Consumer Interest in and Willingness-to-Pay for Pesticide Free Production Food Products: A Probit Analysis

BY

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A Thesis
Submitted to the Faculty of Graduate Studies
in Partial Fulfillment of the Requirements
for the Degree of

MASTER OF SCIENCE

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Winnipeg, Manitoba

0-612-76798-1

THE UNIVERSITY OF MANITOBA

FACULTY OF GRADUATE STUDIES

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A Thesis/Practicum submitted to the Faculty of Graduate Studies of The University

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Master of Science

ACKNOWLEDGMENTS

I would like to thank my advisor, Dr. John Cranfield for his advice and guidance throughout the course of this project. I would also like to thank Dr. Gary Johnson and Dr. Rene Van Acker for their assistance. I would like to acknowledge the J.C. Gilson Agribusiness Fellowship and the Social Sciences and Humanities Research Centre, via a grant held by Dr. Martin Entz in the Department of Plant Science, for providing financial support for two years of my studies.

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ABSTRACT

This project assesses the market potential for Pesticide Free Production (PFP) food products. Pesticide Free Production is a new reduced input crop production system currently being developed by plant scientists and commodity producers in Manitoba. Assessing the market potential for a new product requires gauging consumer interest in the product. Understanding consumer preferences toward food products containing PFP inputs will provide information that potentially enables producers, processors and retailers to capitalize on the reduced chemical input nature of the PFP system.

This study assesses consumer interest in PFP food products using individual household level data gathered via a consumer survey of three Canadian cities, Calgary, Toronto and Winnipeg. Based on a random utility framework, binary and ordered probit models are used to assess consumer interest in purchasing PFP food products and consumer willingness-to-pay (WTP) a premium for PFP food products.

The results provide evidence that consumers would purchase PFP food products. The predicted probabilities for the binary probit models of PFP food product demand indicate that there is strong interest among respondents in PFP food products. Twenty-four of 25 potential PFP food products have a predicted probability of purchase over 50% and 10 products have predicted probabilities of approximately 70% or more.

The ordered probit WTP model results show that there is a high probability that respondents are willing-to-pay low to moderate premiums. There is a small, but significant probability that respondents are willing-to-pay high premiums for PFP food products. Health conscious and environmentally conscious consumers are more likely to

pay high premiums. Therefore, targeting marketing efforts at consumers with these characteristics could increase the likelihood of success in the marketplace.

The results are positive as they indicate strong interest in PFP food products in general and that a potential niche market exists of consumers who are willing-to-pay higher premiums for PFP food products.

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LIST OF ABBREVIATIONS

PFP	Pesticide Free Production
WTP	Willingness-to-pay
IPM	Integrated pest management
CV	Contingent valuation
Pr	Probability
LR	Likelihood ration
H-L	Hosmer-Lemeshow
Std. Dev.	Standard deviation
ww br	Whole wheat bread
Dbeans	Dry beans
Dpeas	Dry peas
Cpeas	Chickpeas
Cchips	Corn chips
Sseed	Sunflower seeds
Mg br	Multigrain bread
Wt br	White bread
Can oil	Canola oil
Marg	Margarine
Dlentil	Dry lentils
Bbean	Baked beans
Soup	Lentil, pea or bean soup
Gbars	Granola bars
Bw ndl	Buckwheat noodles

CHAPTER 1 - INTRODUCTION

1.0 Introduction

Agriculture on the Canadian prairies has been going through difficult and changing times in recent years. Conventional agricultural crop production, typified by large-scale monoculture, has led to fewer and larger farming operations. Many farms have increased in size in attempts to capture economies of scale, while many others have ceased to exist. One consequence of large-scale monoculture crop production is a reliance on chemical inputs to protect crops against disease, insect and weed pressures in order to maintain yields. Chemical inputs are not inexpensive and commodity prices have been low recently. Profit margins have been small or negative for many producers operating in this climate.

Loss of control over the production system is another reality for many producers. As agri-services companies become increasingly integrated the following scenario is not uncommon. Based on recommendations by an agri-service company, producers purchase specific seed to go along with certain chemicals (or vise versa). Producers then sell their output to the company they bought their inputs from. In essence, taking on much of the risk and cost to produce the raw product for a large corporation.

Concerns about the ecological sustainability of conventional production systems are another reality. Crop production systems which rely on chemical use can lead to pesticide resistance, disease outbreaks, increased risk of crop failure, soil nutrient loss and a lack of stability. Many farms are getting larger and less stable, making farming an increasingly risky occupation.

Consumer concerns about pesticide use in agriculture is another important factor producers must face. Increased use of chemicals in agriculture has heightened consumers' concerns regarding the health hazards of chemical residues in food (Henneberry, Piewthongngam and Qiang, 1999). Pesticide residues are often rated as a top concern by consumers in relation to other food safety issues. For instance, consumers have ranked pesticide and herbicide residues as the number one concern compared to other food safety concerns, and these differences are statistically significant at the 5% level (Byrne, Gempesaw and Toensmeyer 1991). Ott, Huang and Misra (1991) found that foods grown with pesticides were the highest ranked food safety concern among Georgia consumers. Bruhn *et al.* (1992) report that 48% of consumers in their study of California food shoppers list pesticide residues as a food safety concern. Anderson *et al.* (1996) indicate that 91% of respondents in a US national poll were concerned about pesticides and chemicals used to grow food. In a survey of Alberta households, pesticides were the most frequently cited high and moderate health risk (Kuperis *et al.* 1996).

Concern for the environment is another factor related to consumer preference for reduced input agriculture. In a study of Alaskan consumers, Swanson and Lewis (1993) conclude that preference for organic produce is related to both environmental and food safety concerns. The environmental aspect of reduced input agriculture is an important consideration for some consumers when making purchase decisions. Anderson *et al.* (1996) found similar results when assessing the effect of informing respondents about the production practices of integrated pest management (IPM), a production system which reduces chemical use. Eighty-five percent of respondents indicated they would rather buy IPM certified sweet corn after hearing a definition which stressed IPM's environmental benefits.

The factors described above have contributed to the development of alternative crop production systems. Plant scientists and commodity producers in Manitoba are currently developing a new reduced input crop production system called Pesticide Free Production. Pesticide Free Production (PFP) crops are grown without the use of chemical pest control methods during the crop year. Pesticides cannot be applied while crops are growing, during harvest or while in storage. Fertilizers may be used throughout the year, and certain pesticides can be applied prior to seeding. However, PFP crops cannot be grown where pesticides remain commercially active in the soil. PFP Canada defines PFP as follows:[1]

> PFP crops are non-GMO crops, that have not been treated with pesticides from the time of crop emergence until the time of marketing. In addition, such crops cannot be grown where residual pesticides are considered to be commercially active. (PFP Canada).

PFP has the potential to alleviate some of the problems associated with conventional crop production systems. Reducing reliance on chemical inputs and substituting agronomic knowledge to control pests is one way producers can take control of their production systems. Growing crops in a PFP system requires the use of diverse cropping systems and pest control practices. Greater diversity leads to more stable and sustainable agroecosytems (PFP Canada). PFP can potentially offer a raw food commodity which may be more appealing to consumers. Namely, a commodity produced in a PFP cropping system. Consumers are often willing-to-pay a premium for

[1] Pesticide Free Production Canada, or PFPC, is an organization composed of farmers working in association with federal, provincial and university researchers. PFPC is dedicated to research and education activities that support reduced pesticide crop production.

products they value, thus PFP food products may be able to generate additional revenue for producers. However, producers will see additional revenue only if they can capture a share of the premium consumers are willing-to-pay. Increased revenue and/or reduced input costs could potentially offer a viable alternative to expanding farm size.

PFP follows other reduced input production systems, such as integrated pest management (IPM) and organic farming. PFP falls between these other production systems in terms of reduction in chemical use. There is a continuum with respect to chemical use ranging from conventional agriculture which relies heavily on chemicals, to organic agriculture, which (although certification standards vary depending on the agency) generally uses no synthetic pesticides or fertilizers. PFP and IPM fall somewhere in the middle, with PFP being more restrictive on chemical use than IPM.

1.1 Motivation

Since PFP is a very new concept there has been little research on the market potential for PFP food products. There is some literature regarding consumer risk aversion to pesticide residues and the market potential for IPM and organic foods. However, PFP differs from IPM and organic production systems in a number of ways and this lessens the extent to which one can extrapolate findings from previous studies onto PFP. Moreover, this project goes beyond the scope of existing research, which has primarily focused on produce, and addresses PFP on field crops (e.g. cereal grains, pulse crops, oilseed crops).

Focusing on field crops has implications when assessing consumer demand since it is easier to assess consumer demand for produce than for commodities. For example, one can more easily answer how many apples or tomatoes they consume than how much wheat or flax they consume, as consumers usually buy the latter two after they have been processed into everyday food products. This project will focus on the market for processed food products containing ingredients produced in a PFP system. This study is also unique, as it is one of few to study the market potential for reduced input food products in Canada.

This project should be of interest to producers, processors and retailers who are looking for ways to add value to their products, capture new markets and increase revenues. The project should also be relevant to policy makers, as the sustainability of conventional agriculture and the viability of Canadian farms and rural communities has become increasingly uncertain. PFP may offer a financially, and environmentally sustainable alternative to current large-scale monoculture that has become prevalent on the Canadian prairies. This project contributes a valuable component to the analysis of the financial prospects for PFP. Results could help policy makers decide if PFP is a concept worth supporting and help producers, processors and retailers decide if PFP food products are concepts worth developing.

1.2 Objective

The purpose of this thesis is to assess the market potential for food products containing agricultural inputs produced in a PFP system. Assessing the market potential for a new product requires gauging consumer interest in the product. Since consumers' preferences drive the market, the overall ruler and coordinator of marketing activity in a private enterprise economy is the consumer. Failure to recognize the importance of consumer preferences has resulted in the downfall of many firms, and even entire industries (Kohls and Uhl 1980). Understanding consumer preferences toward food products containing PFP inputs will help provide information to decision makers that potentially enables producers, processors and retailers to capitalize on the reduced chemical input nature of the PFP system.

The objective of assessing the market potential for PFP food products will be accomplished in two ways.

i. Determine what PFP food products would be demanded by consumers and assess how demand for PFP food products is affected by consumers' demographic, attitudinal and behavioural profile.

ii. Determine consumer willingness-to-pay (WTP) for PFP food products and assess how WTP is affected by consumers' demographic, attitudinal and behavioural profile.

1.3 Research Problem

A problem often encountered at the developmental stage of a consumer good is that the product concept is just that, a concept. A tangible, marketable product may not exist. At present PFP food products fit this description. This makes measurement of consumer preference of such products difficult. To overcome this issue, this study assesses consumer interest in hypothetical PFP food products based on individual household level data gathered via a consumer survey. Qualitative response models based on a random utility theoretical framework are then used to assess consumer interest in PFP food products.

1.4 Research Procedures

Consumer interest in PFP food products is assessed in two stages. Both stages of the research will use data gathered in a consumer survey of grocery shoppers in randomly selected households in Calgary, Winnipeg and Toronto. The first stage of the analysis assesses whether respondents are interested in buying PFP food products and if so, what products. Here, *binary* probit models are used to calculate the predicted probability that respondents would purchase each of the potential PFP food products.[2] Marginal effects of explanatory variables on the predicted probabilities are calculated for eight selected PFP food products. The binary model results indicate how likely respondents are to purchase a variety of potential PFP food products. The results also indicate what characteristics affect respondent interest in PFP food products and the magnitude of these affects on a selection of products.

The second stage assesses respondent willingness-to-pay (WTP) a premium for PFP food products. In the second stage, an *ordered* probit model is estimated to predict the probability that respondents are willing-to-pay one of five premium levels for PFP food products. Marginal effects of respondent characteristics on each of the five predicted probabilities are also calculated. This model will indicate the likelihood that PFP products will generate additional revenue, and will indicate the characteristics of those most likely to contribute the additional revenue.

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[2] A list of 25 potential PFP food products was presented to respondents in the PFP consumer survey to gather information about what products people would purchase in a PFP form.

1.5 Literature Review

PFP is a new system, but concerns about pesticide residues and food safety are not a new phenomenon. There are a number of existing studies regarding consumer concerns with pesticide residues in food and consumer preference for reduced input food products. This section provides a background on the existing literature studying consumer preference for reduced input food products.

Several authors have mentioned that consumer perceptions of pesticide residues have an impact in the marketplace. Public perceptions of the risk posed by pesticides used in food production can translate into very real effects in the market place (Dunlap and Beus 1992). Consumers' concerns about the use of pesticide chemicals in food production will translate into market behaviour and alter demand for food products (Huang 1996). Bruhn *et al.* (1992) report that more than half the respondents in their California study have changed their food buying practices because of food safety concerns. Participants made changes in response to numerous food safety concerns, of which pesticide residues made up a small portion. Consumers clearly change purchasing behaviour to avoid products they perceive as unsafe. These comments reinforce the statements by Kohls and Uhl cited earlier about the importance of understanding consumers' preferences.

Socio-demographic variables are frequently studied to determine whether they play a role in consumer concerns about pesticides and food safety. Govindasamy and Italia (1998) report that females, households with children, and suburban households were more likely to be concerned about pesticide residue. Individuals under the age of 35, those with higher incomes and higher education are less concerned about pesticide residue. Among Taiwanese consumers, households with small children are more likely to be willing-to-pay a higher price for hydroponically grown vegetables, which are free of pesticides (Huang, Kan and Fu 1999). A study of Italian food shoppers' response to organic fresh produce indicates that males, and those with a university degree, were less likely to be willing-to-pay for organic produce. Income had a positive effect on WTP for organic produce, and had the largest impact on WTP (Boccaletti and Nardella 2000).

Byrne, Gempesaw and Toensmeyer (1991) found that concern about pesticide residues was lower for males, persons with at least a bachelors degree and high income households. Buzby, Ready and Skees (1995) examine consumer WTP for safer grapefruit (grapefruit produced without a specific, widely-used pesticide called sodium ortho-phenylphenate), and report that income and age are inversely related to WTP. Baker (1999) found that females, consumers who are white and those with larger households are more concerned about the pesticide policy under which fruits and vegetables are grown. Higher income households, larger households, those with higher education and organic food consumers are more likely to buy eco-labeled apples (Blend and van Ravenswaay 1998). Dunlap and Beus (1992) found that being female and having more education have a positive relationship with pesticide concerns, while age and income have a negative relationship with pesticide safety concerns. In Alberta, females were found to be WTP more to restrict pesticide use than males (Kuperis *et al.* 1996).

The studies listed above report differing results regarding the effects of socio-demographic characteristics on pesticide residue concerns, food safety concerns and consumer preferences. The effects of education and income seem to be the most variable in the existing literature. What is clear however, is that some consumers prefer (and are willing-to-pay more for) reduced input food products. Therefore, it could be expected that some consumers will prefer PFP food products. One of the objectives of this study is to see how demographic variables impact interest in PFP food products.

Factors influencing consumer preference for reduced input food products are not limited to socio-demographic characteristics. Consumers who are concerned about the use of chemical pesticides, those who feel that produce should be tested and certified residue free, and those who are nutritionally conscious are more likely to purchase organically grown produce (Huang 1996). Buzby, Ready and Skees (1995) found that WTP increased with the strength of consumers' attitudes that pesticides pose a risk and that the government should ban all pesticides. Targeting marketing efforts at consumers with these attitudes may be more difficult than with socio-demographic characteristics, but such information is important. Knowledge of the importance of non-socio-demographic variables is valuable, as it can be used to highlight the attributes of the product that match these characteristics or attitudes.

To summarize, pesticide residue has been shown to be a major concern among consumers in recent literature. Socio-demographic characteristics of consumers appear to play a role in concern about pesticide use. Information about the production practices of reduced input agriculture has also influenced consumer preference for IPM or organic food. Based on past research, it could be hypothesized that similar factors would affect consumer demand of, or preference for, PFP food products. It is the goal of this project to determine if this is indeed the case.

1.6 Thesis Outline

This thesis has 6 chapters. This *Introduction* chapter described Pesticide Free Production (PFP), defined the research problem, outlined the objectives and procedures, addressed the relevance of the study and provided a background on related literature. Chapter 2, the *Conceptual and Empirical Framework*, describes the theoretical background and the empirical models used to analyze the research problem. *Data and Methods* (Chapter 3) describes the data used in this study, model specification and the method of generating empirical estimates. Chapters 4 and 5, the *PFP Food Product Demand Model Results and Analysis* and *Willingness-to-Pay Model Results and Analysis*, analyze the results of the empirical models. Chapter 6, Summary *and Conclusions*, outlines marketing implications and conclusions drawn from this research.

CHAPTER 2 - CONCEPTUAL AND EMPIRICAL FRAMEWORK

2.0 Introduction

This chapter outlines the theoretical background used to frame the problem of assessing consumer interest in, and WTP for, PFP food products based on data gathered at the individual household level. The appropriate empirical model will be described in the empirical framework section. The empirical framework outlines the two similar models used to estimate consumer interest in specific PFP food products and consumer WTP a premium for PFP food products.

2.1 Conceptual Framework

Neo-classical consumer demand theory is based on the assumption that quantities are non-negative continuous variables. However, this is not always a realistic representation of the choice situation consumers face. Often consumer decisions are made from limited or discrete, finite choice sets. When quantities are limited, the variables are referred to as qualitative or discrete, as opposed to continuous variables.

When considering consumer demand at the household or individual level, it is apparent that choices are made from discrete choice sets. Train (1986) uses the example of auto demand to illustrate the difference between continuous and discrete choices. The aggregate demand for a particular make and model of car can be considered a continuous variable that varies over time and geographic regions, but the demand for that model by any one household is not continuous, each household either buys that model or not. A theoretical framework for assessing individual choices must take into account the behavioural situation.

The demand for PFP food products can be represented in a discrete choice framework. The decision about which products to purchase in a PFP form can be thought of as a number of separate discrete choice situations. Individuals will choose to either purchase a specific PFP food product or not.

The willingness-to-pay decision can also be represented as a discrete choice, even though it may appear to be a continuous choice. In the survey used for this project, respondents were given a choice of five categories to indicate how much more they would be willing-to-pay for a PFP food product. The choice respondents face in this willingness-to-pay scenario is a limited or discrete choice situation.

The theoretical framework for this project is based on discrete choice theory, as the information gathered is measured at the individual household level. Consequently, a discussion of discrete choice theory is needed to appreciate the empirical framework developed later in this chapter.

2.1.1 Discrete choice theory

In consumer theory, demand functions are typically derived using calculus by maximizing the utility function with respect to quantities, subject to the budget constraint. "However if the consumption of one or more commodities can be zero, the maximization problem may have a 'corner' solution, a point where the usual first-order conditions for an optimum do not hold." (Ben-Akiva and Lerman 1985) In a discrete choice situation the consumption of one or more commodities can be zero and therefore, the maximization techniques of calculus cannot be used to formulate demand functions. Instead, discrete choice analysis involves working with utility functions without the use of calculus based optimization techniques. For example, U_{in} is the utility of alternative i for individual n, and the individual is assumed to have utility functions for each alternative in the choice set. Utility is still being maximized in discrete choice analysis and consumers are assumed to be rational in that they seek to maximize their utility over all possible choices subject to their constraints. Thus, alternative i will be chosen if and only if, $U_{in} > U_{jn} \ \forall j \neq i$. That is, alternative i will be chosen if the utility from i is greater than the utility from all other alternatives in the choice set.

In his 1966 paper, *A New Approach to Consumer Theory*, Lancaster introduced the idea that consumers demand goods based on the attributes they possess, and thus utility is defined in terms of the attributes of the alternatives. Lancaster's approach is an extension of consumer theory, as consumer theory does not make any assumptions about the nature of the alternatives (Ben-Akiva and Lerman 1985). This concept has been built on, and made use of in discrete choice theory. For example, $U_{in} = U(Z_{in})$, where Z_{in} is a vector of attributes of alternative i as viewed by individual n. In the context of selecting between alternative food products, individual n may select a PFP food product because they perceive it to contain certain attributes that they desire, such as increased food safety (*i.e.*, reduced pesticide inputs).

Individuals seek to maximize their utility subject to the constraints they face. Budget and time constraints are examples of restrictions that determine the choice set for individual decision makers. The indirect utility interpretation means that these budgets can also be included in the utility function (Ben-Akiva and Lerman 1985). The concept of the indirect utility function in consumer theory arises from substituting the optimal demand functions into the utility function, thus incorporating the budget constraint into the utility function. In discrete choice analysis this idea is combined with the idea that consumers demand goods based on the attributes they possess. In the discrete choice approach, the characteristics of the individual (W_n) are included in the utility function, and these characteristics may reflect income, time and other constraints. W_n is a vector of the characteristics of individual n, and the indirect utility function can be represented by: $U_{in} = U(Z_{in}, W_n)$. The utility function in discrete choice theory typically contains attributes of the alternatives as viewed by the individual and characteristics of the individual.

The individual decision maker is assumed to behave by choosing the alternative that maximizes their utility and to make this choice based on all relevant factors. The researcher will presumably know some of the attributes of the alternatives, but not all of the attributes as seen by the individual. As well, the researcher typically will not be able to observe all of the relevant characteristics of the individual. Since the researcher cannot observe all relevant factors the utility function is used to represent consumer preferences.

The unobserved components of utility have ramifications for assessing consumer preferences. If the utility function was known exactly, then predicting the choice of the individual would be as simple as finding the alternative with the highest utility. However, the researcher cannot know the individuals exact utility function. The information that is observable is combined with a random component, which represents the unobservable portion of utility, to estimate the predicted probability that an individual will select a given alternative. The important distinction is that when the utility function is not known with certainty, which it cannot be, then it is the **predicted probability** of selecting a given alternative that is being estimated.

2.1.2 Random Utility Model

A common framework for modeling individual decision makers probabilistic choice behaviour is the random utility model. As Manski (1977) states (in a paper described by Ben-Akiva and Lerman (1985) as the first formalization of random utility models):

> ". . . if decision makers are utility maximizers and if the process associating decision makers with choice sets can be specified, then, to an observer possessing incomplete knowledge of the characteristics of decision makers and alternatives, a random utility model describes behavior."

Hanemann cited in Fry *et al.* (1993) expands and provides more clarity in describing random utility models.

> "A random utility model arises when one assumes that, although a consumers utility function is deterministic for *him*, it contains some components which are unobservable to the econometric investigator and are treated by the observer as random variables. The unobservables could be characteristics of the consumer and/or attributes of the commodities. This concept, therefore, combines two ideas that have a long history in economics – the idea of a variation in tastes among individuals in a population and the idea of unobserved variables in econometric models."

Daniel McFadden is a major contributor to the development of discrete choice analysis. In his 2001 paper, *Economic Choices*, McFadden summarizes the development of economic models designed to analyze individual level discrete choice data based on the random utility framework.

The following are some examples of the use of random utility models in empirical research. Eom (1994) uses a random utility approach to analyze food safety valuations by consumers when integrating pesticide risk perceptions. Bell *et al.* (1994), use a random utility model to estimate the probability that a landowner will choose to take part in the Tennessee Forest Stewardship Program. Kuperis, Veeman and Adamowicz (1999), use a random utility model to assess consumer response to milk produced with bovine somatotrophin (bst). Veeman and Adamowicz (2000), also use this approach as a theoretical framework in examining consumer demand for food safety and perception of environmental risks. Quagrainie, Untershultz and Veeman (1998), use a random utility model to examine the effect of product and consumer characteristics on consumers' choice of red meats. These studies are a few of the applications of random utility models to discrete or qualitative choice situations.

The utility function in a random utility model is typically defined as the sum of two parts. One part is the deterministic or observable aspects of utility, and the second part is the unobservable aspect, which is treated as random. The utility function is defined in the following equation.

$$U_{in} = V_{in} + \varepsilon_{in}, \tag{2.1}$$

where V_{in} is the deterministic component, and

ε_{in} is the random component.

The deterministic component of the utility function, V_{in}, can be broken down further to show the different factors that make up the observable aspect of utility:

$$V_{in} = V(Z_{in}, W_n, \beta),$$

where Z_{in} is a vector representing attributes of alternative i as viewed by individual n,

W_n is a vector representing characteristics of individual decision maker n, and

β is a vector of parameters to be estimated.

The random component ε_{in} represents unobservable factors such as unobservable variations in preferences, random individual behaviour and measurement error. These are things that the researcher cannot observe about individuals. Unobservable factors may also include things the individual does not observe about the alternatives in the choice set. For example, an individual may not observe that product a is of superior quality to product b. The probabilistic description of choice is used not to reflect that behavior is probabilistic, but the lack of information leads the analyst to treat utility as a random variable. Consequently choice must be described in a probabilistic fashion (Baltas and Doyle 2001).

In the case of selecting between different food products, Z_{in} could include attributes like production method (*i.e.*, organic, IPM, PFP), taste, cost, appearance, nutritional content and safety. W_n could include variables such as age, income, gender and education. The variables that are thought to be relevant, and hypotheses about the effects of these variables on utility, will be discussed in detail in the "Data and Methods" chapter (Chapter 3). At this point, for the sake of simplicity Z_{in} and W_n can be combined into a single vector x_i representing all the factors that influence the utility of alternative i. Thus, $V_{in} = V(x_i \beta)$, and since $U_{in} = V_{in} + \varepsilon_{in}$, the utility of alternative i can be represented as,

$$U_i = V(x_i \beta) + \varepsilon_i \tag{2.2}$$

(where the individual subscript has been dropped for the sake of simplicity).

The probability that alternative i is selected from choice set C is the probability that $U_i > U_j \quad \forall i, j \in C, \quad j \neq i$. That is, the probability that i is chosen is equal to the probability that the utility of i is greater than the utility of all other alternatives that are elements of the choice set C. A two-alternative scenario can be used to illustrate the choice situation. The probability that alternative one is selected over alternative zero is equal to the probability that the utility of alternative one is greater than the utility of alternative zero. Following Cooper and Osborn (1998), this can be thought of as the unobserved difference in utility, ΔU^*. Where $\Delta U^* = U_1 - U_0$, and alternative one is selected if ΔU^* is positive.

The utilities are expressed as:

$$U_i = (x_i'\beta) + \varepsilon_i \quad i \in \{1,0\} \tag{2.3}$$

The probability that alternative one is chosen is expressed as $\Pr(y=1) = \Pr(\Delta U^* > 0)$, which, upon substitution of the appropriate utility function from equation 2.3, results in $\Pr(y=1) = \Pr(\varepsilon > -x'\beta)$. Where, $x = x_1 - x_0$ and $\varepsilon = \varepsilon_1 - \varepsilon_0$. Thus, $\Pr(y=1) = 1$ if the difference in the random component is greater than the negative of the difference in the deterministic component. The distributions commonly used in modeling discrete choice data are symmetric. Therefore, $\Pr(y=1) = \Pr(\varepsilon < x'\beta) = F(x'\beta)$, where F represents the cumulative distribution function to be used to predict the probability that alternative one is chosen.

Since the random component of the utility function is unobservable a cumulative distribution function for the random component must be assumed in order to estimate the model. The two distributions typically used in qualitative choice models are the standard normal distribution and the logistic distribution. Both distributions are symmetric bell shaped curves. Since the distribution is symmetric the probability that $(y=1)$ can be cast as the probability that the difference in the random component is less than the difference in the observable component, [$i.e., \Pr(y=1) = \Pr(\varepsilon < x'\beta)$].

The two distributions commonly used in qualitative response models lead to different (but very similar) probability models, probit and logit. The probit model is based on the assumption that the random components of utility ε_{in} are distributed jointly normal with a standard normal distribution function, whereas the logit model is based on the assumption that ε_{in} is independently identically distributed (iid) in accordance with the extreme value distribution, which leads to a logistic distribution function. Since the distributions are similar, the results derived using the two models will also be quite similar. Maddala (1983) states that, ". . . unless samples are very large and the observations at the tails exert a large influence, one obtains similar results using probit analysis and logit analysis." The parameter estimates of the two models will differ, but can be transformed to reflect the corresponding estimate from the alternate model. Amemiya (1981) suggests multiplying the estimated probit coefficients by 1.6 to yield an approximation of the corresponding logit coefficient.

