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Predicting Purchase Timing, Brand Choice and Purchase Amount of Firm Adoption of Radically Innovative Information Technology: A Business to Business Empirical Analysis

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PREDICTING PURCHASE TIMING, BRAND CHOICE AND PURCHASE AMOUNT OF FIRM ADOPTION OF RADICALLY INNOVATIVE INFORMATION TECHNOLOGY: A BUSINESS TO BUSINESS EMPIRICAL ANALYSIS

BY

TIMOTHY RICHARD BOHLING

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ACCEPTANCE

This dissertation was prepared under the direction of the TIMOTHY RICHARD BOHLING Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Executive Doctorate in Business in the J. Mack Robinson College of Business of Georgia State University.

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PREDICTING PURCHASE TIMING, BRAND CHOICE AND PURCHASE AMOUNT OF FIRM ADOPTION OF RADICALLY INNOVATIVE INFORMATION TECHNOLOGY: A BUSINESS TO BUSINESS EMPIRICAL ANALYSIS

BY

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Knowing what to sell, when to sell, and to whom to sell is essential buyer behavior insight to allocate scarce marketing resources efficiently and effectively. Applying the theory of relationship marketing (Morgan and Hunt 1994), this study seeks to investigate the link between commitment and trust and firm adoption of radically innovative information technology (IT). The construct of radical innovation is operationalized through the use of cloud computing. A review of the vast scholarly literature on radical innovation diffusion and adoption, and modeling techniques used to analyze buyer behavior is followed by empirical estimation of each of the radical innovation adoption questions of purchase timing, brand choice, and purchase amount. Then, the inefficiencies in the independent model process are highlighted, suggesting the need for an integrated model. Next, an integrated model is developed to link the purchase timing, brand choice, and purchase amount decisions. The essay concludes with insight for marketing practitioners on the strength of the factors of commitment and trust on adoption of radical innovation, an improved methodology for the business-to-business marketing literature, and potential further research paths.

CHAPTER I: INTRODUCTION

This section will center the thesis topic of predicting purchase timing, brand choice, and purchase amount of firm adoption of radically innovative IT within the business context and scholarly research field.

I.I BUSINESS DOMAIN

Marketing managers continuously seek to deliver increased return on investment from constrained operating budgets. Investment decisions include trade-offs between initiatives to acquire new clients and initiatives to drive deeper relationships from existing clients. A key ingredient to improve decision making performance for marketing managers is knowledge of both current and anticipated buyer behavior. The tenets of relationship marketing, based on the foundations of commitment and trust (Morgan and Hunt 1994), drive both the framework chosen in this study and the choice of the drivers that will predict firm adoption of radically innovative IT from a specific cloud provider through purchase timing, brand choice, and purchase amount models. The marketing practitioner questions that this study answers include the following: which commitment and trust factors are associated with firm adoption of radically innovative IT? When is this adoption likely to happen? And, how much annual revenue are these firms anticipated to spend on the adoption of radically innovative IT?

With the adoption of cloud computing, firm IT consumption buyer behavior changes dramatically. The National Institute of Standards and Technology (2011) defines cloud computing as “a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.” Conceptually, cloud computing is a paradigm shift in IT delivery and computing consumption whereby computing resources and underlying technical infrastructure are abstracted away from the user.

Marketing practitioners who aim to attract buyers of this new IT consumption model will benefit greatly from knowing the importance of commitment and trust factors on adoption of radical innovation, as well as which analytic modeling technique can predict purchase timing, brand choice and purchase amount for firm adoption of radically innovative IT.

I.II SCHOLARLY RESEARCH

Radical innovation is defined as innovation that incorporates a substantially different core technology and provides substantially greater customer benefits than previous products in the industry (Chandy and Tellis 1998). For this study, cloud computing proximates radical innovation as guided by Armbrust, et. al. (2009), claiming that cloud computing has the potential to transform both a large part of the information technology industry and the long-held dream of computing utility. The literature on radical innovation is vast and covers multiple conventional disciplinary boundaries. Researchers have studied radical innovation from both a provider of innovation and an adopter of innovation, as well as from an individual and firm perspective (see Figure 1).

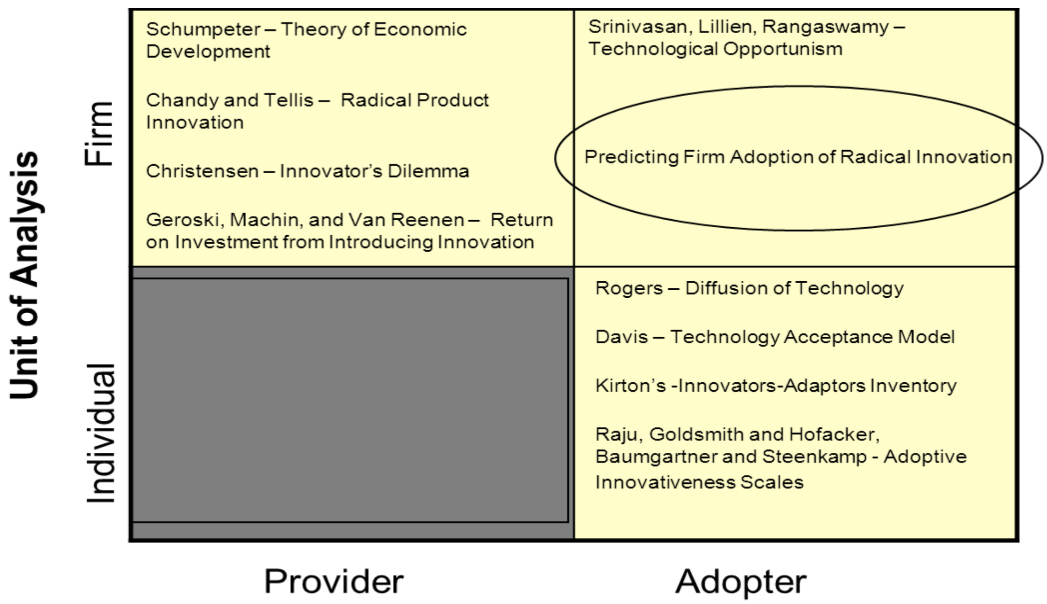
A comprehensive body of research on an organization's ability to innovate includes theories on radical innovation diffusion and the benefits which accrue to the provider of innovation. Schumpeter (1942) suggested that firm size is the key predictor of radical product innovation and is credited with initiating the theory that small, entrepreneurial firms are most likely to be the greatest source of innovation. Subsequent research in this field has been inconclusive on this point. Schumpeter (1950) later claimed that large, established firms that possess some degree of monopoly power are the stronger agents of technical progress given their superior access to capital and skilled labor and their ability to appropriate innovations from the smaller start-ups. Clayton Christensen (2000) posits that industry leading companies never introduce, or cope well with, disruptive innovations. Chandy and Tellis's (2000) research concluded that large firms and incumbents have introduced the majority of radical product innovations after World War II.

A deep stream of research focused on individual level adoption of radical innovation provides the following theories and innovativeness adoption measurement scales. Rogers (1995) suggests the innovation characteristics of relative advantage, compatibility, complexity, and observability, as perceived by individuals, help explain the individual rate of adoption and conclude that technological innovations are adopted at different times and at different rates. Additionally, Davis' (1989) well known Technology Acceptance Model (TAM) theorizes how perceived ease of use and perceived usefulness are key drivers of innovation adoption. Hauser, Tellis, and Griffin (2006) provide a taxonomy for innovation measurements including life innovativeness scales such as Kirston's (1976, 1989) innovators-adaptors inventory and various adoptive innovativeness scales (Raju 1980, Goldsmith and Hofacker 1991, and Baumgartner and Steenkamp 1996).

The research streams on firms as providers of innovation, and on individuals as adopters of innovation are robust and deep. The literature on firm-level adoption of radical innovation is much narrower. Srinivasan, Lillien, and Rangawamy (2002) provide the theory termed technological opportunism, positing that the differences in adoption of radical technologies among firms can be attributed to a sense-and-respond capability.

While these established theories provide knowledge on radical innovation diffusion and provider benefits, there are fewer scholarly papers focused on key drivers and techniques to predict firm-level adoption of innovation. This dissertation research, as shown in Figure 1, is designed to fill a gap in the literature and develop knowledge focused on identifying firms most likely to adopt radical innovation.

Figure 1: Radical Innovation Adoption Theory Matrix



From an analytic modeling perspective, there is extensive research in the field of marketing to deeply understand current and future buyer behaviors including purchase timing, brand choice, and purchase amount decisions in a variety of industries and business settings (Kumar and Man Luo 2008).

Within the purchase timing models, research has adopted the approach of whether to buy or when to buy, depending on the researcher's point of view. Additionally, research has studied cross-category dependence that captures a consumer's tendency to buy multiple products from certain categories. Therefore, depending on interest and modeling assumptions, a researcher can model timing through one of these approaches and decide whether or not to address multi-category dependence.

Academics and practitioners are interested in learning how a consumer's previous brand choice affects his or her future brand choice behavior. Research has addressed this issue through measurements of brand loyalty and lagged choice, among other techniques. A stream of research has also been dedicated exclusively to the investigation of state dependence.

Modeling purchase amount relies largely on the researcher's view of the dependence between choice and amount decisions. Multiple approaches employed include correcting for selection bias in the amount decision through a Heckman procedure, or using a bivariate logit model to jointly estimate amount and choice decisions.

Depending on the assumptions of the interdependence of the three decisions (purchase timing, brand choice, and purchase amount), analytic models are built either individually or jointly. Modeling the three decisions individually cannot account for the selection bias in purchase amount and brand choice, as the three decisions may not be independent given the same mechanism such as income, marketing response elasticity, or consumption pattern may drive these three decisions simultaneously. The jointly estimated model allows a firm to maximize utility over a period of time and therefore reflects dynamically changing firm purchase behavior.

CHAPTER II: LITERATURE REVIEW

This section provides a review of two major streams of scholarly literature. First, the vast body of knowledge on the introduction and adoption of radical innovation is presented. Next, the deep field of buyer behavior analytic modeling is reviewed. Major theories and contributions from the radical innovation literature, as well as the purchase timing, brand choice and purchase amount modeling literature are included.

II.I RADICAL INNOVATION

SUPPLY-SIDE PERSPECTIVE

The recent introduction of cloud computing has the potential to transform the delivery and consumption models in the IT industry (Armbrust, et. al 2009). Cloud computing represents substantially greater customer benefits, including easy access to best-in-class IT functions at lower cost points with flexible pricing structures, enhanced security and reliability, and rapid provisioning. Cloud computing conforms to Chandy and Tellis' (1998) definition of radical innovation, as cloud computing can provide a substantially different core technology model and substantially greater customer benefits than previous products in the IT industry.

Given the recent introduction of cloud computing into the marketplace, there are limited scholarly publications to date which focus specifically on cloud computing. However, mapping cloud computing to radical innovation opens up a plethora of scholarly publications. Several studies provide valuable insight into the provider-side factors related to the introduction of radical innovation into the marketplace. Theoretical constructs highlighted in the literature center on a firm's ability and willingness to introduce radical innovation.

Following Schumpeter (1942), many researchers have suggested that firm size is the key predictor of radical product innovation. Authors such as Galbraith (1952) and Ali (1994) have built on Schumpeter's arguments and suggest that large firms have many advantages over small firms in their ability to produce radical innovation. Large firms enjoy economies of scale in research and development, can spread risks widely, and have greater access to financial resources.

An additional factor is the greater degree to which incumbent firms are associated with radical innovations than non-incumbent firms. Chandy and Tellis (2000) challenged the common perception that large, incumbent firms rarely introduce radical product innovations, given such firms focus on solidifying their market positions with relatively incremental innovations. Moreover, Christensen (1997) posits that large companies, no matter what the source of their capabilities, are successful with evolutionary changes, although find serious trouble in handling disruptive innovation. Subsequent research by Chandy and Tellis (2000) concludes that since World War II, large firms and incumbents have introduced the majority of radical product innovations.

Supplementing the knowledge base focused on an organization's ability to introduce innovation are studies on organizational willingness to introduce innovation into the marketplace. Management's willingness to cannibalize (Chandy and Tellis 1998) can be a powerful driver of radical innovation. For example, when managers believe new technology is likely to make the existing products less competitive or even obsolete, they exhibit energetically innovative behavior.

The effect of introducing radical innovation on a firm's profits can be large, positive, and long-lasting (Geroski, Machin, and Van Reenen 1993). Insight from research in the pharmaceutical industry (Sorescu, Chandy, et. al. 2003) indicates that a large majority of radical innovation comes from a minority of firms, and the financial rewards of innovation are closely tied to a firm's resource base. Firms that have a greater depth and breadth in their product portfolio also gain from their radical innovations. Using data on more than 20,000 new products from the consumer packaged goods industry, Sorescu and Spanjol (2008) find that radical innovation is associated with increases in both normal profits and economic rents. Radical innovation is also associated with increases in the risk of the innovating firm, but this risk is offset by above-normal stock returns. In contrast, incremental innovation is associated with increases in normal profits only and has no impact on economic rents or firm risk.

In summary, the following theories provide valuable knowledge regarding radical innovation diffusion and provider benefits of introducing radical innovation into the marketplace.

- Large firms and incumbents have introduced the majority of radical product innovations since World War II (Chandy & Tellis 2000)
- Managerial expectations and willingness to cannibalize are factors that can be powerful drivers to providing radical innovation (Chandy and Tellis 1998)
- The effects of providing radical innovation on a firm's profits can be large, positive, and long-lasting (Geroski, Machin, and Van Reenen 1993)
- Radical innovation increases the financial risk of the innovating firm, but this risk is offset by above-normal stock returns (Sorescu and Spanjol 2008)

DEMAND-SIDE PERSPECTIVE

An additional body of scholarly research focuses on the individual level adoption of innovation. Davis' (1985) technology acceptance model (TAM) examined the mediating role of perceived ease of use and perceived usefulness in relation to information systems characteristics (external variables) and the probability of system use (an indicator of system success). More recently, Davis proposed a new version of his model (TAM2) which includes subjective norms and tested with longitudinal research designs. Legis, Ingham and Collerette (2001) posit that TAM is a useful model and should be integrated into a broader model that includes variables related to both human and social change processes.

