model, and the consistency and reliability of its estimates.

4.5.6 Conclusion

Study 5 is conducted for the purpose of testing the predictive performance of Theory of Due Repurchase. The study uses FHL's 1/10th Sample to test H_{5_A} and H_{5_B}. A logistic regression model is developed to test whether purchase frequency, LPQ and IPT homogeneity are predictors of repurchase behaviour, and whether they accurately classify more than 69% of customers. The model controls for the effects of monetary value, relationship length and clumpiness. The results provide evidence supporting H_{5_A} and H_{5_B}. Purchase frequency, LPQ and IPT homogeneity are significant predictors of repurchase behaviour. While statistically significant and a good fit, the logit model correctly classifies 88.8% of customers in the estimation sample and 90.3% of customers in the validation sample. Two robustness checks provide theoretical and practical evidence on the robustness of the model. First, dropping the control variables out of the model does not significantly change the model's intercept and estimates. Second, applying the logit model to the dataset shows that the vast majority (85%) of customers who have 90% or more probability of repurchasing did, indeed, repurchase, whereas only 79% of customers who have 50% or more probability of repurchasing did repurchase. The predicted probability of repurchasing increases as the model's predicative accuracy improves.

While Study 5's findings are promising, would the model also perform well and accurately predict customers in other samples? The extent to which the findings are externally valid has not been investigated. The next section involves a replication of Study 5.

4.6 Study 6: A Replication of Study 5

4.6.0 Introduction

Study 6 is conducted to replicate Study 5's findings and ensure that no error affected these results. This study retests the model (H_5) using the same method, procedures, and analytical tools as in Study 5. Instead of using FHL's 1/10th Sample, however, Study 6 uses Samples A, B and C as in Studies 2 and 4. Using two or more large samples to replicate studies in social science uncovers errors and provides supporting evidence on the in/existence of an event or a phenomenon (Mackey, 2012). Consistency in the results should increase confidence in the generalisability of the findings.

Three logistic regression analyses are run to test whether a) the probability of making a repurchase is determined by purchase frequency, LPQ and IPT homogeneity (H_{5_A}= β_1, β_2, and β_3); and b) the model correctly classifies more than 69% of customers (H_{5_B}). The model controls for the effects of monetary value (β_4), relationship length (β_5) and clumpiness (- β_6). To examine the predictive validity of the model, customers in each sample are split into estimation and validation samples using their IDs. The estimation sample is made up of the first 70% of customers IDs and the rest (30%) is used as a validation sample.

4.6.1 Results

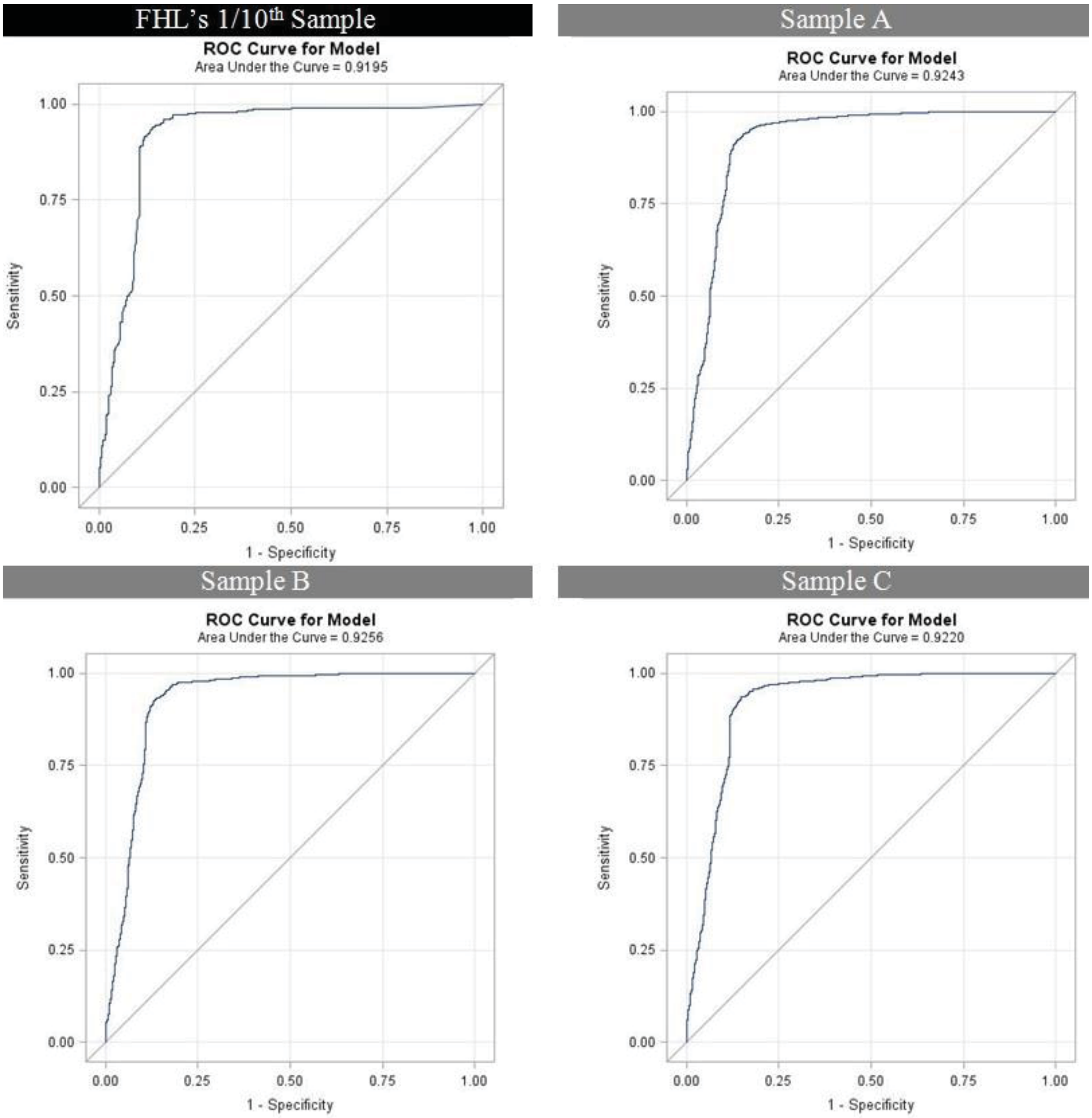

Figure 4.7: ROC Curves for the Four Models

Figure 4.7 compares the ROC curve plot derived in Study 5 with the three ROC curve plots derived using Samples A, B and C. The model predictions agree with the data in each of the four samples. The model still classifies a large proportion of repurchasers at the expense of misclassifying a small proportion of skippers. The area below the ROC curve is very large across the four samples. All four models are associated more with sensitivity than with 1-specificity. This indicates that the model's performance is excellent (Peng & So, 2002).

Table 4.10: Models' Estimates and Statistics (Across Samples)

	FHL's Sample		Sample A		Sample B		Sample C	
	Full Model		Full Model		Full Model		Full Model	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.
α	0.970	1.151	2.238*	0.941	3.048**	0.967	1.085	0.935
Variables								
F	0.535***	0.106	0.119*	0.057	0.212**	0.064	0.315***	0.059
LPQ	-4.261***	0.227	-3.818***	0.138	-3.868***	0.141	-3.929***	0.137
H_{IPTs}	1.213**	0.463	1.344***	0.285	1.533***	0.298	1.285***	0.282
MV	-0.003**	0.001	0.001	0.001	0.000	0.001	-0.001	0.001
T	-0.003	0.005	0.002	0.004	-0.003	0.004	0.003	0.004
C	1.467	1.151	-2.698***	0.481	-2.340***	0.530	-1.372**	0.479
R^2 =	70.7%		67%		69%		68%	
-2LL=	429.075		1539.013		1471.096		1575.920	
	Samples		Samples		Samples		Samples	
% correct:	Estimation	Validation	Estimation	Validation	Estimation	Validation	Estimation	Validation
	88.8%	90.3%	88%	90%	88.5%	89.9%	88.5%	88.7%

R^2 is Nagelkerke
-2LL = -2 Log Likelihood
$^{*}p<0.05$
$^{**}p<0.01$
$^{***}p<0.001$

Table 4.10 reports the results of Study 5's findings and one regression analysis for each of the three tested samples. The models tested using Samples A, B and C are significant ($p<0.001$) and fit the data very well (67%, 69% and 68%, respectively). Across the three samples, frequency of past purchases (β_1), LPQ (β_2) and homogeneity of IPTs (β_3) significantly affect the probability of repurchase. This provides further evidence supporting H_{5_A}. As the model correctly classifies much more than 69% of customers across the samples, H_{5_B} is further supported. In Sample A, the model correctly classifies 88% of customers in the estimation sample and 90% in the validation sample. In Sample B, 88.5% of customers in the estimation sample and 89.9% in the validation sample are correctly classified by the model. In Sample C, the model correctly classifies

88.5% of customers in the estimation sample and 88.7% in the validation sample. The model's predictive accuracy is consistent and high.