It should be noted that the logit model is more restrictive, as the assumption of iid disturbances leads to a property in logit models known as independence from irrelevant alternatives (IIA). The IIA property can be restrictive as it means that the introduction of a new alternative to the choice set does not change the ratio of choice probabilities between the existing alternatives. This is not always a realistic representation of individual behaviour. A popular example used to illustrate this problem is the red bus, blue bus example (Train 1986). Suppose that an individual has existing choice probabilities for two alternate modes of travel. One is auto $(\Pr_{auto})$, the other is a red bus

$(\Pr_{redbus})$. The probability for each alternative is $\Pr_{auto} = \frac{1}{2}$ and $\Pr_{redbus} = \frac{1}{2}$. The ratio $\Pr_{auto} / \Pr_{redbus} = 1$. Now suppose a new bus is added to the choice set that has the same attributes as the existing bus except for its colour, this bus is blue. One would expect that the choice probability for auto should remain unchanged as the new bus is the same as the existing bus, but the IIA property implies that the ratio of choice probabilities for two alternatives is unaffected by the introduction of a new alternative. Thus the probabilities must now be $\Pr_{auto} = \frac{1}{3}$, $\Pr_{redbus} = \frac{1}{3}$, and $\Pr_{bluebus} = \frac{1}{3}$ in order for the ratio $\Pr_{auto} / \Pr_{redbus}$ to remain equal to one. This is why the IIA property is said to impose unrealistic restrictions on choice behaviour in certain situations.

In the following section, the structure of logit and probit models is examined further. Particular attention is paid to probit models as probit is the method used in this project to evaluate consumer interest in PFP food products. However, most of the commentary is also applicable to logit models as the two are quite similar.

To summarize the theoretical approach, a random utility model is used as the basic framework to assess consumer interest in PFP food products. The underlying concept is that individual decision makers will select the alternative that provides them with the greatest utility. An individual's utility function is treated as a random variable since the researcher cannot observe all aspects of utility. In the following section, this random utility framework is built upon to develop an empirical model to estimate the predicted probability of consumer purchase, and willingness-to-pay for, PFP food products.

2.2 Empirical Framework

As outlined in the conceptual framework, the appropriate theoretical model is based in discrete choice theory. The corresponding empirical model must be a discrete choice model. Classical regression models cannot be used to analyze discrete data, as:

> "Standard econometric methods like regression were designed for analyzing variables that can assume any value within a range, that is, for continuous variables. These methods are usually appropriate for examining aggregate data. When the underlying behaviour of the individual decision making units is examined, however, it is often found that the outcome of the behaviour is not continuous and standard regression procedures are inappropriate." (Train 1986)

Since the data gathered for this analysis is at the individual decision-making unit level, as opposed to aggregate level data, Ordinary Least Squares regression analysis is not appropriate; a discrete or qualitative response variable model is needed. These models are sometimes referred to as probability models because they are designed to assess choice as probabilistic behaviour. It is important to reiterate that individual behaviour is not truly probabilistic. The fact that the researcher lacks complete knowledge makes the problem probabilistic.

2.2.1 Probit or Logit Models

As mentioned in the conceptual framework section there are two popular choices among probability models: the probit and logit models, which are both widely used. Logit models are frequently used because of their mathematical simplicity and the ease of interpretation of the choice probabilities (Fry *et.al.* 1993). It should be noted that concern about computational difficulty with probit models is not as serious as it once was. Increased computer power and modern econometric software has greatly minimized these difficulties. Therefore, probit models are also widely used.

The difference between the logit and probit models is the assumption regarding the underlying cumulative density function for the random component of the utility function ε_{in}. The observed information in the deterministic component combined with the assumption about the distribution of the random component allows the calculation of choice probabilities.

In the conceptual framework section the IIA property was described as a drawback of logit models. However, it is believed that the IIA property would not be a problem if a logit model was used for this project. The IIA property is only restrictive in multinomial logit models, and the models in this project are either binary or ordered. Although, questions could be raised about the choices respondents face in the survey when answering the question about which products they would purchase in a PFP form. Respondents where given a list of 25 potential PFP food products and asked to indicate which PFP products they would purchase if available. This could be interpreted as a multinomial choice situation and hypothetically, a new choice alternative could be added to the product list (choice set) similar to the red bus, blue bus scenario. Therefore, the IIA restriction could be considered a problem in this situation if the random component was assumed to be logistically distributed. Assuming a standard normal distribution allows for a more flexible interaction between choice probabilities as the normal distribution does not imply the IIA property. As probit models do not have this property they provide a more realistic relationship among probabilities.

The drawback with probit models is that the standard normal distribution lacks a closed form solution and the calculation of choice probabilities is intuitively less appealing. Probit choice probabilities are less appealing because they are more difficult to calculate than logit probabilities. To see this, note that the choice probabilities from the two models are represented as:

$$\text{Logit} \quad \Pr(y=1) = \frac{e^{x'\beta}}{1+e^{x'\beta}} \quad \text{and} \tag{2.4}$$

$$\text{Probit} \quad \Pr(y=1) = \int_{-\infty}^{x'\beta} \frac{1}{\sqrt{2\pi}} e^{-\varepsilon^2/2} d\varepsilon, \tag{2.5}$$

where ε is a standard normal random variable (Griffiths, Hill and Judge 1993) with zero mean and a variance that has been normalized to one.[1] The logit probabilities could be easily calculated by hand with the aid of a calculator, while probit probabilities require the use of computer software. This is a minor issue in practice because the probabilities are usually calculated using computer software regardless of the model used. The point is merely that it is easier to intuitively understand how the logit probabilities are calculated. Therefore, this computationally based criticism against probit models is a minor detraction.

Greene (2000) argues that it is difficult to justify the choice of one distribution over the other on theoretical grounds. However, assuming a normal distribution is a common practice when the true distribution is unknown. Given that the two models are similar, that assuming a normal distribution is common and a desire to avoid concerns

[1] Greene states that the assumption of a variance of 1 is an innocent normalization. If it is assumed that the variance of ε is σ^2 instead of 1, and likewise multiply the coefficients by σ the observed data will be unchanged. y is 0 or 1, depending only on the sign of $U_1 - U_0$, not the scale. (Greene 2000)

about the restrictive IIA property; the probit model was selected as the probability model for this project.

2.3 The Probit Model

Given the choice of the probit model, additional detail regarding its structural characteristics is provided below. Recall that, $\Pr(y=1) = \Pr(\varepsilon < x'\beta) = F(x'\beta)$. Assuming the random error component has a standard normal distribution allows one to represent the choice probability via equation 2.5, which results in:

$$\Pr(y=1) = \int_{-\infty}^{x'\beta} \frac{1}{\sqrt{2\pi}} e^{-\varepsilon^{1/2}} d\varepsilon$$

$$\Pr(y=1) = \int_{-\infty}^{x'\beta} \phi(\varepsilon) d\varepsilon \text{, or}$$

$$\Pr(y=1) = \Phi(x'\beta) \text{, and} \tag{2.6}$$

$$\Pr(y=0) = 1 - \Phi(x'\beta). \tag{2.7}$$

Where $\Phi(\cdot)$ is used to represent the standard normal probability distribution function, and ϕ represents the standard normal density function. The question now becomes how to use the probit model to calculate the choice probabilities and the effect of a change in an explanatory variable on the choice probabilities, which are called marginal effects.

2.3.1 Choice Probabilities and Marginal Effects

The choice between making a purchase or not is assumed to be based on which alternative provides the greatest utility. At the simplest level the choice between a PFP food product and the conventional counterpart is a choice between two alternatives. Suppose that U_1 and U_0 are the utilities of a PFP and a conventional food product, respectively. Recall that $y = 1$ if the difference in utility $\Delta U^* = U_1 - U_0 > 0$, and $y = 0$ if $\Delta U^* \leq 0$. In this case, equation 2.6 shows the probability of choosing the PFP alternative, while equation 2.7 shows the probability of not choosing the PFP alternative.

Equation 2.6 and 2.7 show that the probability of a purchase being made can be predicted based on the explanatory variables (x's), the estimated parameters (β's) and the assumed standard normal cumulative distribution function. From a marketing perspective this is very useful. A probit model can be used to predict the probability of a purchase, or the probability that an individual is willing-to-pay a premium without knowing all the factors in the utility function. This allows the estimation of probabilities, without complete knowledge of utility, that otherwise would not be possible.

The predicted probabilities are an indication of consumer preferences, as they are a measure of the likelihood that respondents would purchase a specific PFP food product or pay a specific premium for PFP food products. The $\beta's$ will be estimated by the probit model using all information and then the predicted probabilities will be calculated using these estimated parameters, $\beta's$, and the $x's$ each set at their sample means. Therefore, the predicted probabilities calculated in this project will be considered the predicted probability that the average respondent would purchase the specific PFP food product. In the WTP model the predicted probabilities will be interpreted as the probability that the average respondent is willing-to-pay a specific premium for PFP food products.

In the case of PFP food products, which have yet to be developed, a marketer could use the predicted probabilities to determine if the probability of acceptance by respondents is strong enough to warrant moving ahead with product development. The probabilities can also be used to determine which potential PFP food products have the greatest likelihood of acceptance in the marketplace. Products with the high predicted probabilities make for logical choices as 'flagship' PFP food products in the marketplace (providing that these products are derived from crops that are viable in the PFP system).

Marketers will also be interested in how deviations from the average respondent effect the choice probabilities. As such, marginal effects of the explanatory variables on the predicted probabilities will also be calculated. The marginal effects indicate the magnitude of the effect on the predicted probability due to a change in a specific explanatory variable. For example, a marketer may want to know the effect education has on the predicted probability that the average respondent will purchase the PFP food product. Are higher educated respondents more or less likely to purchase PFP food products? Knowing what effects different factors have on the predicted probability allows the marketer to focus their efforts on reaching consumers with characteristics that have a strong positive effect on the predicted probability of purchase, or WTP a premium.

It is important to note that the estimated parameters of the probit models cannot be interpreted as the marginal effects. Deriving the marginal effect of an explanatory variable in probit models requires additional calculation. In the general case the marginal effects are calculated as,

$$\frac{\partial \Pr(y=1)}{\partial x_k} = \frac{d\Phi(x'\beta)}{d(x'\beta)}\beta_k$$

$$\frac{\partial \Pr(y=1)}{\partial x_k} = \phi(x'\beta)\beta_k \tag{2.8}$$

where, ϕ is the standard normal density function, and x_k is a continuous explanatory variable.

2.4 The Empirical Model

As outlined in the introduction, this project will examine consumer demand for PFP food products in two stages, requiring two different variations of the probit model. The first stage involves using binary probit models to assess respondent interest in various PFP food products. The second stage requires an ordered probit model to assess respondent willingness-to-pay a premium for PFP food products. The reason a different model is required for the second stage is because the dependent variable can take more than two values.

2.4.1 Stage 1 – Binary Probit Model of PFP Food Product Demand

The objective in this stage is to analyze consumer interest in various types of products if they were available in a PFP form. Binary probit models are used to estimate the probability that respondents will purchase individual PFP food products. Individual products are analyzed because responses to a survey question asking respondents if they would purchase a PFP food product were very positive. After reading the following definition of PFP food products respondents were asked whether they would prefer to purchase a PFP alternative over a conventional food product:

> A PFP alternative is a food product in which the main ingredient(s) have been produced in a pesticide free production system, but other ingredients may have been produced with pesticides.

While details of the survey data are provided in the Chapter 3, note that approximately 83% (238 of 286) of respondents said yes, they would purchase a PFP food product, while only 1% (3 of 286) said no. The remaining 16% (45 of 286) would want more information, were unsure or gave a multiple response. Since the vast majority said yes, and a small percentage said no, it is clear that there is strong interest in PFP food products in general. Therefore, the decision was made to analyze consumer interest in specific PFP food products.

To gauge consumer interest in specific PFP food products respondents were asked the following question:

> Consider the following list of food products. Suppose that a PFP alternative were available for each item, at the same price and with no difference in taste. Please indicate which of the food products you would purchases in the PFP form.

❑ Pasta	❑ Multi grain bread
❑ Whole wheat bread	❑ White bread
❑ Crackers	❑ Bagels
❑ Muffins	❑ Cookies
❑ Breakfast cereal	❑ Oatmeal
❑ Granola	❑ Canola oil
❑ Corn oil	❑ Margarine
❑ Dry beans	❑ Dry lentils
❑ Dry peas	❑ Baked beans
❑ Canned chickpeas	❑ Lentil, pea, or bean soups
❑ Corn chips	❑ Granola bars
❑ Sunflower seeds	❑ Buckwheat noodles
❑ Beer	❑ Other (please list below)

A binary probit model is estimated for each of the 25 products listed in the survey question. The "other" category is excluded, as it is difficult to infer any quantitative meaning from this response option. This option was included in the survey to find out what other products respondents would be interested in if available in a PFP form. Many respondents who selected the "other" category indicated they would purchase PFP fruits or vegetables if they were available. The reason produce was not included in the list of potential products is that PFP research to date has focused on field crops produced on the

Canadian prairies. The list of potential PFP food products is comprised of products derived from field crops grown in Manitoba.

The 25 probit models will provide the predicted probability that the average respondent would purchase the respective potential PFP food product, and will indicate the direction of the effects of the explanatory variables on the predicted probabilities. The sign of the coefficient estimates indicate the direction of effect the variable has on the predicted probabilitiy, but not the magnitude of effect. If $\hat{\beta}_k$ is positive, then an increase in x_k will lead to an increase in the predicted probability. Out of these 25 basic probit models, eight models (products) will be analyzed in more detail. Marginal effects of the explanatory variables on the predicted probabilities will be calculated for these eight selected products.

Calculating marginal effects for all 25 binary probit models would require extensive calculations. Therefore, the subset of eight potential PFP food products have been selected to be fully modeled (*i.e.* marginal effects calculated). The eight selected products are; pasta, breakfast cereal, dry peas, sunflower seeds, beer, multigrain bread, canola oil and dry lentils. These eight products represent a cross section of product types from the full list of 25 products. As these eight products are representative of the full product list, minimal additional information (relative to the cost of the extra calculations) would be gathered from calculating marginal effects for all products.

Equation 2.8 described the method of calculating marginal effects, however deriving the marginal effects of binary variables precludes the use of the calculus. One cannot take the partial derivative of the probability function with respect to a binary (*i.e.*, 0/1) variable. As such, a numerical scheme is used to calculate the marginal effects for the binary variables in the models. The first step is to calculate the predicted probability with the explanatory variable of interest set at one, while the remaining explanatory variables are held constant at their sample means. Next, calculate the predicted probability with the explanatory variable of interest set at zero (again all other explanatory variables are held constant at their sample means). The marginal effect is calculated as the difference in the two predicted probabilities. This procedure is repeated for each individual variable in the model.

The information derived from the binary model stage will provide an indication of the products respondents are likely to purchase in a PFP form, and the factors that influence the probability that respondents will purchase these products. The following discussion will outline the details of the binary probit model.

As shown earlier (in equations 2.6 and 2.7) for a binary dependent variable, the probabilities of the two potential outcomes are represented in the following way:

$$\Pr(y=1) = \Phi(x_i \beta)\text{, and}$$

$$\Pr(y=0) = 1 - \Phi(x_i \beta)\text{.}$$

In this project the dependent variable in each binary model is the probability that the average respondent will purchase the specific PFP food product. The dependent variable will be referred to as $\Pr(BuyPFP = 1)$ and $(BuyPFP)$ is defined as follows,

$BuyPFP = 1$ if the individual indicates they would buy the PFP product,

$BuyPFP = 0$ otherwise.

Following the conceptual framework, the model is formulated in the following way:

$$U_{PFP} = x'_{PFP}\beta + \varepsilon_{PFP} \quad \text{and} \quad U_{conv.} = x'_{conv.}\beta + \varepsilon_{conv.} \quad \text{where,}$$

U_{PFP} represents the utility the individual derives from the PFP food product,

$U_{conv.}$ represents the utility the individual derives from the conventional food product, and

x_i represents a vector of the characteristics of the individual and the attributes of the alternative, or the deterministic components of the utility function,

β represents parameters to be estimated.

It then follows that:

$$\Delta U^* = (U_{PFP} - U_{conv.}),$$

$$\Delta U^* > 0 \ \ if \ \ U_{PFP} > U_{conv.}, \text{ therefore}$$

$$\begin{aligned}
\Pr(BuyPFP = 1) &= \Pr(\Delta U^* > 0) \\
&= \Pr(U_{PFP} - U_{conv.} > 0) \\
&= \Pr[(x'_{PFP}\beta + \varepsilon_{PFP}) - (x'_{conv.}\beta + \varepsilon_{conv.}) > 0] \\
&= \Pr[(x_{PFP} - x_{conv.})'\beta + \varepsilon_{PFP} - \varepsilon_{conv.} > 0] \\
&= \Pr(\varepsilon < x'\beta) \\
&= \Phi(x'\beta) \quad \text{and,}
\end{aligned}$$

$$\begin{aligned}
\Pr(BuyPFP = 0) &= \Pr(\Delta U^* \leq 0) \\
&= 1 - \Phi(x'\beta),
\end{aligned}$$

Interpretation of binary probit model estimates, calculation of predicted probabilities and marginal effects are discussed in the "PFP Food Product Demand Model Results and Analysis" chapter (Chapter 4).

2.4.1 Stage 2 – Ordered Probit Model of Willingness-to-Pay for PFP Food Products

The objective of this stage is to analyze consumer willingness-to-pay for PFP food products. Given the nature of the survey question used to solicit WTP values, an ordered probit model is used to assess consumer willingness-to-pay for PFP food products. Specifically, the question presented to respondents was:

> Suppose your favorite food product regularly costs $2.00 for each unit you purchase. Assuming no difference in taste and nutritional content, would you pay slightly more for a PFP version of the same food product?

- ❑ No
- ❑ Yes, I would pay between 1 cent and 10 cents more for the PFP version
- ❑ Yes, I would pay between 11 cents and 20 cents more for the PFP version
- ❑ Yes, I would pay between 21 cents and 40 cents more for the PFP version
- ❑ Yes, I would pay more than 40 cents more for the PFP version

In this model the dependent variable is a multiple response variable which has an intrinsic order. Therefore, a variation of the probit model is required. Since there are more than two response categories and the categories have an intrinsic order, an ordered probit model must be used. A multinomial model would not make full use of the ordinal nature of the WTP variable (Cooper and Osborn 1998). The dependent variable, WTP, can take one of five possible values as there are five choice options. The five options were presented to respondents in absolute monetary terms. An important principle of survey methodology is to minimize the effort required by the respondent to complete the survey, and this format was used to reduce the energy expended by respondents. However, percentage terms are desirable for analysis and discussion so the response options have been converted to percentages.

The WTP variable can take the following values:

No	=	Willing-to-pay 0% more	$\rightarrow WTP = 1$
Yes, 1-10 cents more	=	Willing-to-pay 1%-5% more	$\rightarrow WTP = 2$
Yes, 11-20 cents more	=	Willing-to-pay 6%-10% more	$\rightarrow WTP = 3$
Yes, 21-40 cents more	=	Willing-to-pay 11%-20% more	$\rightarrow WTP = 4$
Yes, >40 cents more	=	Willing-to-pay >20% more	$\rightarrow WTP = 5$

The same theoretical framework, a random utility model, used in the binary choice situation can be applied to the willingness-to-pay model. Consumers are assumed to choose the alternative that provides them with the maximum utility. Similar to the binary case, the WTP model probabilities are built around the change in utility (ΔU^*) received from each of the alternatives, which in this case are various WTP categories. The utility function consists of an observable component $(x_i \beta)$, and an unobservable component (ε_i). The utility functions are as follows:

$$U_1 = x_1'\beta + \varepsilon_1$$

$$U_2 = x_2'\beta + \varepsilon_2$$

$$U_3 = x_3'\beta + \varepsilon_3$$

$$U_4 = x_4'\beta + \varepsilon_4$$

$$U_5 = x_5'\beta + \varepsilon_5$$

Again ΔU^*, is used to represent the unobserved difference in utility. As there are five alternative WTP response options, and each alternative presumably represents a different level of utility, the decision is based on which of the five provide the greatest utility. Similar to the binary case, except now there are five alternatives, the change in utility is represented by:

$$\Delta U^* = (U_5 - U_4 - U_3 - U_2 - U_1)$$

$$\Delta U^* = [(x_5'\beta + \varepsilon_5) - (x_4'\beta + \varepsilon_4) - (x_3'\beta + \varepsilon_3) - (x_2'\beta + \varepsilon_2) - (x_1'\beta + \varepsilon_1)]$$

$$= [(x_5 - x_4 - x_3 - x_2 - x_1)'\beta + (\varepsilon_5 - \varepsilon_4 - \varepsilon_3 - \varepsilon_2 - \varepsilon_1)]$$

$$\Delta U^* = x'\beta + \varepsilon$$

where; x represents a vector of the difference in the observable components,

ε represents the difference in the unobservable component, and

ΔU^* (unobservable to the researcher) is treated as a random variable.

What the researcher does observe is the outcome of the individual's decision-making process. In this case the outcome of the decision-making process is the WTP response by individuals to the WTP scenario.

The observed responses of the willingness-to-pay decision process are:

$$\begin{array}{lll} WTP = 1 & \text{if} & \Delta U^* \leq \gamma_1 \\ WTP = 2 & \text{if} & \gamma_1 < \Delta U^* \leq \gamma_2 \\ WTP = 3 & \text{if} & \gamma_2 < \Delta U^* \leq \gamma_3 \\ WTP = 4 & \text{if} & \gamma_3 < \Delta U^* \leq \gamma_4 \\ WTP = 5 & \text{if} & \gamma_4 < \Delta U^* \end{array}$$

where, ΔU^* is the unobserved difference in utility and γ_m are unknown threshold points that are to be estimated along with the coefficients. Given this, the WTP probabilities are represented as:

$$\Pr(WTP = 1) = \Pr(\Delta U^* \leq \gamma_1) \tag{2.9}$$

$$= \Phi(\gamma_1 - x_i\beta)$$

$$\Pr(WTP = 1) = \Pr(\Delta U^* \leq \gamma_1)$$

$$= \Phi(\gamma_1 - x_i\beta)$$

$$\Pr(WTP = 2) = \Pr(\Delta U^* \leq \gamma_2) - \Pr(\Delta U^* < \gamma_1)$$

$$= \Phi(\gamma_2 - x_i\beta) - \Phi(\gamma_1 - x_i\beta)$$

$$\Pr(WTP = 3) = \Pr(\Delta U^* \leq \gamma_3) - \Pr(\Delta U^* < \gamma_2)$$

$$= \Phi(\gamma_3 - x_i\beta) - \Phi(\gamma_2 - x_i\beta)$$

$$\Pr(WTP = 4) = \Pr(\Delta U^* \leq \gamma_4) - \Pr(\Delta U^* < \gamma_3)$$

$$= \Phi(\gamma_4 - x_i\beta) - \Phi(\gamma_3 - x_i\beta)$$

$$\Pr(WTP = 5) = \Pr(\Delta U^* > \gamma_4)$$

$$= 1 - \Phi(\gamma_4 - x_i\beta)$$

Where

x_i represents a vector which contains the explanatory variables,

β represents a vector of coefficients to be estimated, and

γ_m represents unknown threshold points that are to be estimated along with the coefficients.

The WTP ordered probit model will facilitate the generation of two interrelated types of information, predicted probabilities and marginal effects. The ordered probit model will produce predicted probabilities for each of the five WTP categories. The model estimates will also be used to calculate the marginal effects of explanatory variables on the predicted probabilities. The predicted probabilities in the WTP model can be used in the same way as the predicted probabilities in the binary models. The probabilities will indicate the likelihood that the average respondent is willing-to-pay each of the five premium levels. The predicted probabilities provide valuable insight into consumer preferences as they can be used to gauge the level of respondents WTP for PFP food products. The marginal effects will indicate the magnitude of the effect on the predicted probabilities due to a change in each of the explanatory variables.

In the WTP Model Results and Analysis chapter (Chapter 5), the predicted probabilities and marginal effects will be used to develop profiles of consumers most likely to be willing-to-pay the different premium levels. The profiles will highlight the characteristics of respondents who are most likely to be willing-to-pay no, moderate and high premiums. Interpretation of ordered probit estimates, calculation of predicted probabilities and marginal effects will be discussed in the WTP model results and analysis chapter.

2.5 Summary of Conceptual and Empirical Framework

This chapter presented the conceptual and empirical models used to address the problem of assessing consumer interest in PFP food products. Since data for this study was gathered at the individual level the theoretical background is based in discrete choice theory. A random utility model is used to account for the fact that not all of the factors contributing to respondents' utility functions can be observed. Utility is defined as the sum of the observable or deterministic components, and the unobservable or random component.

The empirical model used to estimate consumer interest in PFP food products, due to the nature of the data, is a qualitative response model. A probit model will be used to estimate the predicted probability that respondents will purchase PFP food products, and the probability that respondents are willing-to-pay a premium for PFP food products. As a probit model has been selected, the empirical framework focused on the describing the structure of probit models.

CHAPTER 3 - DATA AND METHODS

3.0 Introduction

The purpose of this chapter is to describe the data gathered for this project and how it is used to evaluate consumer interest in PFP food products. The chapter begins with a description of the PFP consumer survey that was used to collect information from households in three Canadian cities, Calgary, Winnipeg and Toronto. After describing the survey, the discussion turns to how the survey data is used to create explanatory variables for the empirical models. Each of the explanatory variables are defined and hypotheses regarding their effects on consumer preferences for PFP food products are discussed. The discussion then moves on to specify the probit models used in this project and to describe the procedure for generating parameter estimates in probit models.

3.1 Description of the Consumer Survey

At the time of survey implementation, PFP food products were purely hypothetical, as they were not available in the marketplace. (To date only very limited ventures into the marketplace have occurred and PFP food products remain largely hypothetical.) As such, consumers' actual decisions to purchase and pay a premium cannot be observed. To address this issue a consumer survey was developed to gather consumers stated preferences for different potential PFP food products and willingness-to-pay values. The survey also collected demographic, attitudinal and behavioural information about the respondents. A survey was sent to 2000 households in three Canadian cities Toronto, Calgary and Winnipeg in March of 2001. One thousand surveys were sent to households in Toronto, 500 surveys were sent to households in Winnipeg and Calgary. All data used in this project is based on the responses from the PFP consumer survey.

Household addresses were acquired from Watts List Brokerage Ltd. a division of the Watts Group. The Watts Group is a large Canadian direct marketing services organization. The company's background was investigated to ensure addresses were purchased from a reputable source.[1] Only names and addresses were purchased, and the mailing lists were generated from a random selection of the "Canadians at Home" database. This database contained 1.75 million households in the three cities that were surveyed at the time addresses were acquired.

The PFP consumer survey was developed following many of the mail survey design principles outlined by Dillman's (1978) Total Design Method. The survey is loosely modeled on a survey used by Govindasamy and Italia (1997), from Rutgers University, to assess consumer response to IPM and organic agriculture. Survey development began in the summer of 2000, and the survey evolved until the format was finalized in February 2001.

Several pre-tests were conducted throughout the survey development process. A small pre-test of 7 volunteer respondents was conducted using the first draft of the survey in August 2000. A number of revisions were made in areas where respondents appeared to have difficulty. In the fall of 2000, the revised survey was circulated to a number of people involved in the PFP research program to get additional feedback. In January 2001, a larger pre-test was undertaken to test the mail out procedures and the "final" draft

[1] Watts List Brokerage Ltd. is a member of the CMA (Canadian Marketing Association), which has a code of ethics and standards that is compulsory for all members. The Watts Group has been in business in Canada since 1952.

of the survey. In the January 2001 pre-test, 100 surveys were sent to households in Winnipeg, Calgary and Toronto. Returned pre-tests were examined, and further changes were made to clarify questions, shorten the survey and reduce the effort required to complete the survey.

In February 2001, a small focus group was conducted to get direct feedback in an attempt to detect any difficulties that could not be picked up from the previous pre-tests. The WTP question was revised following the focus group. After the focus group, the survey format was finalized in February 2001. The survey mail out took place in March 2001.