For decades, researchers have developed and proposed innovation adoption measurement scales that differ in theoretical premise, internal structure, and purpose. Roehrich (2004) reviewed and classified the different scales into either life innovativeness scales or adoptive innovativeness scales. The life innovativeness scales focus on the propensity to innovate at a general behavioral level and describe attraction to any kind of newness and not to the adoption of specific products. Kirton's (1976, 1989) innovators-adaptor inventory (KAI) is the most popular of this set of scales. However, because it measures innovativeness in general, its predictive validity tends to be low (Roehrich 2004).

The adoptive innovativeness scales focus specifically on the adoption of new products. Examples of these scales are Raju (1980), Goldsmith and Hofacker (1991), and Baumgartner and Steenkamp 1996). Raju's (1980) scale has good internal consistency, but Baumgartner and Steenkamp (1996) criticize its structure. Goldsmith's and Hofacker's scale (1991) measures domain specific innovativeness, but Roehirch (2004) questions its discriminant validity. Despite extensive research, progress in this area has been hindered by a lack of consensus about the most appropriate scale.

Few scholarly research papers have been published on firm-level drivers of adoption of radical innovation. Most studies of firm-level adoption of innovation are performed to understand why some firms are more innovative than others, and therefore analyze characteristics of the firm's leader, the environment in which the firm operates, and structural factors such as firm decision making being centralized (Fichman 2001). Srinivasan, Lilien and Rangaswamy (2002) posit that differences in adoption levels of innovation among organizations can be attributed to the sense-and-respond capability of a firm, a difference they refer to as technological opportunism. A firm's future focus, top management's advocacy of new technologies and organizational culture, along with the external technological turbulence the firm is facing are the components of the conceptual model of technological opportunism.

While these theories provide valuable knowledge regarding radical innovation diffusion, provider benefits, and individual level adoption, there are fewer scholarly papers focused on firm behaviors or factors to predict firm-level adoption of radical innovation. This dissertation research is designed to investigate the utility of applying Morgan and Hunt's (1994) commitment-trust theory of relationship marketing to develop knowledge on predicting firm-level adoption of radical innovation. Armed with this understanding, practitioners can build and execute targeted marketing strategies to attract new clients and strengthen existing client relationships. With knowledge of a customer's behavior in terms of purchase timing, brand choice, and purchase amount, a firm can decide what to sell, when to sell, and to whom to sell in order to maximize profitability (Kumar, Venkatesan, and Reinartz 2006).

II.II MODELING PURCHASE TIMING, BRAND CHOICE AND PURCHASE AMOUNT

For decades, research has been published in the marketing literature focused on the key drivers of purchase behavior, including purchase timing, brand choice, and purchase amount. A firm's decision to purchase in a category often depends on the timing of the firm's previous purchase in that category, the decision to buy in a related category, marketing variables, and consumer heterogeneity. Similarly, the choice of brand is often determined by a firm's previous choice of brand through state dependence, the relative utilities of brands in the consideration set, marketing activities, and the firm's heterogeneous brand preference. Additionally, a firm's heterogeneous response to marketing variables and inventory level affects the purchase amount decision.

Robust literature exists (see Table 1) analyzing purchase timing, brand choice, and purchase amount decisions (Kumar and Man Luo's 2008). Most of the studies focus on business-to-consumer applications, while fewer studies model purchase decisions in a business-to-business application.

Table 1: Select Purchase Timing, Brand Choice, and Purchase Amount Models

Studies	Timing/ Incidence	Choice	Amount	Business Type
Neslin, Henderson, and Quelch (1985)	Yes		Yes	B-C
Krishnamurthi and Raj (1988)		Yes	Yes	B-C
Chiang (1991)	Yes	Yes	Yes	B-C
Bucklin and Gupta (1992)	Yes	Yes		B-C
Chintagunta (1993)	Yes	Yes	Yes	B-C
Tellis and Zufryden (1995)		Yes	Yes	B-C
Ainslie and Rossi (1998)	Yes	Yes		B-C
Arora, Allenby and Ginter (1998)	Yes	Yes	Yes	B-C
Boatwright, Borle, and Kadane (2003)	Yes		Yes	B-C
Zhang and Krishnamurthi (2004)	Yes	Yes	Yes	B-C
Kumar, Venkatesan, and Reinartz (2006)	Yes	Yes		B-B
Borle, Singh and Jain (2008)	Yes		Yes	B-C
Jen, Chou, Allenby (2009)	Yes		Yes	B-C
Andrews and Currim (2009)	Yes	Yes		B-C
Youngsoo, Telang, Vogt, Krishnana (2010)	Yes		Yes	B-C
Mehta, Chen, Narsimhan (2010)	Yes	Yes	Yes	B-C

The following paragraphs summarize the vast research providing insight into modeling purchase timing, brand choice, and purchase amount independently, and into analyzing these three decisions in an integrated model.

Purchase Timing

In order to model purchase timing, the researcher often decides between modeling a firm's decision of whether to buy or when to buy. As Table 2 shows, the general approaches to model whether to buy are either through a logit function for purchase timing decisions alone or a single utility function. To estimate when to buy, one can propose a parametric distribution for the elapsed time or capture such phenomena within the framework of a Hazard Function.

Table 2: Review of Purchase Timing Models

Research Interest	Specification	Representative Studies
Whether to buy	Logit	Bucklin and Gupta (1992)
		Zhang and Krishnamurthi (2004)
	Single utility function	Chiang (1991)
		Chintagunta (1993)
		Arora, Allenby and Ginter (1998)
		Andrews and Currim (2009)
		Jen, Chou, Allenby (2008)
		Mehta, Chen, Narsimhan (2010)
When to buy	Distribution of Elapse Time	Boatwright, Borle, and Kadane (2003) - CM Poisson
	Hazard function	Jain and Vilcassim (1991)
		Seetharaman and Chintagunta (2003)
		Kumar, Venkatesan, and Reinartz (2006)
		Ainsle and Rossi (1998)
		Borie, Singh, Jain (2008)
Overview of cross - category dependence		Manchanda, Ansari, and Gupta (1999)

Brand Choice

Lilien, Kotler, and Moorthy (2003) propose that most brand choice models differ in how they handle population heterogeneity, purchase-event feedback, and exogenous market factors. The authors define this difference by specifying which marketing factors should be included in the model and whether such effects cause structural shift. There are three different types of models that incorporate purchase-event feedback: the zero-order model, the Markov model, and the learning model. Difference among the three types of models depends on how great of an effect previous purchase history has on brand choice probability. As shown in Table 3, purchase-event feedback is captured through brand loyalty measurements based on choice history, lagged choice, and lagged marketing variables.

Table 3: Review of Brand Choice Models

Research Interest	Specification	Representative Studies
Purchase Event Feedback	Exponentially weighted averages of past purchases	Krishnamurthi and Raj (1988)
		Chiang (1991)
		Kannan and Wright (1991)
		Chintagunta (1993)
		Andrews and Currim (2009)
	Lagged Choice	Zhang and Krishnamurthi (2004)
		Bucklin and Gupta (1992)
	Lagged marketing variable	Zhang and Krishnamurthi (2004)
		Kumar, Venkatesan, and Reinartz (2006)
		Silva - Risso and Ionova (2008)
Overview of State Dependence		Seetharaman (2003)
		Roy, Chintagunta, and Haldar (1996)
		Seetharaman (2004)
		Mehta, Chen, Narasimhan (2010)

Purchase Amount

Differences in modeling purchase amount rely on the researcher's views of the dependence between choice and amount decisions. As shown in Table 4, the approaches for modeling purchase amount include the following: correcting for selection bias in the amount decision through a Heckman procedure, using a single utility function, or a bivariate logit model to jointly estimate purchase amount and choice decisions.

Table 4: Review of Purchase Amount Models

Research Interest	Specification	Representative Studies
	Heckman procedure	Krishnamurthu and Raj (1988)
	Single utility function	Chiang (1991)
Dependence between amount and choice (brand/category)		Borle, Singh, Jain (2008)
		Mehta, Chen, Narasimhan (2010)
		Chintagunta (1993)
		Arora, Allenby and Ginter (1998)
		Andrews and Currim (2009)
	Bivariate logit model	Zhang and Krishnamurthi (2004)
		Jen, Chou, Allenby (2009)

Modeling multiple decisions

The following general approaches (see Table 5) are employed when a researcher is interested in modeling at least two of the three decisions. As shown in Table 5, there are various combinations of modeling approaches for estimating at least two of these decisions. For example, purchase timing and brand choice can be modeled through a nested logit, hierarchical latent regression, hazard model, or a probit model. Purchase amount can be estimated using a regression model with selection bias corrected, and purchase timing can be modeled with a logit model or a probit model. If purchase amount is incorporated in the utility function, all three decisions can be captured using a single direct utility function. Chintagunta (1993) posits that the decisions of purchase timing, brand choice, and purchase amount should be modeled jointly to ensure the observed choices provide the highest utility to a consumer. Chintagunta research includes a direct utility function with all three decisions incorporated, thereby assuming that consumers will make the optimal decision of whether to buy, which brand to buy, and how much to buy, given the price of each brand, quality attributes of each brand, and budget constraint.

Table 5: Review of Integrated Purchase Decision Models

Decisions Studied	Model Specification(s)	Representative Studies
	Nested logit	Bucklin and Gupta (1992)
		Silva-Risso and Ionova (2008)
Timing/incidence and brand choice	Hierarchical latent regression	Ainslie and Rossi (1998)
	Hazard (timing)	Kumar, Venkatesan, and Reinartz (2006)
	Probit (choice)	Kumar, Venkatesan, and Reinartz (2008)
		Li, Sun, Montgomery (forthcoming)
Brand choice and purchase amount	Probit/logit (choice)	Krishnamurthi and Raj (1988)
	Regression (elapse time)	Neslin, Henderson, and Quelch (1985)
	Regression (amount)	
	CM-Poisson/logit (timing)	Boatwright, Borle, and Kadane (2003)
Timing/incidence and purchase amount	Hazard function (timing)	Borle, Singh, Jain (2008)
		Chiang (1991)
Timing/incidence and purchase amount and brand choice	Single direct utility function subject to budget constraint	Chintagunta (1993)
		Arora, Allenby, and Ginter (1998)
		Mehta, Chen and Narasimhan (2010)
		Andrews and Currim (2009)
	Bivariate logit	Zhang and Krishnamurthi (2004)
		Jen, Chou, Allenby (2009)

As noted earlier (see Table 1), the preponderance of research on purchase timing, brand choice, and purchase amount models has been conducted within the business-to-consumer context. This dissertation research tests both the single models of purchase timing, brand choice, and purchase amount, as well as the simultaneous estimation of purchase timing, brand choice, and purchase amount decisions within the business-to-business context of firm-level adoption of radically innovative IT.

Typically, products/services' needs drive the purchase timing, brand choice and purchase amount decisions. Timing of purchase can vary depending on what is bought and how much of it is bought (Mehta and Ma 2012). For example, in the case of a high tech firm, the timing of the purchase of a printer cartridge may depend on the type of printer cartridge and the purchase amount of the printer cartridges. Alternatively, the amount being purchased can also depend on the timing of the purchase and the type of printer cartridges being purchased. Thus, the decisions could be inter-related and therefore highlights the need to model the three decisions (purchase timing, brand choice and purchase amount) jointly.

CHAPTER III: MODELING FRAMEWORK

This section describes the conceptual framework, hypotheses tested, modeling approach and specifications for this dissertation research. Firm's decisions to purchase products or services are more likely to happen when there are unmet needs present (V. Kumar & Shah 2004). The foundation of the purchase timing, brand choice, and purchase amount models can be attributed to the theory of relationship marketing, a theory based on commitment and trust (Morgan and Hunt 1994). Moorman, Zaltman, and Deshpande (1992) define relationship commitment as an enduring desire to maintain a valued relationship, and trust as a willingness to rely on an exchange partner in whom one has confidence.

III.I. CONCEPTUAL FRAMEWORK & HYPOTHESES

Building on the theory of relationship marketing and the main tenants of commitment and trust proposed by Morgan and Hunt (1994), coupled with existing literature regarding behavior based determinants of purchase decisions (see Tables 1 – 5), this research seeks to investigate the link between need, commitment, and trust with firm adoption of radically innovative IT (See Table 6).

Table 6: Radical Innovation Adoption Matrix

Construct	Definition	Sample of Measures
Need	The extent to which a firm has a lack of something deemed necessary	Degree to which a firm has recently purchased products to fulfill what is deemed necessary
Commitment	The extent to which a firm desires to maintain a relationship with a particular vendor	Behavior brand loyalty as measured by the annual purchases
Trust	The extent to which a firm is confident in an exchange partner's reliability	Experience an organization has with a supplier

Need:

In this dissertation study, the level of firm need is anticipated to be associated with the adoption of radical innovation. Firm need is defined in the literature as the extent to which an organization has a lack of something deemed necessary, and can be measured by the purchase behavior of products that satisfy what is deemed necessary within a certain time period (V. Kumar & Shah 2004). To investigate the relationship of firm need with adoption of radically innovative IT, the latent construct of purchasing alternative products (see Table 7) is tested.

Table 7: Construct and Measurement of Need

Latent Construct	Measured Variable
Purchase of Alternative Products	Purchase behavior of non-cloud alternative products from 2008-2009

Commitment:

In this dissertation study, the level of firm commitment is anticipated to be associated with the adoption of radical innovation. Relationship commitment is defined in the literature as an enduring desire to maintain a valued relationship, and can be measured by annual purchases within a certain time period (Morgan and Hunt 1994). To investigate the relationship of firm commitment with adoption of radically innovative IT, the latent construct of annual purchases (see Table 8) is tested.