The effects of control variables vary across samples. While insignificant across all samples, the relationship length correlates negatively with repurchase behaviour in FHL's Sample and Sample B, but positively in Samples A and C. Monetary value has an insignificant effect and its relationship with repurchase behaviour is positive in Samples A and C only. Unlike the testing using FHL's 1/10th Sample, clumpiness has a significant negative effect on repurchase behaviour.

4.6.2 Robustness Checks

Table 4.11: Robustness Check - Variables Dropped Out (Across Samples)

	FHL's Sample		Sample A		Sample B		Sample C	
	Model		Model		Model		Model	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.
α	1.091**	0.214	0.821***	0.135	0.687***	0.140	0.798***	0.131
Variables								
F	0.322***	0.049	0.367***	0.034	0.407***	0.036	0.381***	0.033
LPQ	-4.162***	0.219	-3.782***	0.135	-3.891***	0.139	-3.941***	0.136
H_{IPTs}	1.213**	0.459	1.453***	0.282	1.655***	0.299	1.310***	0.278
MV	---	---	---	---	---	---	---	---
T	---	---	---	---	---	---	---	---
C	---	---	---	---	---	---	---	---
R^2 =	70.1%		66%		68.3%		68%	
-2LL=	438.015		1572.464		1493.958		1586.186	
	Samples		Samples		Samples		Samples	
% correct:	Estimation	Validation	Estimation	Validation	Estimation	Validation	Estimation	Validation
	88.7%	90.3%	87.8%	90.1%	88.5%	89.8%	88.4%	88.9%

R^2 is Nagelkerke
-2LL = -2 Log Likelihood
* p<0.05
** p<0.01
*** p<0.001

Table 4.11 shows the model's performance in each of the four samples without the control variables. Across samples, the probability of repurchasing is still determined by frequency, LPQ and IPT homogeneity. Neither the significance nor the direction of effects changed. Dropping the control variable results in the intercept decreasing from 2.238 to 0.821, from 3.048 to 0.687, and from 1.085 to 0.798 in Samples A, B and C, respectively. Across the three samples, the magnitudes of frequency and IPT homogeneity effects slightly increase in the absence of the control variables. The magnitude of the LPQ effect slightly decreases in Sample A, but increases in Samples B and C when dropping the control variables from the model. These minor changes encourage one to examine whether the model remains robust when applied to real-life data.

Table 4.12: Robustness Check - Model's Actual Performance across Samples

FHL's 1/10th Sample

		Repurchased		Skipped	
P(RB=1)	Total	N	%	N	%
90%+	40	34	85.00	6	15.00
80%+	68	56	82.00	12	18.00
70%+	92	76	83.00	16	17.00
60%+	127	100	79.00	27	21.00
50%+	158	125	79.00	33	21.00

Sample Size = 958

Sample A

		Repurchased		Skipped	
P(RB=1)	Total	N	%	N	%
90%+	294	254	86.00	40	14.00
80%+	521	427	82.00	94	18.00
70%+	731	570	78.00	161	22.00
60%+	917	690	75.00	227	25.00
50%+	1103	803	73.00	300	27.00

Sample Size = 3,166

Sample B

		Repurchased		Skipped	
P(RB=1)	Total	N	%	N	%
90%+	705	562	80.00	143	20.00
80%+	1023	750	73.00	273	27.00
70%+	1294	905	70.00	392	30.00
60%+	1489	1001	67.00	488	33.00
50%+	1604	1068	67.00	536	33.00

Sample Size = 3,175

Sample C

		Repurchased		Skipped	
P(RB=1)	Total	N	%	N	%
90%+	331	282	85.00	49	15.00
80%+	545	443	81.00	102	19.00
70%+	737	580	79.00	157	21.00
60%+	931	703	76.00	228	24.00
50%+	1087	787	72.00	300	28.00

Sample Size = 3,259

Table 4.12 reports the number and percentage of repurchasers and skippers who have repurchase probabilities of more than 50% in each of the four samples. The results are obtained by calculating the probability of repurchasing for each customer across samples. The vast majority of customers, who have a probability of repurchasing equal or above 90%, did repurchase. This result is consistent across the four samples. One the other hand, over two-thirds of customers who have a repurchase probability of 50% or more, did repurchase. This result is also consistent across the four samples. The results in Table 4.12 display a pattern; as the predicted probability of repurchasing increases, the model's predicative accuracy improves.

4.6.3 Discussion

Study 6 uses Study 5's methodology to replicate its findings. Three different samples, which are three times larger than the one used in Study 5, are used to retest H_{5_A} and H_{5_B}. The results, obtained from running logistic regression analyses, provide further evidence supporting the retested hypotheses and are consistent with Study 5's results.

The findings across the three samples are consistent with Study 5's findings. All tested models are significant and fit the data very well; repurchase behaviour is predicted by frequency, LPQ and IPT homogeneity. Across the four samples, repurchase probability becomes higher when frequency and/or IPT homogeneity increases, and lower when the customer's LPQ is above average. The effects of control variables on repurchase behaviour are inconsistent across the four samples[5]. The predictive accuracy of the model is high and consistent across the four samples. The percentages of correctly classified customers range from 88% to 90.3% in the full model and from 87.8% to 90% when the control variables are dropped from the model. Despite the inclusion or exclusion of control variables, the model correctly classifies more than 69% of customers across the four samples. When testing the model's predicative validity, the percentages of correctly classified customers in the estimation and validation samples are similar and high across the four models. This increases confidence in the generalisability of these findings.

[5] See Appendix 8.3 for discussion on the inconsistent effect of clumpiness.

The robustness checks yield values that are similar to the ones obtained in Study 5. When the control variables are dropped from the model, the model and its predictors remain significant across the four samples. In addition, the direction of each effect stays as it is; the probability to repurchase is positively affected by frequency and IPT homogeneity, but negatively affected by LPQ. Also, the changes to the strengths of these effects are hardly noticeable. These results are consistent across the four samples, reducing the error probability. Seeking empirical evidence on the robustness of the model, the probability of repurchasing is calculated for each customer in each of the four samples. The results show that only 1 in 6 customers, whose calculated repurchase probability is 90% or more, do not repurchase. However, this number increases as the calculated probability decreases. These results are consistent across samples, provide empirical evidence on the robustness of the model, replicate Study 5 and further increase the generalisability of the model.

Given the above, neither Type I nor II error is of concern and one should be assured that the findings are robust. This is because, generally, the probability of error is too small to be threatening. The fact that the four samples are drawn from one cohort of customers might be a source of error. However, each of the three samples drawn in this thesis has a distinct distribution of customers. Even with the different size and units in each sample, the results are significant and consistent across the four samples. This makes one able to state, with confidence, that frequency, LPQ and IPT homogeneity are determinants of repurchase behaviour and accurately predict more customers than do existing models.

4.6.4 Conclusion

Study 6 provides further evidence supporting H_{5_A} and H_{5_B}, replicates Study 5's findings, and enhances the reliability and generalisability of the model. The probability of repurchase is affected by the customer's purchase frequency, LPQ and IPT homogeneity. Shopping more frequently and purchasing at more homogeneous time intervals result in a higher probability of repurchasing. A larger than usual LPQ lowers the probability to repurchase. There is no evidence of a systematic, procedural and/or human error. These three behavioural dimensions could actually be a practical definition of behavioural loyalty as a singular concept. According to East et al. (2005), a useful definition of customer loyalty is one which predicts a marketing phenomenon.

4.7 Chapter Summary

This chapter conducted six studies to empirically test and examine the predictive accuracy of the Theory of Due Repurchase. Study 1 was conducted to test H_1 and H_2 and establish the foundation of the Theory of Due Repurchase. Study 2 was run to replicate Study 1’s findings. Study 3 was run to test H_3 and H_4 in order to build on Study’s 1 findings, and to challenge and provide insights into the theory. Study 3’s findings were replicated in Study 4. Study 5 was conducted to test H_5 and learn whether purchase frequency, LPQ and IPT homogeneity are predictors of repurchase behaviour and how accurately they predict it. These findings were replicated in Study 6. The next chapter connects and discusses the studies’ findings.

5 General Discussion

5.0 Introduction

In the previous chapter, six studies were conducted to empirically test the Theory of Due Repurchase, examine its accuracy in predicting repurchase behaviour, and replicate findings. The results of each study were presented and discussed. The purpose of this chapter is to review the main results of the six studies with respect to research objectives. Research findings will be connected and discussed. This will be followed by a discussion of the validity of these findings. The chapter will then provide academic and managerial insights on effective targeting.

5.1 Theory of Due Repurchase

This thesis aims at enhancing the current knowledge on repurchase behaviour and equipping marketing practitioners with a conceptual model which enables them to gain more from using less. A small improvement in predicting repurchase behaviour can increase profits substantially (Baesens et al., 2002; Van den Poel, 2003). Thus, for a business to 'gain more from using less', repurchase behaviour should be well predicated using underutilized resources, namely purchase-history data. This is the rationale behind the Theory of Due Repurchase.