Each household received one survey, a cover letter explaining the purpose of the study and a stamped return-addressed envelope. Of 2000 surveys, approximately 200 were returned as undeliverable. From the remaining 1800 surveys, 374 were completed and returned. This equals a 20% response rate, which is an acceptable rate for a mail survey. From the 374 returned surveys, another 88 were deemed unusable for various reasons mostly due to non-response to certain questions. This makes the total usable surveys 286 and an effective response rate of about 16%, which is still strong. Two hundred and eighty six provides enough observations to ensure there will not be degrees of freedom problems. More observations are always desirable; however, time and financial constraints limit the amount of surveying that can be done.

Table 3.1, outlines the breakdown of survey response by city. Of the 286 usable surveys, 69 are from Calgary households, 141 are from Toronto households and 76 are from Winnipeg households. The proportion of completed surveys by city closely reflects the numbers distributed to each city.

Table 3.1: Survey Response By City				
City	Calgary	Toronto	Winnipeg	Total
#	69	141	76	286
%	24.1%	49.3%	26.6%	100.0%

3.1.1 Summary of Information Collected in the Consumer Survey

Information was collected on respondent shopping habits, attitudes, knowledge of reduced input food products and demographic characteristics. Respondents were asked if they would be interested in purchasing PFP food products, and if so, which products. Respondents were also asked to indicate how much they would be willing-to-pay for a PFP food product. The questions regarding interest in PFP food products and WTP are the basis for empirical analysis on the demand for PFP food products. Appendix 1 contains a copy of the consumer survey along with the accompanying cover letter.

3.2 The Contingent Valuation Approach to Valuing Goods

The elicitation of WTP information was done using a question which falls in the broad category of survey methodology known as Contingent Valuation (CV). CV is, as the name suggests, a technique used to elicit the value respondents place on certain non-market goods contingent upon a description of the good in question. Hausman (1993) describes CV as a survey method that attempts to estimate individual values for economic goods by asking people hypothetical questions about their WTP for such goods.

CV is a popular technique to gather WTP information for non-market goods. It is widely used in the environmental economics and resource economics literature. Mitchell and Carson (1989) have compiled a comprehensive text examining the use of CV to value public goods. The technique is also a common approach to value non-market products in the marketing research literature. Buzby, Ready and Skees (1995), Kuperis *et al.* (1996), Govindasamy and Italia (1997), Baker (1999) and Boccaletti and Nardella (2000) are a few examples of food safety and reduced input food product related marketing research that use CV techniques. Much of the work on consumer food safety preferences has utilized the CV method (Baker 1999).

CV differs significantly from most empirical research in economics, which is typically based on observed data caused by real-world decisions made by consumers and firms (Hausman 1993). The technique is not without its critics, as the hypothetical non-market nature of the method raises concerns about its validity. For this project (as with other food safety research) concerns about hypothetical bias are minimal because it is not difficult for respondents to relate to the scenario. Evaluating different food products is a common occurrence for most consumers. CV methodology has the highest validity when the hypothetical scenario is similar to familiar market choice situation (Buzby, Ready and Skees 1995).

In the PFP consumer survey, the WTP question closely follows explicit definitions of the PFP production system and PFP food products. The WTP question is close to a real-world scenario, simply asking respondents if they would pay more for a PFP food product than for a conventional food product. Consumers make these types of decisions every time they go shopping. Consumers regularly choose to purchase certain products over others based on numerous factors including product attributes and price.

The further the scenario is from a familiar market situation the greater the concern about the potential hypothetical bias of the results. Much of the criticism of CV arises from situations where attempts are made to value environmental goods, such as eliciting a value for air quality, or some other environmental attribute for which a familiar real-world market context does not exist.

An alternative technique for evaluating consumer WTP is to create an experimental market for the product. Typically, this involves providing subjects with a finite amount of money and observing their decisions from a limited choice set. Experimental markets allow researchers to observe consumer's decisions with actual money. The drawback is that experimental market studies are often limited in size due to the costs involved in running the experiment and recruiting subjects. Interested readers should refer to Roosen *et al.* (1998) who use an artificial auction market to evaluate WTP for apples grown without pesticides.

Shogren *et al.* (1999) examine three alternative methods to evaluate consumer acceptance and WTP for irradiated food products. They monitored actual retail markets, set up experimental auction markets and distributed hypothetical market surveys. The choices made under the three different settings were remarkably similar, particularly at higher prices. The results of their work suggest that consumer response to a CV market survey is a reasonable approximation for true market behaviour.

CV is a common approach to evaluating consumer WTP for non-market products. Measures were taken in the PFP consumer survey to reduce any hypothetical bias. Clear definitions of PFP food products were provided in close proximity to the WTP question. Respondents indicated their WTP in actual monetary amounts, as opposed to percentage amounts to eliminate calculations on the part of the subjects, and to be as true as possible to the retail market situation. The flexibility and cost per subject of the CV market survey approach were also considerations in selecting this method for evaluating WTP for PFP food products.

> "Although there are several economic methodologies to value nonmarket goods, researchers usually consider Contingent Valuation (CV) the most appropriate for measuring food safety. The CV method is more flexible and has a relatively low cost compared to other methods that try to replicate real purchasing situations, such as experimental markets" (Boccaletti and Nardella 2000).

3.3 Explanatory Variables

The following is a discussion about the variables included in the binary and WTP models. All explanatory variables are based on information gathered in the consumer survey. The majority of the explanatory variables are binary or dummy variables. Prior to defining the explanatory variables a brief example is provided describing how variables are formulated from responses to survey questions.

Explanatory Variable Example: Suppose a survey question with four response options was selected as an explanatory variable. As there are four possible response options, four dummy variables are created:

$Dummy_1 = 1$ if option 1 was selected

$Dummy_1 = 0$ otherwise

$Dummy_2 = 1$ if option 2 was selected

$Dummy_2 = 0$ otherwise

$Dummy_3 = 1$ if option 3 was selected

$Dummy_3 = 0$ otherwise

$Dummy_4 = 1$ if option 4 was selected

$Dummy_4 = 0$ otherwise

In order to be able to estimate the model(s) one of the dummy variables must be dropped to avoid the dummy variable trap. In this example there are four dummy variables created from the four potential response options. The model would include only three due to the dummy variable trap. For each set of dummy variables one must be omitted.

The omitted dummy variables are absorbed by the constant term. Therefore, the constant represents a base classification made up of all the omitted dummy variables. This complicates the interpretation of the results somewhat. If there were only one dummy variable then a comparison could be made to the omitted dummy when interpreting the results. For illustration, suppose that $Dummy_4$ was omitted in the above example and that these dummy variables were the only set of dummies in the model. It could then be said that persons in category one are more or less likely (depending on the results) to purchase PFP food products than persons in category four. However, since the models estimated in this project will have many omitted variables absorbed by the constant inference cannot be made with respect to the omitted dummy variable.[2] What can be said is that persons in category one are more or less likely than those not in category one to purchase PFP food products.

For the models estimated in this project the omitted variables will be one of the end point variables for each set of dummy variables. This approach was taken to simplify commentary on and analysis of the results, particularly when dealing with the

[2] Pindyck and Rubinfeld, 1991 present a good discussion on using dummy variables and interpreting results. See pages 104-108 and 121-123.

demographic variables where the response options have a natural and meaningful range. For example, the omitted variable from the household income set of dummy variables will be the highest income range (INC7, >$150,000). The highest or lowest dummy in each range will be dropped, instead of omitting a variable in the middle of the range and having a hole in the range.

Another option, which was explored, is omitting the highest frequency dummy variable from each set. That is, the dummy variable derived from the response option with the highest number of responses. The reasoning for such an approach is that the high frequency variables may lead to multicollinearity. Omitting the high frequency variables allows for more variance in the model as the observations are spread more evenly among the remaining dummy variables. This approach also allows the constant term to reflect the most frequently selected variables. However, the models in this project generally preformed worse (fewer significant variables and performed worse on the goodness-of-fit measures) when specified in this manner.

3.3.1 Definition of Explanatory Variables

The following is a description of the explanatory variables used in the empirical models to estimate consumer interest in, and WTP for, PFP food products. The description of the variables includes an abbreviation that will be used throughout the remainder of the paper to refer to each variable. The majority of the explanatory variables are binary and a description of how each binary variable was coded is also provided. An asterix following a variable name denotes that the variable was omitted to avoid the dummy variable trap. There are some situations where two response options have been combined into one variable. This was done when the frequency of responses was low for certain response options. As a result, some questions generate fewer variables in the model than the response options in the survey would suggest.

City: Respondents were not asked to indicate their city of residence, but the surveys were marked with either a C, T or W to indicate what city it was sent to, Calgary, Toronto or Winnipeg.

- CAL – Survey respondent is from Calgary.
  - $CAL = 1$ if respondent is from Calgary,
  - $CAL = 0$ otherwise.
- TOR – Survey respondent is from Toronto.
  - $TOR = 1$ if respondent is from Toronto,
  - $TOR = 0$ otherwise.
- WPG – Survey respondent is from Winnipeg. *
  - $WPG = 1$ if respondent is from Winnipeg,
  - $WPG = 0$ otherwise.

Try New: This question asked respondents to classify themselves in terms of trying newly introduced food products.

- TNEW1 – among the first to try.
  - $TNEW1 = 1$ if respondent among the first to try,
  - $TNEW1 = 0$ otherwise.

- TNEW2 – among the last to try.

- $TNEW2 = 1$ if respondent among the last to try,
- $TNEW2 = 0$ otherwise.

- TNEW3 – in between the first to try and the last to try.
  - $TNEW3 = 1$ if respondent selects in between,
  - $TNEW3 = 0$ otherwise.
- TNEW4 – never try. *
  - $TNEW4 = 1$ if respondent selects never try,
  - $TNEW4 = 0$ otherwise.

Health food shopper: This question asked respondents to indicate whether they shop at health food stores or nutrition centres.

- HEALTH1 – never shop at health food stores. *
  - $HEALTH1 = 1$ if respondent never shops at health food stores,
  - $HEALTH1 = 0$ otherwise.
- HEALTH2 – occasionally shop at health food stores.
  - $HEALTH2 = 1$ if respondent occasionally shops at health food stores,
  - $HEALTH2 = 0$ otherwise.
- HEALTH3 – usually or always shop at health food stores.
  - $HEALTH3 = 1$ if respondent usually/always shops at health food stores,
  - $HEALTH3 = 0$ otherwise.

Attitude Statements:

The next five sets of variables are derived from five attitude statements, which were presented in the consumer survey. Respondents were asked to state how they felt about each statement by choosing one of five options. The options were scaled using a modified Likert scale: strongly agree, agree, neutral, disagree and strongly disagree.

Environment (ENV): Derived from the statement "I feel the use of synthetic chemicals in agriculture has a negative effect on the environment".

- ENV1 – strongly agree with statement.
    - $ENV1 = 1$ if respondent strongly agrees,
    - $ENV1 = 0$ otherwise.
- ENV2 – agree with statement.
    - $ENV2 = 1$ if respondent agrees,
    - $ENV2 = 0$ otherwise.
- ENV3 – neutral.
    - $ENV3 = 1$ if respondent is neutral,
    - $ENV3 = 0$ otherwise.
- ENV4 – disagree or strongly disagree with statement. *
    - $ENV4 = 1$ if respondent disagrees or strongly disagrees,
    - $ENV4 = 0$ otherwise.

Concerned about pesticide residues (CPR): Derived from the statement "I am concerned about pesticide residues in our food supply".

- CPR1 – strongly agree with statement.

    - $CPR1 = 1$ if respondent strongly agrees,
    - $CPR1 = 0$ otherwise.
- CPR2 – agree with statement.
    - $CPR2 = 1$ if respondent agrees,
    - $CPR2 = 0$ otherwise.
- CPR3 – neutral.
    - $CPR3 = 1$ if respondent is neutral,
    - $CPR3 = 0$ otherwise.
- CPR4 – disagree or strongly disagree with statement. *
    - $CPR4 = 1$ if respondent disagrees or strongly disagrees,
    - $CPR4 = 0$ otherwise.

Label: Derived from the statement "The labeling of food ingredients on food packaging is important to me".

- LABEL1 – strongly agree with statement.
    - $LABEL1 = 1$ if respondent strongly agrees,
    - $LABEL1 = 0$ otherwise.
- LABEL2 – agree with statement.
    - $LABEL2 = 1$ if respondent agrees,
    - $LABEL2 = 0$ otherwise.
- LABEL3 – neutral, disagree or strongly disagree with statement. *
    - $LABEL3 = 1$ if respondent is neutral, disagrees or strongly disagrees,
    - $LABEL3 = 0$ otherwise.

Farm income (FINC): Derived from the statement "I feel it is important to maintain farm income at a level that keeps the family farm viable".

- FINC1 – strongly agree with statement.
    - $FINC1 = 1$ if respondent strongly agrees,
    - $FINC1 = 0$ otherwise.
- FINC2 – agree with statement.
    - $FINC2 = 1$ if respondent agrees,
    - $FINC2 = 0$ otherwise.
- FINC3 – neutral, disagree or strongly disagree with statement. *
    - $FINC3 = 1$ if respondent is neutral, disagrees or strongly disagrees,
    - $FINC3 = 0$ otherwise.

Sustainable agricultural practices (SAP): Derived from the statement "I believe farmers should engage in sustainable agricultural production practices. That is, practices which adopt the goal of ensuring the productive future of agriculture, the environment and the economy of rural communities".

- SAP1 – strongly agree with statement.
    - $SAP1 = 1$ if respondent strongly agrees,
    - $SAP1 = 0$ otherwise.
- SAP2 – agree with statement.
    - $SAP2 = 1$ if respondent agrees,
    - $SAP2 = 0$ otherwise.

- SAP3 – neutral, disagree or strongly disagree with statement. *
    - $SAP3 = 1$ if respondent is neutral, disagrees or strongly disagrees,
    - $SAP3 = 0$ otherwise.

Other variables:

- PALT – The abbreviation stands for respondents who have previously purchased alternative food products. This variable is a combination of two questions on the survey. The first asked respondents if they regularly purchase IPM food products, and the second asked respondents if they regularly purchase organic food products. Since very few respondents indicated they regularly purchase IPM food products the two questions were combined to make one variable referred to as "purchased alternative food products".
    - $PALT = 1$ if respondent purchases alternative food products,
    - $PALT = 0$ otherwise.
- H-PFP – Results from the question asking respondents if they had heard of PFP prior to receiving a survey.
    - $H - PFP = 1$ if respondent has heard of PFP,
    - $H - PFP = 0$ otherwise.

Demographic variables:

- H-SIZE – The number of people in the respondent's household.
- CHILD<17 – The number of children under the age of seventeen in the respondent's household.

(It should be noted that H-SIZE and CHILD<17 are treated as continuous variables while the remainder of the explanatory variables are binary.)

- P-SHOP – Resulting from a question which asked respondents if they were the primary food shopper for the household.
  - $P-SHOP=1$ if respondent is primary food shopper,
  - $P-SHOP=0$ otherwise.
- FEMALE – Respondent were asked to indicate their gender.
  - $FEMALE=1$ if respondent is female,
  - $FEMALE=0$ otherwise.

Age: Respondents were asked to indicate their age from a selection of age ranges.

- AGE1 – 0 to 35 years old.
  - $AGE1=1$ if respondent is 0 to 35 years old,
  - $AGE1=0$ otherwise.
- AGE2 – 36 to 50 years old.
  - $AGE2=1$ if respondent is 36 to 50 years old,
  - $AGE2=0$ otherwise.
- AGE3 – 51 to 65 years old.
  - $AGE3=1$ if respondent is 51 to 65 years old,
  - $AGE3=0$ otherwise.
- AGE4 – greater than age 65. *
  - $AGE4=1$ if respondent is more than 65 years old,
  - $AGE4=0$ otherwise.

Education (EDUC): Respondents were asked to indicate the highest level of education they had achieved.

- EDUC1 – Some grade school or some high school. *
  - $EDUC1 = 1$ if respondent completed some grade school or some high school,
  - $EDUC1 = 0$ otherwise.
- EDUC2 – High school graduate or some university/college.
  - $EDUC2 = 1$ if respondent completed high school or some university/college,
  - $EDUC2 = 0$ otherwise.
- EDUC3 – University/college graduate or some graduate school.
  - $EDUC3 = 1$ if respondent has university/college degree or some grad school,
  - $EDUC3 = 0$ otherwise.
- EDUC4 – Masters Degree or Doctoral Degree.
  - $EDUC4 = 1$ if respondent has a masters or doctoral degree,
  - $EDUC4 = 0$ otherwise.

Monthly food expenditure (EXP): Respondents were asked to indicate how much their household spends on food per month.

- EXP1 – Spend less than $199 per month.
  - $EXP1 = 1$ if household spends less than $199 per month,
  - $EXP1 = 0$ otherwise.
- EXP2 – Spend $200 to $399 per month.
  - $EXP2 = 1$ if household spends $200 to $399 per month,

- $EXP2 = 0$ otherwise.

- EXP3 – Spend $400 to $499 per month.
  - $EXP3 = 1$ if household spends $400 to $499 per month,
  - $EXP3 = 0$ otherwise.
- EXP4 – Spend $500 to $699 per month.
  - $EXP4 = 1$ if household spends $500 to $699 per month,
  - $EXP4 = 0$ otherwise.
- EXP5 – Spend more than $700 per month. *
  - $EXP5 = 1$ if household spends more than $700 per month,
  - $EXP5 = 0$ otherwise.

Annual household income (INC): Respondents were asked to indicate their annual household income range.

- INC1 – Annual income less than $19,999.
  - $INC1 = 1$ if household income is less than $19,999,
  - $INC1 = 0$ otherwise.
- INC2 – Annual income of $20,000 to $39,999.
  - $INC2 = 1$ if household income is $20,000 to $39,999,
  - $INC2 = 0$ otherwise.
- INC3 - Annual income of $40,000 to $59,999.
  - $INC3 = 1$ if household income is $40,000 to $59,999,
  - $INC3 = 0$ otherwise.
- INC4 - Annual income of $60,000 to $79,999.

- $INC4 = 1$ if household income is $60,000 to $79,999,
- $INC4 = 0$ otherwise.

- INC5 - Annual income of $80,000 to $99,999.
  - $INC5 = 1$ if household income is $80,000 to $99,999,
  - $INC5 = 0$ otherwise.
- INC6 - Annual income of $100,000 to $149,999.
  - $INC6 = 1$ if household income is $100,000 to $149,999,
  - $INC6 = 0$ otherwise.
- INC7 – Annual income greater than $150,000. *
  - $INC7 = 1$ if household income is more than $150,000,
  - $INC7 = 0$ otherwise.

Marital status: Respondents were asked to indicate their marital status

- MSTAT1 – single.
  - $MSTAT1 = 1$ if respondent is single,
  - $MSTAT1 = 0$ otherwise.
- MSTAT2 – married.
  - $MSTAT2 = 1$ if respondent is married,
  - $MSTAT2 = 0$ otherwise.
- MSTAT3 – separated, divorced or widowed.
  - $MSTAT3 = 1$ if respondent is separated, divorced or widowed,
  - $MSTAT3 = 0$ otherwise.
- MSTAT4 – other. *

- $MSTAT4 = 1$ if respondents marital status is other,
- $MSTAT4 = 0$ otherwise.

3.4 Summary Statistics

Summary statistics have been tabulated for each of the explanatory variables based on response to the consumer survey. The summary statistics for all of the explanatory variables are contained in Table 3.2. The summary statistics are reported for the entire sample and for each individual city. Highlights of the information found in Tables 3.2 are discussed next.

3.4.1 General Variables

General variables are those which are not demographic in nature. Almost three-quarters of the respondents indicate that they are in between the first to try and last to try new food products (TNEW3). The frequency for TNEW3 is constant across all three cities. About half of the respondents in the total sample and in each city occasionally shop at health food stores (HEALTH2). More respondents in Winnipeg indicate that they never shop at health food stores (HEALTH1) than in Calgary or Toronto. In contrast, Calgary and Toronto have a higher number of respondents who usually or always shop at health food stores (HEALTH3).

The "strongly agree" response option is the most frequent response for each of the attitude questions. Approximately 40% of respondents strongly agree that the use of chemicals in agriculture has a negative effect on the environment (ENV1). Out the five attitude questions the environment statement generated the lowest "strongly agree" frequency. In other words, the concern about chemicals in agriculture appears to be less of a concern then the other attitude statements across the entire sample.

Over 60% of respondents strongly agree (CPR1) that they are concerned about pesticide residues in our food supply. Toronto has a slightly higher CPR1 frequency at 66%, than Calgary and Winnipeg at 56%.

More than 60% of the total sample strongly agree (LABEL1) that labeling of food ingredients is important. Toronto has a slightly higher LABEL1 frequency, while the LABEL1 frequency for Calgary and Winnipeg is a little below 60%.

For the total sample, (FINC1) is the most frequent response to the farm income attitude question, with over 60% of respondents selecting this option. This indicates that over 60% of the sample strongly agree with the farm income attitude statement (*i.e.,* that maintaining farm income at a level that keeps the family farm viable is important). There is some variation across cities, as 50% of Calgary respondents choose this option, compared to almost 70% for Winnipeg respondents and 64% for Toronto.

Over 65% of the total sample selected (SAP1), indicating that the majority of people strongly agree that farmers should use sustainable agricultural production practices. Close to 70% of Winnipeg and Toronto respondents, and 56% of Calgary respondents strongly agree that farmers should use sustainable agricultural production practices.

The majority of respondents indicate they have not purchased either IPM or organic food products (PALT). For the total sample, only 27% answered yes and 73% said no. A larger percentage of respondents in Calgary have purchased alternative food products than in Toronto or Winnipeg. About 33% of the total sample have heard of

PFP, and there is very little variation across cities. A very high percentage of respondents indicated that they were the primary food shoppers for the household. The cover letter accompanying the survey requested that the primary food shopper complete the survey, so this result was expected.

3.4.2 Demographic Variables

The typical respondent to the survey is; female, 36-50 years old, has a university degree, spends $400-$499 per month on food, has an annual household income of $60,000-$79,999, lives in a two or three person household and has one child or less. The most common household size for the total sample is two, with close to 40% of respondents indicate that their household consists of two people. For Toronto and Calgary, the next most common household size is three, while for Winnipeg it is one. For the total sample most households have no children under 17. In Toronto and Winnipeg, three quarters of respondents have no children under 17, and in Calgary 57% of respondents have no children under 17.

Approximately two thirds of the total sample are female; this percentage is fairly constant across the three cities. About two thirds of the total sample are married: Calgary had the highest percentage of married respondents, while Winnipeg had the lowest.

The most frequent age range response for the total sample is 36 to 50 years old (AGE2) with 37% of respondents being in this age range. Calgary had the highest frequency of 36 to 50 year old respondents at 49%. The percentage of Toronto and Winnipeg respondents in the 36 to 50 age range is, 34% and 31% respectively.

Almost half of the total sample has a university or college degree and/or some graduate school (EDUC3). The EDUC3 frequency is relatively constant across the three cities. About one third of the sample are high school graduates and/or attended some university or college (EDUC2), and the frequency for this education level is also constant across cities.

Monthly expenditure on food of $200-$399 (EXP2) is the most frequent response at 31%, just 1% higher than $400-$499 (EXP3) for the total sample. For Calgary and Winnipeg, EXP3 is the most frequent response, while EXP2 is the most common for Toronto.

For the total sample, an annual income of $40,000 to $59,999 (INC3) is the most frequent response; however, there is variation across the three cities. The most commonly cited income range for Winnipeg is $20,000 to $39,999 (INC2). For Toronto INC3 is the most common income range, and for Calgary $100,000 to $149,999 (INC6) is the most common range. In general for Calgary and Toronto, household income among respondents is quite evenly distributed across all income categories. In Winnipeg, the annual household income is not as evenly distributed with a smaller percentage of respondents indicating annual household income in the higher income ranges.

The summary statistics indicate that there is little variation across respondents in the three cities. There are differences for some variables, but in general the samples from the three cities are fairly similar. The differences that do exist may be helpful in explaining any discrepancies between cities regarding consumer interest in, and WTP, for PFP food products.