Table 8: Construct and Measurement of Commitment

Latent Construct	Measured Variable
Annual Purchases	Purchase of annual based non-cloud products from 2008-2009

Trust:

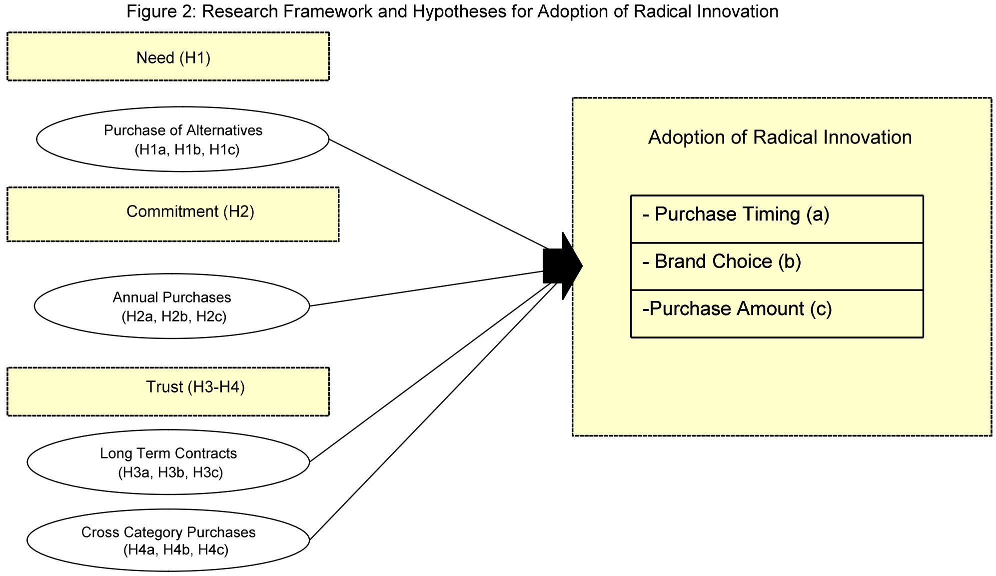
In this study, the level of firm trust is anticipated to be associated with the adoption of radical innovation. Exchange participants are more willing to commit to a relationship if trust is present (Morgan and Hunt 1994). Doney and Cannon (1997) argue that the more experience an organization has with a supplier, the more likely they are to trust that supplier. To operationalize the trust component of the conceptual framework, the constructs of having long-term contracts and purchasing across multiple brands from the same vendor are tested (see Table 9).

Table 9: Constructs and Measures of Trust

Latent Construct	Measured Variable
Long-Term Contract Relationship	Presence of long-term contracts during 2008-2009
Cross Category Purchases	Total purchase number of distinct non-cloud products during the window of 2008-2009

Independent models for each of the purchase decisions of timing, brand choice and amount, and an integrated modeling approach (see Figure 2) were employed to explicate the role of need, commitment, and trust in the adoption of radically innovative IT.

Figure 2: Research Framework and Hypotheses for Adoption of Radical Innovation



*Note: * H1 links need construct to purchase timing, brand choice and purchase amount of radical innovation adoption*
*** H2 links commitment construct to purchase timing, brand choice and purchase amount of radical innovation adoption*
**** H3, H4 links trust construct to purchase timing, brand choice and purchase amount of adoption of radical innovation adoption*

Purchase Timing of Adoption of Radical Innovation:

Drawing from existing literature in commitment and trust, cross-category purchases, and customer lifetime value (Morgan and Hunt 1994, Berry and Parasuraman 1991, Doney and Cannon 1997 and Reinartz and Kumar 2003), the variables that influence the decision of purchase timing were selected. The description, operationalization of the variables, and the expected effects are contained in Table 10.

Table 10: Purchase Timing Model Variables and Operationalization

Dependent Variable: Projected timing of adoption of radical innovation

Driver Category	Variable	Operationalization	Expected Effect	Rationale
Need	Growth in purchase of alternative products	Purchase of alternative category products during 2008-2009	+	Contrary to consumer packaged goods, for high-tech products, the firms typically use the product before purchasing more of the product. Therefore the longer the time since last purchase in a product category, the more likely the customer is to purchase in that category (Kumar et al, 2008).
Commitment	Purchase annual offering	Purchase of annual offering products from 2008-2009	-	Firms which purchase annual offerings from the same vendor exhibit behaviors consistent with desiring to maintain an enduring relationship. Morgan and Hunt (1994) posit that higher level of purchase frequency lead to higher levels of commitment.
Trust	Long term contract relationship	Purchase of non-cloud long-term contracts during 2008-2009	-	Trust is identified in the services marketing literature as important in creating successful exchanges (Berry and Parasuraman 1991). Trust in the supplier is one of the key antecedents to signing a multi-year agreement to outsource the firm's information technology systems integration.
	Cross category purchase behavior	Revenue value from non-cloud products purchased across brand categories during 2008-2009	-	Doney and Cannon (1997) posit that higher levels of experience with a vendor leads to increasing levels of trust. Purchasing multiple products from different categories from the same vendor increases the level of experience a firm has with the vendor's offerings.

Purchase of Alternatives:

Firms that have recently purchased alternative products typically extend the time period for which they will purchase again in the same product category. Contrary to consumer packaged goods, for high-tech products, firms typically use the product before purchasing more of the product. Therefore, the longer the time since last purchase in a product category, the more likely the firm is to purchase in that category (Kumar et al, 2008). The following hypothesis tests the relationship between growth in purchases of alternative products and the adoption of radically innovative IT.

Hypothesis 1a: Firms with higher growth in purchases of alternative products in the past will adopt radical innovation in the future later.

Annual purchases:

Firms which purchase annually from the same vendor exhibit behaviors consistent with desiring to maintain an enduring relationship. Morgan and Hunt (1994) posit that higher levels of annual purchases indicate higher levels of commitment; therefore, commitment is operationalized through measurement of firm annual purchase behavior. The following hypothesis tests the relationship between annual purchases and the adoption of radically innovative IT.

Hypothesis 2a: Firms with higher frequency of annual purchases in the past will adopt radical innovation in the future sooner.

Long-term contract relationship:

Trust is identified in the services marketing literature as important in creating successful exchanges (Berry and Parasuraman 1991). Trust is one of the key antecedents of signing a multi-year agreement with a vendor to outsource a firm's IT. The following hypothesis tests the relationship between signing a long-term contract with a vendor and the adoption of radically innovative IT.

Hypothesis 3a: Firms with long-term contracts in the past will adopt radical innovation in the future sooner.

Cross-category purchases:

Doney and Cannon (1997) posit that higher levels of experience with a vendor leads to increasing levels of trust. Purchasing multiple products from different categories from the same vendor increases the level of experience a firm has with the vendor. Additionally, customers who purchase across several product categories have higher switching costs and recurrent needs (Reinartz and Kumar 2003). The following hypothesis tests the relationship between the levels of cross-category purchases with a vendor and the adoption of radically innovative IT.

Hypothesis 4a: Firms with higher cross-category purchases in the past will adopt radical innovation in the future sooner.

Brand Choice Adoption of Radical Innovation:

Drawing from existing literature in commitment and trust, cross-category purchases and customer lifetime value (Morgan and Hunt 1994, Berry and Parasuraman 1991, Doney and Cannon 1997 and Reinartz and Kumar 2003), the variables which influence the purchase decisions of brand choice were selected. The description, operationalization of the variables, and the expected effects are contained in Table 11.

Table 11: Brand Choice Model Variables and Operationalization
Dependent Variable: Propensity to Adopt Radical Innovation

Driver Category	Variable	Operationalization	Expected Effect	Rationale
Need	Growth in purchase of alternative products	Purchase of alternative category products during 2008-2009	-	Contrary to consumer packaged goods, for high-tech products, the firms typically use the product before purchasing more of the product. Therefore, recent purchases in a product category, decreases the likelihood of a firm to purchase again that category (Kumar et al, 2008).
Commitment	Purchase annual offering	Purchase of annual offering products from 2008-2009	+	Firms which purchase annual offerings from the same vendor exhibit behaviors consistent with desiring to maintain an enduring relationship. Morgan and Hunt (1994) posit that higher level of purchase frequency lead to higher levels of commitment.
Trust	Long term contract relationship	Purchase of non-cloud long-term contracts during 2008-2009	+	Trust is identified in the services marketing literature as important in creating successful exchanges (Berry and Parasuraman 1991). Trust in the supplier is one of the key antecedents to signing a multi-year agreement to outsource the firm's information technology systems integration.
	Cross category purchase behavior	Revenue value from non-cloud products purchased across brand categories during 2008-2009	+	Doney and Cannon (1997) posit that higher levels of experience with a vendor leads to increasing levels of trust. Purchasing multiple products from different categories from the same vendor increases the level of experience a firm has with the vendor's offerings.

Purchase of Alternatives:

Firms that have recently purchased alternative products typically extend the time period for which they will purchase again in the same product category. Contrary to consumer packaged goods, for high-tech products, firms typically use the product before purchasing more of the product. Therefore, recent purchases in a product category, decreases the likelihood of a firm to purchase again that category (Kumar et al, 2008). The following hypothesis tests the relationship between growth in purchases of alternative products and the adoption of radically innovative IT.

Hypothesis 1b: Firms with higher growth in purchases of alternative products in the past will have lower likelihood to adopt radical innovation in the future.

Annual purchases:

Firms that purchase annually from the same vendor exhibit behaviors consistent with desiring to maintain an enduring relationship. Morgan and Hunt (1994) posit that higher level of annual purchase frequency indicates higher levels of commitment; therefore, commitment is operationalized through measurement of annual purchase behavior. The following hypothesis tests the relationship between annual repeat purchases and the adoption of radically innovative IT.

Hypothesis 2b: Firms with higher frequency of annual purchases in the past will have higher likelihood to adopt radical innovation in the future.

Long-term contract relationship:

Trust is identified in the services marketing literature as important in creating successful exchanges (Berry and Parasuraman 1991). Trust is one of the key antecedents of signing a multi-year agreement with a vendor to outsource a firm's IT. The following hypothesis tests the relationship between signing a long-term contract with a vendor and the adoption of radically innovative IT.

Hypothesis 3b: Firms with long-term contracts in the past will have a higher likelihood to adopt radical innovation in the future.

Cross-category purchases:

Doney and Cannon (1997) posit that higher levels of experience with a vendor leads to increased levels of trust. Purchasing multiple products from different categories from the same vendor increases the level of experience a firm has with that vendor. The following hypothesis tests the relationship between the levels of cross-category purchases with a vendor and the adoption of radically innovative IT.

Hypothesis 4b: Firms with higher cross-category purchases in the past will have higher likelihood to adopt radical innovation in the future.

Purchase Amount of Adoption of Radical Innovation:

Drawing from existing literature in commitment and trust, cross-category purchases, and customer lifetime value (Morgan and Hunt 1994, Berry and Parasuraman 1991, Doney and Cannon 1997 and Reinartz and Kumar 2003), the variables that influence the decisions of purchase amount were selected. The description, operationalization of the variables, and the expected effects are contained in Table 12.

Table 12: Purchase Amount Model Variables and Operationalization

Dependent Variable: Purchase Amount of Adoption of Radical Innovation

Driver Category	Variable	Operationalization	Expected Effect	Rationale
Need	Growth in purchase of alternative products	Purchase of alternative category products during 2008 - 2009	-	Contrary to consumer packaged goods, for high-tech products, firms typically use the product before purchasing more of the product. Therefore, those customers who have recently increased their purchases of alternative products will have a lower need for future purchases (Kumar, et al. 2008).
Commitment	Purchase annual offerings	Purchase of Annual offering products from 2008-2009	+	Firms which purchase annual offerings from the same vendor exhibit behaviors consistent with desiring to maintain an enduring relationship. Morgan and Hunt (1994) posit that higher level of purchase frequency lead to higher levels of commitment.
Trust	Long term contract relationship	Growth in purchases of non-cloud long-term contracts during 2008-2009	+	Trust is identified in the services marketing literature as important in creating successful exchanges (Berry and Parasuraman 1991). Trust in the supplier is one of the key antecedents to signing a multi-year agreement to outsource a firm's information technology.
	Cross category purchases	Revenue value from non-cloud products purchased across brand categories during 2008-2009	+	Doney and Cannon (1997) posit that higher levels of experience with a vendor leads to increasing levels of trust. Purchasing multiple products from different categories from the same vendor increases the level of experience a firm has with the vendor's offerings.

Growth in Purchase of Alternatives:

Firms that have recently purchased alternative products typically extend the time period for which they will purchase again in the same product category. Contrary to consumer packaged goods, for high-tech products, firms typically use the product before purchasing more of the product. Therefore, the longer the time since last purchase in a product category, the more likely the firm is to purchase in that category (Kumar et al, 2008). The following hypothesis tests the relationship between growth in purchases of alternative products and the adoption of radically innovative IT.

Hypothesis 1c: Firms with higher growth in purchases of alternative products in the past will have lower purchase amount of radical innovation in the future.

Annual purchases:

Firms that purchase annually from the same vendor exhibit behaviors consistent with desiring to maintain an enduring relationship. Morgan and Hunt (1994) posit that higher levels of purchase frequency indicate higher levels of commitment; therefore, commitment is operationalized through measurement of annual purchase behavior. The following hypothesis tests the relationship between annual purchases and the adoption of radically innovative IT.

Hypothesis 2c: Firms with higher frequency of annual purchases in the past will have higher purchase amount of radical innovation in the future.

Long-term contract relationship:

Trust is identified in the services marketing literature as important in creating successful exchanges (Berry and Parasuraman 1991). Trust is one of the key antecedents of signing a multi-year agreement with a vendor to outsource a firm's IT. The following hypothesis tests the relationship between signing a long-term contract with a vendor and the adoption of radically innovative IT.

Hypothesis 3c: Firms with long-term contracts in the past will have higher purchase amount of radical innovation in the future.

Cross-category purchases:

Doney and Cannon (1997) posit that higher levels of experience with a vendor leads to increasing levels of trust. Purchasing multiple products from different categories from the same vendor increases the level of experience a firm has with that vendor. The following hypothesis tests the relationship between the levels of cross-category purchases with a vendor and the adoption of radically innovative IT.

Hypothesis 4c: Firms with higher cross-category purchases in the past will have higher purchase amount of radical innovation in the future.