5.1.1 Theory Testing

The foundation of Theory of Due Repurchase has been established in Study 1, which resulted in two important findings. First, repurchase frequency differs significantly, and is higher, when the customer is a frequent shopper (vs. infrequent), has increasing purchase quantities (PQs) (vs. decreasing PQs) and has homogeneous interpurchase times (IPTs) (vs. heterogeneous IPTs). Second, satisfying all three repurchase conditions, as the Theory of Due Repurchase suggests, is significantly and strongly associated with the customer's decision to repurchase. In addition, Bayes' Theorem verifies these associations and reveals that customers satisfying all repurchase conditions have a 91% probability of repurchasing. These findings are replicated in Study 2. Repurchase behaviour is significantly and strongly associated with frequency, quantity and time. This supports the view, and the foundation of the Theory of Due Repurchase, that customers consciously or unconsciously answer three frequency-quantity-time based questions to make a purchase decision (Wansink et al., 1998).

The decision to repurchase is strongly associated with customers who are frequent shoppers, have an upward trending PQ and have homogeneous IPTs. There are three factors explaining these associations. First, frequent shoppers are considered behaviourally-loyal customers and, therefore, are expected to continue to repurchase in the future (Buckinx & Van den Poel, 2005). Second, the quantity the customer purchases today appears to capture their consumption plans (Beasley, 1998); hence, a customer with increasing PQs is more likely to repurchase than another with decreasing PQs. Third, purchasing at random times is found to be the behaviour of non-loyal customers (Abe, 2009), which is why heterogeneous IPTs are strongly associated with the decision not to purchase. Simultaneously meeting all the three repurchase conditions[6] is significantly and strongly associated with the decision to repurchase. This, however, raises two questions. One is whether the opposite is also true, so that satisfying none of the three repurchase conditions is associated with the decision to skip the purchase. The other is whether meeting all the three repurchase conditions is not

[6] The customer is a frequent shopper, has an upward-trending PQ and has homogeneous IPTs.

only associated with making one repeat purchase, but is also associated with making many repeat purchases.

Study 3 challenged the Theory of Due Repurchase and provided insights into it. Specifically, the study tested 1) associations between repurchase behaviour and eight possible scenarios[7] of un/satisfying the three repurchase conditions; and 2) whether repurchase frequency differs significantly across the eight scenarios. First, there is a significant and strong association between the choice to skip the purchase and Scenario 8, in which all the three repurchase conditions are unsatisfied. Of those (22%) satisfying none of the three repurchase conditions, about 98% did not repurchase. Secondly, repurchase frequency differs significantly across the eight scenarios and is much higher when all three repurchase conditions are satisfied (Scenario 1). Hence, customers in Scenario 1 do not only make a purchase in the future, but also repurchase more frequently than others. Study 3 is replicated in Study 4.

These findings are in line with previous findings highlighting the significance of the relationship between consumer behaviour and frequency, purchase quantity and IPTs (Buckinx & Van den Poel, 2005; Jen et al., 2009; Ouellette & Wood, 1998). First, performing a certain behaviour in the past is found to be associated with re-performing it in the future (Lemon et al., as cited in Buckinx & Van den Poel, 2005); the frequency of performing that behaviour determines how strong or weak it is (Triandis, as cited in Ouellette & Wood, 1998). Second, a number of studies found behaviourally loyal customers to be heavy buyers (Jacoby & Kyner, and Reichheld, Markey & Hopton, both as cited in Jen et al., 2009; Van den Poel, 2003). A behaviourally non-loyal customer will not purchase in large quantities every time s/he buys. Third, similar IPTs form a purchasing pattern that is likely to be repeated in the future (Ouellette & Wood, 1998).

[7] Refer to Table 4.3 for more details.

For example, buying groceries every Thursday night, on which the customer's wages are paid, forms a purchasing pattern that is likely to be repeated.

As the Theory of Due Repurchase suggests, Studies 3 and 4 found that the customer's next purchase can be considered due, or highly expected, under three repurchase conditions. These conditions are 1) being a frequent shopper; 2) having an upward-trending PQ; and 3) having homogeneous IPTs. Under these conditions, not only one future purchase is made but the frequency of future purchases is also significantly different and much higher compared to all other possible combinations of the three repurchase conditions. Given the strong association between the three variables and the repurchase decision, two questions come to mind. One is whether these variables determine the decision to repurchase, and the other is whether these can accurately predict purchasers.

5.1.2 Predictive Accuracy

Study 5 addresses these questions through conducting a logistic regression analysis, which provides strong evidence on the predictive performance of the Theory of Due Repurchase. Purchase frequency, LPQ and homogeneity of IPTs are predictors of repurchase behaviour and classify customers more accurately than existing behaviour-behaviour models. These three behavioural predictors correctly classify over 88% of customers. These findings are replicated in Study 6. The predictive validity of the theory is high and consistent across the four regression models.

The probability to repurchase is affected significantly by purchase frequency, LPQ and ITP homogeneity with, and without, the inclusion of control variables in the model. While repurchase probability increases as a result of making a repeat purchase and/or the customer's IPTs being more homogeneous, an LPQ that is greater than average reduces it. In line with previous findings in the marketing literature, purchase frequency affects the probability to repurchase positively (De Cannière et al., 2009; Van den Poel, 2003; Ouellette & Wood, 1998). The more frequently the customer purchases, the more likely s/he will repurchase. IPT homogeneity positively affects the probability to repurchase. This is consistent with Abe's (2009) finding that the times at which loyal customers purchase are more regular than the times at which non-loyal customers purchase. This also supports the view that purchasing patterns, which are likely to be repeated in the future, are formed by similarities in the customer's IPTs (Ouellette & Wood, 1998). The more homogeneous the customer's IPTs become, the higher the probability that a repurchase will be made. LPQ has a negative effect on the probability to repurchase. Purchasing a larger-than-average quantity indicates holding a larger-than-average inventory (Neslin et al., 1985), leading the customer to wait longer than usual to repurchase (Beasley, 1998). Perhaps this extends the period during which the customer is inactive, resulting in the customer being more behaviourally disconnected, more open to new experiences and alternatives, and more likely to switch to competitors. This is an area that needs exploring.

Predictions by the Theory of Due Repurchase appear, to a satisfying extent, accurate. Searching the literature, the best performing behaviour-behaviour model could classify 69% of customers (Van den Poel, 2003). Here, the Theory of Due Repurchase correctly classifies over 88% of customers. This is an improvement on the current predictive accuracy of about 19 percentage points. There are two factors which could have contributed to this remarkable improvement in predictive accuracy.

These factors are the number of predictors in the model and the addition of the customer's LPQ to the model. First, the Theory of Due Repurchase is based on three behavioural variables, whereas the best-performing model is based on five behavioural variables, including RFM (Van den Poel, 2003). The computational performance improves when a model is built on fewer behavioural predictors; algorithms gain more predictive power as redundant and/or irrelevant predictors are dropped from a model (Viaene et al., 2001). Second, capturing the customer's consumption plan at a particular point of time, the LPQ construct adds value to the predictive accuracy of repurchase behaviour. The quantity of purchased items appears to be a better reflection of the customer's behavioural commitment and consumption plans than other measures such as monetary value. Money is more likely to be perceived differently than purchase quantity is. For example, an employee who has been recently promoted may now purchase national brand kitchen towels instead of private labels. While the employee's spend increased, s/he still consumes the same quantity of kitchen towels.

5.2 Research Validity

The research uses a quantitative method and longitudinal data to investigate correlational and causal relationships as well as differences between groups. The method and data are appropriate for this research and should not be sources of statistical error. The present thesis adopts three approaches to check and verify the results obtained. First, each study is followed by a replication study using three different samples which are much larger than the one used in the preceded study. All studies were replicated and the results found to be consistent across the samples. Second, a statistical technique is employed to examine the predictive validity of the models developed in Studies 5 and 6. That is, each sample is divided into estimation and validations samples which both, across all samples, yielded similar and high percentages of correct classification, leading to the conclusion that the model is generalisable. Third, all regression models were tested for robustness using theoretical and empirical techniques.

The theoretical technique checked the model's performance with the control variables being dropped out. Doing so revealed that the significance, direction and magnitude of the effects did not change significantly in the absence of the control variables. The empirical technique investigated the actual performance of the model through using its coefficient estimates to calculate the probability to repurchase. The probability of repurchasing was calculated for each customer across four datasets. About three-quarters of customers whose calculated probability is above 50% did actually repurchase. A clear pattern that is consistent across the samples is that the higher the predicted probability, the more accurate the model's predictions.

These three approaches of validity-and-reliability checking should increase confidence in the research findings. Across the studies and samples, all tests yielded *p*-values that are lower than 0.1%, reducing the chance of making a Type I error. In addition, the results are consistent across the studies although the samples are of different sizes, reducing the likelihood of having made a Type II error (Mackey, 2012). Because the studies have been replicated, the models are robust, and no evidence of any systematic, procedural and/or human errors was found, one can be confident about the validity of the research findings.