Table: 3.2 Summary Statistics – Survey Data								
	Total Sample		Calgary		Toronto		Winnipeg	
TNEW	#	%	#	%	#	%	#	%
TNEW1	37	12.9%	9	13.0%	17	12.1%	11	14.5%
TNEW2	31	10.8%	7	10.1%	18	12.8%	6	7.9%
TNEW3	210	73.4%	50	72.5%	105	74.5%	55	72.4%
TNEW4	7	2.4%	3	4.3%	1	0.7%	3	3.9%
Other	1	0.3%	0	0.0%	0	0.0%	1	1.3%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
HEALTH	#	%	#	%	#	%	#	%
HEALTH1	106	37.1%	26	37.7%	44	31.2%	36	47.4%
HEALTH2	160	55.9%	38	55.1%	85	60.3%	37	48.7%
HEALTH3	20	7.0%	5	7.2%	12	8.5%	3	3.9%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
ENV.	#	%	#	%	#	%	#	%
ENV1	123	43.0%	26	37.7%	65	46.1%	32	42.1%
ENV2	86	30.1%	25	36.2%	39	27.7%	22	28.9%
ENV3	58	20.3%	14	20.3%	29	20.6%	15	19.7%
ENV4	19	6.6%	4	5.8%	8	5.7%	7	9.2%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
CPR.	#	%	#	%	#	%	#	%
CPR1	176	61.5%	39	56.5%	94	66.7%	43	56.6%
CPR2	94	32.9%	28	40.6%	45	31.9%	21	27.6%
CPR3	12	4.2%	1	1.4%	1	0.7%	10	13.2%
CPR4	4	1.4%	1	1.4%	1	0.7%	2	2.6%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
LABEL	#	%	#	%	#	%	#	%
LABEL1	181	63.3%	40	58.0%	96	68.1%	45	59.2%
LABEL2	88	30.8%	25	36.2%	37	26.2%	26	34.2%
LABEL3	15	5.2%	4	5.8%	7	5.0%	4	5.3%
LABEL4	2	0.7%	0	0.0%	1	0.7%	1	1.3%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
FINC.	#	%	#	%	#	%	#	%
FINC1	177	61.9%	34	49.3%	90	63.8%	53	69.7%
FINC2	77	26.9%	28	40.6%	38	27.0%	11	14.5%
FINC3	26	9.1%	7	10.1%	10	7.1%	9	11.8%
FINC4	6	2.1%	0	0.0%	3	2.1%	3	3.9%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
	Shaded cells represent the most frequently selected response option							

Table: 3.2 Summary Statistics – Survey Data (Continued)								
	Total Sample		Calgary		Toronto		Winnipeg	
SAP.	#	%	#	%	#	%	#	%
SAP1	188	65.7%	39	56.5%	98	69.5%	51	67.1%
SAP2	84	29.4%	26	37.7%	36	25.5%	22	28.9%
SAP3	14	4.9%	4	5.8%	7	5.0%	3	3.9%
SAP4	0	0.0%	0	0.0%	0	0.0%	0	0.0%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
PALT	#	%	#	%	#	%	#	%
Yes	78	27.3%	25	36.2%	40	28.4%	13	17.1%
No	208	72.7%	44	63.8%	101	71.6%	63	82.9%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
H-PFP	#	%	#	%	#	%	#	%
Yes	94	32.9%	26	37.7%	42	29.8%	26	34.2%
No	192	67.1%	43	62.3%	99	70.2%	50	65.8%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
P-SHOP	#	%	#	%	#	%	#	%
Yes	276	96.5%	68	98.6%	135	96%	73	96.1%
No	10	3.5%	1	1.4%	6	4%	3	3.9%
Total	286	100.0%	69	100.0%	141	100%	76	100.0%
Gender	#	%	#	%	#	%	#	%
Male	104	36.4%	21	30.4%	52	36.9%	31	40.8%
Female	182	63.6%	48	69.6%	89	63.1%	45	59.2%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
H-SIZE	#	%	#	%	#	%	#	%
1	51	17.8%	5	7.2%	25	17.7%	21	27.6%
2	114	39.9%	26	37.7%	60	42.6%	27	35.5%
3	50	17.5%	18	26.1%	26	18.4%	6	7.9%
4	45	15.7%	10	14.5%	22	15.6%	14	18.4%
5	23	8.0%	9	13.0%	7	5.0%	7	9.2%
6	3	1.0%	1	1.4%	1	0.7%	1	1.3%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
Mean	2.59		2.93		2.50		2.47	
Std.Dev.	1.24		1.22		1.14		1.37	
	Shaded cells represent the most frequently selected response option							

Table: 3.2 Summary Statistics – Survey Data (Continued)								
	Total Sample		Calgary		Toronto		Winnipeg	
Child<17	#	%	#	%	#	%	#	%
0	200	69.9%	39	56.5%	104	73.8%	56	73.7%
1	39	13.6%	16	23.2%	18	12.8%	6	7.9%
2	37	12.9%	10	14.5%	14	9.9%	13	17.1%
3	9	3.1%	3	4.3%	5	3.5%	1	1.3%
4	1	0.3%	1	1.4%	0	0.0%	0	0.0%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
Mean	0.50		0.71		0.43		0.46	
Std. Dev.	0.86		0.97		0.81		0.82	
AGE	#	%	#	%	#	%	#	%
AGE1	58	20.3%	12	17.4%	27	19.1%	19	25.0%
AGE2	106	37.1%	34	49.3%	48	34.0%	24	31.6%
AGE3	73	25.5%	16	23.2%	41	29.1%	16	21.1%
AGE4	49	17.1%	7	10.1%	25	17.7%	17	22.4%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
Mean	49.1 years		46.9 years		50.1 years		49.3 years	
Std. Dev.	15.7 years		13.8 years		15.7 years		17.5 years	
EDUC.	#	%	#	%	#	%	#	%
EDUC1	22	7.7%	4	5.8%	5	3.5%	13	17.1%
EDUC2	92	32.2%	23	33.3%	42	29.8%	27	35.5%
EDUC3	136	47.6%	35	50.7%	68	48.2%	33	43.4%
EDUC4	33	11.5%	7	10.1%	23	16.3%	3	3.9%
Other	3	1.0%	0	0.0%	3	2.1%	0	0.0%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
Mean	2.61 (EDUC3)		2.65 (EDUC3)		2.73 (EDUC3)		2.34 (EDUC2)	
Std. Dev.	0.82		0.74		0.85		0.81	
EXP.	#	%	#	%	#	%	#	%
EXP1	33	11.5%	5	7.2%	14	9.9%	14	18.4%
EXP2	89	31.1%	14	20.3%	53	37.6%	22	28.9%
EXP3	86	30.1%	20	29.0%	41	29.1%	25	32.9%
EXP4	55	19.2%	19	27.5%	23	16.3%	13	17.1%
EXP5	23	8.0%	11	15.9%	10	7.1%	2	2.6%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
Mean	$431.4		$498.5		$417.9		$395.2	
Std. Dev.	$167.9		$181.6		$161.9		$149.9	
	Shaded cells represent the most frequently selected response option							

Table: 3.2 Summary Statistics – Survey Data (Continued)								
	Total Sample		Calgary		Toronto		Winnipeg	
INC.	#	%	#	%	#	%	#	%
INC1	23	8.0%	3	4.3%	6	4.3%	14	18.4%
INC2	53	18.5%	11	15.9%	20	14.2%	22	28.9%
INC3	58	20.3%	12	17.4%	29	20.6%	17	22.4%
INC4	49	17.1%	13	18.8%	23	16.3%	13	17.1%
INC5	36	12.6%	7	10.1%	24	17.0%	5	6.6%
INC6	42	14.7%	14	20.3%	24	17.0%	4	5.3%
INC7	25	8.7%	9	13.0%	15	10.6%	1	1.3%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
Mean	$72,097		$81,594		$79,361		$49,999	
Std. Dev.	$40,422		$42,595		$40,039		$29,911	
M-STAT.	#	%	#	%	#	%	#	%
MSTAT1	37	12.9%	4	5.8%	21	14.9%	12	15.8%
MSTAT2	182	63.6%	54	78.3%	86	61.0%	42	55.3%
MSTAT3	48	16.8%	7	10.1%	23	16.3%	18	23.7%
MSTAT4	19	6.6%	4	5.8%	11	7.8%	4	5.3%
Total	286	100.0%	69	100.0%	141	100.0%	76	100.0%
	Shaded cells represent the most frequently selected response option							

The means and standard deviations reported in Table 3.2 for the demographic variables were calculated by taking the mid point of the ranges and assigning that value to all observations in the range. For example, the variable EXP2 represents the expenditure range of $200-$399; all observations for EXP2 were given the value of $300 for the purpose of calculating the mean and standard deviation. The end point categories were generally assigned the upper limit value on the low end and the lower limit value on the high end. To illustrate, INC1 observations were assigned a value of $19,999 and INC7 observations a value of $150,000. An exception was made for AGE4 (>65) where a value of 75 was assigned to all AGE4 observations. Also, the age question on the PFP consumer survey had five response options which were transformed into four variables by combining the lowest two age groups (*i.e.,* under 20 and 20-35 were combined). The calculation of the mean and standard deviation for age used the survey classifications in order to provide a more accurate summary, as very few respondents were under 20 and the AGE1 grouping would have skewed the mean downward. For the education variables a value of 1, 2, 3 or 4 was assigned to categories EDUC1, EDUC2, EDUC3 and EDUC4 and the calculations done based on these values. A value of 2.51 would be rounded up and EDUC3 reported as the mean, while a value of 2.49 would be rounded down.

Table 3.3 Summary Statistics – Population

	Combined		Calgary		Toronto		Winnipeg	
Age	#	%	#	%	#	%	#	%
15-34	1,855,538	35.7	290,755	38.0	1,374,862	35.9	189,921	34.6
35-44	1,152,678	22.5	183,595	24.0	855,234	22.3	113,849	20.7
45-64	1,431,525	28.0	206,137	26.9	1,070,488	27.9	154,900	28.2
>65	706,462	13.8	84,604	11.1	531,301	13.9	90,557	16.5
* Total	5,146,203	100.0	765,091	100.0	3,831,885	100.0	549,227	100.0
Mean	42.9 years		41.5 years		43.1 years		44.2 years	
Gender	#	%	#	%	#	%	#	%
Female	2,629,978	51.1	381,211	49.8	1,965,966	51.3	282,801	51.5
Male	2,516,225	48.9	383,880	50.2	1,865,919	48.7	266,426	48.5
Total	5,146,203	100.0	765,091	100.0	3,831,885	100.0	549,227	100.0

* population over age 15
Source: Statistics Canada – Market Research Handbook, 2001

Table 3.3 Summary Statistics – Population (Continued)

	Calgary	Toronto	Winnipeg
Education	%	%	%
< High School	27.0	30.7	35.3
High School Diploma/Some University	24.1	24.8	25.0
University Degree	18.5	19.0	14.7
Other	30.3	25.6	25.0
Total	100.0	100.0	100.0
Household Size			
Mean Household Size	2.72	2.87	2.66
Children (under age 15)			
Mean Children per Household	0.56	0.57	0.54
Annual Income			
Mean Household Income	$68,908	$67,014	$53,951
Monthly Food Expenditure			
Mean Household Food Expenditure	$548	$584	$512

Source: Statistics Canada – Market Research Handbook, 2001

3.4.3 Comparison of Sample and Population Demographics

Demographic information about the population of the three surveyed cities was gathered from Statistics Canada's Market Research Handbook and is presented in Table 3.3. The survey sample summary statistics from Table 3.2 can be compared to the population data to get an idea of how they match up. It should be noted that comparison is hindered somewhat due to the fact that the Statistics Canada data is classified slightly differently than the data gathered in the survey. For example, the age groupings are slightly different. The following discussion will comment on the comparison between the survey sample demographics and the population demographics.

The sample respondents are slightly older than the general population, as there is a larger proportion of the population under the age of 35 and a smaller proportion over age 65 than is reflected in the sample. The middle two age groups do not match up in terms of how they are defined, but also indicate that the sample is slightly older than the population. The mean age numbers also indicate that the sample is older than the population. The sample of respondents has a larger proportion of females than the population. This is not surprising as the primary food shopper for the household was asked to complete the survey and it is likely that females are the primary food shoppers in many households. (178 of the 276 respondents who indicated they are the primary food shopper for their household are female.)

In general the sample of respondents is more educated than the population. The population statistics indicate a much higher proportion having less than a high school level education and a smaller proportion having completed a university degree. This could be a reflection of respondents with higher education being more willing to take part in a university research project. It is interesting to note that Winnipeg respondents are generally less educated than their counterparts in the other cities and this is also reflected in the population data. In both the survey sample and the population Winnipeg has a larger proportion of people with less than a high school diploma level education and a slightly smaller proportion with a university degree.

Household size is very similar in the sample and the population, as is the number of children per household. The sample mean household income is slightly higher, while the mean monthly food expenditure is slightly lower than the population. The average income range of the sample respondents is approximately \$80,000 for Calgary and Toronto and is \$50,000 for Winnipeg. The population average household incomes are \$68,908 for Calgary, \$67,014 for Toronto and \$53,951 for Winnipeg. The average monthly food expenditure for the sample respondents is \$498 for Calgary, \$417 for Toronto and \$395 for Winnipeg. The population average monthly food expenditure is \$548 for Calgary, \$584 for Toronto and \$512 for Winnipeg. These differences could be due to respondents self reporting of their monthly expenditures.

Generally, the sample summary data is similar to the entire population summary data for the three cities that were surveyed. Differences do exist, but these differences are, at least partially, explained by the nature of the survey.

3.5 Hypotheses

The explanatory variables were chosen based on hypotheses about which factors may affect consumer interest in, or WTP for, PFP food products. Explanatory variables were included because it is believed that they may affect consumer preferences. Certain variables are expected to have positive or negative effects on the predicted probability that consumers will purchase PFP food products, or be willing-to-pay a premium for PFP food products. Part of the objective of empirical estimation is to determine whether the explanatory variables do in fact influence consumer preference for PFP food products, and if so how. The hypotheses for the explanatory variables will be discussed next.

Try new (TNEW): The hypothesis for TNEW1 is that it will have a positive effect on consumer interest in PFP food products. The belief is that consumers who are among the first to try new food products would be more likely to try PFP food products. TNEW2 is expected to be negative as those who are among the last to try new food products are expected to be less likely to try PFP food products. TNEW3 could be positive or negative, because consumers who are in between the first to try and the last to try are expected to be more likely than those who are among the last to try, and less likely than those who are among the first to try to be interested in PFP food products.

HEALTH: The expectation for the health food shopping habits variables is that both HEALTH2 and HEALTH3 will be positive. The reason behind this expectation is that consumers who shop at health food stores are thought to be health conscious and therefore would be interested in PFP food products. HEALTH2 may not be that strong of an indicator, but HEATLTH3 is definitely expected to be positive. HEALTH3 represents consumers who usually or always shop at health food stores. These consumers are expected to be quite health conscious and PFP food products may appeal to them as a healthier alternative. Consumers who occasionally shop at health food stores (HEALTH2) may not have strong concerns about the health attributes of conventional food products.

Attitude Questions: The expectation for each of the five attitude questions is that consumers who strongly agree or agree with the statements will likely be interested in PFP food products. The PFP concept encompasses each of these attitudes or beliefs in some way therefore, it is hypothesized that ENV1, ENV2, CPR1, CPR2, LABEL1, LABEL2, FINC1, FINC2, SAP1 and SAP2 will be positive.

PALT: PALT is also expected to be positive. Consumers who have purchased organic or IPM food products in the past are likely to be interested in PFP food products. These consumers have shown an interest in other reduced input food products, so they may also find PFP food products attractive. However, the effect of PALT could be negative if these consumers view PFP food products as an inferior good compared to IPM and/or organic products.

CHILD<17: Having children in the household is expected to have a positive effect on interest in PFP food products. Consumers with children are expected to be more concerned with food safety and more likely to be interested in PFP food products.

P-SHOP: The primary food shopper variable (P-SHOP) is expected to be positive, as the food shopper for the household may be more concerned about food safety issues such as pesticide residues.

FEMALE: Females are expected to be more interested in PFP food products, as it is hypothesized that females are more concerned about food safety risks than males. A number of existing studies about consumer preferences for food safety and reduced input food products indicate that females are generally more concerned about food safety (Byrne, Gempesaw and Toensmeyer 1991; Dunlap and Beus 1992; Kuperis *et al.* 1996;

Baker 1999). Therefore, it is hypothesized that females will be more interested in PFP food products.

Other Demographic Variables: It is difficult to provide hypotheses for the rest of the demographic variables. Some preliminary hypotheses are that younger consumers, those spending more on food, larger households, and those who are married, may be willing-to-pay higher premiums for PFP food products. Previous food safety literature has reported conflicting results regarding the effects of some demographic variables. As such, the question of direction of effect for these variables is an empirical question that can be answered only after conducting the analysis.

3.6 Model Specification

Example - Binary Probit PFP Food Product Demand Model Specification

Recall from the empirical framework section (equation 2.6), that the binary probit model for estimating the probability that consumers would purchase a PFP food product is represented as, $\Pr(BuyPFP = 1) = \Phi(x'\beta)$. Inserting the explanatory variables described above into this expression leads to the following representation of a binary probit model for a PFP food product:

$$
\begin{aligned}
\Pr(BuyPFP = 1) = \Phi[&\beta_0 + \beta_1(CAL) + \beta_2(TOR) + \beta_3(TNEW1) \\
&+ \beta_4(TNEW2) + \beta_5(TNEW3) + \beta_6(HEALTH2) \\
&+ \beta_7(HEALTH3) + \beta_8(ENV1) + \beta_9(ENV2) + \beta_{10}(ENV3) \\
&+ \beta_{11}(CPR1) + \beta_{12}(CPR2) + \beta_{13}(CPR3) + \beta_{14}(LABEL1) \\
&+ \beta_{15}(LABEL2) + \beta_{16}(FINC1) + \beta_{17}(FINC2) + \beta_{18}(SAP1) \\
&+ \beta_{19}(SAP2) + \beta_{20}(PALT) + \beta_{21}(H - PFP) + \beta_{22}(H - SIZE) \\
&+ \beta_{23}(CHILD < 17) + \beta_{24}(P - SHOP) + \beta_{25}(FEMALE) \\
&+ \beta_{26}(AGE1) + \beta_{27}(AGE2) + \beta_{28}(AGE3) + \beta_{29}(EDUC2) \\
&+ \beta_{30}(EDUC3) + \beta_{31}(EDUC4) + \beta_{32}(EXP1) + \beta_{33}(EXP2) \\
&+ \beta_{34}(EXP3) + \beta_{35}(EXP4) + \beta_{36}(INC1) + \beta_{37}(INC2) \\
&+ \beta_{38}(INC3) + \beta_{39}(INC4) + \beta_{40}(INC5) + \beta_{41}(INC6) \\
&+ \beta_{42}(MSTAT1) + \beta_{43}(MSTAT2) + \beta_{44}(MSTAT3)].
\end{aligned} \tag{3.1}
$$

And, the probability that consumers will not purchase the PFP food product is $\Pr(BuyPFP = 0) = 1 - \Phi(x'\beta)$.

The specification of the WTP ordered probit model is similar to the binary probit model of PFP food product demand. The same explanatory variables are used to explain the predicted probability that consumers are willing-to-pay a premium for PFP food products. The difference between the binary and ordered models is that in the WTP model the dependent variable can take one of five possible values, while in the binary model the dependent variable can take only two possible values.

3.7 Estimating Probit Models

The typical approach for estimating parameters for probit models is maximum likelihood estimation. The models used in this project will be estimated using the Eviews econometric program. Maximum likelihood estimation is the procedure Eviews uses to generate parameter estimates for probit models. Pindyck and Rubinfeld (1991) define the maximum likelihood estimate of a parameter β as the value of $\hat{\beta}$ which most likely would generate the observed sample observations.

The likelihood function, L, is the joint probability, or the product of the likelihoods of the individual observations. It measures the probability of observing the particular set of dependent variable values that occur in the sample. The likelihood function can be written as,

$$L(\beta) = \prod_{i=1}^{n} [\Phi(x_i'\beta)]^{y_i} [1 - \Phi(x_i'\beta)]^{1-y_i} . \tag{3.2}$$

Where, Φ represents the standard normal cumulative distribution function.

i represents observations $i = 1, \ldots, n$,

x represents a vector of characteristics of the explanatory variables,

β represents the unknown parameters to be estimated.

$y_i = 1$ if individual i selected alternative one, and $\Pr(y = 1) = \Phi(x_i'\beta)$.

$y_i = 0$ otherwise, and $\Pr(y = 0) = 1 - \Phi(x_i'\beta)$.

It is easier to work with the logarithm of the likelihood function, as taking the log of L makes the function additive. This is an acceptable procedure because L is always nonnegative and the logarithmic function preserves ordering (Pindyck and Rubinfeld 1991). The log likelihood function is then expressed as:

$$l(\beta) = \sum_{i=1}^{N} \{y_i \log \Phi(x_i'\beta) + (1 - y_i) \log[1 - \Phi(x_i'\beta)]\} . \tag{3.3}$$

Where, $l = \log L$, and log refers to the natural logarithm.

In order to find the maximum of the log likelihood function it is necessary to differentiate l with respect to each of the unknown parameters $\beta_1, \ldots, \beta_k$. The first derivatives are as follows,

$$\frac{\partial l}{\partial \beta_k} = \sum_{i=1}^{N} \left[\frac{y_i \phi(x_i' \beta)}{\Phi(x_i' \beta)} - \frac{(1 - y_i \phi(x_i' \beta)}{1 - \Phi(x_i' \beta)} \right] x_k \qquad for\ k = 1, \ldots, K, \tag{3.4}$$

where ϕ is the standard normal density function. To find the maximum each of the derivatives are set equal to zero and then solved for $\hat{\beta}_1, \ldots, \hat{\beta}_k$. The probabilities are non-linear so it requires an iterative process to solve for the values of $\hat{\beta}$. Maximum likelihood estimation involves a search over alternative parameter estimates to find those estimates which most likely would generate the sample (Pindyck and Rubinfeld 1991).

The preceding description of maximum likelihood estimation outlined the likelihood function for a binary probit model. For an ordered probit model, such as the WTP model to be estimated in the second stage of this project, the maximum likelihood estimation procedure is basically the same as it is for a binary probit model. The difference being the addition of the limit point parameters γ_m that are unknown and also must be estimated.

The likelihood function becomes,

$$L(\gamma, \beta) = \prod_{i=1}^{n} \prod_{m=1}^{M} [\Phi(\gamma_m - x_i' \beta) - \Phi(\gamma_{m-1} - x_i' \beta)]^{y_{im}}, \tag{3.5}$$

where, $i = 1, \ldots, n$ is the number of observations,

$m = 1, \ldots, M$ is the number of potential outcomes for the dependent variable (which in the case of the WTP question is five),

γ represents the unknown break points or limit points to be estimated, and

y_{im} is an indicator variable that equals one if the ith observation y_i selects the mth outcome. The probability that the mth outcome is selected is,

$$\Pr(y_i = m) = [\Phi(\gamma_m - x_i'\beta) - \Phi(\gamma_{m-1} - x_i'\beta)].$$

The log likelihood function becomes,

$$l(\gamma, \beta) = \sum_{i=1}^{n}\sum_{m=1}^{M} y_{im} \log[\Phi(\gamma_m - x_i'\beta) - \Phi(\gamma_{m-1} - x_i'\beta)]. \tag{3.6}$$

Just as with the binary model estimation procedure, the maximum likelihood estimates of the parameters $\hat{\gamma}_1, \ldots, \hat{\gamma}_m$ and $\hat{\beta}_1, \ldots., \hat{\beta}_k$ will be those that maximizes the log likelihood such that,

$$\frac{\partial l}{\partial \gamma} = 0, \text{ and } \frac{\partial l}{\partial \beta} = 0. \tag{3.7}$$

The basic principle of maximum likelihood is that it involves searching for the estimates of the unknown parameters that maximize the likelihood of generating the observed sample observations.[3]

3.7.1 An Iterative Procedure for Maximum Likelihood Estimation

To solve for the maximum of the log likelihood function Eviews uses a second derivative method, known as the quadratic hill-climbing method. The quadratic hill-climbing algorithm is used for iteration and computation of the covariance matrix of the parameter estimates. Iteration updates are obtained by, $\beta_{(t+1)} = \beta_{(t)} - \tilde{H}_{(t)}^{-1} g_{(t)}$, where

[3]Interested readers are referred to Greene, 2000 p. 820-821, and Ben-Akiva and Lerman 1985 p. 79-87 for further discussion of maximum likelihood estimation of binary choice models.

the subscript t indicates the number of the iteration. $g_{(t)}$ is a gradient vector

$g_{(t)} = \dfrac{\partial l(\beta_{(t)})}{\partial \beta_{(t)}}$, and $-\widetilde{H}_{(t)}$ is a modified Hessian matrix where, $-\widetilde{H}_{(t)} = -H_{(t)} + \alpha I$,

where I is the identity matrix and α is a positive number chosen by the algorithm. H is the Hessian matrix of second derivatives, $H = \left[\dfrac{\partial^2 l(\beta)}{\partial \beta \partial \beta'}\right]$. The αI is a correction matrix, and the effect of this modification is to push the parameter estimates in the direction of the gradient vector. So the process for obtaining iteration updates looks like this:

$$\beta_{(t+1)} = \beta_{(t)} - \left\{\left[\frac{\partial^2 l(\beta)}{\partial \beta \partial \beta'}\right]_t + \alpha I\right\} \frac{\partial l(\beta_{(t)})}{\partial \beta_{(t)}}.$$

3.7.2 Standard Errors and Inference

Eviews computes the asymptotic standard errors of the coefficient estimates from the unmodified Hessian once convergence is achieved. The asymptotic covariance matrix is computed from the negative inverse of the actual Hessian of the log likelihood (Greene 2000). The standard errors of the estimated coefficients are the square roots of the diagonal elements of the covariance matrix. In other words, the standard error of the parameter estimate $\hat{\beta}_k$ is the square root of the kth element of this covariance matrix.

The maximum likelihood estimation procedure has desirable large sample properties. All parameter estimates are consistent and efficient asymptotically, and are known to be asymptotically normal (Pindyck and Rubinfeld 1991). Therefore, t tests can be carried out on the coefficient estimates to test the hypothesis that an individual coefficient is equal to zero. t-statistics are calculated as the ratio of an estimated coefficient to its standard error, $t-stat = \dfrac{\hat{\beta}_k}{std.error\hat{\beta}_k}$. Tests will be carried out on the estimated coefficients at the 1%, 5% and 10% levels of significance for the models estimated in this project. The coefficient estimates that prove to be significant will make up the focus of the results and analysis discussion in Chapters 4 and 5.

3.8 Summary

This chapter has described the data for this project, how it was gathered and how the data was used to generate variables for the empirical model(s). The specification of the models was also discussed, as well as the procedure for generating parameter estimates. One of the primary objectives of this study is to investigate the effects that the explanatory variables outlined in this chapter have on consumer interest in PFP food products. The following chapters (Chapters 4 and 5) will analyze and discuss the results of the empirical models.

CHAPTER 4 – PFP FOOD PRODUCT DEMAND MODELS: RESULTS AND ANALYSIS

4.0 Introduction

The results of the binary probit model(s) of PFP food product demand will be analyzed in this chapter. As outlined in Chapter 2, 25 binary probit models are estimated to predict the probability that the average respondent would purchase each of the potential PFP food products listed in the survey. Eight products are selected for more detailed analysis. For the eight selected product models the marginal effects of all explanatory variables are calculated. The eight selected products are pasta, breakfast cereal, dry peas, sunflower seeds, beer, multigrain bread, canola oil and dry lentils.

The first section of this Chapter section contains a discussion of the predicted probability that the average respondent would purchase each product if it were available in a PFP form. Attention then moves to outline the significant variables and the direction of effects of these variables across all models. The third sub-section contains an analysis of the marginal effects of the explanatory variables for the eight selected product models.

4.1 Predicted Probabilities

The objective of this part of the study is to assess consumer interest in PFP food products based on the predicted probability that consumers would purchase PFP food products. Probit models are thus estimated and used to predict these probabilities for an average respondent, using data from a three-city survey. Two issues must be discussed before proceeding; these are re-specification or the original model and testing for differences in the data across the three sampled cities.

4.1.1 Model Specification Issues

Regarding model re-specification it is important to note that for some models the null hypothesis that all slope coefficients are jointly equal to zero cannot be rejected. (The likelihood ratio or LR statistic tests this hypothesis and will be discussed in more detail later in this chapter.) As such alternative specifications were examined for the models that have poor fit. Re-specifying models leads to a couple of problems, both of which are unappealing. First, a large number of variables were dropped from these models to increase the overall significance of the model. Such a procedure is akin to a method known as stepwise regression. A stepwise regression approach evaluates the coefficients sequentially and adds or deletes variables based on the significance of the variables. Greene states that economists tend to avoid stepwise regression methods, as there is reason to be skeptical of a model that is constructed entirely by such mechanical means.[1]

A second problem arises when examining re-specification of models related to goodness-of-fit measures. As will be noted later, several goodness-of-fit measures were used to assess each model's performance. When the poorer fitting models were altered in an attempt to improve the LR statistic, which is one of the goodness-of-fit measures, other goodness-of-fit measures and predictive ability declined. Since estimates in probit models are not designed to maximize any of the measures used, it is a debatable procedure to re-specify models to improve one measure at the expense of others.

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[1] His argument is as follows: suppose a stepwise method is used to ensure all the variables have *F* statistics greater than four (t-statistics are used for testing hypothesis here so t-statistics of approximately two would be desirable, but the argument is analogous), these *F* statistics should not be used to base inference on as it is not appropriate to consider them to have been drawn from a *F* distribution when it is known that they will be significant.

Given these two issues, re-specification was abandoned. However, it should be noted that the predicted probabilities in the models where re-specification was examined remained relatively constant. This indicates that the most important results of the models (*i.e.*, the probability that respondents would purchase PFP food products and the probability that they will be WTP a premium for PFP food products) are quite stable despite alternative model specification.

Another aspect of model specification is whether differences exist between the three cities in which households were surveyed. Specifically, this analysis would test whether the samples drawn from the three cities are from the same population. In this regard, Fisher's test could be used. This test (see Fisher 1970 for details) requires estimation of the models with the data pooled and also with the data separated into sub-samples from each individual city. The error sum of squares from the pooled and sub-sample models are used in an F-test where the null hypothesis is that the vector of disturbances from the pooled and sub-samples are the same.

Unfortunately, in the city sub-sample models there are a number of instances where some dummy variables have none or very few one observations. If one dummy from a set of dummy variables is zero for all (or nearly all) observations, the model cannot be estimated due to linear dependency. To estimate the city sub-sample model in such an instance, additional dummy variables would have to be omitted. This means that the city sub-sample models and the pooled models would no longer have the same set of regressors. In order to conduct Fisher's test the pooled sample model and the sub-sample models must have the same specification. Therefore, the test cannot be carried out on the data used in this project.

Alternatively, one could incorporate interaction effects between the city dummy variables and other explanatory variables as follows:

$$\begin{aligned}\Pr(y=1) = \Phi[\alpha_0 + \alpha_C CAL + \alpha_W WPG + \beta_1 x_1 + \beta_{1C}(CAL * x_1) + \beta_{1W}(WPG * x_1) \\ + \ldots\ldots\ldots\ldots + \beta_k x_k + \beta_{kC}(CAL * x_k) + \beta_{kW}(WPG * \beta_k)]\end{aligned} \quad (4.1)$$

where, *CAL* and *WPG* are the city dummy variables, $\alpha_0, \alpha_1, \alpha_2$ are intercept and intercept shifters, and $\beta_1, \beta_{1C}, \beta_{1W}, \ldots, \beta_k, \beta_{kC}, \beta_{kW}$ are slope and slope shift coefficients. While this is not the same as Fisher's test, it does allow for testing of significant differences between the co-efficients representing the effects of different cities. To test if all three cities can be modeled together the following joint null hypothesis would be tested $\alpha_C = \alpha_W = 0,\ \beta_{1C} = \beta_{1w} = 0,\ \beta_{kC} = \beta_{kW} = 0$, which tests the null hypothesis that the intercept and slope shifters due to city differences are equal to zero. If this hypothesis was accepted then the model could be estimated independent of city effects. If these coefficients were jointly equal to zero the model that remains would be free of any city effects. However, the same problem arises with this approach as Fisher's test; unless additional variables are dropped from the model, there are insufficient observations to estimate the model.