III.II. DATA DESCRIPTION

The data leveraged for this study was provided by a large global IT firm serving business clients within the observation period of 2008 to 2010. This firm sells a broad range of IT offerings, including software, hardware, and services. Firms included in the study sample are medium to large size companies that have been customers of the global IT firm for many years. Firms selected were those that made a minimum number of purchases so that variation in purchase behavior could be observed over time.

The information about each firm includes the purchase history (in terms of what was purchased, how much was purchased, and when the firm made the purchase), and profile data including industry and employee size. Such data provide enough information to derive firm level parameters that capture observed and unobserved heterogeneity. In addition to the variables provided in the original data set leveraged for this analysis, the following variables were imputed to enrich the final model building data set.

- Cross buy behavior = the total number of purchases of distinct non-cloud products during the window of 2008-2009
- Average inter-purchase time of non-cloud product during the window of 2008-2009
- Total purchase frequency of non-cloud product for customer during the window of 2008-09
- Total $ value of non-cloud product for customer during the window of 2008-2009
- $ value per transaction of non-cloud product for customer during the window of 2008-2009, calculated by $\frac{total\ value\ (in\ dollars)}{total\ purchase\ frequency}$ within the two years across all products
- $ value per product of non-cloud product for customer, calculated as $\frac{total\ value\ (in\ dollars)}{cross - buy}$ within two years across all products
- Growth of $ value of non-cloud product, calculated by total purchase value in 2009 – total purchase value in 2008
- Growth of purchase frequency of non-cloud product, calculated by the total purchase frequency in 2009 – total purchase frequency in 2008
- Growth of $ value per transaction of non-cloud product, calculated by $\frac{total\ value\ (in\ dollars)}{total\ purchase\ frequency}\ in\ 2009 - \frac{total\ value\ (in\ dollars)}{total\ purchase\ frequency}\ in\ 2008$
- Growth of $ value per product of non-cloud product, calculated by $\frac{total\ value\ (in\ dollars)}{cross - buy}\ in\ 2009 - \frac{total\ value\ (in\ dollars)}{cross - buy}\ in\ 2008$
- Product ownership of non-cloud product XX
- Purchase frequency of non-cloud product XX
- Purchase $ value of non-cloud product XX
- Growth of purchase frequency of non-cloud product XX, calculated by the total purchase frequency in 2009 - total purchase frequency in 2008 for non-cloud product XX

- Growth of $ value for non-cloud product XX, calculated by the total $ value in 2009 - total $ value in 2008 for non-cloud product XX.

Note: "XX" represents the non-cloud product name

III.III. INDEPENDENT MODEL FOR PURCHASE TIMING - ESTIMATION & RESULTS

The independent purchase timing modeling process tests two different survival analytic methods and two different dependent variables. Both LIFEREG and PHREG survival models were built and tested. Additionally, the dependent variables of time since last purchase, and time since first purchase were estimated.

Description of two modeling approaches: Proc LIFEREG and Proc PHREG

Both approaches (LIFEREG and PHREG) are widely used survival analysis methods in statistics and marketing applications.

LIFEREG is a parametric regression model known as the "*accelerated failure time*" (AFT) model, which estimates the survival function by assuming that the shape of the survival distribution is known. The LIFEREG model is set up as:

$$T_i = \exp(X_i\beta + \sigma\varepsilon_i)$$

Where T_i is the event time for ith individual, X_i are k-dimensional covariates, ε_i is the random disturbance term, and **both $\boldsymbol{\beta}_{1\,x\,k}$ and $\boldsymbol{\sigma}$** are the parameters to be estimated.

PHREG is a semi-parametric regression model known as the proportional hazard model which, unlike LIFEREG, does not require a selection of distribution to represent the survival times. The PHREG model is set up as:

$$h_i(t) = h_0(t)\exp(X_i\beta)$$

where $h_i(t)$ is the hazard for ith individual, $h_0(t)$ is the baseline hazard denoting the hazard of the ith individual when all covariates are equal to zero, and β s are the parameters to be estimated.

A major difference between LIFEREG and PHREG is that LIFEREG requires the survival time to follow an existing, known distribution regulated by the β'**s and** σ terms to be estimated. Conversely, PHREG relaxes this distribution assumption by replacing the estimation of σ with a baseline hazard $h_0(t)$ that is decided by the data.

The pros and cons of LIFEREG and PHREG models are highlighted in Table 13. In this study, both modeling approaches are employed in order to select the most suitable model to predict the timing of firm adoption of radically innovative IT.

Table 13: Pros and Cons between two Survival Model Approaches

	Proc LIFEREG	Proc PHREG
Pros	• Estimation is more efficient when the distribution fits the data • Accommodates left censoring and interval censoring • Results are easier for interpretation • Can generate predicted event time at a given survival probability for any specified set of covariate values	• Does not require the data to fit an existing distribution • Estimation results are more consistent with the data especially when existing distribution doesn't fit the data • Handles time-dependent covariates • Provides stepwise selection of covariates
Cons	• Estimation can be biased if the selected distribution doesn't fit the data • Does not handle time-dependent covariates • Cannot perform stepwise selection of covariates	• Results are relatively harder for interpretation • Major limitation on prediction ability (described below)

It is important to note that a major limitation of Proc PHREG is prediction ability. The prediction generated by Proc PHREG is the predicted survival probability at each given event time in the sample for each firm. Therefore, Proc PHREG cannot provide a prediction on the survival probability beyond the maximum observed event time in the data. This limitation significantly constrains the application of PHREG in this study.

Description of two dependent variables: "Time since last purchase" vs. "Time since first purchase"

Time since last purchase is the time period between the first purchase of a cloud-product in 2010 and the last purchase of a non-cloud-product during 2008-2009.

Time since first purchase is the time period between the first purchase of a cloud-product in 2010 and the first purchase of a non-cloud-product during 2008-2009.

Final Model Approach and Dependent Variable

Based on multiple analytical tests, including hit ratios, mean absolute deviation, and prediction ability, time since first purchase is used as the dependent variable, and LIFEREG is used as the modeling technique employed to build the final independent purchase timing model.

Hold-out Sample Parameter Estimation and Validation

A hold-out sample prediction is used in the purchase timing model. The hold-out sample enables the testing of whether or not the model obtains consistent results between in-sample and hold-out samples. The data is split into 70% vs. 30% for parameter estimation and prediction validation. Both the 70% and 30% samples have the same proportion of cloud-buyers as the full sample.

Results of Hypotheses H1a, H2a, H3a and H4a

The results of the purchase timing hazard model (see Table 14) indicate that need, commitment, and trust variables are statistically significant in relation to the timing of firm adoption of radically innovative IT. The results confirm the originally proposed hypotheses, suggesting that the extent to which a firm has purchased alternatives exhibits a positive relationship and therefore extends the firm's purchase timing for adoption of radical innovation. Conversely, both commitment and trust variables exhibit negative relationships relative to a firm's purchase timing for adoption of radical innovation. These negative parameter estimates indicate the firm's purchase timing of radical innovation adoption is significantly decreased when firms have higher levels of commitment and trust as measured by annual purchases and having long-term contracts established. These findings suggest need as a key antecedent of purchase decision, along with both commitment and trust factors, in regards to the purchase timing for firm adoption of radical innovation.

Table 14: Purchase Timing Independent Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	Chi-Square	Pr>ChiSq
Need measure	Growth in Purchases of Alternative Products Gth_pfq_#F	.306	.116	6.94	.0084
Commitment measure	Growth in purchase frequency of annual software products Gth_pfq_A	-0.009	.002	14.35	.0002
Trust measure	Long-term contracts Pvalue_#B	-1.630E-09	4.788E-10	11.59	.0007
	Cross-category Purchases CB	-.022	.006	13.08	.0003

Significant at p=0.05

III.IV. INDEPENDENT MODEL FOR BRAND CHOICE – ESTIMATION & RESULTS

Logistic regression is used extensively in marketing applications to predict a customer's propensity to purchase a product or service. Like many forms of regression analysis, logistic regression can have several predictor variables that are either numerical or categorical. Since the dependent variable (Y), “brand choice,” is a binary variable, purchase (Y=1) or non-purchase (Y=0) of cloud products, the logit model is used. The independent variables are presumed to affect the brand choice to adopt or not to adopt cloud computing. The logit model used in this study is as follows:

$$Logit_i = \ln\left(\frac{prob_{purchase}}{1 - prob_{purchase}}\right) = X\beta$$

where,

$$Dependent\ Variable, Y = Cloud\ Purchase\ \left(\ln\left(\frac{prob_{purchase}}{1 - prob_{purchase}}\right)\right)$$

$$Independent\ Variables, X = Product - level\ characteristics\ \&\ Exchange\ Characteristics$$

$$Parameter\ Estimates, \beta = Estimated\ coefficients\ for\ each\ of\ X$$

In-Sample Parameter Estimation and Validation

The data used for the above estimation was created by aggregating monthly purchase of non-cloud product data to the yearly level (2008 and 2009) and then aggregating it to create two-year data (2008 & 2009 combined). This dataset was then merged with the cloud purchase data. The logit model was estimated on a merged dataset consisting of a random sample from the non-cloud purchase group and the complete cloud purchase group.

With the number of cloud-buyers and non-buyers in the data set being unbalanced (67 buyers versus 228 non-buyers), the brand choice model was built using all cloud buyers and 134 randomly selected non-buyers. This was necessary because an unbalanced sample could lead to a visually optimal but expressively biased prediction outcome. Given the sample size is relatively small, only in-sample parameter estimation and validation are provided. The hold-out prediction is expected to be similar to the in-sample results.

Results of Hypotheses H1b, H2b, H3b, and H4b

The results of the brand choice logit model (see Table #15) indicate that both trust variables and the commitment variable are statistically significant in relation to the brand choice purchase decision of firm adoption of radically innovative IT. These results suggest that both trust variables (long-term contract relationships and cross category purchase behavior), along with the commitment variable of annual purchases exhibit positive relationships relative to a firm's brand choice for adoption of radical innovation. The positive coefficients from the trust and commitment measures indicate the propensity of radical innovation adoption is significantly increased for firms with higher annual purchases, long-term contracts, and cross-category purchases.

Table 15: Brand Choice Independent Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	Chi-Square	Pr>ChiSq
Need measure	Growth in Purchases of Alternative Products Gth_ACB	Not Sig.	Not Sig.	Not Sig.	Not Sig.
Commitment measure	Total annual purchase frequency of IT services products Offerings Pfq_#O	.07810	.0252	9.6462	.0019
Trust measure	Long-term contracts Pvalue_#B	2.65E-07	1.17E-07	5.1134	.0237
	Cross-category Purchases Yr_valueCB	3.47E-06	1.19E-06	8.4906	.0036

Significant at p=0.05

III.V. INDEPENDENT MODEL FOR PURCHASE AMOUNT– ESTIMATION & RESULTS

In addition to being able to predict purchase timing and brand choice with regard to firm adoption of radically innovative IT, it is important to understand how much money the firm is projected to spend on the adoption purchase. In modeling purchase amount, the following linear regression model is used:

$Y = X\beta + \varepsilon$

where,

$Dependent\ Variable, Y = Cloud\ Purchase\ Amount, in\ dollars\ \left(tot_{cloud_{value}}\right)$

$Independent\ Variables, X = Product - level\ characteristics\ \&\ Exchange\ Characteristics\ (matrix\ form) Pa$

$\varepsilon = Random\ Error \sim Normal\ Distribution$

In-Sample Parameter Estimation and Model Validation

The data used for the above estimation was created by aggregating monthly purchase data to the yearly level (2008 and 2009) and then aggregating it to create two-year data (2008 & 2009 combined). This dataset was then merged with the cloud purchase data (which contains the cloud purchase amount information). This was the final dataset used to model purchase amount for cloud products. After creating the independent variables (X) using the aforementioned dataset, the regression model was run. Several iterations of the model were estimated using various combinations of Xs (product-level and exchange characteristics). In order to maintain the model's logical relevance, preference was given to the exchange variables in the estimation process.

Results of Hypothesis H1c, H2c, H3c, and H4c

The results of the purchase amount OLS regression model (see Table #16A) indicate that both trust and commitment variables are statistically significant in relation to purchase amount decision of firm adoption of radically innovative IT. The results suggest that both trust variables (long-term contract relationships, cross category purchase behavior) along with the commitment variable of annual purchases exhibit positive relationships relative to the purchase amount for adoption of radical innovation. The positive coefficients from the trust and commitment measures indicate that the purchase value of radical innovation adoption is significantly increased for firms with growth in annual purchase frequency, long-term contracts and cross-category purchases.

Table 16A: Purchase Amount Independent Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	t Value
Need measure	Growth in Purchases of Alternative Products Growth_ACB	Not sig.	Not sig.	Not sig.
Commitment measure	Growth in annual total purchase frequency gth_pfq_#A	14240	3673.2212	3.88
Trust measure	Long-term contracts gth_pfq_#B	712.32007	235.94453	3.02
	Cross-category Purchases Yr_valueCB	.00859	.00292	2.94

Significant at p=0.05

Log-Transformed Purchase Amount Model Results

Both commitment and trust variables are statistically significant. The trust variables (long-term contract relationships, cross-category purchase behavior) along with the commitment variable of annual purchases exhibit positive relationships relative to the purchase amount for adoption of radical innovation. The positive coefficients from the trust and commitment measures indicate the purchase value of radical innovation adoption is significantly increased for firms with increased growth in annual purchases, long-term contracts and cross-category purchases.

Table 16B: Purchase Amount Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	t Value	Pr>ltl
Need Measure	Growth in purchases of Alternative Products Growth_ACB	Not Sig.	Not Sig.	Not Sig.	Not Sig.
Commitment Measure	Growth in annual total purchase frequency gth_pfq_#A	0.26697	0.07162	3.73	.0002
Trust Measures	Long-term contracts gth_pfq_#B	0.01001	0.0046	2.18	0.0304
	Cross-category Purchases Yr_valueCB	1.467E-07	5.699E-8	2.57	0.0107

Significant at P = 0.05

III.VI. BENEFITS OF AN INTEGRATED MODEL

The following paragraphs highlight several reasons why building an integrated model for purchase timing, brand choice, and purchase amount will produce improved insight and model performance than the independent decision models, from both a statistical validity and practitioner perspective.