5.3 Academic and Managerial Insights

There are a number of findings that are of scientific interest to researchers and of practical value to practitioners. First, customers in Scenarios 1 and 8 represent the largest and second largest customer segments in the sample and make up about 24% and 22% of the sample respectively. This is interesting because it reflects how influential the customers' answers to the *when*, *what* and *how much/many* questions are in the building of their purchase histories (Wansink et al., 1998). In practical terms, targeting customers in Scenario 1 means investing in 23% of customers, of whom 91% are likely to respond. Avoiding communication with customers in Scenario 8 means saving the cost of targeting 22% of customers, of whom 98% are unlikely to respond.

Second, the decision to repurchase is completely associated with being an infrequent shopper whose PQs are trending upward (Scenarios 5 and 7) where all (100%) customers did repurchase. This finding has been replicated and is consistent across the four different samples. Further analysis revealed that these customers have the lowest PQ averages. One explanation of this phenomenon is that these customers have recently become loyal and are increasingly becoming behaviourally committed to buying from CDNow.com. So, their purchase frequency will increase and their purchasing patterns will be clearly formed. One piece of evidence supporting this explanation is that these two groups have significantly high repurchase frequency (refer to Figure 4.5). It is important to emphasise, however, that lower frequency values are good news as long as the customer's PQs are increasing over time.

Third, the decision to skip the purchase is completely associated with being an infrequent shopper whose PQs are trending downward and IPTs are homogeneous (Scenario 6). All (100%) customers in Scenario 6 have skipped their next purchases. This finding has been replicated and is consistent across the four samples. There are three reasons that explain this phenomenon. First, as found and emphasised in Studies 1-4, performing a certain action in the past is associated with re-performing it in the future (Lemon et al., as cited in Buckinx & Van den Poel, 2005; Ouellette & Wood, 1998). In other words, deciding not to purchase today seems to make it more likely that the customer will skip the purchase in the future. Second, the increasing tendency to purchase fewer quantities indicates a lack of behavioural commitment. The cause of this lack is beyond the scope of this research; however, possible causes may include finding alternatives, switching to a competitor, and/or a fulfilled need. Third, homogenous IPTs form purchasing patterns featuring 1) infrequency of purchase; and 2) decreasing PQs. These two behaviours are likely to be repeated in the future or, in this case, result in the choice to skip the purchase. However, further analysis shows that these are buyers who, for some reason beyond the scope of this research, take longer than others to repurchase.

Fourth, plugging the coefficient estimates into the regression model to calculate probability of repurchasing for customers, higher levels of predicted probability result in a better accuracy in predicting repurchase behaviour. However, the cost of choosing higher calculated probability levels, or precision, is being able to target fewer customers only. This is due to the trade-off between accuracy of prediction and number of customers. A risk-averse practitioner may choose to target customers with a 90%+ probability of repurchasing; these customers form a small segment (17% of the sample). Choosing lower probability levels, on the other hand, leads to the opposite which is targeting more customers at the expense of being more accurate in predicting behaviours.

These findings should help reduce marketing costs and improve the return on marketing investment (ROMI). Customers in Scenarios 5, 6 and 7 combined, account for about 24% of the sample. Given that customers in Scenario 6 have 0% chance of repurchasing, avoiding communication with customers in Scenarios 6 and 8 saves the costs of targeting about 30% (7.9%+22%) of existing customers, of whom 98% are unlikely to respond. On the other hand, targeting customers in Scenarios 1, 5 and 7 involves investing the marketing dollar on 40% of existing customers who are more than 90% likely to respond (23%+8%+9%).

5.4 Chapter Summary

This chapter reviewed the main results of six studies with respect to research objectives. It discussed and connected all of the research findings to further explain the Theory of Due Repurchase. This was followed by a discussion of the validity of these findings. A number of academic and managerial insights on effective targeting were then provided. The next chapter will conclude the thesis, present managerial implications, outline the limitations of the research, and signal areas for future research.

6 Conclusions

6.1 Thesis Purpose and Contributions

The thesis aims at enhancing current knowledge on repurchase behaviour and providing a marketing model that helps businesses not only survive but also succeed in this competitive business environment. Driven by the need for *efficient marketing*, the model is developed to enable businesses to ‘gain more for less’ by reallocating marketing resources and investing more in inexpensive, underutilised customer data. To be efficient in marketing is to produce a desired response using the least costly marketing actions (Kotler, 1972).

An accurate prediction of repurchase behaviour is required, however, in order to produce the desired response (Jebarajakirthy & Thaichon, 2016). Predicting repurchase behaviour is not a simple straightforward task (Ajzen, 1991; Wójcik & Doligalski, 2014). Theories and models predicting repurchase behaviour in non-contractual settings exist (Fader & Hardie, 2009) and are influenced by either the attitudinal or behavioural schools of thought. As described in Chapter 2, while the two schools share the same goal of predicting consumer behaviour, they differ in how to accomplish this goal. The attitudinal school aims at more fully explaining the variance in repurchase behaviour, whereas the aim of the behavioural school is to improve the accuracy in predicting repurchase behaviour. Neither school, however, accomplishes the goal satisfactorily (Day et al., 1991; Sutton, 1998). Combinations of behavioural and/or attitudinal constructs have been proposed to build and extend models predicting repurchase behaviour.

As shown in §2.1 and §2.2, none of these models and extensions has considered the roles of PQ and IPTs in predicting repurchase behaviour at the consumer-level. Whereas much of the focus has been sharpened on *when* a purchase is made and *what* brand/category is purchased, little attention is given to *how much/many* is purchased (Wansink et al., 1998). PQ decisions made today seem to reflect future consumption plans (Beasley, 1998). In addition, customer activity and behavioural commitment could be assessed by looking at their IPTs (Buckinx & Van den Poel, 2005), which form purchasing patterns (Ouellette & Wood, 1998).

In §2.3, the literature shows that, in every purchase incidence, there are three questions the answers to which build the customer's purchase history (Wansink et al., 1998). These questions provide three pieces of information related to frequency, quantity and time of purchase. Hence, these three variables are crucial to producing a desired response. Given that purchase decisions, in non-contractual settings, are affected by routine and opportunity (East et al., 2005), the Theory of Due Repurchase suggests that the customer's next purchase is due (highly expected) when the following repurchase conditions are satisfied:

1. The customer is a frequent shopper;
2. The customer's LPQ builds on an existing trend of increasing PQs; and
3. The customer's IPTs are homogeneous.

Satisfying each and all of the three conditions is expected to be associated with the decision to repurchase, as well as higher repurchase frequency. Satisfying none of the three repurchase conditions is, however, expected to be associated with the decision to skip the purchase. Combinations of repurchase conditions are expected to have different repurchase frequencies. Purchase frequency, LPQ, and IPT homogeneity are not only expected to be significant predictors of repurchase behaviour but to also predict it more accurately than existing behavioural models.

With the goal being to build and empirically test the Theory of Due Repurchase and subsequently examine its accuracy in predicting repurchase behaviour, five hypotheses were developed. The first hypothesis is that repurchase frequency differs significantly and is high when each of the three repurchase condition is satisfied (H_1). The second hypothesis is that the likelihood of the next purchase is associated more with satisfying the three conditions (H_2). The first and second hypotheses are formulated to establish the foundation for the Theory of Due Repurchase. The third hypothesis is that meeting none of the three repurchase conditions is associated more with the decision not to purchase (skip) (H_3). The fourth hypothesis is that repurchase frequency varies across customers satisfying different combinations of repurchase conditions, with customers satisfying all conditions being the most frequent shoppers (H_4). The third and fourth hypotheses are developed to furnish perspective into the Theory of Due Repurchase. The fifth hypothesis is that purchase frequency, LPQ and IPT homogeneity are predictors of repurchase behaviour and, together, correctly classify more customers than the best-performing behavioural model does (69%) (H_5). This hypothesis is developed to examine the predictive performance of the theory.

As discussed in Chapter 3, to test these hypotheses the thesis adopts a quantitative approach and uses longitudinal data. CDNOW, a well-known transaction dataset provided by Fader and Hardie (2001), has been utilised in this thesis. An existing CDNOW sample drawn by FHL (2005b) is used to test the hypotheses. The present thesis draws three large samples from the full CDNOW dataset and labels them Sample A, B and C for replication purposes. Six studies are conducted to test the hypotheses and replicate the findings.

In §3.4, the thesis elaborates on the measures used. While it utilises existing measures for repurchase behaviour, repurchase frequency and frequency of past purchases, it develops new measures for LPQ and IPT homogeneity as dichotomous variables. The cumulative average is used to measure whether the customer's PQ is increasing or decreasing. In addition, the thesis develops a new measure for IPT homogeneity as a dichotomous variable. This measure shows potential to solve, and control for the effect of, the "increasing frequency paradox" explained by FHL (2005a, pp.422-423).

In §4.1, Study 1 is conducted to establish the foundation of the Theory of Due Repurchase. Evidence supporting H_1 and H_2 is found, showing that repurchase frequency is different and higher when the consumer is a frequent shopper, having an upward-trending PQ, and having homogeneous IPTs. The study also found that simultaneously satisfying these three repurchase conditions is significantly and strongly associated with the choice to repurchase. These findings are replicated in Study 2.