Alternatively, a number of categories could be combined to reduce the variables in the models to the point where all city sub-sample models would have the same specification. However, combining categories would mean broader classifications and less detailed analysis. As such, it was deemed better to estimate the models with a combined sample than to lose the ability to provide detailed analysis. Consequently, a hypothesis in the analysis that follows is that the data from the three cities is drawn from same underlying population.

4.1.2 Predicted Probabilities Evaluated at the Means of the Data

Table 4.1 contains the predicted probability results for each of the 25 potential PFP food products evaluated at the means of the data. The predicted probability information is important in a marketing context, as it is a measure of the level of consumer interest in each potential PFP food product. The predicted probabilities range from a low of .3278 for "buckwheat noodles" to a high of .9710 for "pasta." Of note is that buckwheat noodles is the only product whose predicted probability is less than .50. This is encouraging as it suggests strong interest among respondents in PFP food products.

The wide range in probabilities indicates that although the average respondent is interested in PFP alternatives, they are not necessarily interested in purchasing all of the potential PFP food products. This is a reasonable conclusion as most consumers likely do not regularly purchase all of the potential PFP food products. If a household does not typically consume a specific product it is unlikely they would purchase the PFP alternative even if they were interested in PFP food products.

The predicted probabilities are indicators of the likelihood that the products will be accepted by consumers if available in a PFP form. The top ten products are pasta, whole wheat bread, breakfast cereal, multigrain bread, bagels, crackers, oatmeal, canola oil, margarine and cookies. Nine of these potential PFP food products have predicted probabilities greater than 70%, while the top four have predicted probabilities over 80%. Given these results, PFP producers and processors should consider developing products from the top ten list for initial entry of PFP food products into the marketplace in order to maximize the likelihood of success.

Table 4.1: Predicted Probabilities – PFP Food Products		
Rank	**Product / Model**	**Predicted Probability**
1	Pasta	0.9710
2	Whole wheat bread	0.8956
3	Breakfast cereal	0.8815
4	Multigrain bread	0.8109
5	Bagels	0.7783
6	Crackers	0.7339
7	Oatmeal	0.7147
8	Canola oil	0.7078
9	Margarine	0.7021
10	Cookies	0.6875
11	Baked beans	0.6406
12	Muffins	0.6406
13	Corn oil	0.6377
14	Dry beans	0.6025
15	Lentil, pea, bean soup	0.5951
16	Sunflower seeds	0.5875
17	White bread	0.5771
18	Corn chips	0.5609
19	Dry peas	0.5456
20	Chickpeas	0.5263
21	Granola	0.5202
22	Dry lentils	0.5185
23	Beer	0.5137
24	Granola bars	0.5126
25	Buckwheat noodles	0.3278

4.1.3 Predicted Probabilities Summary:

Consumer response to PFP food products is generally very positive. The predicted probability that the average respondent would purchase the specific PFP food product is high for many of the potential PFP food products and is at least 50% for 24 of the 25 products. Most respondents probably do not regularly purchase all of the potential

PFP food products, and this may partially explain some of the lower predicted probabilities. The products with high predicted probabilities are good candidates to be flagship PFP food products in the marketplace.

4.2 All Models – Significant Variables and Direction of Effects

This section focuses on the significance of the explanatory variables across all 25 PFP food product models. Results for each model are presented in Table 4.2 significant variables are denoted by highlighting the cell corresponding to that variable for each particular model. The direction of effect is indicated with either a plus sign "+" for a positive effect, or a minus sign "-" for a negative effect. The following discussion will summarize the information presented in Table 4.2. The significant variables provide the most pertinent information, and the discussion will focus on these variables.

4.2.1 Significant Variables Discussion

City: The CAL variable is significant in four models (beer, cookies, baked beans and lentil-pea-bean soups), and the coefficient estimates are positive in three of the four. The TOR variable is significant in eight models (pasta, crackers, muffins, chickpeas, multigrain bread, canola oil, margarine and dry lentils), with six of these estimates being negative. The city variables do play a role in consumer interest in PFP food products, as respondents from Calgary appear to be more likely to purchase PFP food products and respondents from Toronto appear to be less likely.

Try new: The TNEW1 (the first to try new food products) coefficient is significantly negative in eight models. This is counter to what was expected, as consumers who are among the first to try newly introduced food products were expected to be more likely to purchase PFP food products. The TNEW2 (the last to try new food products) variable is significant in seven models and of these, six have negative coefficients. This indicates that TNEW2 has a primarily negative effect on the predicted probabilities. TNEW2 was expected to be negative, as it was hypothesized that those among the last to try new food products would be less likely to purchase PFP food products.

Coefficient estimates for the TNEW3 (in between the first and last to try) variable are significant in five models, of which, four have a negative effect on the predicted probability of purchasing PFP food products. The expectation for this variable was somewhat uncertain as consumers in between the two extremes were expected to have mixed preferences towards purchasing new food products.

Health: The variables regarding health food store shopping habits offer some interesting results. The variable HEALTH3, which represents the usually or always shop at health food stores response options, is significant in five models, with the corresponding coefficient estimates all being negative. This indicates that respondents who usually or always shop at health food stores are less likely to purchase PFP food products.

It was hypothesized that consumers who regularly shop at health food stores would be more interested in PFP food products than consumers who do not. Perhaps very health conscious consumers do not see PFP food products as an adequate alternative to conventionally produced food. People who shop at health food stores may not see a distinction between PFP and conventional food products due to the fact that PFP allows for some chemical use (fertilizers and non-residual pesticides outside the growing season). This could be an area for further research, as it cannot be inferred from this study why some health food shoppers are not interested in PFP food products. Gaining further insight into why consumers would not purchase PFP food products could help in developing products and marketing strategies that enhance the appeal of PFP food products.

The HEALTH2 (occasionally shop at health food stores) variable is significant in eight models and the coefficient estimates are positive in all eight. Respondents who occasionally shop at health food stores are more likely to purchase PFP food products. This is in line with the expectation that health conscious consumers will be more likely to purchase PFP food products. It is interesting that very health conscious respondents (HEALTH3) are less likely to purchase PFP food products, while respondents who are moderately health conscious (HEALTH2) are more likely to purchase PFP.

It should be noted that a generalization is being made here by implying that health food store shoppers are very/moderately health conscious and that those who never shop at health food stores are not. There undoubtedly are many people who are extremely concerned about the food they eat who never shop at health food stores. It is not the intent to use these variables as a strict measure of health consciousness but simply as a variable that may help identify the consumers most likely to purchase PFP food products. That being said, it is highly probable that people who do regularly shop at health food stores are indeed very health conscious and it is interesting that HEALTH3 is consistently negative while HEALTH2 is consistently positive.

Attitude Statement Variables: The attitude questions also offer some interesting results, as some results match expectations while others do not. It was hypothesized that respondents who share these attitudes would be more likely to purchase PFP food products. The results for each of the five attitude questions will be discussed next. Recall that respondents were asked to rate their level of agreement with the five attitude statements on a modified Likert scale ranging from strongly agree to strongly disagree.

Environment: The first attitude statement is in regards to concern about the impact of chemical use in agriculture on the environment. The variables for this question are ENV1 (strongly agree), ENV2 (agree) and ENV3 (neutral). For the most part these variables are not significant. However, ENV1 has a positive and significant effect in the dry lentil model, ENV2 has a significantly negative effect on the baked bean model, and ENV3 has a significantly negative effect on the white bread model. ENV1 and ENV2 were expected to have positive effects, as it was hypothesized that respondents who are concerned about the environmental impact of pesticide use would view PFP food products favourably. Perhaps people do not make the connection between PFP food products and the potential reduction in chemical use resulting from food produced in a PFP system.

Concerned about pesticide residues: The second attitude statement is in regard to respondents' concerns about pesticide residues in our food supply. There are three variables based on this question CPR1 (strongly agree), CPR2 (agree) and CPR3 (neutral). CPR1 is significant and has a positive coefficient in six models, CPR2 is significant and the coefficient is positive in four models and the CPR3 coefficient estimate is significant and positive in one model. These results indicate that concern about pesticide residues in the food supply has a consistent positive effect on the predicted probability that the average respondent would purchase potential PFP food products. These results are consistent with the expectation that respondents who are concerned about pesticide residues in our food supply would be interested in PFP food products.

Labeling: The third set of attitude variables is derived from the attitude statement regarding the importance of labeling on food packaging. The LABEL1 (strongly agree) coefficient is significant and positive in six models. LABEL2 (agree) is less definitive, as it is significant in just one model. The LABEL1 and LABEL2 coefficient estimates indicate that a positive relationship exists between the attitude that labeling of food ingredients is important and the predicted probability of purchasing PFP food products.

Farm income: The fourth set of attitude variables, FINC1 (strongly agree) and FINC2 (agree), arise from the statement regarding maintaining farm income at a level which keeps the family farm viable. FINC1 is significant in seven models and has a negative effect in six of these. FINC2 is significant in 10 models and has a negative effect in all 10 cases. Respondents who share the belief that maintaining farm income at levels that keep the family farm viable are less likely to purchase PFP food products. This result is the opposite of what was expected. A possible explanation is that the connection between an alternative production system and maintaining farm income is not made among respondents. This could be a reflection of a growing distance between consumers and food producers or farmers, especially considering that respondents to the survey were from three urban centres. Many urban consumers may be relatively disconnected from rural agricultural life. The connection between an alternative production system and the potential impact for the family farm may well not be intuitive to the average urban dweller.

Sustainable agricultural practices: The final set of attitude variables, SAP1 (strongly agree) and SAP2 (agree), are derived from the statement regarding farmers using sustainable production practices. The hypothesis underlying this question is that consumers who feel that farmers should engage in sustainable agricultural production practices are more likely to purchase PFP food products than those who disagree with this statement. The SAP1 coefficient is significant and positive in 12 models. SAP2 also has a consistently positive effect, as it is significant in five models and its coefficient is positive in all five cases. These results are consistent with the expectation that people who agree with this attitude statement would view PFP food products favourably.

Purchase alternative food products: Respondents who have previously purchased alternative food products (IPM or organic) are more likely to purchase PFP food products than those who have not. PALT is significant in seven models and has a positive coefficient in each case. This indicates that respondents who already buy alternative food products are more likely to purchase PFP food products.

It is interesting that respondents who have purchased alternative food products are more likely to purchase PFP food products, while those who usually shop at health food stores (HEALTH3) are less likely. Purchasing alternative food products does not imply that consumers shop at health food stores. Reduced input food products such as, IPM and organic food products are available at numerous locations including most mainstream grocery stores. Therefore, it is not unreasonable to have conflicting results between the PALT and HEALTH3 variables.

Heard of PFP: H-PFP is significant in three models. An interesting result is that in the three models where H-PFP is significant, respondents who have previously heard of PFP are less likely to purchase PFP food products. H-PFP has a negative effect in the pasta, white bread and margarine models. It is somewhat surprising that previous knowledge of PFP had a negative impact on the predicted probability that respondents would purchase these PFP food products. It is difficult to draw conclusions as to why respondents with previous knowledge of PFP are less likely to purchase PFP food products. Again, further research into why some consumers are not interested in PFP may provide insight regarding marketing PFP food products.

Household size & number of children: Household size (H-SIZE) is significant in only one model (Beer) and the coefficient estimate is negative. This indicates that as household size increases the predicted probability that the average respondent would purchase PFP beer decreases.

Having children appears to be an important factor in the average respondents' interest in PFP food products. The CHILD<17 variable is significant and has a positive coefficient in 11 models. The positive coefficients mean that as the number of children increases, households are more likely to purchase PFP food products. This is consistent with the expectation that consumers with children are more concerned about the safety of the food they purchase and therefore, likely to be interested in PFP food products.

The effects of household size and the number of children seem to have conflicting results. H-SIZE has a negative effect on the one model in which it is significant, while CHILD<17 has a positive effect on the models in which it is significant. Household size increases either through marriage/co-habitation or by having children and therefore, both variables were expected to have a positive effect. Household size is significant in just one model and this could be an isolated case. CHILD<17 is significant in 11 models which provides strong evidence that as the number of children increase so does the predicted probability of purchasing PFP food products.

Primary food shopper: The prime food shopper variable (P-SHOP) is significant in six models and has a positive coefficient in all six. This is consistent with the hypothesis that the primary food shopper for the household would be more likely to purchase PFP food products as they are the "gatekeepers" to the household.

Female: Interestingly, despite the fact that most primary grocery shoppers are female (178 of the 276 respondents who indicated they are the primary food shopper are female), females are actually less likely to purchase PFP food products. The female variable is significant in four models and has a negative effect in all four. This result is surprising, as it was hypothesized that females would be more likely to purchase PFP food products. Previous literature has indicated that females are more concerned about food safety and it was expected that this would also be the case for PFP food products.

Age: Age appears to play a role in the predicted probability that respondents would purchase PFP food products. AGE1 (<36) is significant in three models, and its coefficient is negative in two of these. AGE2 (36-50) has a negative effect in all four models in which it is significant, while AGE3 (51-65) has a negative coefficient in the five models it is significant in. The higher age groups have significant and negative effects in a larger number of models.

Education: EDUC2 (high school graduate/some university) is significant in one model, EDUC3 (university degree/some graduate school) is significant in two models and EDUC4 (graduate degree) is significant in one model. These education variables have negative coefficients in all of the models in which they are significant. The negative coefficients on EDUC2, EDUC3 and EDUC4 indicate that respondents with higher levels of education are less likely to purchase PFP food products. Although being significant in such few models indicates that education plays a limited role in respondents' interest in PFP food products.

Expenditure: Monthly food expenditure is a significant factor in predicting the probability of purchasing PFP food products. The lowest expenditure category (EXP1, <

$199) is significant in 10 models and has negative effect in nine of these. EXP2 ($200-$399) is significant in three models and has a negative effect in two of them, while EXP3 ($400-$499) is significant in two models with a positive coefficient estimate in both. Lastly, EXP4 ($500-$699) is significant in two models with a positive effect in one model. It is concluded that respondents who spend the least on food are less likely to purchase PFP food products.

These results are not surprising, as people spending less than $199 on food per month probably have a limited means. People with limited means have a tighter budget constraint and likely know exactly what they can afford and may not be willing to try many new products. This may also be related to age as older consumers typically have lower incomes and, as shown earlier, as age increases there are a larger number of negative effects on the probability of purchasing PFP food products.

Income: Among all of the income variables there are few models in which these variables are significant. The exception is that coefficients for the INC6 variable (annual household income between $100,000 - $149,999) is significantly positive in seven models. The trend for the income variables shows that as income increases so does the number of models in which the income variables are significant. INC1 (<$19,999) is significant in one model and has a negative effect, INC2 ($20,000 - $39,999) is significant in one model and has a positive effect, while INC3 ($40,000 - $59,999) is significant in two models with a positive coefficient estimate in one of these. INC4 ($60,000 - $79,999) is significant in three models with a positive effect in two models, while INC5 ($80,000 - $99,999) is not significant in any model. These income variable results indicate that higher income respondents are more likely to purchase PFP food products, as the number of positive effects is greatest for the higher income categories.

Marital status: The marital status variables are significant in only a few models. MSTAT1 (single) is significant in two models and the coefficient is positive in both, indicating that single respondents were more likely to purchase PFP food products. MSTAT2 (married) has a negative coefficient in the one model in which it is significant. The MSTAT3 (separated/divorced/widowed) coefficient is negative in the two models in which it is significant. In general the effect of marital status on the probability that respondents would purchase PFP food products is minimal, as these variables are significant in only a few models.

4.2.2 Significant Explanatory Variables Summary:

The 25 potential PFP food products binary model results provide important information. Some variables are significant in enough models that they represent a trend throughout the range of potential PFP food products. The following variables are significant in at least one third or more of the potential PFP food product models: TOR, TNEW1, TNEW2, HEALTH2, FINC2, SAP1, CHILD<17, EXP1 and INC6. (INC6 is significant in only seven models but is included because it is positive in all seven and provides insight into the effect of income on consumer interest in PFP.)

The following list indicates which models each of these frequently significant variables are significant in. The variable name is followed by the names of the models it is significant in and a note in brackets indicating the direction of effect the variable has in that model. For example; Variable *ABC*: pasta (neg.), indicates that variable *ABC* is significant in the pasta models and has a negative effect on the predicted probability that respondents would purchase PFP pasta.

List of models for frequently significant variables:

TOR: pasta (neg.), cracker (neg.), muffin (neg.), chickpeas (pos.), multigrain bread (neg.), canola oil (neg.), margarine (neg.), and dry lentil (pos.).

TNEW1: dry beans (neg.), dry peas (neg.), sunflower seeds (neg.), beer (neg.), white bread (neg.), dry lentils (neg.), baked bean (neg.), buckwheat noodles (neg.).

TNEW2: pasta (pos.), dry peas (neg.), sunflower seed (neg.), beer (neg.), white bread (neg.), canola oil (neg.), baked bean (neg.), buckwheat noodles (neg.).

HEALTH2: whole wheat bread (pos.), granola (pos.), dry beans (pos.), dry peas (pos.), chickpeas (pos.), dry lentils (pos.), baked bean (pos.), lentil, pea, bean soup (pos.).

FINC2: muffin (neg.), granola (neg.), dry beans (neg.), dry peas (neg.), chickpeas (neg.), beer (neg.), multigrain bread (neg.), baked beans (neg.), lentil, pea, bean soup (neg.), buckwheat noodles (neg.).

SAP1: pasta (pos.), whole wheat bread (pos.), crackers (pos.), dry beans (pos.), dry peas (pos.), chickpeas (pos.), white bread (pos.), bagels (pos.), cookies (pos.), baked bean (pos.), lentil, pea, bean soup (pos.), granola bars (pos.).

CHILD<17: cracker (pos.), muffin (pos.), corn oil (pos.), corn chips (pos.), beer (pos.), white bread (pos.), bagels (pos.), cookies (pos.), margarine (pos.), dry lentil (pos.), granola bars (pos.).

EXP1: pasta (pos.), dry beans (neg.), dry peas (neg.), chickpeas (neg.), beer (neg.), baked bean (neg.), lentil, pea, bean soup (neg.), buckwheat noodles (neg.).

INC6: pasta (pos.), muffin (pos.), chickpeas (pos.), corn chips (pos.), white bread (pos.), bagels (pos.), and granola bars (pos.).

The preceding list covers all but two potential PFP food product models (breakfast cereal and oatmeal are the only two not mentioned). The following discussion briefly comments on the predictive ability and goodness-of-fit of the above mentioned models to provide an idea of how well these models predict. (For a detailed description of these predictive ability and goodness-of-fit measures refer to section 4.3.3.) All of the above mentioned models show good predictive ability over models estimated with the intercept only, with most showing significant predictive gain. These models also have satisfactory H-L statistics indicating that the models are not misspecified.

A few of the models (sunflower seeds, multigrain bread, cookies, margarine, granola bars) have poor LR statistics which means that the hypothesis that all slope coefficients are equal to zero cannot be rejected. However, as mentioned in section 4.1.1. re-specifying models to improve the LR statistics leads to some undesirable problems and therefore the models were left as specified despite some poor LR statistics.

Based on the sign of the significant coefficient estimates across all 25 PFP food product demand models the respondents most likely to purchase PFP food products are best described as: People who occasionally shop at health food stores, believe that farmers should use sustainable agricultural production practices, have children and have high incomes.

The above profile is based on the sign of the coefficient estimates. However, the coefficient estimates do not indicate the magnitude of the effect on the predicted probability. Marginal effects must be calculated to determine the size of the effect a

Table 4.2: Direction of Effects – All Binary Models

Var.	Pasta	ww br.	Cracker	Muffin	Bcereal	Granola	Cornoil	Dbeans	Dpeas
Cal	-	-	-	-	+	+	-	+	+
Tor	-	-	-	-	-	+	-	+	+
Tnew1	+	+	-	-	+	-	+	-	-
Tnew2	+	+	+	-	+	+	-	+	-
Tnew3	+	+	+	-	+	+	+	n/a	-
Health2	-	+	-	-	+	+	-	+	+
Health3	-	+	-	-	-	-	-	+	+
Env1	+	-	+	-	-	+	-	+	+
Env2	+	+	-	-	-	+	-	+	-
Env3	+	-	-	-	-	+	-	+	-
Cpr1	+	+	+	+	+	+	+	+	+
Cpr2	+	+	+	+	+	+	+	+	+
Cpr3	+	+	+	+	+	+	+	+	+
Label1	+	+	-	+	+	+	+	+	+
Label2	+	+	-	+	+	+	+	+	+
Finc1	+	-	-	-	-	-	-	-	-
Finc2	+	-	-	-	-	-	-	-	-
Sap1	+	+	+	+	+	+	+	+	+
Sap2	+	+	+	+	+	-	-	+	+
Palt	-	-	+	+	+	+	+	+	+
H-pfp	-	-	+	+	+	+	+	+	+
H-size	+	-	-	-	+	+	-	-	-
Child<17	+	+	+	+	+	+	+	+	+
P-Shop	+	+	+	+	+	+	+	+	+
Female	-	-	-	-	+	-	-	-	-
Age1	+	+	-	-	+	-	-	-	-
Age2	-	+	-	+	+	-	-	-	-
Age3	+	+	+	+	-	-	-	-	-
Educ2	+	-	+	-	-	+	+	-	-
Educ3	+	-	+	-	-	+	+	+	-
Educ4	-	-	+	-	-	+	+	-	-
Exp1	+	+	+	-	-	+	-	-	-
Exp2	+	+	+	-	+	+	-	-	-
Exp3	+	-	+	+	+	+	+	-	-
Exp4	+	+	-	-	+	+	+	-	-
Inc1	-	-	-	-	-	-	+	-	-
Inc2	-	-	-	+	+	+	+	+	+
Inc3	-	-	-	-	+	+	+	+	+
Inc4	-	+	-	+	-	+	+	+	+
Inc5	+	+	-	+	-	+	+	+	+
Inc6	+	+	+	+	+	+	+	+	+
Mstat1	+	+	+	-	+	+	+	-	-
Mstat2	+	+	+	-	+	+	+	-	-
Mstat3	+	+	-	-	+	-	-	-	-
C	-	-	-	+	-	-	-	-	+

Represents significant variables

Table 4.2: Direction of Effects – All Binary Models (continued)								
Var.	Cpeas	Cchips	Sseed	Beer	Mg br.	Wt br.	Bagels	Cookie
Cal	-	-	+	+	-	-	+	-
Tor	+	-	-	+	-	-	+	-
Tnew1	-	-	-	-	+	-	+	-
Tnew2	-	-	-	-	+	-	-	-
Tnew3	-	-	-	-	+	-	+	+
Health2	+	-	+	-	+	-	+	-
Health3	-	-	-	-	+	-	-	-
Env1	-	+	-	+	+	-	+	+
Env2	-	+	-	+	+	-	+	-
Env3	-	+	-	-	+	-	+	-
Cpr1	+	+	+	+	+	+	+	+
Cpr2	+	+	+	+	+	+	+	+
Cpr3	+	-	+	+	+	+	+	+
Label1	+	+	+	+	+	+	+	+
Label2	+	-	+	-	-	+	-	+
Finc1	-	-	-	-	-	-	-	-
Finc2	-	-	-	-	-	+	-	-
Sap1	+	+	+	-	+	+	+	+
Sap2	+	+	+	-	+	+	+	+
Palt	+	+	+	+	+	+	+	+
H-pfp	+	-	-	+	-	-	-	-
H-size	-	-	-	-	-	+	-	-
Child<17	+	+	+	+	-	+	+	+
P-Shop	+	+	+	+	+	+	+	+
Female	-	-	-	-	+	-	-	-
Age1	-	+	+	+	-	-	+	-
Age2	-	+	+	-	-	-	+	+
Age3	-	+	+	-	-	-	-	-
Educ2	-	+	+	-	+	-	-	+
Educ3	-	+	+	+	+	-	-	+
Educ4	-	-	-	-	+	-	-	+
Exp1	-	+	-	-	-	-	+	-
Exp2	-	+	-	-	-	+	+	+
Exp3	-	+	-	-	-	-	+	+
Exp4	-	+	-	-	-	-	+	-
Inc1	+	-	-	+	-	-	+	-
Inc2	+	-	+	-	-	+	+	+
Inc3	+	-	+	+	-	+	+	-
Inc4	+	+	+	+	-	+	+	-
Inc5	+	+	+	+	-	+	+	-
Inc6	+	+	+	+	-	+	+	+
Mstat1	+	+	+	-	+	+	+	+
Mstat2	-	-	+	-	+	+	+	+
Mstat3	-	-	-	-	-	+	-	-
C	-	-	-	+	-	-	-	-

Table 4.2: Direction of Effects – All Binary Models (continued)								
Var.	Oatmeal	Can oil	Marg	Dlentil	Bbean	Soup	Gbars	Bw ndl
Cal	+	+	-	+	+	+	+	+
Tor	-	-	-	+	+	+	+	+
Tnew1	+	-	-	-	-	-	-	-
Tnew2	+	-	-	-	-	-	+	-
Tnew3	+	-	-	-	-	-	+	-
Health2	+	+	-	+	+	+	+	+
Health3	-	-	-	+	-	-	-	-
Env1	-	+	-	+	+	+	+	+
Env2	-	-	-	+	-	+	-	-
Env3	-	-	-	+	-	+	+	+
Cpr1	+	+	+	+	+	+	+	+
Cpr2	+	+	+	+	+	+	+	+
Cpr3	+	+	+	+	+	+	n/a	+
Label1	+	+	+	+	+	+	+	+
Label2	-	+	+	+	+	+	+	+
Finc1	-	+	-	-	-	-	-	-
Finc2	-	-	-	-	-	-	-	-
Sap1	+	+	+	+	+	+	+	+
Sap2	+	-	+	+	+	+	+	+
Palt	+	-	+	+	+	+	+	+
H-pfp	+	+	-	-	+	+	+	-
H-size	-	-	-	-	-	-	-	-
Child<17	+	+	+	+	+	+	+	+
P-Shop	+	+	+	+	+	+	+	+
Female	+	-	+	-	-	-	+	-
Age1	+	-	-	-	-	+	+	-
Age2	-	-	-	-	-	-	-	-
Age3	-	-	-	-	-	-	-	-
Educ2	-	-	-	+	+	+	+	+
Educ3	-	-	-	+	+	-	+	+
Educ4	-	-	-	+	+	+	-	+
Exp1	-	-	-	-	-	-	-	-
Exp2	+	+	+	-	-	-	-	-
Exp3	+	+	+	-	-	-	+	-
Exp4	+	+	+	-	-	-	-	-
Inc1	+	-	-	-	+	-	+	+
Inc2	+	+	-	+	+	+	+	+
Inc3	+	+	-	+	-	+	+	+
Inc4	+	+	-	+	+	+	+	+
Inc5	+	+	-	+	+	+	+	+
Inc6	+	+	+	+	+	+	+	+
Mstat1	+	+	+	-	-	-	+	+
Mstat2	+	+	+	-	-	-	+	-
Mstat3	-	-	-	-	-	-	+	-
C	-	-	-	+	+	-	-	+

variable has on the predicted probability. Knowing which variables have the largest effects on the predicted probability is valuable in developing effective marketing strategies. This information can aid a marketer in distributing their resources among activities directed at reaching consumers who have certain characteristics. Targeting marketing efforts at consumers who are most likely to be interested in PFP food products will increase the likelihood of success (*i.e.*, consumer acceptance). The next section will address this issue as it focuses on the marginal effects of the explanatory variables for a subset of the potential PFP food products.