1. From a modeling methodology perspective, the use of linear regression for estimating purchase amount is often not the theoretically correct method. Since the dataset consists of customers who did not make cloud purchases at all, their total cloud value is coded as zero. There are a total of 228 firms who have not purchased cloud coded as zeros (and 67 cloud buyers coded as 1) in the dataset and the use of linear regression on these zero values can lead to biased results. The more theoretically correct method to use is a Type II Tobit regression model, which allows for a selection step wherein the model chooses the customers who actually make a purchase and estimates their slopes separately.

2. According to existing literature, timing models are centered on the estimation of when an existing customer will purchase again, instead of the time of adopting a new product. The focus of this dissertation research is estimating the adoption of a new product.

3. The dependent variable selection for the purchase timing model is problematic. Two purchase timing model dependent variable options were tested (time since last purchase and time since first purchase.)

    a. For time since last purchase, the time horizon is calculated as the time duration between first cloud purchase in 2010 and last purchase of any non-cloud product from 2008-2009. This dependent variable is more likely to give prediction on when the customers will purchase in 2010 instead of when the customer will purchase cloud in 2010.

    b. For time since first purchase, the time horizon is calculated as the time duration between first cloud purchase in 2010 and first purchase of any non-cloud product from 2008-2009, which not only contains the same predictive constraint noted above in time since last purchase, but also introduces a left-censoring condition, (i.e. the first purchase between 2008 and 2009 wouldn't be the customer's actual acquisition time.) Consequently, the data is both right and left censored.

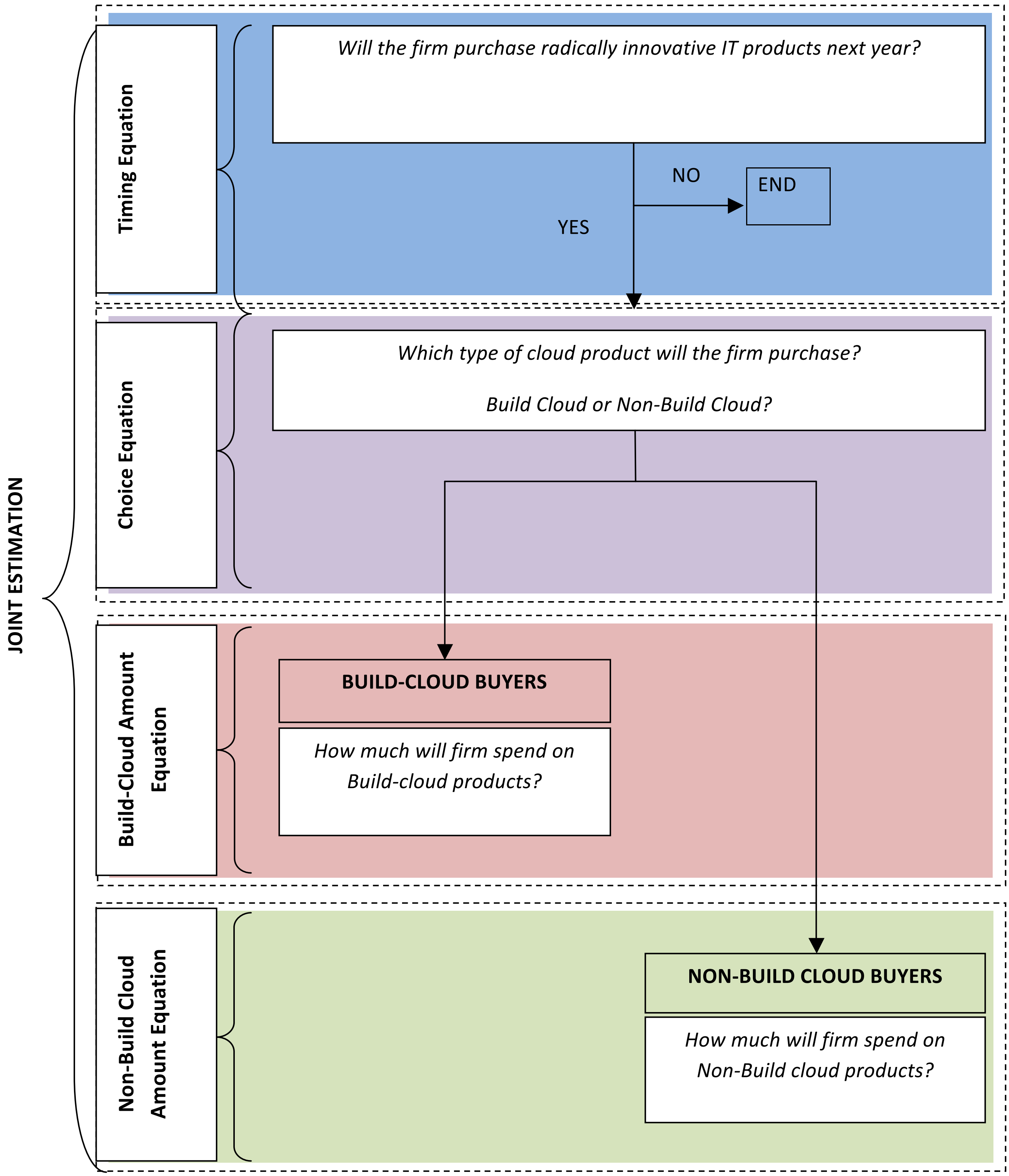
In conclusion, given the data available for this research, building an integrated model for purchase timing, brand choice, and purchase amount will produce improved theoretical rigor, model performance and practitioner relevance. For example, building a choice-amount model (e.g. using Type II Tobit model approach) will provide a more reliable prediction on whether the firm will buy cloud within one transaction year and the revenue associated with the purchase. Moreover, marketing practitioners ideally would like to simultaneously understand the timing of firm adoption of radically innovative IT, the specific type of anticipated adoption and the estimated expenditure on adoption to drive different marketing strategies to attract new and retain existing customers. Therefore, inserting time as a factor in a choice-amount model yields an integrated model for three decisions empirically.

An important aspect of the three-decision joint model is to decide how to make the prediction results consistent between both the choice model and timing model. For example, the independent choice model suggests that firm A would buy cloud within one specific year while the independent timing model predicts purchase timing outside the year. One way to address this is to only select those customers who are predicted to purchase cloud within one specific year by both choice model and timing model and to estimate their purchase quantities. The underlying logic is that the confidence level of the predictions will increase if both the choice and timing models suggest the customer would purchase cloud within the year.

III.VII. INTEGRATED MODEL FOR PURCHASE TIMING, BRAND CHOICE, AND PURCHASE AMOUNT - ESTIMATION & RESULTS

This research study is designed to explain and predict purchase timing, brand choice, and purchase amount of radically innovative information technology. Section 3.3-3.5 addresses each of the purchase decisions independently, by making the implicit assumption that each decision does not influence the next. However, there is evidence in marketing literature that these decisions are not independent but, in fact, do influence each other. Chiang (1991) demonstrated that the influence of marketing variables on a customer's purchase timing, brand choice, and purchase quantity decisions occur simultaneously. To account for this, the purchase decisions are modeled jointly (see Figure 3) using the recommendations of Kumar and Luo (2008).

Figure 3- Joint Modeling Framework



Marketing literature has attempted to address the interrelationships between decisions for the following reasons (Kumar and Luo 2008):

a) Independent models cannot account for selection bias in quantity and choice models.

b) Marketing variables could affect each of the firm's purchase decisions simultaneously. This cannot be captured accurately if the decisions are treated as independent.

c) An independently estimated model can only capture the firm's purchase behavior as a snapshot with regard to that specific decision. For example, independent models cannot uncover the effect of the firm's timing decision on the quantity of cloud purchased.

In order to overcome the challenges that independent models pose, the study also estimates the purchase decisions jointly using a Bayesian estimation framework.

Timing Model: The first decision in terms of firm adoption of radical innovation is 'whether or not the firm will purchase a cloud product in the next year'. To answer this, the 'timing' model is built to estimate whether the firm will purchase a cloud product, and whether the purchase will be made in the coming year.

Choice Model: Next, if the firm is projected to adopt cloud; it's important to know whether the firm is going to adopt the current IT providers 'Build-cloud' offerings or any other cloud product. To answer this, a multivariate probit choice model is estimated. The brand choice model is developed by leveraging the utility maximization theory in economics, wherein the customer makes a 'choice' decision that would maximize their relative utility between the available choices. ΔU_c is the latent utility term which indicates the "difference" of utility between purchasing "build" cloud and "Non-build" cloud. When $\Delta U_c > 0$, the firm is predicted to purchase a Build-cloud product and when $\Delta U_c < 0$ the firm is predicted to purchase a Non-build cloud product.

Build-Cloud Amount Equation: The Build-cloud amount equation indicates how much the firm is predicted to spend on the Build-cloud products if the firm makes a Build-cloud purchase. This equation is specified as a linear regression of the independent variables on the log of the total cloud purchase value for each firm.

Non-Build Cloud Amount Equation: The Non-Build cloud amount equation is specified similar to the Build-cloud amount equation. The Non-Build cloud model indicates how much the firm is projected to spend on the Non-Build cloud product if the firm makes a Non-Build cloud purchase.

$$(1)\quad \begin{cases} \mathrm{Log}(T_i) = \beta_t' X_{ti} + \varepsilon_{it} & \rightarrow \text{Timing Model} \\ \Delta U_{ci} = \beta_c' X_{ci} + \varepsilon_{ic} & \rightarrow \text{Choice Equation} \\ \log(Q1_i) = \beta_{q1}' X_{q1i} + \varepsilon_{iq1} & \rightarrow \text{Build-Cloud Quantity Equation} \\ \log(Q2_i) = \beta_{q2}' X_{q2i} + \varepsilon_{iq2} & \rightarrow \text{Non-Build cloud Quantity Equation} \end{cases}$$

Where, $$\begin{bmatrix} \varepsilon_{it} \\ \varepsilon_{ic} \\ \varepsilon_{iq1} \\ \varepsilon_{iq2} \end{bmatrix} \sim MVN(\vec{0}, \quad \Omega\ ); \ \Omega = \begin{bmatrix} \sigma_t & \sigma_{tc} & \sigma_{tq1} & \sigma_{tq2} \\ \sigma_{tc} & \sigma_c & \sigma_{cq1} & \sigma_{cq2} \\ \sigma_{tq1} & \sigma_{cq1} & \sigma_{q1} & \sigma_{q1q2} \\ \sigma_{tq2} & \sigma_{cq2} & \sigma_{q1q2} & \sigma_{q2} \end{bmatrix}$$

$X_{ti}, X_{ci}, X_{q1i}, X_{q2i} = \mathit{independent\ variables}$

$Log(T_i) = \log(\mathit{Time\ since\ first\ purchase})$

$\Delta U_c = \mathit{difference\ in\ latent\ utility\ between\ Build\ \&\ Non\ Build\ cloud\ alternatives}\ (\mathit{denoted\ by\ subscript\ c})$

$\log(Q1_i) = \log(\mathit{purchase\ amount\ for\ Build - cloud})$

$\log(Q2_i) = \log(\mathit{purchase\ amount\ for\ Non - Build\ cloud})$

$i = \mathit{customer\ ID}$

Error Structure: The final aspect of the equation is the error structure, $[\varepsilon_{it}, \varepsilon_{ic}, \varepsilon_{iq1}, \varepsilon_{iq2}]$, which captures the variances of each decision (Purchase Timing, Brand Choice, Build-cloud amount, and Non-Build cloud amount) that cannot be explained by the independent variables

$(X_1ti, X_1ci, X_1q1i, X_1q2i)$. Since the decisions are assumed to affect one another, a multivariate probit specification is used. Given the underlying distribution for the Probit specification is a truncated normal distribution, a multivariate Probit specification works in the model estimation. The error terms are assumed to follow four-dimensional multivariate normal distribution with mean=0 and variance-covariance = Ω . The components in Ω are allowed to vary freely in order to capture the inherent property that customers make all four purchasing decisions jointly.

Model Estimation & Validation

Choice of Estimation Method

The Bayesian estimation method is applied to the model specification for the following reasons:

1) Main objective is to estimate decisions jointly (Purchase Timing, Brand Choice, Build-Cloud amount, Non-Build Cloud amount). Therefore, the likelihood function is based on a four-dimensional joint distribution. Estimating this multidimensional joint distribution iteratively using the conventional Maximum Likelihood Estimation (MLE) method would exponentially increase the computational burden.
2) The MLE method to derive the full likelihood function for joint model becomes very complicated when modeling multiple decisions involving 'latent' dependent variables.
3) Model specification involves estimation of a large number of parameters and the likelihood functions are not concave for most of the situation. In such cases, the MLE estimation will encounter difficulties to find the global optimum, a pitfall that Bayesian estimation can overcome.

Model Validation

In order to measure the performance of the modeling framework, the Hit-Ratio and Mean Absolute Percentage Error (MAPE) are employed. Hit-Ratio metric measures the performance of the Purchase Timing model and the Brand Choice model. Hit-Ratio is measured as the percentage of observations that have been correctly predicted by the model. With regard to continuous dependent variables (Purchase Amount equations), the Mean Absolute Percentage Error (MAPE) is used to evaluate the model. MAPE is a statistic used to evaluate the model performance and is based on the "regression error" relative to "the actual value" of the dependent variables. A smaller number of MAPE suggests a better model performance.

$$MAPE = \frac{\sum_{i=1}^{N} APE_i}{N};$$

$$where\ APE_i = \frac{|observed\ Q - predicted\ Q|_i}{observed\ \ Q_i} * 100\%$$

Where,

Q = Dependent Variable (Purchase Amount, in dollars)

N= number of customers

i = customer id

Purchase Timing Model Results for Hypotheses H1a, H2a, H3a

The results of the purchase timing hazard model (see Table 17) indicate that need, commitment, and trust variables are statistically significant in relation to the timing of firm adoption of radically innovative IT. The results confirm the originally proposed hypotheses, suggesting that the extent to which a firm has purchased alternatives exhibits a positive relationship and therefore extends the firm’s purchase timing for adoption of radical innovation. Conversely, both commitment and trust variables exhibit negative relationships relative to a firm's purchase timing for adoption of radical innovation. These negative parameter estimates indicate the firm's purchase timing of radical innovation adoption is significantly decreased when firms have higher levels of commitment and trust as measured by annual purchase behavior and have long-term contracts established. These findings suggest need as a key antecedent of purchase decision, along with both commitment and trust factors, in regards to the purchase timing for firm adoption of radical innovation.