In §4.3, Study 3 is run to challenge and furnish a perspective of the Theory of Due Repurchase. It found evidence supporting H_3 and H_4, revealing that satisfying none of the three conditions is significantly and strongly associated with the choice to skip the purchase. Also, it finds that repurchase frequency differs significantly between customers meeting all repurchase conditions and others; those satisfying all repurchase conditions have the highest repurchase frequency. Study 4 replicates Study 3.

Conducted to examine the predictive performance of Theory of Due Repurchase, Study 5's results provide evidence supporting H_5, as shown in §4.5. The study runs a logistic regression analysis to identify whether repurchase behaviour is determined by purchase frequency, LPQ and IPT homogeneity, and whether these factors accurately predict it. The results show that the probability of repurchase changes in response to variations in the three variables. It increases when shopping more frequently, and when times between purchases become more homogenous. It decreases when the LPQ is higher than usual. While significant and well fit, the model correctly classifies over 88% of customers. The predictive validity test reveals that the percentage of correct classifications in the validation sample is high and similar to the one in the estimation sample. Along with replicating all these findings in Study 6, these theoretical and empirical robustness checks led to the conclusion that the model is robust and generalizable.

As found in §4.5 and replicated in §4.6, the predictive accuracy of the Theory of Due Repurchase is higher than the predictive accuracy of existing behaviour-behaviour models. Whereas the best performing behaviour-based model could correctly classify 69% of customers (Van den Poel, 2003), Theory of Due Repurchase correctly classifies over 88% of customers, with this rate being consistent across the samples. This improves the current level of predictive accuracy by about 19 percentage points.

As explained in §5.1.2, factors contributing to this improvement may include the number of predictors in the model, as well as the inclusion of LPQ. The computational performance of the models is better when the model is built on fewer predictors, allowing the algorithms to gain more predictive power (Viaene et al., 2001). The inclusion of LPQ adds predictive value as it captures the customer's behavioural commitment and consumption plans.

As stated by Baesens et al. (2002), and underscored by Van den Poel (2003), this improvement in customer predictability could raise profits substantially. Retailers can 'gain more from using less' thought reallocating their resources and investing in the underutilised purchase-history data. Knowing who existing customers really are, and which of them is more likely to respond than others, should result in a major reduction in the marketing spend and increases in profits.

6.2 Managerial Implications

In §5.3, the thesis suggests that the marketing costs can be reduced significantly, while improving the return on marketing investment (ROMI) figures. It has been found in §4.3 and §4.4 that customers (24%) satisfying all repurchase conditions (Scenario 1)[8] and those (22%) satisfying none of them (Scenario 8) make up 46% of the sample. Those in Scenario 1 have a 91% probability of repurchasing, whereas those in Scenario 8 have a 98% probability of skipping the purchase. In addition, about 24% of the sample is accounted for by customers who are infrequent shoppers but have increasing PQs (Scenarios 5 and 7), and others who are infrequent shoppers, have downward-trending PQs and heterogeneous IPTs (Scenario 6). Surprisingly, customers in Scenarios 5 and 7 have a 100% probability of repurchasing as all of them did, indeed, repurchase. On the other hand, customers in Scenario 6 have a 100% probability of not purchasing as all of them did skip their purchases. Therefore, targeting customers in Scenarios 1, 5 and 7 is investing the marketing dollar on 40% (23%+8%+9%) of existing customers who are more than 90% likely to respond favourably. Given that customers in Scenario 6 have 0% chance of repurchasing, avoiding communication with customers in Scenarios 6 and 8 saves the cost of targeting about 30% (7.9%+22%) of existing customers who are 98% unlikely to respond.

When calculating the probability of repurchasing for each customer across four datasets using the regression model's estimates, a clear pattern emerges, as shown in §4.5 and §4.6. That is, the higher the predicted probability, the more accurate the model's predictions become. The precision of the Theory of Due Repurchase in identifying

[8] Refer to Table 4.3

customers who are more likely to repurchase appears satisfactory. Those with 50% repurchase probability constitute around 34% of customers, whereas others with 90% repurchase probability account for 17% of customers. Consistent across the samples, about three-quarters of customers whose calculated repurchase probability is above 50% did repurchase, while the vast majority (about 85%) of customers whose calculated repurchase probability is above 90% did, in fact, repurchase. Therefore, a marketer may choose the level of precision based on the predicted probability; the higher level of repurchase probability, the fewer the target customers, the more precise the predictions are, and the lower the non-response rate.

6.3 Research Limitations

Although the transaction dataset utilised in this thesis is still acceptable and recently used in the literature (Abe, 2009; Ma & Büschken, 2011; Zhang et al., 2015), it is considered a source of limitations. First, the data were collected late in the 1990s. The intervening time is a period during which the global economy and consumers experienced many significant changes, including the global financial crisis in 2008 and the increasing reliance on electronic devices and smart phones. It is likely that consumers' purchasing power and behaviour have changed accordingly. Marketing practitioners may need to try the model first on a group of customers with recent purchase histories before applying it to the entire customer base. Second, the effect of product category has not been controlled for, as the dataset contains the purchase data of only one product category, namely music. Music is not a necessity; consumers of music could be differently involved in this culture and have significantly different preferences which also change over time. Thus, caution should be taken when applying the theory to customers buying different product categories. Third, the data are purchase transactions made online, which is a different context to offline purchase transactions. Because differences between online and offline shopping behaviours exist (Danaher, Wilson & Davis, 2003; Degeratu, Rangaswamy & Wu, 2000; Levin, Levin & Weller, 2005), marketers should pay attention to these differences when applying the theory to offline customers. Finally, the dataset contains data of one cohort of customers only which, according to FHL (2005a), may not be representative of all customers. Assuming that this is the case, unobserved heterogeneity could have a stronger effect on the model's estimates.

6.4 Future Research

There are a number of areas future research can focus on. At this stage, however, the most important step to take is to replicate the studies in this thesis using more recent transaction data, different product categories, and/or offline purchase histories. All these should further increase the generalisability of the Theory of Due Repurchase, as well as provide more insights into it. Additionally, future research could investigate the links between Theory of Due Repurchase and other behavioural frameworks such as RFM, as well as compare the frameworks to each other. Such research should enhance knowledge on customer predictability. Another area of research interest is explaining the psychology behind the Theory of Due Repurchase. Researchers could study the drivers of being a loyal customer while being an infrequent shopper, having a more/less than usual LPQ, and/or IPTs becoming more/less homogeneous. In addition, extending the Theory of Due Repurchase is one area of future research. Adding new variables that may further explain relationships and/or improve the predictive accuracy might be required. Future research could also examine what the optimal level of the calculated repurchase probability is. When targeting customers using the regression model's estimates, accuracy of prediction is traded-off with the number of target customers.

Finding the optimal level of repurchase probability that results in a satisfying accuracy and a large-enough number of target customers is of scientific and managerial interest.

7 References

Abe, M. (2009). “Counting your customers” one-by-one: A hierarchical Bayes extension to the Pareto/NBD model. *Marketing Science*, *28*(3), 541-553.

Ajzen, I. (1988). *Attitudes, personality and behavior*. Chicago, IL: Dorsey Press.

Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behavior and Human Decision Processes*, *50*, 179-211.

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behaviour*. Englewood Cliffs, NJ: Prentice-Hall.

Al-Shayea, Q. K., & Al- Shayea, T. L. (2014). Customer behavior on RFMT model using neural Networks. *Proceedings of the World Congress on Engineering*, *1*, 49-52.

Anderson, E. W., Fornell, C., & Lehmann, D. R. (1994). Customer satisfaction, market share, and profitability: Findings from Sweden. *Journal of Marketing*, *58*(3), 53-66.

Baesens, B., Viaene, S., Van den Poel, D., Vanthienen, J., & Dedene, G. (2002). Bayesian neural network learning for repeat purchase modelling in direct marketing. *European Journal of Operational Research*, *138*(1), 191-211.

Bagozzi, R. P., & Warshaw, P. R. (1990). Trying to consume. *Journal of Consumer Research*, *17*(2), 127-140.

Beasley, F. M. (1998). An examination of stockpiling behaviour in response to price deals. *Academy of Marketing Studies Journal*, *2*(1), 23-34.

Beasley, F. M., & Shank, M. D. (1994). An examination of the incidence of purchase quantity and timing acceleration. *Journal of Promotion Marketing*, *2*(3/4), 89-103.

Berg, G. D., & Mansley, E. C. (2004). Endogeneity bias in the absence of unobserved Heterogeneity. *Annals of epidemiology*, *14*(8), 561-565.

Bergès, F., & Orozco, V. (2010). Measures of store loyalty in French food retailing. *Review of Agricultural and Environmental Studies*, *91*(3), 261-277.

Blattberg, R. C., Kim, B. D., & Neslin, S. A. (2008). *Why database marketing?* New York, NY: Springer.

Boatwright, P., Borle, S., & Kadane, J. B. (2003). A model of the joint distribution of the purchase quantity and timing. *Journal of the American Statistical Association*, *98*(463), 564-572.