4.3 Selected PFP Product Models

This section focuses on the results of the eight selected PFP food product models. The eight selected products are; pasta, breakfast cereal, dry peas, sunflower seeds, beer, multigrain bread, canola oil and dry lentils. As described in Chapter 2, these products were selected as a representative group of products. Pasta, breakfast cereal, multigrain bread and beer are derived from cereal crops, peas and lentils are pulse crops, canola oil is derived form canola which is an oilseed crop and sunflower is a specialty crop. Dry peas, dry lentils and sunflower seeds require minimal processing where the other products all require extensive processing. Sunflower seeds and beer are unique as the former is primarily a snack food, and the later is the only beverage on the list. An attempt was made to select products that were varied, unique and representative of broad food product categories for which PFP food products could feasibly be developed. The marginal effects of the significant explanatory variables in each of the selected PFP food products will be the focus of this section.

Unlike Ordinary Least Squares regression, the estimated coefficients from a binary probit model cannot be interpreted as the marginal effect on the dependent variable (Eviews 1998). The sign of the estimated probit coefficients do provide the direction of the effect, but not the magnitude. The coefficients give a rough idea of the magnitude, as larger coefficients typically mean larger marginal effects. However, as equation 2.8 illustrates, the actual magnitude or marginal effect depends on the coefficient of interest (β_k), as well as all other coefficients and the values of all the variables $(x'\beta)$.

4.3.1 Calculation of Marginal Effects

The partial derivative approach (illustrated by equation 2.8) to calculating marginal effects is only appropriate for continuous variables. For binary variables, the marginal effect cannot be calculated by taking the partial derivative, as the partial derivative of a binary variable does not exist. The marginal effect of a binary variable must be determined by calculating the change in probability. The change in probability is derived by taking the difference between the predicted probability calculated with the variable of interest set equal to one and the predicted probability calculated with the variable of interest set equal to zero, with all other variables being held constant at their sample means. (This is the typical method used to calculate the marginal effects for binary variables in probit models and the procedure used in this project.) The change in probability due to a change in a specific variable is shown in equation 4.2.

$$\Delta \Pr(BuyPFP=1)/\Delta x_k = [\Pr(BuyPFP=1) \mid x_k = 1] - [\Pr(BuyPFP=1) \mid x_k = 0)] \qquad (4.2)$$

What is not shown in this equation is the fact that all other variables are held fixed at their sample means during calculation of the two right hand side terms. The other variables are held constant to isolate the effect of the variable of interest.

4.3.2 Interpretation of Marginal Effects

Before the results of the selected models are discussed, the interpretation of the marginal effects will be explained. The basis for analysis is a unit change in a given explanatory variable. The interpretation of the marginal effects of continuous variables is straightforward; all other things being equal a unit change in the explanatory variable will result in an increase or decease in the predicted probability equivalent to the size of the marginal effect. For binary variables the interpretation is slightly different. A unit change in the case of a binary variable is a change from zero to one, which means either falling in that category or not, and the marginal effect is interpreted as the effect on the predicted probability of being in that category or not.

For example, assume AGE1 (<36 years old) has a marginal effect of .25 on the predicted probability of purchasing a PFP food product. A unit change in AGE1 means an individual is either under age 36 or not. Therefore, the marginal effect of .25 is interpreted as respondents under the age of 36 are 25% more likely to purchase the PFP food product compared to other respondents who are not under age 36, but possess the same set of all other characteristics (*i.e.* the average respondent). Marginal effects of binary variables are interpreted as, respondents who have the characteristic in question are more or less likely than those who do not have that characteristic, all other things being equal, to purchase the specific PFP food product. This perspective is taken while discussing the analysis of the marginal effects of binary variables.

4.3.3 Goodness-of-fit

Before analyzing the results it is important to discuss some goodness-of-fit measures used to examine how well the estimated models fit the data. Four goodness-of-fit measures were used in this regard: results of the Hosmer-Lemeshow (H-L) goodness-of-fit test, a predictive ability measure, the McFadden R^2 and results of a likelihood ratio test. Briefly, the H-L test is a Pearson χ^2 type test of goodness-of-fit.[2] The idea is to compare fitted expected values to actual observed values by group. If these differences are large, the model is rejected as providing insufficient fit. The H-L test groups observations on the basis of the predicted probability that $y=1$. The data is grouped into $j=1,\ldots,J$ groups, where m_j is the number of observations in group j (Eviews groups the data into 10 groups by default), and the following test statistic calculated:

$$HL=\sum_{j=1}^{J}\frac{(y_j-m_j\overline{p}_j)^2}{m_j\overline{p}_j(1-\overline{p}_j)}\sim\chi^2\quad df(J-2)\,. \tag{4.3}$$

Where, $y_j=\sum_{i\in j}y_i$ is the number of $y=1$ observations in group j, and

$\overline{p}_j=\sum_{i\in j}\frac{\hat{p}_i}{m_j}=\sum_{i\in j}=\frac{1-\Phi(x_i'\beta)}{m_j}$ is the average of the predicted values in group j.

[2] Moore and McCabe 1993 p.604-608 provide a good introductory discussion of Pearson χ^2 tests.

The null hypothesis is that the model is not misspecified, which is supported by a high p-value. As such, the H-L statistic and the corresponding p-value are reported for each model.

Predictive ability is often used as a means of assessing a model's fit/performance. For a probit model, predictive ability is calculated by constructing a table showing the number correct and incorrect predictions based on a rule such as $\hat{y} = 1$ if $\Pr(y_i = 1) > .5$ and $\hat{y} = 0$ otherwise. In other words, if the predicted probability for a given observation is greater than .5 then it is classified as a one, if it is less than .5 it is classified as a zero. In this *prediction evaluation* table, the classifications based on this prediction rule are tabulated and compared to the actual observed responses for the dependent variable. The same classification is also calculated for a model with the intercept term only. The estimated model is compared to the constant only model to provide a measure of the improvement in predictive ability of the estimated model.

A second predictive ability measure classifies responses based on expected value calculations. The expected value is calculated as the sum of the predicted probabilities that $y = 1$ and $y = 0$ for the estimated model. The *expected value* evaluation table reports the difference between the observed counts versus the expected counts and compares the predictive ability of the estimated model against the counts from a model with only the intercept term. The predictive ability tables are presented in Appendix 2. At the bottom of each table the percent gain is reported which indicates the success the estimated model has in predicting responses compared to the constant only model. A larger percent gain indicates a better fit as the model has greater success than the base model in predicting responses.

The McFadden R^2 measure is analogous to the R^2 in conventional regression in that it is bounded by zero and one and its value increases with the explanatory power of the model. This measure is calculated as $R^2 = 1 - \left(\frac{l}{l_0}\right)$ where, l is the maximized value of the log likelihood function and l_0 is the log likelihood computed with only the constant term. "If the maximization procedure suggests that there is no gain from changing any of the estimated parameters from zero, then the McFadden R^2 will equal zero as well" (Pindyck and Rubinfeld 1991). Hence, if l is the same as l_0 then McFadden's R^2 equals zero ($R^2 = 1 - 1 = 0$). The McFadden R^2 is reported for each model. Note, however, that R^2 values are typically low for cross-section data and this is reflected in the McFadden R^2 values for the models estimated in this project.

As noted earlier, the Likelihood Ratio (LR) statistic tests the null hypothesis that all slope coefficients are jointly equal to zero. If this null hypothesis cannot be rejected, one may conclude the model provides a poor fit. The LR statistic is computed as $LR = -2(l_0 - l)$. The LR statistic is asymptotically distributed as a χ^2 variable with degrees of freedom equal to the number of restrictions (*i.e.*, the number of slope coefficients in the model). The LR statistic and the associated p-value are reported for each model

The goodness-of-fit measures are reported for the models estimated in this project, as all are suggested means for evaluating goodness-of-fit. However, there is no set way to evaluate the goodness-of-fit of probit models. Greene states that it is important to bear in mind that the coefficients in qualitative response models (such as probit or logit) are not chosen so as to maximize any fit measure, as they are in the linear regression model in which *b* (the least squares estimates) maximizes R-squared. Nevertheless, the goodness-of-fit summary measure statistics can be found at the bottom of each selected PFP food product model results table (Tables 4.3 to 4.10), except for the predictive ability tables which are grouped together in Appendix 2.

4.4 Selected PFP Food Product Model Results

4.4.1 Pasta Model

The results of the pasta model are shown in Table 4.3. The LR statistic for this model is strong as it indicates that the hypothesis that all slope coefficients are equal to zero is rejected at the 1% level of significance. The H-L statistic is also strong, indicating that the model is not misspecified. The McFadden R^2 for the pasta model is the highest of any model at .36 and the predictive ability tables indicate good predictive ability. The predicted probability that the average respondent would purchase PFP pasta is .9710 or 97%. The pasta model has fourteen significant variables, TOR, TNEW2, TNEW3, CPR1, CPR3, LABEL1, FINC1, SAP1, SAP2, H-PFP, P-SHOP, EXP1, INC1 and INC6. Variables are considered significant if they have coefficient estimates that are significant at the 10% level or better (*i.e.* at the 10%, 5% or 1% level).

The marginal effect of TOR is –.0770, indicating that people from Toronto are approximately 8% less likely to purchase PFP pasta. Respondents who are among the last to try newly introduced food products (TNEW2) are 7% more likely to purchase a PFP pasta. Those who are in between the first to try and the last to try new food products (TNEW3) are 18% more likely to purchase PFP pasta.

A number of the attitude variables are significant in this model. Those who are very concerned about pesticide residues in the food supply (CPR1) are 25% more likely and those who are neutral (CPR3) in their attitude are 5% more likely to purchase a PFP. People who feel that labeling on food products is important (LABEL1) are 21% more likely to purchase a PFP pasta. Respondents who strongly agree that maintaining farm income at a level that keeps the family farm viable (FINC1) are 21% more likely to purchase PFP pasta. Those who strongly agree that farmers should engage in sustainable agricultural practices (SAP1) are 14% more likely to purchase PFP and people who agree (SAP2) are 10% more likely to purchase PFP pasta.

Having previously heard of PFP (H-PFP) has a negative impact on the probability of purchasing PFP pasta, as people who have heard of PFP are 5% less likely to purchase PFP pasta. Primary food shoppers (P-SHOP) are 27% more likely to purchase PFP pasta. Households spending less than \$199 per month (EXP1) on food are 6% more likely to purchase a PFP pasta product. Households with an annual income of less than \$19 999 (INC1) are 39% less likely to purchase PFP pasta. Higher income has a positive effect, as households with income between \$100,000 and \$149,999 (INC6) being 7% more likely to purchase PFP pasta.

Respondents most likely to purchase PFP pasta are; among the last to try and in between the first and last to try new food products (TNEW2, TNEW3), people who agree or strongly agree with the majority of the attitude statements (*i.e.*, CPR1, LABEL1, FINC1, SAP1, SAP2), primary food shoppers, households spending less than \$199 per month on food and people with higher household incomes. Primary food shoppers and those who are concerned about pesticide residues in the food supply have the largest positive marginal effects.

4.4.2 Breakfast Cereal Model:

The results of the breakfast cereal model are presented in Table 4.4. The LR statistic for this model is reasonably strong as it indicates that the hypothesis that all slope coefficients are equal to zero is rejected at the 10% level of significance. The H-L statistic is also strong, indicating that the model is not misspecified. The McFadden R^2 for the breakfast cereal model is .22 and the predictive ability tables indicate good predictive ability. The predicted probability that the average respondent would purchase PFP breakfast cereal is .8815 or approximately 88%. CPR1, CPR2, INC4 and MSTAT1 are the significant (at the 10% level or better) variables in this model.

People who are concerned about pesticide residues in our food supply (CPR1, CPR2) are much more likely to be interested in PFP breakfast cereal. Those who strongly agree with the statement "I am concerned about pesticide residues in our food supply" are 45% more likely, and those who agree are 26% more likely to purchase PFP breakfast cereal. Respondents in the income range of $60,000 to $79,999 (INC4) are 22% less likely to purchase PFP breakfast. Single respondents (MSTAT1) are 11% more likely to purchase PFP breakfast cereal.

Respondents most likely to purchase PFP breakfast cereal are; people concerned about pesticide residue in our food supply and single people. Concern about pesticide residue has the largest positive impact on the probability that respondents would purchase PFP breakfast cereal. It could be expected that married people (MSTAT2) may be more likely to purchase PFP breakfast cereal, as they would be more likely to have children.

Table 4.3: PFP Pasta Probit Model Results			
Variable	**Coefficient**	**t-ratio**	**Marginal Effect**
CAL	-0.0527	-0.1225	-0.0036
TOR	-1.0339 ***	-2.7246	-0.0770
TNEW1	1.1929	1.5959	0.0577
TNEW2	1.9790 ***	2.5897	0.0681
TNEW3	1.1906 **	1.9669	0.1820
HEALTH2	-0.0743	-0.2489	-0.0069
HEALTH3	-0.1199	-0.1925	-0.0123
ENV1	0.3486	0.6585	0.0316
ENV2	0.8931	1.6150	0.0658
ENV3	0.7408	1.3542	0.0494
CPR1	1.7177 *	1.9367	0.2503
CPR2	1.3260	1.5493	0.0979
CPR3	2.5309 **	2.1674	0.0552
LABEL1	1.4759 ***	2.6041	0.2087
LABEL2	0.1796	0.3440	0.0159
FINC1	1.3068 ***	2.6836	0.2072
FINC2	0.5871	1.3077	0.0447
SAP1	1.0782 *	1.9394	0.1410
SAP2	1.5617 ***	2.7980	0.1043
PALT	-0.0121	-0.0380	-0.0011
H-PFP	-0.4879 *	-1.7613	-0.0533
H-SIZE	0.0058	0.0283	0.0005
CHILD<17	0.2990	1.1536	0.0268
P-SHOP	1.2534 **	2.0039	0.2707
FEMALE	-0.3037	-1.0152	-0.0267
AGE1	0.7524	1.4099	0.0499
AGE2	-0.1085	-0.2491	-0.0104
AGE3	0.2715	0.6186	0.0228
EDUC2	0.4690	0.9960	0.0387
EDUC3	0.3509	0.7406	0.0327
EDUC4	-0.2281	-0.4055	-0.0248
EXP1	1.6375 **	2.1196	0.0643
EXP2	0.3995	0.6461	0.0333
EXP3	0.7610	1.3259	0.0576
EXP4	0.3124	0.5525	0.0249
INC1	-1.6564 **	-2.1406	-0.3957
INC2	-0.0100	-0.0160	-0.0009
INC3	-0.3311	-0.5890	-0.0367
INC4	-0.6825	-1.2980	-0.0934
INC5	0.4716	0.8021	0.0330
INC6	1.6963 **	2.2972	0.0722
MSTAT1	0.1331	0.2128	0.0115
MSTAT2	0.7929	1.4228	0.0922
MSTAT3	0.3207	0.5294	0.0252
C	-6.9179	-3.5887	

Predicted Probability = 0.9710
McFadden R^2 = 0.3611
LR Stat = 87.44 p-value = 0.0001
H-L Stat = 2.77 p-value = 0.9477

*** significant at 1% level
** significant at 5% level
* significant at 10% level

Table 4.4: PFP Breakfast Cereal Probit Model Results			
Variable	Coefficient	t-ratio	Marginal Effect
CAL	0.3519	1.0389	0.0626
TOR	-0.1634	-0.5648	-0.0325
TNEW1	0.9550	1.4469	0.1228
TNEW2	0.9566	1.4496	0.1194
TNEW3	0.8723	1.5565	0.2152
HEALTH2	0.2169	0.8963	0.0437
HEALTH3	-0.1836	-0.3596	-0.0399
ENV1	-0.1555	-0.2884	-0.0312
ENV2	-0.6079	-1.1617	-0.1383
ENV3	-0.3568	-0.6813	-0.0798
CPR1	1.8317 *	1.9430	0.4483
CPR2	1.7093 *	1.8253	0.2575
CPR3	1.6661	1.6136	0.1302
LABEL1	0.2322	0.5065	0.0478
LABEL2	0.1480	0.3202	0.0284
FINC1	-0.0579	-0.1367	-0.0114
FINC2	-0.5415	-1.3179	-0.1237
SAP1	0.6934	1.3856	0.1559
SAP2	0.7080	1.5080	0.1186
PALT	0.1730	0.6395	0.0327
H-PFP	0.0196	0.0814	0.0039
H-SIZE	0.0674	0.4472	0.0131
CHILD<17	0.0192	0.1024	0.0037
P-SHOP	0.1908	0.3614	0.0419
FEMALE	0.1899	0.7756	0.0388
AGE1	0.1388	0.3246	0.0262
AGE2	0.1751	0.4583	0.0338
AGE3	-0.2968	-0.7911	-0.0640
EDUC2	-0.7303	-1.5692	-0.1678
EDUC3	-0.7048	-1.4882	-0.1436
EDUC4	-0.5245	-0.9461	-0.1293
EXP1	-0.0743	-0.1221	-0.0152
EXP2	0.3308	0.6532	0.0610
EXP3	0.7474	1.5083	0.1250
EXP4	0.3630	0.7656	0.0629
INC1	-0.7663	-1.1721	-0.2096
INC2	0.1843	0.3221	0.0341
INC3	0.0828	0.1611	0.0160
INC4	-0.8365 *	-1.7390	-0.2198
INC5	-0.2071	-0.4062	-0.0449
INC6	0.0088	0.0174	0.0017
MSTAT1	0.8520 *	1.6786	0.1146
MSTAT2	0.6070	1.5021	0.1327
MSTAT3	0.3108	0.6351	0.0544
C	-2.5979	-1.6403	

Predicted Probability = 0.8815
McFadden R^2 = 0. 2196
LR Stat = 57.53 p-value = 0.0828
H-L Stat = 6.32 p-value = 0.6110

*** significant at 1% level
** significant at 5% level
* significant at 10% level

The MSTAT2 coefficient estimate is positive, but it is not significant. So indication of a positive relationship exists, however it is not strong enough to conclude that married respondents are more likely to purchase PFP breakfast cereal.

4.4.3 Dry Peas Model:

Results from the dry peas model are presented in Table 4.5. The LR statistic for this model is strong as it indicates that the hypothesis that all slope coefficients are equal to zero is rejected at the 5% level of significance. The H-L statistic is also strong, indicating that the model is not misspecified. The McFadden R^2 for the dry peas model is .18 and the predictive ability tables indicate strong predictive ability. This model has eleven variables that are significant at the 10% level or better and the predicted probability that the average respondent would purchase PFP dry peas is .5456 or about 55%. The significant variables are TNEW1, TNEW2, TNEW3, HEALTH2, FINC2, SAP1, AGE2, AGE3, EXP1, MSTAT2 and MSTAT3.

Across all three of the "try new food products" variables people who fall into any of these categories are less likely to purchase PFP. Those who are among the first to try new food products (TNEW1) are 57% less likely to purchase PFP Peas. People who are among the last to try new food products (TNEW2) are 46% less likely to purchase PFP peas, and people who are in between the first and last to try newly introduced food products (TNEW3) are 50% less likely to purchase PFP peas.

Respondents who occasionally shop at health food stores (HEALTH2) are 17% more likely to purchase PFP peas. People who agree with the statement "I feel it is important to maintain farm income at a level that keeps the family farm viable" (FINC2) are 22% less likely to purchase PFP peas. Respondents who strongly agree with the attitude that farmers should engage in sustainable agricultural production practices (SAP1) are 40% more likely to be interested in purchasing PFP peas.

Respondents in the middle age ranges are less likely to purchase PFP peas. People aged 36-50 (AGE2) are 25% less likely, and those aged 51-65 (AGE3) are 20% less likely to purchase PFP peas. Households spending less than $199 (EXP1) per month on food are 40% less likely to purchase PFP peas. People who are married (MSTAT2) and those who are separated, divorced or widowed (MSTAT3) are less likely to purchase PFP peas. The former are 29% less likely, and the later are 35% less likely to purchase PFP peas.

Respondents most likely to purchase PFP dry peas are: those who agree that farmers should use sustainable production practices and occasionally shop at health food stores. SAP1 has the largest positive marginal effect on the probability that respondents will purchase PFP dry peas.

4.4.4 Sunflower Seed Model:

Results of the sunflower seed model are contained in Table 4.6. The LR statistic for this model is not strong as it indicates that the hypothesis that all slope coefficients are equal to zero cannot be rejected at the 10% level of significance. However, the H-L statistic is strong, indicating that the model is not misspecified. The McFadden R^2 for the sunflower seed model is .11 and the predictive ability tables indicate good predictive ability. The predicted probability that the average respondent would purchase PFP sunflower seeds is .5875 or 58%. This is another model with few significant variables, with TNEW1, TNEW2, TNEW3 and AGE1 being the only significant variables.

Table 4.5: PFP Dry Peas Probit Model Results			
Variable	Coefficient	t-ratio	Marginal Effect
CAL	0.3277	1.2772	0.1276
TOR	0.3047	1.3201	0.1203
TNEW1	-1.8499 **	-2.5180	-0.5709
TNEW2	-1.3220 *	-1.7779	-0.4581
TNEW3	-1.4997 **	-2.1666	-0.4998
HEALTH2	0.4220 *	2.1953	0.1665
HEALTH3	0.2712	0.6791	0.1050
ENV1	0.1757	0.4291	0.0694
ENV2	-0.0663	-0.1663	-0.0263
ENV3	-0.0103	-0.0257	-0.0041
CPR1	0.9302	1.2036	0.3581
CPR2	0.6246	0.8234	0.2395
CPR3	1.0861	1.2731	0.3485
LABEL1	0.5005	1.2069	0.1974
LABEL2	0.5359	1.2714	0.2065
FINC1	-0.4556	-1.3754	-0.1777
FINC2	-0.5547 *	-1.7337	-0.2185
SAP1	1.0547 **	2.3414	0.4016
SAP2	0.6191	1.4265	0.2363
PALT	0.1729	0.8022	0.0681
H-PFP	0.0519	0.2764	0.0205
H-SIZE	-0.0339	-0.2693	-0.0134
CHILD<17	0.1418	0.9442	0.0562
P-SHOP	0.4897	1.0730	0.1922
FEMALE	-0.2535	-1.2644	-0.0997
AGE1	-0.4180	-1.2034	-0.1655
AGE2	-0.6302 **	-2.0277	-0.2472
AGE3	-0.5077 *	-1.6798	-0.2004
EDUC2	-0.4375	-1.2208	-0.1730
EDUC3	-0.3523	-0.9691	-0.1391
EDUC4	-0.7029	-1.6311	-0.2716
EXP1	-1.0950 **	-2.1974	-0.3987
EXP2	-0.4404	-1.0932	-0.1742
EXP3	-0.4111	-1.0834	-0.1628
EXP4	-0.2920	-0.7902	-0.1161
INC1	-0.1516	-0.2822	-0.0603
INC2	0.5509	1.3532	0.2084
INC3	0.2133	0.5773	0.0836
INC4	0.5151	1.4042	0.1954
INC5	0.3400	0.8718	0.1311
INC6	0.3859	1.0737	0.1483
MSTAT1	-0.4004	-0.8731	-0.1586
MSTAT2	-0.7698 *	-1.9557	-0.2929
MSTAT3	-0.9214 **	-1.9853	-0.3490
C	0.6084	0.4318	

Predicted Probability = 0.5456
McFadden $R^2 = 0.1855$
LR Stat = 73.34 p-value = 0.0036
H-L Stat = 9.08 p-value = 0.3354

*** significant at 1% level
** significant at 5% level
* significant at 10% level

Table 4.6: PFP Sunflower Seed Probit Model Results			
Variable	Coefficient	t-ratio	Marginal Effect
CAL	0.0881	0.3540	0.0341
TOR	-0.1639	-0.7349	-0.0638
TNEW1	-1.2498 *	-1.8305	-0.4561
TNEW2	-1.2895 *	-1.8749	-0.4643
TNEW3	-1.2081 *	-1.8782	-0.4059
HEALTH2	0.1009	0.5413	0.0393
HEALTH3	-0.0677	-0.1739	-0.0265
ENV1	-0.0662	-0.1703	-0.0258
ENV2	-0.4268	-1.1370	-0.1674
ENV3	-0.3238	-0.8504	-0.1276
CPR1	0.8694	1.1525	0.3339
CPR2	0.7807	1.0550	0.2861
CPR3	0.8672	1.0455	0.2803
LABEL1	0.1922	0.4939	0.0751
LABEL2	0.0351	0.0892	0.0136
FINC1	-0.2557	-0.7813	-0.0986
FINC2	-0.2365	-0.7502	-0.0928
SAP1	0.6028	1.4285	0.2351
SAP2	0.5393	1.3263	0.2014
PALT	0.1811	0.8719	0.0697
H-PFP	-0.0935	-0.5134	-0.0365
H-SIZE	-0.1740	-1.4620	-0.0678
CHILD<17	0.2076	1.4405	0.0808
P-SHOP	0.2701	0.6201	0.1069
FEMALE	-0.0766	-0.4043	-0.0297
AGE1	0.6121 *	1.8605	0.2222
AGE2	0.3523	1.2133	0.1350
AGE3	0.0824	0.2935	0.0319
EDUC2	0.3395	0.9958	0.1296
EDUC3	0.3233	0.9312	0.1251
EDUC4	-0.0342	-0.0816	-0.0134
EXP1	-0.5783	-1.2193	-0.2275
EXP2	-0.0233	-0.0614	-0.0091
EXP3	-0.0069	-0.0195	-0.0027
EXP4	-0.0904	-0.2614	-0.0354
INC1	-0.0004	-0.0008	-0.0002
INC2	0.1563	0.3964	0.0601
INC3	0.4097	1.1216	0.1532
INC4	0.2512	0.6983	0.0955
INC5	0.0367	0.0986	0.0143
INC6	0.2018	0.5719	0.0770
MSTAT1	0.1577	0.3876	0.0604
MSTAT2	0.0880	0.2620	0.0343
MSTAT3	-0.0900	-0.2208	-0.0353
C	-0.2287	-0.1702	

Predicted Probability = 0.5875
McFadden R^2 = 0.1075
LR Stat = 41.91 p-value = 0.5616
H-L Stat = 7.90 p-value = 0.4432

*** significant at 1% level
** significant at 5% level
* significant at 10% level

All of the “try new” variables have negative marginal effects. Respondents who are among the first to try new food products (TNEW1) are 46% less likely to purchase PFP sunflower seeds. People who are among the last to try (TNEW2) are also 46% less likely to purchase PFP sunflower seeds and those in between the first and last to try (TNEW3) are 41% less likely to purchase PFP sunflower seeds. Age is an important factor as people who are less than 35 years old (AGE1) are 22% more likely to purchase PFP sunflower seeds.

Respondents most likely to purchase PFP sunflower seeds tend to be younger, as AGE1 is the only variable with a positive marginal effect in this model. The fact that younger respondents are more likely to purchase PFP sunflower seeds could be a reflection of the anecdotal observation that sunflower seeds are a popular snack food among younger consumers.

4.4.5 Beer Model:

The beer model results can be found in Table 4.7. The LR statistic for this model is strong as it indicates that the hypothesis that all slope coefficients are equal to zero is rejected at the 1% level of significance. The H-L statistic is a little weak, but still indicates that the model is not misspecified. The McFadden R^2 for the beer model is .19 and the predictive ability tables indicate good predictive ability. The predicted probability that the average respondent would purchase PFP beer is .5137 or 51%. There are eleven variables significant at the 10% level or better for the beer model: CAL, TNEW1, TNEW2, TNEW3, HEALTH3, FINC2, H-SIZE, CHILD<17, FEMALE, EXP1 and MSTAT3.

Once again all of the try new variables are significant, and again, all three have negative effects. People who are among the first to try new food products are 49% less likely to purchase PFP beer. Respondents who are among the last to try new food products are 39% less likely to purchase PFP beer. Those in between the first and last to try new food products are 40% less likely to purchase PFP beer.

Shopping at health food stores has a negative impact on the probability of the average respondent purchasing PFP beer. People who usually or always shop at health food stores (HEALTH3) are 27% less likely to purchase PFP beer. This result could be a reflection of the perception that beer is unhealthy, and thus, respondents who are very health conscious may be less inclined to drink beer.