Table 17: Purchase Timing Integrated Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	t Value
Need measure	Growth in Purchases of Alternative Products gth_ACB	.192	.076	2.526
Commitment measure	Purchase of Annual Brand products Pdt #H	-.024	.009	-2.667
Trust measure	Long-term contracts Pdt #G	-.044	.009	-4.889

Significant at p=0.05

Brand Choice Model Results for Hypotheses H1b, H2b and H4b

The results of the brand choice model estimate the propensity of the firm to choose to purchase a Build cloud product over a Non-Build cloud product. The multivariate probit choice model indicates that both commitment and trust variables are statistically significant in relation to the brand choice adoption of radically innovative IT. The positive and negative signs associated with purchases of annual offerings and cross buy purchases, respectively, suggest that firm propensity to purchase Build cloud products over Non-Build cloud products is increased when firms have recently purchased annual offerings and do not have cross-category buy behavior.

Table 18: Brand Choice Integrated Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	t Value
Need measure	Growth in Purchases of Alternative Products Gth_pvalueQ_1	Not Sig.	Not Sig.	Not Sig.
Commitment measure	Purchase Annual Offerings pdt #P	.056	.026	2.154
Trust measure	Cross-category Purchases CB	-.611	.311	-1.964

Significant at p=0.05

Purchase Amount Models' Results of Hypothesis H1c, H2c, H3c, and H4c

In addition to being able to predict firm purchase timing and brand choice with regard to firm adoption of radically innovative IT, it is important to understand how much money the firm is projected to spend on the adoption purchase. The results of the purchase amount OLS regression model (see Tables 19 and 20) indicate that trust variables are statistically significant in relation to purchase amount decision of firm adoption of radically innovative IT. The positive parameter estimates associated with the trust variables indicate the firm's purchase amount of radically innovative information technology is significantly higher with higher levels of trust. Conversely, the need and commitment variables are not estimated to be significant in regards to firm purchase amount of adopting radical innovation. While not entirely conclusive relative to the originally proposed hypotheses, the results suggest that trust has a stronger relationship with regards to predicting the purchase amount for firm adoption of radically innovative IT. These results appear to be promising with respect to using trust to operationalize a firm's purchase amount decision for adoption of radical innovation.

Table 19: Build Cloud Purchase Amount Integrated Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	t Value
Need measure	Growth in Purchases of Alternative Products gth_ACB	Not sig.	Not sig.	Not sig.
Commitment measure	Purchase Annual Offerings gth_pfq#T	Not sig.	Not sig.	Not sig.
Trust measure	Cross-category Purchases CB	.184	.079	2.329

Significant at p=0.05

Table 20: Non-build Cloud Purchase Amount Integrated Model Parameter Estimates

	Variable	Parameter Estimate	Standard Error	t Value
Need measure	Growth in Purchases of Alternative Products Gth_ACB	Not sig.	Not sig.	Not sig.
Commitment measure	Purchase Annual Offerings gth_pfq#T	Not sig.	Not sig.	Not sig.
Trust measure	Long Term contract relationship Gth_pvalue #Q	2.079	.889	2.338

Significant at p=0.05

Variance-Covariance Estimation

The variance-covariance estimation provides the quantification of whether the four decisions are correlated. It is worth mentioning that, the variance-covariance term only captures the unobserved correlation between four decisions.

Table 21: Variance-Covariance Estimation of the Joint Decision Model

	Variance-Covariance Estimation			
	T	C	A1	A2
T	0.149458	-0.01903	-0.14005	0.096778
C		1	-0.22757	0.083508
A1			14.74294	0
A2				4.980139
	Correlation Estimation			
	T	C	A1	A2
T	1	-0.04922	-0.09435	0.112175
C		1	-0.05927	0.03742
A1			1	0
A2				1
	T-value of Correlation Estimation			
	T	C	A1	A2
T		-0.42142	-0.80162	0.964515
C			-0.22597	0.158998
A1				
A2				

Table 21 shows the variance-covariance estimation of the four decisions: Time (T), Choice (C), Build-cloud purchase amount (A1) and Non-Build cloud purchase amount (A2). For identification issue, the “Choice” variance is constrained to be 1 and the covariance between A1 and A2 is constrained to be zero. The “Choice” variance is constrained to be 1 because in choice model, the scale of the latent utility is arbitrary. The covariance between A1 and A2 is constrained to be zero because there is no information on customers who bought both Build and

Non-Build cloud. Thus, the covariance of purchase amount between Build and Non-Build cloud product is not identifiable.

To show the insights of estimation more straightforward, the "correlation estimation" from the "variance-covariance estimation" are computed. The correlation estimation results after controlling for other variables in the model show that:

1) The correlation between "Time" and "Choice" decision is negative. This suggests that, as the "time" since last purchase become longer, customers become less likely to make a cloud-purchase.

2) The correlation between "Time" and "A1" decision is negative. This suggests that, as the "time" since last purchase becomes longer, customers tend to spend less on "Build" cloud product.

3) The correlation between "Time" and "A2" decision is positive. This suggests that, as the "time" since last purchase become longer, customers tend to spend more on "Non-Build" cloud product.

4) The correlation between "Choice" and "A1" is negative. This suggests that, customers could be more likely to purchase "Build" cloud product when their purchase amount is relatively low.

5) The correlation between "Choice" and "A2" is positive. This suggests that, customers could be more likely to purchase "Non-Build" cloud product when their purchase amount is relatively high.

The "T-value of correlation" table shows the relative importance of the estimation results. The correlation t-values indicate not significant.

CHAPTER IV: CONTRIBUTIONS

This section describes the contributions to both practice and theory through the application and extension of Morgan and Hunt's (1994) Commitment-Trust Theory to firm level buyer behavior decisions of purchase timing, brand choice, and purchase amount for the adoption of radically innovative IT.

IV.I. CONTRIBUTION TO PRACTICE

Practitioner contributions include knowing when to sell, what to sell, and how much is likely to sell for radically innovative IT offerings. Armed with an understanding of unique firm level factors more often associated with radical innovation adopters than non-adopters, marketing managers can improve the efficiency and effectiveness of allocating scarce marketing resources. Marketing managers can build and execute more targeted marketing strategies to attract new clients and strengthen existing client relationships, incorporate key learning into the message themes their firm advertises in the marketplace and emphasize the key drivers that are associated with radical innovation adoption into sales enablement materials.

Marketing managers can build and execute more targeted marketing strategies to attract new clients and strengthen existing client relationships through the deployment of insight generated from this study. For example, as marketing managers build and prioritize the prospecting list of clients to target for marketing tactics designed to drive trial sales of radically innovative IT offerings, this study suggests those clients that have an unmet need and strong commitment and trust associations with the existing firm will deliver higher adoption rates than those firms which have recently purchased alternative offerings and have lower levels of commitment and trust. Alternatively, if the marketing execution objective is to drive high volume of sales from radically innovative information technology offerings, this study suggests that those clients with higher levels of trust will deliver higher revenues than those clients with lower levels of trust in the firm.

Advertising messages play an important role in conditioning the marketplace. The findings from this research suggest that suppliers who seek to realize high volumes of usage should consider delivering a message of trust throughout their marketing mix. Driving increased firm confidence in an exchange partner's reliability and experience levels with a supplier will likely lead to improved sales generation from the introduction of radically innovative IT into the marketplace. For example, highlighting that the firm is uniquely qualified to ensure clients can trust them as an IT provider, may help accelerate larger sales engagements for radically innovative information technology.

In addition to leveraging the key factors that drive radically innovative information technology adoption for prioritizing business development prospecting lists and marketing mix theme consideration, this study's findings can be helpful in the development of compelling sales enablement materials. Arming a firm's sales force with enablement materials which highlight firm need, commitment, and trust factors may help increase their client adoption rates for radically innovative information technology. These important factors can be incorporated by thoughtfully creating client reference use cases.

These are just a few examples of how the application of these findings can improve the performance associated with marketing decisions that seek to attract and deepen client relationships through the introduction of radically innovative information technology.

IV.II. CONTRIBUTION TO THEORY

While vast and robust theories have been developed, tested, and proven over the years to provide knowledge on radical innovation diffusion and provider benefits, there are fewer scholarly papers focused on key drivers and techniques to predict firm-level adoption of innovation. This dissertation research begins to fill the gap in the literature by providing knowledge focused on identifying the key firm level factors associated with the adoption of radical innovation as well as a methodology to jointly predict firm level purchase timing, brand choice, and purchase amount of radically innovative information technology.

This research extends relationship theory to explain firm buyer behavior regarding adoption of radically innovative information technology. Multiple hypotheses have been formulated regarding influences on adoption of radically innovative information technology, and evidence has been presented supporting most of the hypotheses. Overall, the findings point to a conclusion that firms that exhibit an unmet need and have commitment and trust characteristics towards buying from a firm will have a higher likelihood to purchase radically innovative information technology from said firm. These findings highlight the importance relationship marketing can play in accelerating the adoption of radically innovative information technology.

From a methodological perspective, prior research has focused on purchase timing, brand choice, or purchase amount largely in business to consumer applications, and often as independent decisions. This study tests the relationship marketing theories of commitment and trust (Morgan and Hunt 1994) and is the first to jointly estimate purchase timing, brand choice, and purchase amount within a business to business application for the adoption of radical innovation.

CHAPTER V: FUTURE RESEARCH PATHS

While this study provides advances in both scholarly theory and business application, there are limitations and future research paths to consider.

As with any empirical study, there are limitations. Although the sample is comprehensive in regards to firm adoption of cloud computing, it is limited to a specific innovation (cloud computing) and to firm purchases in the United States. Additionally, the data source leveraged for this study is from a specific information technology provider. Other factors may be at work for other radical innovations, for purchases made in other countries and from other radical innovation providers. However, while this may limit the substantive findings regarding the effect of specific variables, it does not limit the main conclusion regarding the importance of commitment and trust factors on adoption of radically innovative information technology. Expanding future studies to leverage data sources which include additional types of radical innovation, countries beyond the United States and purchases from multiple providers could enhance the robustness of the implications.

There are multiple future research paths to consider. A few of the future research paths for consideration include an in-market field study, analyzing early adopters versus late adopters of radically innovative information technology, and testing the impact of the tenants of relationship marketing on the purchase behavior post adoption of radically innovative IT.

CHAPTER VI: REFERENCES

VI.I APPENDIX: MODEL ESTIMATION OUTPUTS

The reported values throughout this paper have been expressed as a multiple of the actual numbers to ensure confidentiality is maintained.

SAS CODE AND OUTPUTS – INDEPENDENT MODELS

The reported values throughout this paper have been expressed as a multiple of the actual numbers to ensure confidentiality is maintained.

Independent Purchase Timing Model:

The model selection process provides the results between two dependent variables (time since last purchase and time since first purchase) and two modeling approaches (LIFEREG and PHREG). The following two statistics are used to evaluate the performance of each model: Hit-Ratio of 2x2 table and mean absolute deviation (MAD) of predicted purchase timing. The Hit-Ratio table indicates the model prediction accuracy on whether or not the firm will purchase cloud by the end of 2010.

The MAD denotes the accuracy of predicted purchase timing for cloud buyers and is calculated by:

$$MAD = \frac{\sum_{i=1}^{N} AD_i}{N}; where\ AD_i = |observed\ T - predicted\ T|_i$$

Where:

N= number of customers

i = customer id

Based on the above formulation, a higher Hit-Ratio and smaller MAD indicates better model performance. Given the relatively small sample size, all prediction related results shown below are in-sample predictions. Additionally, since LIFEREG models are unable to provide stepwise selection, to compare the performance between LIFEREG and PHREG, stepwise selection in PHREG was leveraged to select covariates for both modeling approaches.

<u>Model Testing LIFEREG vs. PHREG on DV = time since last purchase</u>

To determine whether or not the firm is predicted to *survive* (that is, remain a customer), the general rule is to detect whether that firm will have a survival probability (P) lower than 0.5 at time (T). If the predicted P < 0.5 at time T, it is concluded that the firm is more likely to not survive at or beyond time T.

When selecting time since last purchase as the dependent variable, the maximum observed event time $T_{max} = 14$. Therefore, PHREG can only predict the survival probability for each firm at each event time of $T \leq 14$. In order to get comparable results between LIFEREG and PHREG, a cut-off point of T = 14 is also used for the LIFEREG model.

PHREG procedure

1. If the predicted P < 0.5, then the firm is predicted to purchase cloud, and the first (or the smallest) event time (T) when P is less than 0.5 is assigned as the predicted purchase time.

2. If the predicted P never becomes less than 0.5 for all event times until $T_{max} = 14$, then the firm is predicted to not purchase cloud.

LIFEREG procedure

1. If the first (or the smallest) event time is T $\leq$ 14 and predicted P < 0.5, then the firm is predicted to purchase cloud, and such event time is assigned as the predicted purchase time.

2. If the predicted P never becomes less than 0.5 for all event time up to $T = 14$; then the firm is predicted to not purchase cloud.

The results (see Table 22) suggest that when using DV = time since last purchase, the model performance is very close between the two models. First, the models' hit-ratios of 88.9% and 88.5% are essentially the same. Second, the MAD is smaller in PHREG than in LIFEREG, although the SD of AD is smaller in LIFEREG than PHREG.