Broderick, A. J., Greenley, G. E., & Mueller, R. D. (2007). The behavioural homogeneity evaluation framework: Multi-level evaluations of consumer involvement in international segmentation. *Journal of International Business Studies*, *38*(5), 746-763.

Buchanan, R. W. T., & Gillies, C. S. (1990). Value managed relationship: The key to customer retention and profitability. *European Management Journal*, *8*(4), 523-526.

Buckinx, W., & Van den Poel, D. (2005). Customer base analysis: Partial defection of behaviourally loyal clients in a non-contractual FMCG retail setting. *European Journal of Operational Research*, *164*(1), 252-268.

Bult, J. R. (1993). Semiparametric versus parametric classification models: An application to direct marketing. *Journal of Marketing Research*, *30*(3), 380-390.

Calkins, S. (1983). The new merger guidelines and Herfindahl-Hirschman Index. *California Law Review*, *71*(2), 402-429.

Chintagunta, P. K. (1993). Investigating purchase incidence, brand choice and purchase quantity decisions of households. *Marketing Science*, *12*(2), 184-208.

Coussement, K., Van den Bossche, F. A., & De Bock, K. W. (2014). Data accuracy's impact on segmentation performance: Benchmarking RFM analysis, logistic regression, and decision trees. *Journal of Business Research*, *67*(1), 2751-2758.

Cramer, J. S. (2007). Robustness of logit analysis: Unobserved heterogeneity and misspecified Disturbances. *Oxford Bulletin of Economics and Statistics*, *69*(4), 545-555.

Danaher, P. J., Wilson, I. W., & Davis, R. A. (2003). A comparison of online and offline consumer brand loyalty. *Marketing Science*, *22*(4), 461-476.

Day, D., Gan, B., Gendall, P., & Esslemont, D. (1991). Predicting purchase behaviour. *Marketing Bulletin*, *2*, 18-30.

De Cannière, M. H., De Pelsmacker, P., & Geuens, M. (2009). Relationship quality and the Theory of Planned Behavior models of behavioral intentions and purchase behaviour. *Journal of Business Research*, *62*, 82-92.

Degeratu, A. M., Rangaswamy, A., & Wu, J. (2000). Consumer choice behavior in online and traditional supermarkets: The effects of brand name, price, and other search attributes. *International Journal of research in Marketing*, *17*(1), 55-78.

D’Haen, J., Van den Poel, D., & Thorleuchter, D. (2013). Predicting customer profitability during acquisition: Finding the optimal combination of data source and data mining technique. *Expert systems with applications*, *40*(6), 2007-2012.

Drossaert, C. H. C., Boer, H., & Seydel, E. R. (2003). Prospective study on the determinants of repeat attendance and attendance patterns in breast cancer screening using the theory of planned behaviour. *Psychology and Health*, *18*(5), 551-565.

East, R., Gendall, P., Hammond, K., & Lomax, W. (2005). Consumer loyalty: Singular or interactive? *Australian Marketing Journal*, *13*(2), 10-26.

Fader, P. S., & Hardie, B. G. S. (2001). Forecasting repeat sales at CDNOW: A case study. *Interfaces*, *31*(May-June), S94-S107.

Fader, P. S., & Hardie, B. G. S. (2009). Probability models for customer base analysis. *Journal Interactive Marketing*, *23*, 61-69.

Fader, P. S., Hardie, B. G. S., & Lee, K. L. (2005a). RFM and CLV: Using iso-value curves for customer base analysis. *Journal of Marketing Research*, *42*(4), 415-430.

Fader, P. S., Hardie, B. G. S., & Lee, K. L. (2005b). "Counting your customers" the easy way: An alternative to the Pareto NBD model. *Marketing Science*, *24*(2), 275-284.

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.

Frank, R. E., & Strain, C. E. (1972). A segmentation research design using consumer panel data. *Journal of Marketing Research*, *9*(4), 385-390.

Ghani, R., Probst, K., Liu, Y., Krema, M., & Fano, A. (2006). Text mining for product attribute Extraction. *ACM SIGKDD Explorations Newsletter*, *8*(1), 41-48.

Grewal, D., Levy, M., & Kumar, V. (2009). Customer experience management in retailing: An organizing framework. *Journal of Retailing*, *85*(1), 1-14.

Gupta, S. (1988). Impact of sales promotions on when, what, and how much to buy. *Journal of Marketing Research*, *25*(4), 342-355.

Gupta, S. (1991). Stochastic models of interpurchase time with time-dependent covariates, *Journal of Marketing Research, 28*(1), 1-15.

Han, H., & Ryu, K. (2012). The theory of repurchase decision-making (TRD): Identifying the critical factors in the post-purchase decision-making process. *International Journal of Hospitality Management*, *31*, 786-797.

Helsen, K., & Schmittlein, D. C. (1992), Some characteristics of stockpiling behaviour under Uncertainty. *Marketing Letters*, *3*(1), 5-16.

Hughes, A. M. (2000). *Strategic database marketing: The masterplan for starting and managing a profitable, custom-based marketing program* (2nd ed.). New York, NY: McGraw-Hill.

Hyman, D. A., & Kovacic, W. E. (2004). Monopoly, monopsony, and market definition: An antitrust perspective on market concentration among health insurers. *Health Affairs*, *23*(6), 25-28.

Jebarajakirthy, C., & Thaichon, P. (2016). Marketing microcredit to bottom of the pyramid Market. *International Journal of Bank Marketing*, *34*(2), 191-215.

Jen, L., Chou, C. H., & Allenby, G. M. (2009). The importance of modeling temporal dependence of timing and quantity in direct marketing. *Journal of Marketing Research*, *46*(4), 482-493.

Kotler, P. (1972). A generic concept of marketing. *Journal of Marketing*, *36*(2), 46-54.

Krishnamurthi, L., & Raj, S. P. (1988). A model of brand choice and purchase quantity price sensitivities. *Marketing Science*, *7*(1), 1-20.

Laroche, M., Pons, F., Zgolli, N., & Kim, C. (2001). Consumers use of price promotions: A model and its potential moderators. *Journal of Retailing and Consumer Services*, *8*, 251-260.

Levin, A. M., Levin, I. P., & Weller, J. A. (2005). A multi-attribute analysis of preferences for online and offline shopping: Differences across products, consumers, and shopping stages. *Journal of Electronic Commerce Research*, *6*(4), 281.

Levin, N., & Zahavi, J. (1998). Continuous predictive modelling- A comparative analysis. *Journal of Interactive Marketing*, *12*(2), 5-22.

Lucas, J. W. (2003). Theory-testing, generalization, and the problem of external validity. *Sociological Theory*, *21*(3), 236-253.

Lumsden, S. A., Beldona, S., & Morrison, A. M. (2008). Customer value in an all-inclusive travel vacation club: An application of the RFM framework. *Journal of Hospitality & Leisure Marketing*, *16*(3), 271-285.

Ma, S., & Büschken, J. (2011). Counting your customers from an "always a share" perspective. *Marketing Letters*, *22*(3), 243-257.

Mackey, A. (2012). Why (or why not), when, and how to replicate research. In G. Porte (Ed.), *Replication research in applied linguistics* (pp. 21-30). Cambridge, England: Cambridge University Press.

Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A comparison of the Theory of Planned Behavior and the Theory of Reasoned Action. *Personality and Social Psychology Bulletin*, *18*(1), 3-9.

Marcus, C. (1998). A practical yet meaningful approach to customer segmentation. *Journal of Consumer Marketing*, *15*(5), 494-504.

Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, *26*(1), 67-82.

Nash, E. L. (1994). *Direct marketing: Strategy, planning, execution* (3rd ed.). New York, NY: McGraw- Hill.

Neslin, S. A., Henderson, C., & Quelch, J. (1985). Consumer promotion and the acceleration of product purchases. *Marketing Science*, *4*(2), 147-165.

Ouellette, J., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behaviour. *Psychological Bulletin*, *124*, 54-74.

Pauwels, K., Hanssens, D. M., & Siddarth, S. (2002). The long-term effects of price promotions on category incidence, brand choice, and purchase quantity. *Journal of Marketing Research*, *39*(4), 421-439.

Payne, A. (1994). Relationship marketing- Making the customer count. *Managing Service Quality*, *4*(6), 29-31.

Peng, C. Y. J., & So, T. S. H. (2002). Logistic regression analysis and reporting: A primer. *Understanding Statistics: Statistical Issues in Psychology, Education, and the Social Sciences*, *1*(1), 31-70.

Peoples, G. (2013, May 1). Business matters: Nielsen study examines who is buying music, media. *Billboard*. Retrieved from http://www.billboard.com/biz/articles/1560117/business-matters-nielsen-study-examines-who-is-buying-music-media

Perugini, M., & Bagozzi, R. P. (2001). The role of desires and anticipated emotions in goal-directed behaviours: Broadening and deepening the theory of planned behaviour. *British Journal of Social Psychology*, *40*, 79-98.

Peterson, R. A., & Wilson, W. R. (1992). Measuring customer satisfaction: Fact and artifact. *Journal of the Academy of Marketing Science*, *91*(1), 61-71.