People who agree with the statement "I feel it is important to maintain farm income at a level that keeps the family farm viable" (FINC2) are 36% less likely to buy PFP beer. As household size increases the probability that the typical consumer will purchase PFP beer declines. A one unit or one person increase in household size (H-SIZE) would cause an 11% decrease in the predicted probability of the typical respondent purchasing PFP beer. As the number of children in the household (CHILD<17) increases so does the predicted probability that the typical respondent will purchase PFP beer. A unit increase or one child increase would result in an 11% increase in the probability of an average respondent purchasing PFP beer. Recall that H-SIZE and CHILD<17 are continuous variables and the marginal effects are calculated and interpreted slightly differently than the binary variables. The marginal effects of continuous variables are calculated using partial derivatives and thus are interpreted as a rate of change.

Table 4.7: PFP Beer Probit Model Results			
Variable	Coefficient	t-ratio	Marginal Effect
CAL	0.4457 *	1.6765	0.1744
TOR	0.0510	0.2180	0.0203
TNEW1	-1.5205 **	-2.4550	-0.4927
TNEW2	-1.0914 *	-1.7588	-0.3867
TNEW3	-1.0779 *	-1.8854	-0.3951
HEALTH2	-0.0875	-0.4454	-0.0349
HEALTH3	-0.7296 *	-1.7517	-0.2743
ENV1	0.6419	1.5670	0.2510
ENV2	0.0558	0.1416	0.0223
ENV3	-0.0693	-0.1733	-0.0276
CPR1	0.6521	0.8419	0.2554
CPR2	0.8271	1.0882	0.3161
CPR3	1.3168	1.4930	0.4108
LABEL1	0.1184	0.2894	0.0472
LABEL2	-0.0549	-0.1342	-0.0219
FINC1	-0.5769	-1.6165	-0.2258
FINC2	-0.9639 **	-2.7730	-0.3641
SAP1	-0.2170	-0.4673	-0.0862
SAP2	-0.3441	-0.7690	-0.1365
PALT	0.2631	1.1932	0.1042
H-PFP	0.1724	0.9320	0.0685
H-SIZE	-0.2753 **	-2.1759	-0.1098
CHILD<17	0.2701 *	1.7364	0.1077
P-SHOP	0.0638	0.1369	0.0255
FEMALE	-0.6597 ***	-3.3135	-0.2566
AGE1	0.2747	0.7990	0.1085
AGE2	-0.0602	-0.1959	-0.0240
AGE3	-0.0837	-0.2790	-0.0334
EDUC2	-0.0843	-0.2298	-0.0336
EDUC3	0.0820	0.2217	0.0327
EDUC4	-0.0520	-0.1192	-0.0208
EXP1	-0.8614 *	-1.6968	-0.3198
EXP2	-0.2906	-0.7474	-0.1155
EXP3	-0.1984	-0.5418	-0.0790
EXP4	-0.2510	-0.6958	-0.0998
INC1	0.3550	0.6357	0.1385
INC2	-0.1269	-0.3118	-0.0506
INC3	0.1615	0.4342	0.0641
INC4	0.3637	0.9875	0.1426
INC5	0.2688	0.6958	0.1060
INC6	0.5197	1.4226	0.2003
MSTAT1	-0.1373	-0.3243	-0.0547
MSTAT2	-0.0302	-0.0848	-0.0120
MSTAT3	-0.8113 *	-1.8393	-0.3069
C	1.9542	1.4205	

Predicted Probability = 0.5137
McFadden $R^2 = 0.1977$
LR Stat = 78.39 p-value = 0.0011
H-L Stat = 14.15 p-value = 0.0780

*** significant at 1% level
** significant at 5% level
* significant at 10% level

The last two results mentioned in the previous paragraph appear to be at odds with each other, as a one child increase would increase the probability of purchase for PFP beer while a one person increase in household size would decrease the probability. These conflicting results were also seen earlier when discussing the direction of effects across all models. Perhaps there is an age factor influencing the results. People with children tend to be younger and may be more inclined to purchase beer, while older respondents who may still have larger households may not purchase beer.

Females are 26% less likely to purchase PFP beer. This result is not surprising even though females were expected to be more interested in PFP alternatives. In general, based on anecdotal observations, females are less interested in beer than males, and thus, were expected to be less likely to be interested in PFP beer than males.

Consumers in the lowest monthly food expenditure category (EXP1) are 32% less likely to purchase PFP beer. Beer is a relatively expensive product and it could be expected that those spending less would be less likely to purchase it. Respondents, who are separated, divorced or widowed (MSTAT3) are 31% less likely to purchase PFP beer.

It appears that standard beer consumption patterns impact the interest in PFP beer quite strongly. Examples of this are the results that females, health conscious people, and those with low monthly food expenditure are all less likely to purchase PFP beer. Respondents most likely to purchase PFP beer are consumers from Calgary and those with children (however people with children tend to be younger and the results may be picking this effect up).

4.4.6 Multigrain Bread Model:

The multigrain bread model results are presented in Table 4.8. The LR statistic for this model is not strong as it indicates that the hypothesis that all slope coefficients are equal to zero cannot be rejected at the 10% level of significance. The H-L statistic is strong and indicates that the model is not misspecified. The McFadden R^2 for the multigrain bread model is .17 and the predictive ability tables indicate good predictive ability. The predicted probability that the average respondent would purchase PFP multigrain bread is .8109 or 81%. There are five variables with coefficient estimates that are significant at the 10% level or better for the multigrain bread model: TOR, CPR1, CPR2, FINC2 and INC3.

Respondents from Toronto are 16% less likely to be interested in purchasing PFP multigrain bread. People who are concerned about pesticide residues in our food supply are more likely to be interested in PFP multigrain bread. Those who strongly agree with the attitude statement regarding pesticide residues (CPR1) are 43% more likely to purchase PFP multigrain bread. Those who agree with the concerned about pesticide residue attitude statement (CPR2) are 32% more likely to purchase PFP multigrain bread.

Respondents who agree that maintaining farm income at a level that keeps the family farm viable is important (FINC2) are 25% less likely to purchase PFP multigrain bread. Income is also important as households with an annual income in the range of $40,000 - $59,999 (INC3) are 26% less likely to purchase PFP multigrain bread.

Respondents most likely to purchase PFP multigrain bread are those who are concerned about pesticide residues in the food supply.

Table 4.8: PFP Multigrain Bread Probit Model Results			
Variable	**Coefficient**	**t-ratio**	**Marginal Effect**
CAL	-0.0133	-0.0445	-0.0036
TOR	-0.5911 **	-2.2746	-0.1600
TNEW1	0.0918	0.1522	0.0241
TNEW2	0.2737	0.4464	0.0670
TNEW3	0.3891	0.7119	0.1134
HEALTH2	0.1574	0.7282	0.0429
HEALTH3	0.2823	0.5867	0.0681
ENV1	0.6027	1.4811	0.1566
ENV2	0.2943	0.7554	0.0755
ENV3	0.4930	1.2324	0.1161
CPR1	1.4418 *	1.7393	0.4269
CPR2	1.5305 *	1.8818	0.3245
CPR3	0.7892	0.8613	0.1474
LABEL1	0.3175	0.7832	0.0890
LABEL2	-0.1565	-0.3788	-0.0434
FINC1	-0.6344	-1.4555	-0.1599
FINC2	-0.8118 *	-1.9777	-0.2510
SAP1	0.6228	1.3023	0.1817
SAP2	0.5113	1.1322	0.1253
PALT	0.2418	0.9559	0.0622
H-PFP	-0.2976	-1.4670	-0.0840
H-SIZE	-0.0739	-0.5412	-0.0200
CHILD<17	-0.0910	-0.5340	-0.0246
P-SHOP	0.1794	0.3416	0.0520
FEMALE	0.1712	0.7910	0.0473
AGE1	-0.0979	-0.2612	-0.0272
AGE2	-0.1663	-0.4936	-0.0459
AGE3	-0.3157	-0.9943	-0.0910
EDUC2	0.2528	0.7118	0.0657
EDUC3	0.2572	0.7241	0.0692
EDUC4	0.3683	0.7983	0.0871
EXP1	-0.7817	-1.3936	-0.2591
EXP2	-0.1115	-0.2342	-0.0307
EXP3	-0.2284	-0.5047	-0.0642
EXP4	-0.0424	-0.0944	-0.0116
INC1	-0.6326	-1.0169	-0.2066
INC2	-0.7999	-1.5379	-0.2576
INC3	-0.8162 *	-1.6744	-0.2613
INC4	-0.6656	-1.3503	-0.2110
INC5	-0.6164	-1.2379	-0.1972
INC6	-0.6657	-1.3349	-0.2132
MSTAT1	0.1868	0.3751	0.0474
MSTAT2	0.0654	0.1554	0.0178
MSTAT3	-0.2647	-0.5323	-0.0770
C	-0.4940	-0.3257	

Predicted Probability = 0.8109
McFadden R^2 = 0.1737
LR Stat = 53.68 p-value = 0.1503
H-L Stat = 4.83 p-value = 0.7751

*** significant at 1% level
** significant at 5% level
* significant at 10% level

4.4.7 Canola Oil Model:

The canola oil model results are contained in Table 4.9. The LR statistic for this model is strong as it indicates that the hypothesis that all slope coefficients are equal to zero can be rejected at the 5% level of significance. The H-L statistic is also strong and indicates that the model is not misspecified. The McFadden R^2 for the canola oil model is .19 and the predictive ability tables indicate good predictive ability. The predicted probability that the average respondent would purchase PFP canola oil is .7078 or approximately 71%. There are seven variables that are significant at the 10% level or better for the canola oil model: TOR, TNEW2, LABEL1, LABEL2, EDUC2, EDUC3 and EXP1.

Respondents from Toronto are 18% less likely to be interested in purchasing PFP canola oil. People who are among the last to try newly introduced food products are 43% less likely to be interested in purchasing PFP canola oil. Respondents who believe that the labeling of food ingredients on packaging is important are more likely to purchase PFP food products. Those who strongly agree that labeling on food packaging is important (LABEL1) are 35% more likely and people who agree (LABEL2) are 31% more likely to purchase PFP canola oil.

Respondents with a high school diploma and/or some university (EDUC2) are 29% less likely to purchase PFP canola oil, while people with a university degree and/or some graduate school (EDUC3) are 35% less likely. Monthly food expenditure is also important, as households in the lowest food expenditure category are 36% less likely to purchase PFP canola oil.

Table 4.9: PFP Canola Oil Probit Model Results			
Variable	Coefficient	t-ratio	Marginal Effect
CAL	0.2611	0.9311	0.0861
TOR	-0.5302 **	-2.1661	-0.1810
TNEW1	-0.7548	-1.1209	-0.2843
TNEW2	-1.1554 *	-1.6872	-0.4348
TNEW3	-0.6405	-1.0303	-0.1986
HEALTH2	0.0217	0.1069	0.0075
HEALTH3	-0.1680	-0.4126	-0.0598
ENV1	0.2559	0.6102	0.0869
ENV2	-0.1113	-0.2728	-0.0387
ENV3	-0.0785	-0.1901	-0.0273
CPR1	1.1646	1.5274	0.4075
CPR2	1.2041	1.6105	0.3522
CPR3	0.9441	1.1033	0.2326
LABEL1	0.9831 **	2.3781	0.3480
LABEL2	1.0499 **	2.5301	0.3100
FINC1	0.0118	0.0340	0.0040
FINC2	-0.1427	-0.4310	-0.0499
SAP1	0.2377	0.5143	0.0831
SAP2	-0.1424	-0.3274	-0.0497
PALT	-0.2401	-1.0869	-0.0847
H-PFP	0.1876	0.9432	0.0632
H-SIZE	-0.1077	-0.8531	-0.0037
CHILD<17	0.0770	0.5006	0.0264
P-SHOP	0.6180	1.3119	0.2349
FEMALE	-0.3250	-1.5370	-0.1085
AGE1	-0.1925	-0.5368	-0.0681
AGE2	-0.3153	-0.9917	-0.1103
AGE3	-0.4841	-1.5289	-0.1748
EDUC2	-0.8152 *	-1.9325	-0.2932
EDUC3	-1.0632 **	-2.4794	-0.3580
EDUC4	-0.7960	-1.6356	-0.3010
EXP1	-0.9436 *	-1.8997	-0.3573
EXP2	0.1381	0.3466	0.0467
EXP3	0.0925	0.2462	0.0314
EXP4	0.2274	0.6237	0.0749
INC1	-0.2012	-0.3671	-0.0720
INC2	0.2053	0.4989	0.0679
INC3	0.3945	1.0429	0.1258
INC4	0.1316	0.3544	0.0441
INC5	0.1968	0.5073	0.0647
INC6	0.4533	1.2359	0.1402
MSTAT1	0.4681	1.0520	0.1434
MSTAT2	0.2390	0.6477	0.0834
MSTAT3	-0.2441	-0.5524	-0.0872
C	-0.2022	-0.1418	

Predicted Probability = 0.7078
McFadden R^2 = 0.1872
LR Stat = 67.56 p-value = 0.0127
H-L Stat = 2.97 p-value = 0.9365

*** significant at 1% level
** significant at 5% level
* significant at 10% level

Respondents most likely to purchase PFP canola oil are those who agree and strongly agree that the labeling of food products is important.

4.4.8 Dry Lentil Model:

The dry lentil model results are presented in Table 4.10. The LR statistic for this model is strong as it indicates that the hypothesis that all slope coefficients are equal to zero can be rejected at the 1% level of significance. The H-L statistic is strong and indicates that the model is not misspecified. The McFadden R^2 for the dry lentil model is .19 and the predictive ability tables indicate good predictive ability. There are eleven variables which have significant coefficient estimates for the dry lentil model: TOR, TNEW1, TNEW3, HEALTH2, ENV1, PALT, CHILD<17, AGE1, AGE2, AGE3 and EXP1. The predicted probability that the average respondent would purchase PFP dry lentils is .5185 or 52%.

Respondents from Toronto are 15% more likely to be interested in purchasing PFP lentils. People who are among the first to try new food products are 40% less likely to purchase PFP lentils. Respondents in between the first to try and the last to try newly introduced food products are 37% less likely to purchase PFP.

People who occasionally shop at health food stores (HEALTH2) are 20% more likely to be interested in purchasing PFP lentils. Respondents who strongly agree with the attitude that the use of synthetic chemicals in agriculture has a negative effect on the environment (ENV1) are 32% more likely to purchase PFP lentils.

Table 4.10: PFP Dry Lentil Probit Model Results			
Variable	**Coefficient**	**t-ratio**	**Marginal Effect**
CAL	0.1907	0.7339	0.0756
TOR	0.3890 *	1.6938	0.1540
TNEW1	-1.1390 *	-1.7790	-0.4046
TNEW2	-0.8464	-1.3177	-0.3175
TNEW3	-1.0103 *	-1.7069	-0.3702
HEALTH2	0.5225 ***	2.7186	0.2059
HEALTH3	0.3479	0.8576	0.1348
ENV1	0.8207 *	1.9162	0.3160
ENV2	0.4895	1.1604	0.1907
ENV3	0.6777	1.5961	0.2560
CPR1	0.5172	0.6681	0.2040
CPR2	0.3127	0.4114	0.1233
CPR3	0.6072	0.7067	0.2249
LABEL1	0.1586	0.3860	0.0631
LABEL2	0.2309	0.5541	0.0913
FINC1	-0.4935	-1.4719	-0.1933
FINC2	-0.5077	-1.5827	-0.2002
SAP1	0.7078	1.5730	0.2764
SAP2	0.5427	1.2502	0.2105
PALT	0.4257 *	1.9513	0.1663
H-PFP	-0.0388	-0.2076	-0.0154
H-SIZE	-0.1047	-0.8287	-0.0417
CHILD<17	0.2736 *	1.7951	0.1090
P-SHOP	0.4092	0.9066	0.1610
FEMALE	-0.1029	-0.5187	-0.0409
AGE1	-0.8826 **	-2.5280	-0.3352
AGE2	-0.8467 ***	-2.7313	-0.3277
AGE3	-0.7933 ***	-2.6220	-0.3061
EDUC2	0.1204	0.3437	0.0478
EDUC3	0.1121	0.3161	0.0446
EDUC4	0.0288	0.0675	0.0114
EXP1	-1.3189 ***	-2.6469	-0.4516
EXP2	-0.5834	-1.4450	-0.2293
EXP3	-0.5322	-1.3933	-0.2097
EXP4	-0.3477	-0.9252	-0.1379
INC1	-0.0390	-0.0728	-0.0155
INC2	0.5427	1.3483	0.2079
INC3	0.2634	0.7132	0.1037
INC4	0.5091	1.3864	0.1955
INC5	0.1913	0.4893	0.0754
INC6	0.5960	1.6431	0.2255
MSTAT1	-0.0320	-0.0719	-0.0128
MSTAT2	-0.6192	-1.6400	-0.2404
MSTAT3	-0.5883	-1.2950	-0.2296
C	0.0438	0.0324	

Predicted Probability = 0.5185
McFadden R^2 = 0.1878
LR Stat = 74.44 p-value = 0.0028
H-L Stat = 1.62 p-value = 0.9906

*** significant at 1% level
** significant at 5% level
* significant at 10% level

Respondents who have previously purchased either organic or IPM food products (PALT) are 16% more likely to be interested in purchasing PFP lentils.

Households with children are more likely to purchase PFP lentils. As the number of children increases, so does the predicted probability that the average respondent will purchase PFP lentils. For a one child increase, the predicted probability of purchasing PFP lentils increases by 11%.

Age is an important factor affecting the interest in PFP lentils as three age variables are significant in this model. People who are less than 36 years old (AGE1) are 34% less likely to purchase PFP lentils. Those in the middle age ranges are also less likely to purchase PFP lentils, as respondents aged 36–50 years old (AGE2) are 33% less likely to purchase PFP lentils and those aged 51–65 (AGE3) are 31% less likely to purchase PFP lentils. Respondents spending less than $199 per month on food are 45% less likely to purchase PFP lentils.

Respondents most like to purchase PFP dry lentils are: consumers from Toronto, those who occasionally shop at health food stores, those who feel chemical use has a negative effect on the environment, those who have previously purchased alternative food products and those with children. ENV1 has the largest positive impact on the probability that the average respondent would purchase PFP lentils.

4.4.9 Selected Product Model Results Summary

On an individual product basis the selected product model results provide valuable insight into what variables effect the probability the average consumer would purchase the specific PFP food product. The discussion of each of the selected product models includes a profile of respondents most likely to purchase that specific PFP food product. Bear in mind that in many cases the predicted probability is quite high and the marginal effects indicate that respondents with certain characteristics are more likely to purchase the PFP food products.

Across products it is somewhat difficult to generalize the factors that influence the predicted probability that respondents will purchase PFP food products, as many variables have different effects in different models. However, a profile of respondents most likely to purchase the eight selected PFP food products has been developed based on the marginal effect results. To be included in the profile a variable must have a positive marginal effect more often than it has a negative marginal effect in the eight selected PFP food product models. It should be kept in mind that the characteristics in this profile do not necessarily have a positive effect for all products, but do have positive effects more often than negative effects. For information about the characteristics affecting each individual product refer to the discussion of the specific product model.

Respondents from Calgary, those who occasionally shop at health food stores, people who believe the use of pesticides has a negative effect on the environment, those concerned about pesticide residues in our food supply, those who believe labeling of food ingredients is important, those who feel it is important to maintain farm income levels, those who believe farmers should engage in sustainable production practices, consumers who have previously purchased alternative food products, primary food shoppers, high income households and single respondents are most likely to purchase PFP food products. The variables representing agreement with the attitude statements tend to have large positive marginal effects on the selected product models. This indicates that respondents who share these beliefs are generally much more likely to purchase PFP food products. The "try new" variables, and EXP1 frequently have large negative marginal effects on the selected product models.

It was hypothesized that those among the first try new food products would more likely be interested in purchasing PFP food products. The results indicate the opposite, as in a number of the models the TNEW1 variable has a negative marginal effect. A possible explanation is that respondents may not necessarily view the PFP version of a food product as a "new" product, but merely a variation of an existing product. Another factor affecting this result could be that since respondents classified themselves in terms of their acceptance of new products rather than being observed some that classify themselves at the first to try may not actually be so. Consumers who are among the last to try were expected to be less likely to purchase PFP food products, and this is the case as TNEW2 has a consistently negative effect.

The other negative effect trend among the selected product models is that EXP1 (monthly food expenditure <$199) has a negative marginal impact on most models. EXP1 is significant in five of the selected product models and has a negative marginal effect on four of them. The only selected product model in which EXP1 is positive (and significant) is the pasta model. This could be due to the fact that pasta is a relatively inexpensive product that even those on limited budgets could afford to purchase regularly. If those with low monthly food expenditure are on tight budgets, and thus are not willing to try many new products pasta may be an exception.

4.5 Summary of PFP Food Product Demand Models

The binary model results provide valuable information about consumer interest in PFP food products. The chapter began with the analysis of the predicted probabilities that the average respondent would purchase each potential PFP food product. The discussion moved on to outline the significant variables across all 25 potential PFP food product models. The chapter concludes with an analysis of the marginal effects of the explanatory variables in eight selected PFP food product models.

The predicted probabilities, which ranged from .32 for buckwheat noodles to .97 for pasta, indicate there is strong interest among respondents in PFP food products. Specifically, 24 of 25 products have predicted probabilities over 50%. This result is encouraging as it indicates a high probability that respondents would purchase PFP food products.

Eight selected product models were used to gain insight into the magnitude of the effects the explanatory variables have on the predicted probability that consumers would purchase PFP food products. The results of each of the selected product models were discussed and information about the characteristics of respondents most likely to purchase each of these selected PFP food products presented. A profile of respondents most likely to purchase the selected PFP food products has been created. This profile provides key information for those considering marketing PFP food products. In some cases certain characteristics vastly increase the probability that consumers would purchase the PFP food product. PFP producers, processors and retailers can use this information to enhance marketing activities by promoting PFP to consumers who share the characteristics of those most likely to purchase PFP food products.

CHAPTER 5 – WILLINGNESS-TO-PAY MODEL RESULTS AND ANALYSIS

5.0 Introduction

An *ordered* probit model was used to estimate the predicted probability that consumers would be willing-to-pay one of five premium levels for PFP food products. The results of the WTP ordered probit model are presented in this chapter. Similar to Chapter 4, the analysis of the WTP model results will focus on the predicted probabilities that consumers are willing-to-pay each of the five premium levels and on the marginal effects of the explanatory variables on the predicted probabilities.

The chapter begins with a review the WTP survey question and response options. Analysis of the WTP model results starts with a discussion of the predicted probabilities, the analysis then moves on to the marginal effects of the explanatory variables which are presented in Table 5.4. Following the analysis of marginal effects, consumer profiles outlining the characteristics of the consumers most likely to be willing-to-pay each of the premium levels are developed. The chapter concludes with a summary of the WTP model results and consumer profiles.

5.1 WTP Contingent Valuation Scenario

As described in Chapter 2, consumers were presented with a scenario in which they were asked how much more they would be willing-to-pay for their favourite food product if it were available in a PFP form. The WTP question had five response options corresponding to the following percentage values, the first response option represents willing-to-pay 0% more, the second option corresponds to willing-to-pay 1-5% more, the third represents 6-10% more, the fourth 11-20% more and the last option corresponds to a

WTP greater than 20%. It should be noted that throughout the survey respondents were questioned about their interest in PFP food products versus conventional food products. The WTP question does not explicitly ask respondent how much they would be willing-to-pay for a PFP food product relative to a conventional food product, but questions preceding this one make it clear that conventional food products are the basis for comparison.

The specification of the WTP model is the same as the binary models. The same explanatory variables are used to predict the probability that the average respondent is willing-to-pay each of the five premiums, as were used to predict the probability that respondents would purchase PFP food products. Also, the hypotheses about the effects of the explanatory variables described in Chapter 3 are the same for the WTP model as for the PFP food product demand models. If an explanatory variable was expected to have a positive effect on consumer interest in PFP food products it is expected to have a positive effect on both the predicted probability of purchase and WTP a premium.

The difference in the WTP ordered probit model is that the dependent variable can take one of five possible values, as opposed to the binary models where the dependent variable takes one of two possible values. The WTP ordered probit model produces five predicted probabilities, one for each of the five possible values of the dependent variable. The structure of the WTP model choice probabilities is described in Chapter 2.

Goodness-of-fit

The goodness-of-fit measures indicate that the WTP model fits the data well. The likelihood ratio statistic is very strong with a p-value indicating a near zero probability that the coefficients are jointly equal to zero. The McFadden R^2 is .2039 and the predictive ability table (Table 5.1) indicates the model has a good predictive ability. There are two comparisons presented in Table 5.1, one measures the difference between the observed count and the number of observations where the predicted probability of that response is the highest. The second measure is a comparison between the actual number of individuals reporting each value and the sum of all of the individual predicted probabilities for that value. Both of these measures are reported as "errors" and the smaller the error the better the fit. The second "error" column shows a small difference between the sum of all the predicted probabilities for each dependent variable category and the observed count from the data, indicating good predictive ability.

Table 5.1: Predictive Ability Table for WTP Model
Dependent Variable: Pr(*WTP* = M)

Value	Observed Count	Count of Observations with Max Prob	Error	Sum of all Predicted Probabilities	Error
1	48	29	19	47.335	0.665
2	107	150	-43	108.258	-1.258
3	80	89	-9	79.499	0.501
4	29	0	29	28.681	0.319
5	17	13	4	17.228	-0.228

5.2 WTP Predicted Probabilities

One of the primary objectives of the study is to quantify the probability that consumers are willing-to-pay different premium levels for PFP food products. The predicted probabilities for each WTP category are reported in Table 5.2. These probabilities represent the predicted probability that the average respondent would be willing-to-pay each specific premium; the probabilities have been calculated with the explanatory variables set at their sample means. The same approach was used to calculate the predicted probabilities for the binary probit models and this is a common practice when using qualitative response models.

Table 5.2: Predicted Probabilities for WTP Model

Category	1	2	3	4	5
Premium	0%	1–5%	6–10%	11–20%	>20%
Pred. Probability	0.0938	0.4927	0.3279	0.0692	0.0164

The predicted probability that the average respondent is willing-to-pay no premium for PFP food products is .0938 or 9%. The predicted probability is 49% for a 1-5% premium, 33% for a 6-10% premium, about 7% for an 11-20% premium and almost 2% for a greater than 20% premium. Note that the predicted probabilities sum to one, which is necessary as the predicted probability is bound between zero and one and the predicted probability must total one for every individual. The predicted probabilities for WTP categories four and five may seem low at 7% and 1.6% respectively. However, these probabilities indicate that a significant niche exists for PFP food products.

It is important to look at the predicted probabilities cumulatively to appreciate the fact that there is a very large predicted probability that the average respondent is willing-to-pay at least some sort of premium. The predicted probability that the average respondent is willing-to-pay at least 1-5% more for a PFP food product is 90.6% (*i.e.,*0.4927 + 0.3279 + 0.0692 + 0.0164 = 0.906 or 90.6%). The predicted probability that the average respondent is willing-to-pay at least 6-10% more is 41.4%, which still represents a large probability. Also, the predicted probability that the average respondent is willing-to-pay at least 11-20% more for PFP food products is 8.5%. These results indicate that there is a very high likelihood that the average respondent is willing-to-pay a premium for PFP food products.

An important caveat is that the WTP estimates are based on retail level price premiums. Retail prices comprise a number of factors, with raw commodities being only a small component. Therefore, PFP producers would not see the entire amount of the premium paid by consumers. That being said, potential PFP producers should consider the fact that their product will be the key factor generating the premiums at the retail level. Combined with the fact that the cost of the raw commodity comprises a fraction of the retail price this can be used as leverage to ensure that producers see a healthy premium.