Table 22: Comparison of Two Independent Model Approaches when DV = Time Since Last Purchase

PHREG result

Table of predicted buy by actual_buy			
predicted buy	**Actual_buy**		
	0	**1**	**Total**
0	188	22	210
1	7	43	50
Total	195	65	260

Analysis Variable : AD				
N	**MAD**	**SD**	**min**	**max**
43	1.58	1.55	0	6

Hit-Ratio = 88.85%

LIFEREG result

Table of predicted buy by actual_buy			
predicted buy	**Actual_buy**		
	0	**1**	**Total**
0	187	22	209
1	8	43	51
Total	195	65	260

Analysis Variable : AD				
N	**MAD**	**SD**	**min**	**max**
43	1.78	1.34	0.05	5.23

Hit-Ratio = 88.46%

Although the results suggest that the two models' performances are almost equal, it is important to understand the implication of the limitation of Proc PHREG on prediction. Because the prediction window is more limited ($T \leq 14$) for Proc PHREG, with comparable model performance, Proc LIFEREG is selected as the better solution.

Model Testing LIFEREG vs. PHREG on DV = time since first purchase

The rule of determining whether or not the firm is predicted to purchase cloud computing is the same as that described above (e.g. using survival probability (P) = 0.5 as the cut-off point).

When selecting time since first purchase as the dependent variable, the maximum observed event time $T_{max} = 35$. Therefore, Proc PHREG can only predict the survival probability for each firm at each event time of $T \leq 35$. In order to get comparable results between LIFEREG and PHREG, the cut-off point of T = 35 is also used for LIFEREG model.

In PHREG

1. If the predicted $P < 0.5$, then the firm is predicted to purchase cloud, and the first (or the smallest) event time (T) when P is less than 0.5 is assigned as the predicted purchase time.

2. If the predicted P never becomes less than 0.5 for all event time up to $T_{max} = 35$, then the firm is predicted to not purchase cloud.

In LIFEREG

1. If the first (or the smallest) event time is $T \leq 35$ and predicted $P < 0.5$, then the firm is predicted to purchase cloud, and such event time is assigned as the predicted purchase time.

2. If the predicted P never becomes less than 0.5 for all event times up to $T = 35$, then the firm is predicted to not purchase cloud.

The results (see Table 23) suggest that when using DV = time since first purchase, the Hit-Ratio between the two models of 88.9% and 89.2% is nearly identical. Both the MAD and SD of MAD are smaller in PHREG than in LIFEREG.

Similar to the time since last purchase models, the results suggest that the two model performances are almost equal. However, considering that the prediction window is more limiting for PHREG, the LIFEREG model is selected as the better solution.

Table 23: Comparison of Two Independent Model Approaches when DV = Time Since First Purchase

PHREG result

Table of predicted buy by actual_buy			
predicted buy	**Actual_buy**		
	0	**1**	**Total**
0	190	24	214
1	5	41	46
Total	195	65	260

Analysis Variable : AD				
N	**MAD**	**SD**	**min**	**max**
41	1.73	2.18	0	13

Hit-Ratio = 88.85%

LIFEREG result

Table of pred_buy by actual_buy			
predicted buy	**Actual_buy**		
	0	**1**	**Total**
0	187	20	207
1	8	45	53
Total	195	65	260

Analysis Variable : AD				
N	**MAD**	**SD**	**min**	**max**
45	2.71	2.56	0.2	13.19

Hit-Ratio = 89.23%

As mentioned earlier, it may not be accurate to conclude that the firms predicted by the model to not purchase cloud are firms that will in fact never purchase cloud. It is more appropriate to interpret that given the models maximum observed window of $T_{max} = 35$, the firms are predicted to not purchase cloud products when T$\leq$ 35.

Both of the above models suggest that LIFEREG would be the better model considering both model performance and prediction capability. Next, the study will determine which DV provides better performance.

LIFEREG model: DV = time since first purchase vs. DV = time since last purchase

To select the better DV, the same two statistics described earlier are used: Hit-Ratio table and MAD of purchase timing. In the LIFEREG model, covariates and model estimation are exactly the same as noted above; however, the two statistical results differ because now there is no constraint of "$T_{\max}$," therefore, the logic of computing the Hit-Ratio and MAD are different.

Logic of computing Hit-Ratio and MAD:

predict_buy = 0 vs. 1 is used to define whether the customer is predicted to make a purchase in 2010. Therefore, the test looks for a condition where the smallest event time (T) for survival P < 0.5 is less than the time interval between last purchase (or first purchase) and Dec. 2010. If this condition is satisfied, then the customers are categorized as predicted to buy cloud in 2010. The smallest event time (T) will be assigned as the predicted purchase time for calculating the model comparison statistics.

MAPE is the statistic used to evaluate model performance and is based on the regression error relative to the actual value of the DV.

$$MAPE = \frac{\sum_{i=1}^{N} APE_i}{N};$$

$$where\ APE_i = \frac{|observed\ T - predicted\ T|_i}{observed\ T_i} * 100\%$$

Where, N= number of customers, and i = customer id

In this DV comparison, MAPE is more helpful than MAD in selecting the better performing DV because the absolute values of the two DVs are different. Similar to MAD, a smaller number of MAPE suggests a better model performance. As shown in Table 24, both the Hit-Ratio and MAPE indicate that DV = time since first purchase is the better option than DV = time since last purchase.

Table 24: Comparison of Two DVs Using LIFEREG

Panel 1: DV=time since last purchase

Table of predicted buy by actual_buy			
predicted buy	Actual_buy		
	0	1	Total
0	186	22	208
1	9	43	52
Total	195	65	260

Hit-Ratio = 88.08%

Analysis Variable : AD				
N	MAD	SD	Minimum	Maximum
43	1.76/(4.85*)	1.34	0.05	5.23

Analysis Variable : APE_Y1				
N	MAPE (%)	SD	Minimum	Maximum
43	56.61	84.03	2.03	438.97

These two MADs are not directly comparable

Panel 2: DV = time since first purchase

Table of predicted buy by actual_buy			
predicted buy	Actual_buy		
	0	1	Total
0	187	19	206
1	8	46	54
Total	195	65	260

Analysis Variable : AD				
N	MAD	SD	Minimum	Maximum
46	2.68(25.96*)	2.21	0.2	9.93

Analysis Variable : APE_Y1				
N	MAPE (%)	SD	Minimum	Maximum
46	9.98	8.23	0. 69	39.73

Hit-Ratio = 89.61%

Combining the results obtained from these tests, time since first purchase is the dependent variable and LIFEREG is the modeling technique employed to build the final purchase timing model. Since a LIFEREG model is a parametric modeling approach that requires selection of a known distribution to fit the data, the Weibull distribution is used as Weibull is the most flexible distribution and also the distribution that the preliminary analysis results favored.

The SAS code for LIFEREG model is shown below:

```
proc lifereg data=timing_model;
model Y_time2*choice(0)=CB int yr_focbuy pdt_#J pdt_#I pdt_#C pdt_#K  pdt_#D pdt_#L pvalue_#I
pvalue_#B gth_pfq_#A gth_pfq_#F gth_pvalue_#F gth_pfq_#D /D=Weibull; run;quit;
```

Table 25: Calibration Sample (70%) Parameter Estimation (N=180) for Year 2010

Analysis of Maximum Likelihood Parameter Estimates							
Parameter	**DF**	**Estimate**	**Standard Error**	**95% Confidence Limits**		**Chi-Square**	**Pr > ChiSq**
Intercept	1	3.580	0.069	3.446	3.715	2720.88	<.0001
CB	1	-0.022	0.006	-0.035	-0.010	13.08	0.0003
Int	1	0.070	0.046	-0.019	0.160	2.38	0.1227
yr_valueperT	1	2.517E-06	6.348E-07	1.273E-06	3.761E-06	15.72	<.0001
Pdt_#J	1	-0.142	0.067	-0.273	-0.011	4.53	0.0332
Pdt_#I	1	0.229	0.104	0.026	0.433	4.88	0.0272
Pdt_#C	1	0.328	0.082	0.167	0.489	15.99	<.0001
Pdt_#K	1	0.185	0.055	0.078	0.291	11.46	0.0007
pdt_#D	1	0.105	0.049	0.009	0.202	4.6	0.032
pdt_#L	1	-0.233	0.048	-0.327	-0.138	23.34	<.0001
Pvalue_#I	1	-3.100E-08	8.172E-09	-4.702E-08	-1.498E-08	14.39	0.0001
pvalue_#B	1	-1.630E-09	4.788E-10	-2.568E-09	-6.916E-10	11.59	0.0007
gth_pfq_#A	1	-0.009	0.002	-0.014	-0.004	14.35	0.0002
gth_pfq_#F	1	0.306	0.116	0.078	0.534	6.94	0.0084
gth_pvalue_#F	1	-1.023E-05	2.759E-06	-1.564E-05	-4.823E-06	13.75	0.0002
Gth_pfq_#D	1	0.007	0.002	0.004	0.010	21.38	<.0001
Scale	1	0.106	0.014	0.082	0.137		
Weibull Shape	1	9.443	1.229	7.317	12.187		

Table 26: Hold-out Sample (30%) Model Validation (N=80) for Year 2010

Analysis Variable : AD_Y1				
N	**MAD**	**Std Dev**	**Minimum**	**Maximum**
12	4.18	3.35	0.89	11.73

Analysis Variable : APE_Y1				
N	**MAPE (%)**	**Std Dev**	**Minimum**	**Maximum**
12	15.70	12.86	3.43	45.12

Table of predicted buy by actual_buy

predicted buy	Actual_buy		
	0	**1**	**Total**
0	55	8	63
1	5	12	17
Total	60	20	80

Hit-Ratio = 83.75%

Applying the purchase timing model to the hold-out sample yields a Hit Ratio = 83.75% and a MAD of 4.18.

Independent Brand Choice Model:

```
proc logistic data=choice_logistic_model out=parameters;

model choice(event='1')=yr_valueperT  yr_valueCB  pdt_#M  pdt_#N

pdt_#L pvalue_#A pvalue_#B Gth_ACB pfq_#O; output out=w1 p=predict; run;
```

Table 27: In-sample Independent Brand Choice Model Parameter Estimation (N=201) for Year 2010

Analysis of Maximum Likelihood Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	-0.6953	0.4138	2.8236	0.0929
yr_valueperT	1	-0.00009	0.000024	13.4755	0.0002
yr_valueCB	1	3.47E-06	1.19E-06	8.4906	0.0036
pdt_#M	1	-2.1935	1.1483	3.6487	0.0561
Pdt_#N	1	2.3857	1.049	5.1726	0.0229
Pdt_#L	1	3.3716	1.0355	10.6018	0.0011
pvalue_#A	1	-3.09E-06	1.01E-06	9.4028	0.0022
pvalue_#B	1	2.65E-07	1.17E-07	5.1134	0.0237
Pfq_#O	1	0.0781	0.0252	9.6462	0.0019

Table 28: In-sample Model Validation for Year 2010

Hit-Ratio				
Frequency Percent		**Predicted Choice**		
		0 (Cloud No Buy)	**1 (Cloud Buy)**	**Total**
Choice	**0 (Cloud No Buy)**	132 65.67%	2 1.00%	134 66.67%
	1 (Cloud Buy)	12 5.97%	55 27.36%	67 33.33%
	Total	144 71.64%	57 28.36%	201 100%

Using the cloud buyer and non-buyer groups to predict their actual purchase, the model shown above has a Hit-Ratio of 93.03%.

Independent Purchase Amount Model:

The SAS code that was used for the Purchase Amount Model is given below.

```
proc reg data=amount_OLS_model;

model tot_cloud_value=

gth_pfq_#A gth_pfq_#B gth_pfq_#C gth_pfq_#D gth_pvalue_#E

CB int tot_pfq yr_valueperT yr_valueCB Growth_ACB

pdt_#F pfq_#G pvalue_#H pvalue_#I;run;quit;
```

The parameter estimation (see Table 29) is included below.

Table 29: In-sample Parameter Estimation for Independent Purchase Amount Model for Year 2010

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	14	8.12E+13	5.80E+12	128.25	<.0001
Error	245	1.11E+13	4.52E+10		
Corrected Total	259	9.22E+13			

Root MSE	212610	**R-Square**	0.8799
Dependent Mean	98946	**Adj R-Sq**	0.8731
Coeff Var	214.87541		

Variable	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	33725	27855	1.21	0.2272
Gth_pfq_#A	14240	3673.2212	3.88	0.0001
Gth_pfq_#B	712.32007	235.94453	3.02	0.0028
Gth_pfq_#C	7645.0814	3871.0954	1.97	0.0494
Gth_pfq_#D	-8126.1423	1837.168	-4.42	<.0001
Gth_pvalue_#E	-0.09094	0.02503	-3.63	0.0003
CB	1638.936	2577.9769	0.64	0.5255
Int	3390.7504	5640.9253	0.6	0.5483
tot_pfq	-18.67404	10.38987	-1.8	0.0735
yr_valueperT	-0.20951	0.06412	-3.27	0.0012
Yr_valueCB	0.00859	0.00292	2.94	0.0036
pdt_#F	514368	107813	4.77	<.0001
pfq_#G	14865	519.56965	28.61	<.0001
pvalue_#H	0.02233	0.01411	1.58	0.1149
pvalue_#I	0.02617	0.00928	2.82	0.0052

Table 30: In-sample Parameter Estimation for Log-Transformed Independent Purchase Amount Model for Year 2010

Analysis of Variance					
Source	**DF**	**Sum of Squares**	**Mean Square**	**F Value**	**Pr > F**
Model	14	2098.98707	149.92765	8.73	<.0001
Error	245	4209.83240	17.18299		
Corrected Total	259	6308.81948			

Root MSE	4.14524	**R-Square**	0.3327
Dependent Mean	2.71504	**Adj R-Sq**	0.2946
Coeff Var	152.67666		

Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t Value**
Intercept	1	1.55805	0.54309	2.87
gth_pfq_#A	1	0.26697	0.07162	3.73
gth_pfq_#B	1	0.01001	0.00460	2.18
gth_pfq_#C	1	0.14122	0.07547	1.87
gth_pfq_#D	1	-0.07442	0.03582	-2.08
gth_pvalue_#E	1	-5.59936E-8	4.88062E-7	-0.11
CB	1	0.16776	0.05026	3.34
Int	1	-0.02495	0.10998	-0.23
tot_pfq	1	-0.00000565	0.00020257	-0.03
yr_valueperT	1	-0.00000423	0.00000125	-3.38
yr_valueCB	1	1.466638E-7	5.699567E-8	2.57
Pdt_#F	1	2.72040	2.10201	1.29
pfq_#G	1	0.01134	0.01013	1.12
Pvalue_#H	1	-4.90232E-8	2.751882E-7	-0.18

Table 31: Correlation between Commitment and Trust for Independent Choice Model

Variables	Total purchase frequency of IT Services products Pfq_#0	Long-term contracts Pvalue_#B	Cross-category Purchases Yr_valueCB
Total purchase frequency of IT Services products Pfq_#0	1	0.01421	0.32708
Long-term contracts Pvalue_#B	0.01421	1	0.30004
Cross-category Purchases Yr_valueCB	0.32708	0.30004	1

Note: Growth in Purchases of Alternative Products Gth_ACB is not significant

Table 32: Correlation between Commitment and Trust for Independent Timing Model

Variable	Growth in purchase frequency of Software products gth_pfq_#A	Long-term contracts Pvalue_#B	Cross-category Purchases CB
Growth in purchase frequency of Software products gth_pfq_#A	1	-0.16954	-0.01698
Long-term contracts Pvalue_#B	-0.16954	1	0.34863
Cross-category Purchases CB	-0.01698	0.34863	1

Note: Growth in Purchases of Alternative Products Gth_ACB is not significant

Table 33: Correlation between Commitment and Trust for Independent Amount Model

Variable	Growth in total purchase frequency gth_pfq_#A	Long-term contracts gth_pfq_#B	Cross-category Purchases Yr_valueCB
Growth in total purchase frequency gth_pfq_#A	1	-0.55318	-0.17015
Long-term contracts gth_pfq_#B	-0.55318	1	0.02108
Cross-category Purchases CB	-0.01698	0.34863	1

Note: Growth in Purchases of Alternative Products Gth_ACB is not significant

Integrated Timing model to predict 'purchase timing'

The timing model predicts whether the firm will purchase a cloud product and when the firm will make the cloud purchase. In order to evaluate the model performance, the Hit-Ratio and the Mean Absolute Percentage Error (MAPE) are analyzed.

Table 34: Integrated Timing Model - Parameter Estimation (N=476) for Year 2010-2011

Parameter	Estimate	Standard Error	t statistic
Intercept	3.561**	0.055	64.745
CB	0.1	0.064	1.562
Int	0.061	0.066	0.924
gth_ACB	0.192**	0.076	2.526
pdt #A	0.172*	0.1	1.72
pdt #B	-0.032	0.063	-0.508
pdt #C	0.357**	0.062	5.758
pdt #D	0.059	0.076	0.776
pdt #E	0.186**	0.067	2.776
pdt #F	0.101	0.081	1.247
pdt #G	-0.044**	0.009	-4.889
pdt #H	-0.024**	0.009	-2.667
pvalue #I_1	-0.054	1.467	-0.037
pvalue #J_1	-0.223	0.456	-0.489
pvalue #K_1	-0.401	0.679	-0.590
pvalue #L_1	0.623	2.223	0.280
pvalue #M_1	-0.2	1.043	-0.192
pvalue #N_1	0.607	1.073	0.566

* - Significant at p=0.1 **- Significant at p=0.05

Table 35: Integrated Timing Model - Validation

Analysis Variable : APE_Time				
N	MAPE (%)	Std Dev	Minimum	Maximum
79	10	7.96	0.57	41.65

Table of predicted buy by actual_buy			
predicted buy	Actual_buy		
	0	1	Total
0	296	90	386
1	11	79	90
Total	307	169	476

Hit-Ratio = 78%

A Hit-Ratio of 78% indicates that the model correctly predicts the purchase time with an accuracy of 78% within the stipulated time window. Additionally, the MAPE of 10% indicates that the model's predicted time deviates from the true value by only 10%.

Integrated Brand Choice Model to predict choices of 'cloud' product purchase

The brand choice model estimates the propensity of the firm to choose to purchase a Build-cloud product over a Non-Build cloud product. The results of the model are reported in Table 36.

Table 36: Integrated Brand Choice Model -- Parameter Estimation (N=169) for Year 2010-2011

Parameter	Estimate	Standard Error	t statistic
Intercept	0.296	0.283	1.046
Int	-0.343	0.272	-1.261
CB	-0.611**	0.311	-1.964
pdt #A	-0.225	0.258	-0.872
pdt #D	-0.075	0.291	-0.258
pdt #O	-0.607**	0.264	-2.299
pdt #G	0.331	0.223	1.484
pdt #P	0.056**	0.026	2.154
pdt #N	-0.692**	0.17	-4.070
gth_pvalue #Q_1	-0.014	0.044	-0.318

* - Significant at p=0.1 **- Significant at p=0.05

Table 37: In-sample Model Validation for Integrated Choice Model

Predicted Choice	Actual choice		
	Non-Build	Build	Total
Non-Build	99	29	128
Build	3	38	41
Total	102	67	169

Hit-Ratio = 81%

A Hit-Ratio of 81% indicates that the model correctly predicts the cloud purchase choice, e.g. Build cloud versus Non-Build cloud with an accuracy of 81% within the stipulated time window.

Integrated Purchase Amount Models predict 'how much' the customer will spend on Build-Cloud and Non-Build cloud products

The purchase amount models estimate the amount the firm will spend on the purchase of Build cloud and Non-Build cloud products. Tables 38 and 39 describe the parameter estimates for each of the purchase amount equations. The models' performance is validated using the Mean Absolute Percentage Error (MAPE) in Table 40. MAPE for those cloud buyers whose purchase amount is greater than $1 is computed. Of the 67 Build cloud buyers, there are 29 buyers whose purchase amount is greater than $1. Therefore, the total sample size for calculating the purchase amount MAPE is 131 after adding the 29 'Build cloud' buyers and the 102 'Non-Build' cloud buyers.

Table 38: Integrated Build Cloud Purchase Amount Model-Parameter Estimation (N=67)

Parameter	Estimate	Standard Error	T statistic
Intercept	2.918**	1.364	2.139
Int	-2.844	2.244	-1.267
CB	0.184**	0.079	2.329
gth_ACB	0.046	0.211	0.218
pdt #R	-0.185	0.589	-0.314
pfq #S_1	-0.262	0.871	-0.301
yr_valueperT_1	1.73	2.442	0.708
yr_valueCB_1	1.515	2.765	0.548
gth_pfq #T_1	-0.34	0.368	-0.924
gth_pvalue #Q_1	-0.401	0.819	-0.489

* - Significant at p=0.1 **- Significant at p=0.05

Table 39: Integrated Non-Build Cloud Purchase Amount Model-Parameter Estimation (N=102)

Parameter	Estimate	Standard Error	t statistic
Intercept	10.672**	0.492	21.691
Int	-0.368	2.654	-0.139
CB	0.038	0.033	1.151
gth_ACB	0.096	0.107	0.897
pdt #R	0.066	0.155	0.426
pfq #S_1	0.441	0.392	1.125
yr_valueperT_1	3.06	2.485	1.231
yr_valueCB_1	0.564	3.242	0.174
gth_pfq #T_1	-0.022	0.058	-0.379
gth_pvalue #Q_1	2.079**	0.889	2.3384

* - Significant at p=0.1 **- Significant at p=0.05

Table 40: In-sample Model Validation for Integrated Purchase Amount Model

Analysis Variable : APE_Q				
N	MAPE (%)	Std Dev	Minimum	Maximum
131	28	47	0.13	332.02

A MAPE value of 28.25% indicates that the joint model predicts the purchase amount of a cloud product with an accuracy of 72%.

Model Estimation Process

Parameters to be estimated: $\tilde{\beta}$; Ω

(Note: $\tilde{\beta}$ is a matrix term including all the βs in all four equations; Ω is the variance-covariance matrix for error terms, including 10 parameters)

Step 1 – Generate ε_{it}

$$[\varepsilon_{it}|\varepsilon_{ic}, \varepsilon_{iq1}, \varepsilon_{iq2}, \tilde{\beta}, \Omega] \sim N(\mu_{\varepsilon_t}, \sigma_{\varepsilon_t})$$

Where $\mu_{\varepsilon_t} = \Sigma_{12}\Sigma_{22}^{-1}\begin{bmatrix}\varepsilon_{ic}\\ \varepsilon_{iq1}\\ \varepsilon_{iq2,}\end{bmatrix}$; $\sigma_{\varepsilon_t} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$

Step 2 – Generate ε_{ic}

$$[\varepsilon_{ic}|\varepsilon_{it}, \varepsilon_{iq1}, \varepsilon_{iq2}, \tilde{\beta}, \Omega] \sim N(\mu_{\varepsilon_c}, \sigma_{\varepsilon_c})$$

Where $\mu_{\varepsilon_c} = \Sigma_{12}\Sigma_{22}^{-1}\begin{bmatrix}\varepsilon_{it}\\ \varepsilon_{iq1}\\ \varepsilon_{iq2,}\end{bmatrix}$; $\sigma_{\varepsilon_c} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$

Step 3 – Generate ε_{iq1}

$$[\varepsilon_{iq1}|\varepsilon_{it}, \varepsilon_{ic}, \varepsilon_{iq2}, \tilde{\beta}, \Omega] \sim N(\mu_{\varepsilon_{q1}}, \sigma_{\varepsilon_{q1}})$$

Where $\mu_{\varepsilon_{q1}} = \Sigma_{12}\Sigma_{22}^{-1}\begin{bmatrix}\varepsilon_{it}\\ \varepsilon_{ic}\\ \varepsilon_{iq2,}\end{bmatrix}$; $\sigma_{\varepsilon_{q1}} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$

Step 4 – Generate ε_{iq2}

$$[\varepsilon_{iq2}|\varepsilon_{it}, \varepsilon_{ic}, \varepsilon_{iq1}, \tilde{\beta}, \Omega] \sim N(\mu_{\varepsilon_{q2}}, \sigma_{\varepsilon_{q2}})$$

Where $\mu_{\varepsilon_{q2}} = \Sigma_{12}\Sigma_{22}^{-1}\begin{bmatrix}\varepsilon_{it}\\ \varepsilon_{iq1}\\ \varepsilon_{iq2,}\end{bmatrix}$; $\sigma_{\varepsilon_{q2}} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}$

Step 5 – Generate $\tilde{\beta}$

Define prior distribution for $\tilde{\beta}$: $\beta \rceil \Omega, \mathbf{Y}, \mathbf{X} \sim \mathbf{MVN}((\beta_{\downarrow}0)^{\sim}, \quad \Omega \otimes [A]^{\wedge}(-1))$

$\beta \rceil \varepsilon, \Omega \sim (\mu_{\downarrow}\beta^{\sim}, \mathbf{V}_{\downarrow}\beta^{\sim})$

$\mu_{\tilde{\beta}} = (X'X + A)^{-1}\left(X'X\hat{\beta} + A\widetilde{\beta_0}\right)$ **Where** $\hat{\beta} = (X'X)^{-1}X'Y$

$\mathbf{V}_{\tilde{\beta}} = \Omega \bigotimes (\mathbf{X'X} + \mathbf{A})^{-1};$

where $Y = [\log(T), \Delta U_c, \log(Q1), \log(Q2)]$

Step 6 – Generate Ω

Define prior distribution for $\Omega \sim$ **inverted Wishart** (υ_0, S_0)

$\Omega | \varepsilon, \beta^{\sim} \sim (N + \upsilon_{\downarrow}0, S + S_{\downarrow}0)$

$\mathbf{N} =$ **sample size;**

$\mathbf{S} = (\mathbf{Y} - \mathbf{X}\beta)'(\mathbf{Y} - \mathbf{X}\beta) + (\tilde{\beta} - \widetilde{\beta_0})'\mathbf{A}(\beta - \widetilde{\beta_0})$

Repeat step 1 to step 6 until $\tilde{\beta}$; Ω converge.

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VI.III VITA

Timothy Richard Bohling has held several Marketing Leadership positions within IBM. Currently, as Vice President, Marketing, Global Technology Services, Growth Markets, Mr. Bohling is responsible for the formulation and execution of the Marketing plan that drives IBM to Capture Markets, Make Markets and differentiate the IBM brand.

Prior to this role, Mr. Bohling was Vice President, Marketing, Global Technology Services, North America. His responsibilities included driving IBM to take better action, fuel new and stronger relationships, enhance sales performance, expand routes to market and differentiate the IBM brand.

In 2008, Mr. Bohling was Vice President, Americas Market Insights. His responsibilities included driving thought leadership and deep market and customer insights, database marketing, competitive intelligence, primary research, secondary research and opportunity analysis.

In 2006, Mr. Bohling was Director, Global Business Services Market Insights. His responsibilities included delivering marketplace and customer insights for Global Business Services to successfully deepen relationships with existing client base, establish new client relationships and to drive new portfolio investments.

In 2004, Mr. Bohling was appointed Director of Worldwide Opportunity Analysis. His responsibilities included timely insights on Information Technology marketplace trends and development of Market Share Assessment Standards to enable and influence investment decisions to grow the business. He has also held other leadership positions across the Marketing organization and is on the Advisory Boards for leading Industry Associations.

Prior to joining IBM, Mr. Bohling held Senior Marketing Management positions with Verizon and Fogarty Klein Monroe.

Mr. Bohling’s research has been published in several scholarly journals including the following:

Bohling, T., Bowman, D., Lavalle, S., Mittal, V., Narayandas, D., Ramani, G., & Varadarajan, R. 2006. CRM Implementation: Effectiveness Issues and Insights. Journal of Service Research, 9(2): 184-194.

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Kumar, V., Venkatesan, R., Bohling, T., & Beckmann, D. 2008. The Power of CLV: Managing Customer Lifetime Value at IBM. Marketing Science, 27(4): 585-599.

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Mr. Bohling received a BBA in Marketing and an MBA with Highest Honors from the University of Houston.