Puccinelli, N. M., Goodstein, R. C., Grewal, D., Price, R., Raghubir, P., & Stewart, D. (2009). Customer experience management: Understanding the buying process. *Journal of Retailing*, *85*, 15-30.

Radjou, N., & Jaideep, P. (2015). *Frugal innovation: How to do more with less* [Kindle version]. Retrieved from http://reader.eblib.com.au.ezproxy.massey.ac.nz/(S(5c25rwt1x3mgzloiduiwqurg))/Reader.aspx?p=1809787&o=76&u=8dk5dLNT67J9rAWYWGPmMw%3d%3d&t=1428457295&h=92DC495658DB1C7026A8D4BD2ED4F7432BB5DE9C&s=18037450&ut=173&pg=1&r=img&c=-1&pat=n&cms=-1&sd=1

Rao, V. R., & Sabavala, D. J. (1981). Inference of hierarchical choice processes from panel data. *Journal of Consumer Research*, *8*(1), 85-96.

Reichheld, F. F. (1996). Learning from customer defections. *Harvard Business Review*, *74*(2), 56-69.

Rhoades, S. A. (1993). The Herfindahl-Hirschman index [technical note]. *Federal Reserve Bulletin*, *1*, 188-189.

Schoenbachler, D. D., Gordon, G. L., Foley, D., & Spellman, L. (1997). Understanding consumer database marketing. *Journal of Consumer Marketing*, *14*(1), 5-19.

Sharma, A. (2007). The metrics of relationships: Measuring satisfaction, loyalty, and profitability of relational customers. *Journal of Relationship Marketing*, *6*(2), 33-50.

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The Theory of Reasoned Action: A meta-analysis of past research with recommendations for modifications and future research. *Journal of Consumer Research*, *15*(3), 325-343.

Simonson, I., & Winer, R. S. (1992). The influence of purchase quantity and display format on consumer preference for variety. *Journal of Consumer Research*, *19*(1), 133-138.

Sutton, S. (1998). Predicting and explaining intentions and behavior: How well are we doing? *Journal of Applied Social Psychology*, *28*(15), 1317-1338.

Thompson, S. K. (1990). Adaptive cluster sampling. *Journal of the American Statistical Association*, *85*(412), 1050-1059.

Tu, J. V. (1996). Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes, *Journal of Clinical Epidemiology*, *49*(11), 1225-1231.

Van den Poel, D. (2003). Predicting mail-order repeat buying: Which variables matter? *Tijdschrift voor Economie en Management*, *XLVIII*(3), 371-403.

Van Heerde, H. J., Leeflang, P. S. H., & Wittink, D. R. (2000). The estimation of pre- and post-promotion dips with store-level scanner data. *Journal of Marketing Research*, *37*(3), 383-395.

Viaene, S., Baesens, B., Van Gestel, T., Suykens, J. A. K., Van den Poel, D., Vanthienen, J., De Moor, B., & Dedene, G. (2001). Knowledge discovery in a direct marketing case using least squares support vector machines. *International Journal of Intelligent Systems*, *16*, 1023-1036.

Vilcassim, N. J., & Jain, D. C. (1991). Modeling purchase-timing and brand-switching behaviour incorporating explanatory variables and unobserved heterogeneity. *Journal of Marketing Research*, 29-41.

Wansink, B., Kent, R. J., & Hoch, S. J. (1998). An anchoring and adjustment model of purchase quantity decisions. *Journal of Marketing Research*, *35*(1), 71-87.

Weber, J. A. (2002). Managing the marketing budget in a cost-constraint environment. *Industrial Marketing Management*, *31*, 705-717.

Webster, F. E. (1992). The changing role of marketing in the corporation. *Journal of Marketing*, *56*(4), 1-17.

Wei, J. T., Lin, S. Y., & Wu, H. H. (2010). A review of the application of RFM model. *African Journal of Business Management*, *4*(19), 4199-4206.

Wheat, R. D., & Morrison, D. G. (1990). Assessing purchasing timing models: Whether or not is preferable to when. *Marketing Science*, *9*(2), 162-170.

Wójcik, J., & Doligalski, T. (2014). Facing complexity in online marketing on consumer market. In T. Marek (Eds.), *Advances in science, technology, higher education and society in the conceptual age: STHESCA* (pp. 269-276). Danvers, MA: AHFE Conference.

Zhang, Y., Bradlow, E. T., & Small, D. S. (2013). New measures of clumpiness for incidence Data. *Journal of Applied Statistics*, *40*(11), 2533-2548.

Zhang, Y., Bradlow, E. T., & Small, D. S. (2015). Predicting customer value using clumpiness: From RFM to RFMC. *Marketing Science*, *34*(2), 195-208.

Zineldin, M. (2006). The royalty of the loyalty: CRM, quality and retention. *Journal of Consumer Marketing*, *23*(6), 430-437.

8 Appendices

8.1 Low-risk Notification

MASSEY UNIVERSITY
ALBANY

1 September 2015

Hussam Aldoaigan
36 Namsan Close
Fairview Heights
Auckland 0632

Dear Hussam

Re: Theory of Due Purchase: RFM Roles in Predicting Repurchase Potential

Thank you for your Low Risk Notification which was received on 26 August 2015.

Your project has been recorded on the Low Risk Database which is reported in the Annual Report of the Massey University Human Ethics Committees.

You are reminded that staff researchers and supervisors are fully responsible for ensuring that the information in the low risk notification has met the requirements and guidelines for submission of a low risk notification.

The low risk notification for this project is valid for a maximum of three years.

Please notify me if situations subsequently occur which cause you to reconsider your initial ethical analysis that it is safe to proceed without approval by one of the University's Human Ethics Committees.

Please note that travel undertaken by students must be approved by the supervisor and the relevant Pro Vice-Chancellor and be in accordance with the Policy and Procedures for Course-Related Student Travel Overseas. In addition, the supervisor must advise the University's Insurance Officer.

A reminder to include the following statement on all public documents:

"This project has been evaluated by peer review and judged to be low risk. Consequently, it has not been reviewed by one of the University's Human Ethics Committees. The researcher(s) named above are responsible for the ethical conduct of this research.

If you have any concerns about the conduct of this research that you wish to raise with someone other than the researcher(s), please contact Dr Brian Finch, Director (Research Ethics), telephone 06 356 9099, extn 86015, e-mail humanethics@massey.ac.nz".

Please note that if a sponsoring organisation, funding authority or a journal in which you wish to publish requires evidence of committee approval (with an approval number), you will have to provide a full application to one of the University's Human Ethics Committees. You should also note that such an approval can only be provided prior to the commencement of the research.

Yours sincerely

B T Finch.

Brian T Finch (Dr)
Chair, Human Ethics Chairs' Committee and
Director (Research Ethics)

cc Dr Andrew Murphy and Associate Professor Jonathon Elms
School of Communication, Journalism and Marketing
Albany Campus

Professor Shiv Ganesh
Head of School of Communication, Journalism and Marketing
Albany Campus

Massey University Human Ethics Committee
Accredited by the Health Research Council

8.2 A Replication of FHL's (2005b) study

Following the instructions provided in FHL (2005a, 2005b), three samples are used to replicate the Beta-Geometric Negative Binomial Distribution (BG/NBD) model developed by FHL (2005b) to predict purchase transactions. The samples are the 1/10th Sample drawn by FHL (2005b), and Sample A and Sample B, which are drawn in this thesis.

Table 8.1 shows the parameter estimates, along with their log-likelihood (LL) values, and compares them across samples starting with the 1/10th sample drawn by FHL (2005a). It should be mentioned that the size of Samples A and B is much larger than the size of the 1/10th sample, which may explain the high LL values.

The table (8.1) supports FHL's method of treating "same-day" transactions as one transaction (combining them, which means a reduction in Frequency/number of transactions). According to the results presented in Table 8.1, the BG/NBD model is better fit to the data when inter-purchase time (IPT) ≠ 0 (LL= -9,740.1 < LL= -9,582.4).

Table 8.1: Model Estimation Results

	FHL (2005)	1/10th Sample	1/10th Sample **(IPT = 0)**	Sample A	Sample B
r	0.243	0.243	0.218	0.101	0.093
α	4.414	4.414	3.273	0.300	0.214
a	0.793	0.793	0.799	0.999	0.999
b	2.426	2.426	2.272	2.766	2.734
LL	*-9,582.4*	*-9,582.4*	*-9,740.1*	*-25,809.6*	*-25,056.6*

FHL (2005b, p. 281) used the chart in Figure 8.1 to present their findings and, visually, examine the fit of BG/NBD and Pareto-NBD models. Unfortunately, it is not possible to obtain the exact same statistics, not only because this "requires a single evaluation of Gaussian Hypergeometric function for any customer of interest" (FHL, 2005b, p.279), but also because information about past observed behaviour ($X = (x, t_x, T)$) used by

FHL is unknown. In other words, the exact same numbers as in FHL (2005b) cannot be obtained.

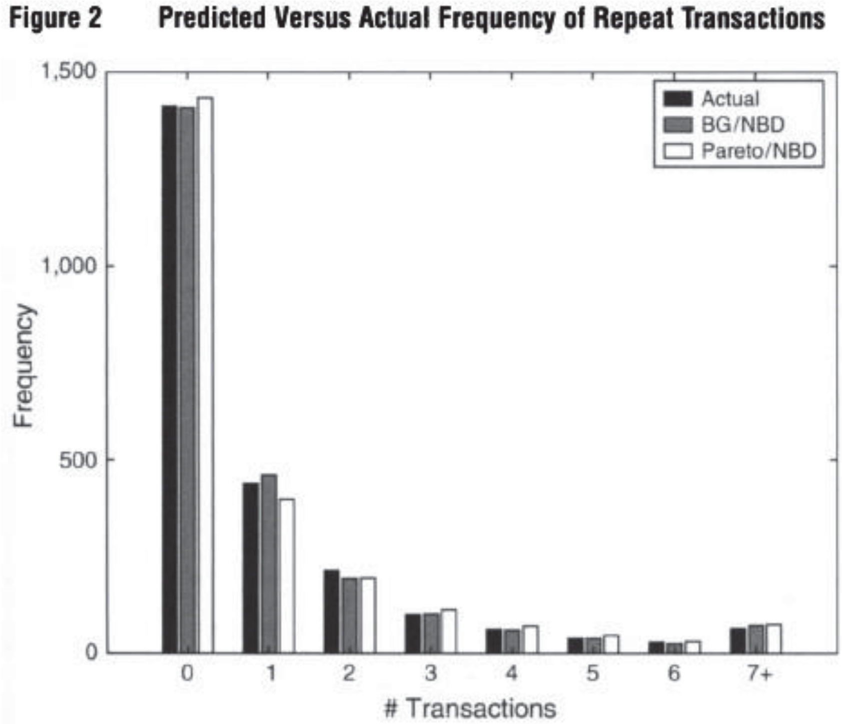

Figure 8.1: Fader et al., 2005b, p.281

Holding t_x $(recency)$ $and\ T$ (time period over which the behaviour is observed) constant, however, the results of applying the GB-NBD model to the 1/10th Sample used in FHL (2005b) and to Samples A and B are presented in Figure 8.2. The clustered charts in Figure 8.2 show the BG/NBD model's prediction of the numbers of people making 0,…7+ transactions in the 39-week calibration period and compare it to the actual frequency/percentage. The charts on the left present the results in frequency, while the ones on the right show the results in percentages.

Overall, these findings appear to replicate FHL's findings. The GB-NBD model's overall performance in this study is not as good as in FHL (2005b); however, it tells the same story and does not seem significantly affected by the identified outlier. Although the GB-NBD tends to overestimate the number of future purchasers with one repeat transaction, it does not completely fail in predicting the numbers of people making 0, 2, 3, 4, 5, 6 and 7+ transactions.

All in all, the results across the three samples are, to a great extent, similar to each other and resemble FHL's (2005b) findings.

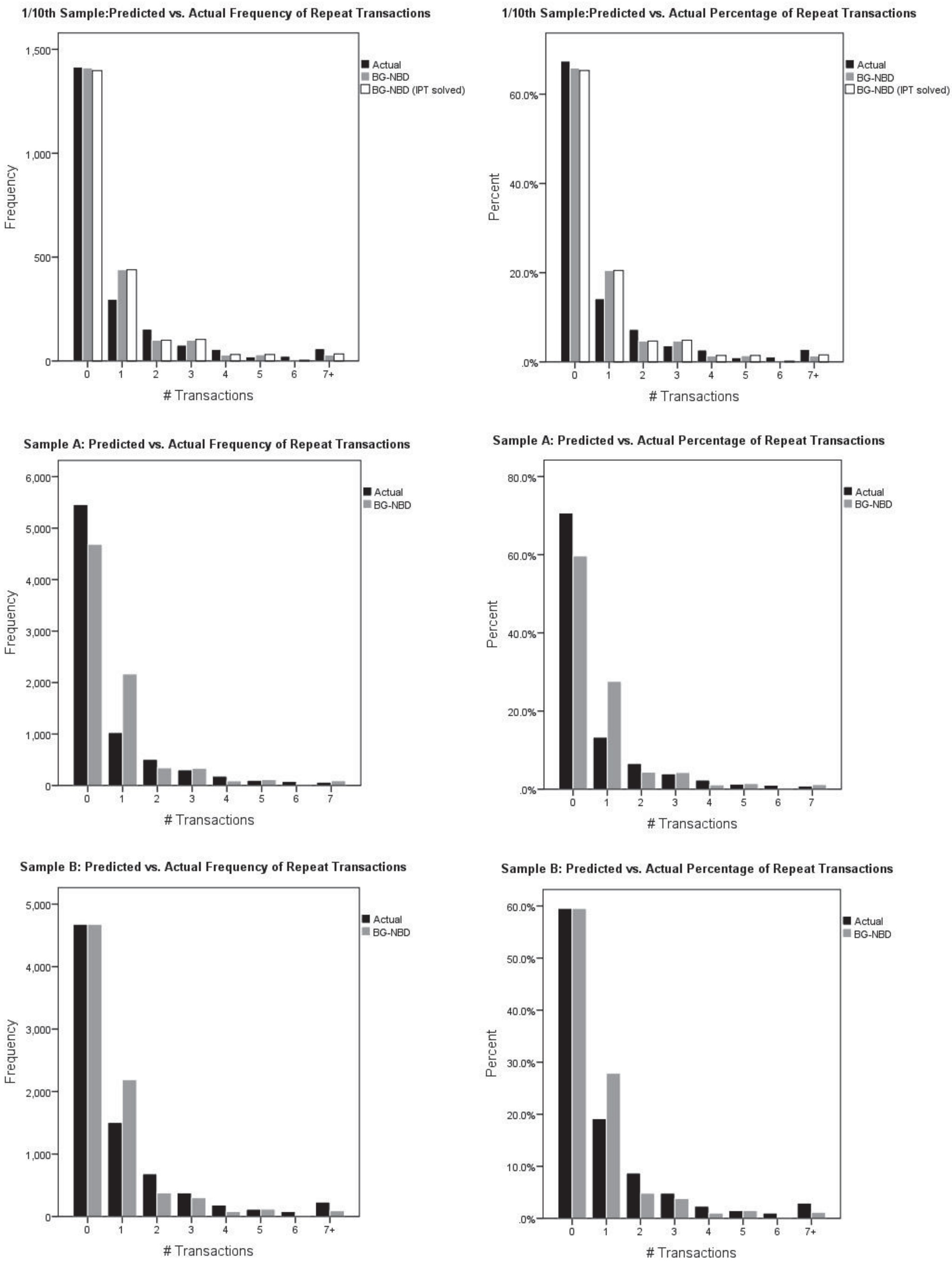

Figure 8.2: Predicted vs. Actual Frequency/Percentage of Repeat Transactions across Three Samples

8.3 Clumpiness Effect

Table 4.10 presents the results of testing the developed logistic regression model across the four samples. The effects of control variables on repurchase behaviour are inconsistent across the four samples. It is worth pointing out how the clumpiness measure performs. The clumpiness effect on repurchase behaviour is insignificant and positive in FHL's 1/10th Sample, whereas it is significant and negative in Samples A, B and C.

When testing the effect of clumpiness on future frequency of purchasing, Zhang et al. (2015) used six different samples and found similar results to those found in this thesis. That is, the effect of visitation-based clumpiness is insignificant in two samples, namely CDNow and Mecoxlane, while it is significant in the other samples, which are Hulu, YouTube, Amazon and eBay. ZBS (2015) ascribe this insignificant effect of clumpiness to the fact that CDNow and Mecoxlane are traditional retailers. They (2015, p.207) then concluded that "the clumpiness phenomenon is widely prevalent on the Internet or at least is worth exploring".

One factor that has been overlooked and needs exploring is the sample size. The sample size seems to play a role in determining the significance of the clumpiness effect. Table 8.2 summarises the performance of the clumpiness measure across 10 samples. As shown, clumpiness has no significant effect on future purchasing behaviour in CDNow, Mecoxlane and the 1/10th Sample. These three samples are small relative to other samples. It is important to point out that the large size of other samples is not due to the length of the period over which the data are collected. Referring to Table 8.2, the length of the period analysed does not seem to play a significant role in capturing the clumpiness phenomenon, while the sample size does.

Table 8.2: The Performance of the Clumpiness Measure across 10 Samples

Sample	Source	Size (customers)	Period	Significance
CDNow	ZBS (2015)	500	18 months	No
Mecoxlane	ZBS (2015)	180	13 months	No
Hulu	ZBS (2015)	1,000	12 months	Yes
YouTube	ZBS (2015)	5,000	12 months	Yes
Amazon	ZBS (2015)	5,000	12 months	Yes
eBay	ZBS (2015)	5,000	12 months	Yes
1/10th Sample	FHL (2005b)	958	18 months	No
A	This Thesis	3,166	18 months	Yes
B	This Thesis	3,175	18 months	Yes
C	This Thesis	3,259	18 months	Yes