The WTP model results are quite promising, as they indicate there is a strong probability that consumers are willing-to-pay more for PFP food products. Obviously, every producer would like to get as much for their product as possible (assuming they are profit maximizers); therefore, if higher premiums are sought then marketing efforts will have to focus on the fraction of consumers willing-to-pay high premiums. However, if the category five (greater than 20% premium) probability is deemed to represent too small of a niche there is strong evidence that the majority of respondents are willing-to-pay at least some level of a premium for PFP food products. For example, there is a 90.6% predicted probability that the average respondent would pay at least 1-5% more. This should provide assurance to producers who are concerned about the price level for PFP food products.

5.3 Marginal Effects

As outlined in the preceding section, the predicted probabilities provide important information. Additional information generated by calculating the marginal effects of explanatory variables on the predicted probabilities is equally important. Marginal effects indicate the magnitude of the effects the variables have on the predicted probability for each WTP category. This information is important in determining the characteristics of consumers most likely to be willing-to-pay each premium level. The discussion will begin with a brief outline of how the marginal effects are derived followed by an analysis of the marginal effects of the significant variables.

5.3.1 Marginal Effects – Calculation

The estimated coefficients (see Table 5.3) from an ordered probit model are less intuitive to interpret than in a binary model. The difference lies in the fact that there are multiple predicted probabilities, and in relation to the sign of the coefficient, only the direction of change for the two end-point probabilities can be determined without further calculation. The predicted probability of the lowest category changes in the opposite direction of the sign of the coefficient, and the predicted probability of the highest category changes in the same direction as the sign of the coefficient. The direction of change for the remaining middle probabilities can only be determined through additional calculation.

The marginal effects of continuous explanatory variables are calculated by taking the partial derivative of the dependent variable (*i.e.*, the probability that $WTP = M$) with respect to the variable in question.

$$\frac{\partial \Pr(WTP = M)}{\partial x_k} = [\phi(\gamma_{m-2} - x'\beta) - \phi(\gamma_{m-1} - x'\beta)]\beta_k, \qquad (5.1)$$

where, M represents the number of values the dependent variable can take. Equation 5.1 is often seen in the literature with γ_{m-1} and γ_m instead of γ_{m-2} and γ_{m-1} because the categories are typically labeled as $y = 0, \ldots, M$ instead of $y = 1, \ldots, M$ as defined here. This is a trivial difference as it amounts to nothing more than different labels and the labels could be any numbers which increase in order and it would not affect the outcome. The marginal effects for each of the five WTP categories are represented by the following equations, which are applications of equation 5.1:

$$\frac{\partial \Pr(WTP = 1)}{\partial x_k} = -\phi(x'\beta)\beta_k,$$

$$\frac{\partial \Pr(WTP = 2)}{\partial x_k} = [\phi(-x'\beta) - \phi(\gamma_1 - x'\beta)]\beta_k,$$

$$\frac{\partial \Pr(WTP = 3)}{\partial x_k} = [\phi(\gamma_1 - x'\beta) - \phi(\gamma_2 - x'\beta)]\beta_k,$$

$$\frac{\partial \Pr(WTP = 4)}{\partial x_k} = [\phi(\gamma_2 - x'\beta) - \phi(\gamma_3 - x'\beta)]\beta_k,$$

$$\frac{\partial \Pr(WTP = 5)}{\partial x_k} = [\phi(\gamma_3 - x'\beta) - \phi(\gamma_4 - x'\beta)]\beta_k.$$

The marginal effects for binary variables cannot be calculated by using partial derivatives. As mentioned previously, the derivative of a dummy variable is not defined. The marginal effects of dummy variables must be determined by calculating the change in probability when the value of the variable in question changes from zero to one. To calculate the marginal effects of dummy explanatory variables the same procedure is followed as outlined for the binary probit models. With all other variables are held constant at their sample means the probabilities are calculated with the variable of interest set equal to one and with the variable of interest set equal to zero. The difference between these probabilities is calculated to get an estimate of the marginal effect.

The marginal effects across the five WTP categories for a particular explanatory variable must sum to zero. This is necessary because the predicted probabilities must always sum to one. The requirement that marginal effects sum to zero provides a quick way to double check the marginal effect calculation results. The marginal effects for the WTP model are presented in Table 5.4.

5.3.2 Marginal Effects – Interpretation

Interpreting the marginal effects of an ordered model is similar to interpreting the effects of a binary model. The difference lies in the fact that the ordered model has five predicted probabilities for each variable, with five corresponding marginal effects for each predicted probability. The effects are interpreted the same way as the effects on any probability. If a variable has a positive marginal effect on the predicted probability for a given category, then an increase in that variable increases the probability for that category. If the marginal effect is negative, then an increase in that variable will decrease the probability for that category.

The marginal effects represent the change in the predicted probability that the average respondent is willing-to-pay each of the specific premium ranges for PFP food products. The marginal effects of the explanatory variables may seem small in some cases when considered in absolute terms, especially for the higher WTP categories. However, when the marginal effects are considered relative to the predicted probabilities they are actually quite large.

The CAL variable, and the HEALTH3 variable will be used to illustrate that the marginal effects are large relative to the predicted probability in many cases. The predicted probability that the average respondent would be willing-to-pay a greater than 20% premium is .0164. The marginal effect of CAL on the predicted probability for this category is .0199, which appears small, but is larger than the predicted probability for this category. This means being from Calgary more than doubles the predicted probability that the average respondent would be willing-to-pay a high premium for PFP food products. As a further example, consider the marginal effect of HEALTH3 on WTP a greater than 20% premium, which at .0513 is more than three times the size of the predicted probability for this category. As such, when considering the marginal effects it is important to assess the magnitude of the effect relative to the predicted probability.

There are a couple of cases where there are "large" negative marginal effects, which means the probability of the event occurring equals zero. By definition probabilities are bounded between zero and one, therefore zero is the lowest possible probability. These cases are a result of the method of calculation. The predicted probabilities are calculated with all the explanatory variables set at their sample means. The marginal effects are calculated by taking the difference in probabilities with the variable of interest set at zero and at one, as opposed to taking the difference between the probability with the variable set at its sample mean and when set at one. This difference may lead to cases where there are negative marginal effects larger than the predicted probabilities. In such cases the probability of the event occurring is interpreted as zero.

5.3.3 Marginal Effects - Analysis

The parameter estimates for the WTP ordered probit models are presented in Table 5.3. There are nine variables with significant coefficient estimates at the 10% level of significance or better in the WTP model. The significant variables are denoted in both Tables 5.3 and 5.4. The significant variables are CAL, TOR, HEALTH3, ENV1, ENV2, PALT, H-PFP, H-SIZE and EDUC2. The discussion of the marginal effects will focus on the variables with statistically significant parameter estimates, but Table 5.4 shows the marginal effects for all variables.

Calgary (CAL): CAL has a negative effect on the probabilities in categories one and two, and a positive effect on the probabilities in categories three, four and five. The marginal effect of CAL on category one is –.0571 (or –5.7%), while means consumers from Calgary are 5.7% less likely than consumers who are not from Calgary to be willing-to-pay no premium. Consumers from Calgary are approximately 10% less likely to be willing-to-pay a 1-5% premium, 8% more likely to be willing-to-pay 6-10% more, 5% more likely to be willing-to-pay 11-20% more, and 2% more likely to be willing-to-pay more than a 20% premium for PFP food products.

Toronto (TOR): Toronto consumers are less likely to be willing-to-pay lower premiums, and more likely to be willing-to-pay high premiums. Consumers from Toronto are 5%

less likely to be willing-to-pay no premium, 7% less likely to be willing-to-pay 1-5% more, 7% more likely to be willing-to-pay a 6-10% premium, 4% more likely to be willing-to-pay 11-20% more, and approximately 1% more likely to be willing-to-pay greater than 20% more for PFP food products.

HEALTH3: (Usually or always shop at health food stores): HEALTH3 has negative marginal effects on the category one and category two predicted probabilities and has a positive effect on the predicted probabilities for categories three, four and five. Consumers who usually or always shop at health food stores are 8% less likely than those who do not fall in this category to be willing-to-pay no premium. Consumers who usually or always shop at health food stores are 19% less likely to be willing-to-pay 1-5% more, 11% more likely to be willing-to-pay a 6-10% premium, 10% more likely to be willing-to-pay 11-20% more and 5% more likely to be willing-to-pay greater than 20% premiums for PFP food products. These results are in line with the expectation for this variable, as consumers who regularly shop at health food stores were expected to be willing-to-pay a premium for PFP food products.

Environment: The ENV1 (strongly agree with the environment attitude statement) variable has negative marginal effects on the predicted probabilities for categories one and two. ENV1 has positive marginal effects on the predicted probabilities for categories three, four and five. Respondents who strongly agree with the statement, "I feel the use of synthetic chemicals in agriculture has a negative effect on the environment," are 16% less likely to be willing-to-pay no premium than respondents who do not strongly agree with this statement. Respondents who strongly agree with the statement regarding the environment are 22% less likely to be willing-to-pay a 1-5%, 20% more likely to be willing-to-pay a 6-10% premium, 12% more likely to be willing-to-pay an 11-20% premium, and 5% more likely to be willing-to-pay more than a 20% premium for PFP food products.

The marginal effects of ENV2 follow the same pattern as those for ENV1. Categories one and two have negative marginal effects, while categories three, four and five have positive marginal effects. These results confirm the hypothesis that consumers who are concerned about the environmental effects of chemical use would be willing-to-pay a premium for PFP food products. Respondents who agree with the statement about the impact of chemical use on the environment are 12% less likely to be willing-to-pay no premium than those who do not agree. Respondents who agree with the environment attitude statement are 23% less likely to be willing-to-pay a 1-5% premium, 17% more likely to be willing-to-pay a 6-10% premium, 12% more likely to be willing-to-pay an 11-20% premium, and are 6% more likely to be willing-to-pay a premium greater than 20%.

PALT: (previously purchased alternative food products) PALT has negative marginal effects on category one and two, and positive marginal effects on categories three, four and five. The marginal effects indicate that respondents who have purchased alternative food products are less likely to be willing-to-pay small premiums. Respondents who have purchased alternative food products are 8% less likely to be willing-to-pay no premium, and 14% less likely to be willing-to-pay a 1-5% premium. Respondents who have previously purchased alternative food products are 11% more likely to be willing-to-pay a 6-10% premium, 7% more likely to be willing-to-pay an 11-20% premium and 3% more likely to be willing-to-pay a greater than 20% premium.

The marginal effects for PALT are in line with the hypothesis for this variable. It was hypothesized that consumers who have purchased organic or IPM food in the past would be willing-to-pay a premium for PFP food products. People who have purchased other reduced input food products likely paid more for these products and are comfortable with paying a premium for products they value.

Heard of PFP (H-PFP): H-PFP has positive marginal effects on category one and category two, and negative effects on categories three, four and five. Respondents who have previously heard of PFP are 5% more likely to be willing-to-pay no premium, 6% more likely to be willing-to-pay 1-5% more for PFP food products, 7% less likely to be willing-to-pay a 6-10% premium, 3% less likely to be willing-to-pay an 11-20% premium and 1% less likely to be willing-to-pay a premium greater than 20%. This result is surprising as it was expected that people who have heard of PFP previously would be more interested in PFP food products and therefore, more likely to pay a premium over conventional food products. A similar effect was seen in the binary models analysis where H-PFP was significant and negative in three of the potential PFP food product models.

The results regarding this variable raise the question, why are people who have heard of PFP less interested in PFP food products than those who have not heard of PFP?

Table 5.3: Willingness-to-pay Model Parameter Estimates

VARIABLE	COEFFICIENT	STD. ERROR	T-RATIO
CAL	0.3879 *	0.2102	1.8456
TOR	0.3245 *	0.1895	1.7126
TNEW1	-0.6716	0.4717	-1.4238
TNEW2	-0.6679	0.4762	-1.4027
TNEW3	-0.6997	0.4328	-1.6169
HEALTH2	0.1940	0.1602	1.2109
HEALTH3	0.6743 **	0.3224	2.0917
ENV1	0.9900 ***	0.3448	2.8709
ENV2	0.9049 ***	0.3367	2.6878
ENV3	0.0745	0.3439	0.2167
CPR1	0.5189	0.7275	0.7132
CPR2	0.5286	0.7182	0.7361
CPR3	-1.0859	0.8706	-1.2473
LABEL1	0.0050	0.3455	0.0145
LABEL2	0.1021	0.3489	0.2927
FINC1	0.3763	0.2739	1.3735
FINC2	0.2360	0.2677	0.8818
SAP1	0.1666	0.3774	0.4415
SAP2	-0.1742	0.3659	-0.4762
PALT	0.5421 ***	0.1743	3.1105
H-PFP	-0.2916 *	0.1520	-1.9191
H-SIZE	-0.2008 **	0.1009	-1.9896
CHILD<17	-0.0001	0.1229	-0.0004
P-SHOP	-0.3620	0.3708	-0.9763
FEMALE	0.0576	0.1612	0.3574
AGE1	0.3916	0.2768	1.4148
AGE2	0.3491	0.2487	1.4038
AGE3	0.2454	0.2451	1.0013
EDUC2	-0.6443 **	0.2878	-2.2384
EDUC3	0.0591	0.2895	0.2040
EDUC4	-0.2796	0.3499	-0.7993
EXP1	-0.0198	0.3955	-0.0500
EXP2	-0.4774	0.3187	-1.4981
EXP3	-0.1666	0.2976	-0.5598
EXP4	0.2801	0.2916	0.9605
INC1	-0.3468	0.4448	-0.7795
INC2	-0.0269	0.3329	-0.0807
INC3	-0.1041	0.3013	-0.3454
INC4	0.1767	0.2988	0.5915
INC5	-0.0033	0.3134	-0.0105
INC6	-0.1684	0.2905	-0.5796
MSTAT1	-0.0613	0.3392	-0.1806
MSTAT2	-0.2759	0.2804	-0.9841
MSTAT3	-0.2446	0.3455	-0.7079
limit point 1	-1.1628	1.1815	-0.9842
limit point 2	0.3735	1.1874	0.3146
limit point 3	1.5231	1.1906	1.2793
limit point 4	2.2890	1.1860	1.9300
LR Stat = 164.01		* significant at 10% level	
LR p-value = 9.99E-16		** significant at 5% level	
McFadden $R^2 = 0.2039$		*** significant at 1% level	

Table 5.4: Willingness-to-Pay Model Marginal Effects					
VARIABLE	1	2	3	4	5
CAL *	-0.0571	-0.0956	0.0833	0.0495	0.0199
TOR *	-0.0542	-0.0718	0.0747	0.0376	0.0136
TNEW1	0.1518	0.0848	-0.1621	-0.0575	-0.0170
TNEW2	0.1530	0.0810	-0.1614	-0.0562	-0.0164
TNEW3	0.0951	0.1781	-0.1366	-0.0941	-0.0426
HEALTH2	-0.0331	-0.0421	0.0454	0.0221	0.0078
HEALTH3 **	-0.0761	-0.1872	0.1126	0.0995	0.0513
ENV1 ***	-0.1578	-0.2173	0.2024	0.1205	0.0522
ENV2 ***	-0.1220	-0.2268	0.1679	0.1221	0.0588
ENV3	-0.0121	-0.0170	0.0171	0.0088	0.0032
CPR1	-0.0949	-0.1020	0.1218	0.0558	0.0193
CPR2	-0.0640	-0.1702	0.0955	0.0906	0.0481
CPR3	0.3042	0.0233	-0.2424	-0.0674	-0.0177
LABEL1	-0.0008	-0.0011	0.0012	0.0006	0.0002
LABEL2	-0.0166	-0.0233	0.0235	0.0121	0.0044
FINC1	-0.0670	-0.0772	0.0886	0.0413	0.0143
FINC2	-0.0368	-0.0559	0.0529	0.0289	0.0109
SAP1	-0.0289	-0.0355	0.0393	0.0187	0.0065
SAP2	0.0306	0.0366	-0.0413	-0.0193	-0.0066
PALT ***	-0.0776	-0.1351	0.1125	0.0706	0.0297
H-PFP *	0.0523	0.0595	-0.0692	-0.0318	-0.0108
H-SIZE **	0.0792	-0.0455	0.0446	-0.0468	-0.0405
CHILD<17	0.00002	-0.00001	-0.00005	-0.00005	-0.00005
P-SHOP	0.0482	0.0953	-0.0730	-0.0492	-0.0212
FEMALE	-0.0097	-0.0127	0.0135	0.0066	0.0023
AGE1	-0.0564	-0.0981	0.0829	0.0508	0.0208
AGE2	-0.0553	-0.0812	0.0783	0.0422	0.0159
AGE3	-0.0379	-0.0585	0.0547	0.0302	0.0115
EDUC2 **	0.1254	0.1142	-0.1521	-0.0655	-0.0220
EDUC3	-0.0099	-0.0131	0.0137	0.0068	0.0024
EDUC4	0.0537	0.0518	-0.0678	-0.0286	-0.0092
EXP1	0.0033	0.0043	-0.0046	-0.0023	-0.0008
EXP2	0.0900	0.0901	-0.1135	-0.0499	-0.0167
EXP3	0.0292	0.0352	-0.0394	-0.0185	-0.0064
EXP4	-0.0418	-0.0686	0.0612	0.0354	0.0139
INC1	0.0698	0.0591	-0.0846	-0.0337	-0.0105
INC2	0.0452	0.0729	-0.0658	-0.0376	-0.0147
INC3	0.0181	0.0221	-0.0246	-0.0116	-0.0040
INC4	-0.0274	-0.0421	0.0396	0.0217	0.0082
INC5	0.0005	0.0007	-0.0008	-0.0004	-0.0001
INC6	0.0304	0.0341	-0.0403	-0.0182	-0.0061
MSTAT1	0.0106	0.0132	-0.0144	-0.0069	-0.0024
MSTAT2	0.0440	0.0639	-0.0624	-0.0332	-0.0124
MSTAT3	0.0455	0.0476	-0.0589	-0.0258	-0.0085

Are people who have heard of PFP disappointed when they learn more about PFP food products? Examining why some people are not interested in PFP food products would provide useful information and could be an area for further research.

Household Size (H-SIZE): H-SIZE is different from most of the variables in the model, as it is one of only two continuous variables. The interpretation of the marginal effects of continuous variables is a little more straightforward than with dummy variables. The marginal effect of H-SIZE on category one is .0792; this indicates that as household size increase by one unit the predicted probability that the average respondent would be willing-to-pay no premium increases by approximately 8%. As household size increases the average respondent is 5% less likely to be willing-to-pay a 1-5%, 4% more likely to be willing-to-pay a 6-10% premium, 5% less likely to be willing-to-pay an 11-20% premium and 4% less likely to be willing-to-pay a premium of more than 20%. It was hypothesized that consumers with larger households would be more interested in PFP food products. However, larger households will typically have more expenses and it is not surprising that as household size increases the probability of WTP high premiums decreases.

Education (EDUC2): This variable represents the education level of high school graduate/some university or college. EDUC2 has a positive marginal effect on categories one and two, and has a negative marginal effect on categories three, four and five. The marginal effect of EDUC2 on category one is .1254, indicating that respondents with a high school diploma and/or some university level education are 13% more likely to be willing-to-pay no premium than respondents who do not fall in this education level. Respondents with a high school diploma and/or some university are 11% more likely to be willing-to-pay a 1-5% premium, 15% less likely to be willing-to-pay a 6-10% premium, 7% less likely to be willing-to-pay an 11-20% premium and 2% less likely to be willing-to-pay a greater than 20% premium.

5.4 Analysis of WTP Model Results

The predicted probability results indicate that there is a strong probability that premiums will exist for PFP food products. The predicted probability that the average respondent is willing-to-pay a greater than 20% premium is 1.6%. The predicted probability that the average respondent is willing-to-pay 11-20% more for PFP food products is 6.9%. Combine the predicted probabilities of the two highest WTP premium ranges and the predicted probability that the average consumer is willing-to-pay at least 11-20% more for PFP food products is 8.5%. If the predicted probability that the average respondent is willing-to-pay 6-10% is also added, there is a predicted probability of 41.3% that the average respondent is willing-to-pay at least 6-10% more for PFP food products.

Grouping the probability that respondents are willing-to-pay a 6-10% premium along with the probability that they are willing-to-pay 11-20% more and greater than 20% more is reasonable because the marginal effects indicate that there is a distinction between those willing-to-pay a 1-5% premium or less and those willing-to-pay a 6-10% premium or more. Table 5.4 illustrates this distinction as the direction of effect changes between categories two and three for nearly every variable. Also, in all but two cases the direction of effect on category one and two's probability is the opposite of the effect on categories three, four and five's probability. In other words, the factors that increase the category one and two probabilities are generally the same and those that increase categories three, four and five are generally the same. The following discussion illustrates this point by developing profiles of consumers most likely to be willing-to-pay moderate to high premiums and of consumers most likely to be willing-to-pay low or no premiums.

Profiles have been derived outlining the characteristics of consumers who are most likely to be willing-to-pay no, low, moderate and high premiums. Variables that are significant and have positive (negative) marginal effects on the relevant WTP categories increase (decrease) the probability that consumers are willing-to-pay the particular premiums make up the most important part of these profiles. Other factors may play a role and some of these will be mentioned. These other factors provide additional information, but are not statistically significant and cannot be weighted heavily in this analysis.

5.4.1 Consumer WTP Profiles:

WTP Profile 1: Respondents most likely to be willing-to-pay high premiums (*i.e.*, willing-to-pay a premium of 11-20% or more) are best described as follows: Respondents from Calgary and Toronto, those who regularly shop at health food stores, people who share the attitude that chemical use in agriculture has a negative impact on the environment, and respondents who have previously purchased alternative food products.

Respondents with the following characteristics may also be more likely to pay high premiums. (These are variables that are not statistically significant, but have positive marginal effects on the higher WTP categories.) Those who occasionally shop at health food stores, those who agree with the other attitude statements, female respondents, those age 0-35, 36-50 and 51-65, those with university degrees and/or some graduate school, people who spend more than $500-$699 per month on food and those who earn between $80,000 and $99,999 annually.

WTP Profile 2: Respondents most likely to be willing-to-pay moderate premiums (*i.e.*, premiums between 6-10%) are the same as that of respondents willing-to-pay high premiums (see WTP profile 1).

WTP Profile 3: Respondents most likely to be willing-to-pay low premiums (*i.e.*, those willing-to-pay a premium of 1-5%) are those who have heard of PFP, people who live in smaller households, and those who have a high school diploma and/or some university education.

WTP Profile 4: Respondents most likely to be willing-to-pay no premium have the same characteristics as those who are willing-to-pay low premiums (see WTP profile 3).

The WTP profiles reflect the fact that there is a distinct break point between WTP categories two and three. This distinction is important because it means that consumers who are willing-to-pay a premium of some sort do not all share the same profile. Respondents who are most likely to be willing-to-pay a 1-5% premium share the same profile as those who are not willing-to-pay a premium. Therefore, it would be a mistake to target consumers who are willing-to-pay a 1-5% premium as potential customers for PFP food products if premiums are desired.

It is unlikely that PFP producers or processors would want to target the low premium category, but it is critical to note that those most likely to be willing-to-pay low premiums share the same characteristics as those who are not willing-to-pay a premium. By recognizing the threshold between categories two and three PFP producers, processors or retailers can focus on marketing to consumers who are most likely to pay high premiums, and avoid inadvertently marketing PFP food products to consumers who are not willing-to-pay a premium.

5.5 WTP Model Summary

The significant variables in the WTP model are CAL, TOR, HEALTH3, ENV1, ENV2, PALT, H-PFP, H-SIZE and EDUC2. Six of the nine significant variables have positive marginal effects on the high WTP categories, while the remaining three have positive effects on the low WTP categories. Respondents who are most likely to be willing-to-pay high premiums are people from Calgary and Toronto, those who shop regularly at health food stores, those who are environmentally conscious and those who have previously purchased alternative food products. People who have previously heard of PFP, those with a high school diploma and/or some university level education and people with larger households are less likely to be willing-to-pay high premiums.

There is a trend among the significant variables that have a positive effect on WTP high premiums. Four of these six variables are related to health or environmental concerns. The other two are the city variables indicating that respondents in Calgary and Toronto are more likely to be willing-to-pay high premiums.

HEALTH3 represents those who regularly shop at health food stores. ENV1 and ENV2 represent respondents who feel that chemical use in agriculture has a negative impact on the environment. The HEALTH3, ENV1 and ENV2 variables are direct indicators of people who are health conscious and environmentally conscious. PALT is the remaining significant variable and is indirectly an indicator of health and environmental concerns. PALT represents having previously purchased either organic or IPM food products. Based on existing literature it is safe to assume that many consumers who purchase reduced input food products do so primarily because they are concerned about the environmental effects of conventional food production systems and health risks (perceived or real) of conventional food products. Therefore, PALT is also viewed as an indicator of health and environmental concerns.

The WTP model results indicate that demographic characteristics do not play a significant role in consumer WTP a premium for PFP food products. Only two demographic variables are significant, H-SIZE and EDUC2. Health and environmental concerns are the most important characteristics of respondents who are willing-to-pay high premiums for PFP food products. Those who regularly shop at health food stores are 10% more likely to be willing-to-pay 11-20% more and 5% more likely to be willing-to-pay greater than 20% more. Those who strongly agree with the environment attitude statement are 12% more likely to be willing-to-pay 11-20% more and 5% more likely to be willing-to-pay greater than 20% more. Those who agree with the environment statement are 12% more likely to be willing-to-pay 11-20% more and 6% more likely to be willing-to-pay greater than 20% more.

These results suggest that marketing efforts should focus on trying to reach consumers who are health conscious and environmentally conscious. Consumers with those characteristics are significantly more likely to be willing-to-pay a high premium. Health food stores could be a potential target to carry PFP food products. A strategy for PFP producers could be to market their products and their production system to processors who supply heath food stores. These processors already produce products designed for health conscious consumers, and may be receptive to the idea of producing PFP food products. These are a couple of examples of how the results of this project can be used in developing a market for PFP food products.

In relation to existing studies of consumer demand for reduced input food products the results of this study are consistent with previous results in the fact that health and environmental concerns are important factors influencing consumers' preference for reduced input food products. Other studies have found that socio-demographic factors play a role in consumer WTP for reduced input food products, although different studies report conflicting effects of such factors. In this study the WTP model results show that socio-demographic factors play a relatively minor role, as only household size and EDUC2 (high school graduate/some university) were significant with both having negative effects on the higher WTP categories.

In summary, there is a small, but significant predicted probability that the average respondent is willing-to-pay high premiums. In addition, the probability is much higher for respondents who share certain characteristics. Focusing on marketing PFP food products to consumers who have the characteristics outlined in WTP Profile 1 (those most likely to be willing-to-pay high premiums) can increase the likelihood of success for PFP food products in the marketplace. The WTP ordered probit model results suggest that average respondents are willing-to-pay premiums and that targeted marketing efforts could increase the likelihood that consumers will pay high premiums and therefore increase the size of the market for PFP food products.

CHAPTER 6 - SUMMARY AND CONCLUSIONS

6.1 Summary

The purpose of this study was to assess the market potential for food products containing agricultural inputs produced in a pesticide free production (PFP) system. Assessing the market potential for a new product requires gauging consumer interest in the product. Individual household level data was collected via a consumer survey. Probit models were used to predict the probability that respondents would purchase a variety of potential PFP food products and to predict the probability that respondents are willing-to-pay different premiums for PFP food products. Binary probit models were used to assess interest in PFP food products and to assess how this interest is affected by respondents' demographic, attitudinal and behavioural profile. Ordered probit models were used to estimate respondents' WTP for PFP food products and to assess how WTP is affected by respondents' demographic, attitudinal and behavioural profile.

6.2 Conclusions

The predicted probabilities for the binary probit models of PFP food product demand indicate that there is strong interest among respondents in PFP food products. Twenty-four of 25 potential PFP food products have predicted probabilities over 50% and 10 products had predicted probabilities of approximately 70% or more. Eight selected PFP food product models were used to gain insight into the magnitude of the effects that the explanatory variables have on the predicted probability that respondents would purchase PFP food products.

A profile of respondents most likely to purchase the eight selected PFP food products has been developed. Respondents from Calgary, those who occasionally shop at health food stores, people who believe the use of pesticides has a negative effect on the environment, those concerned about pesticide residues in our food supply, those who believe that labeling of food ingredients is important, those who feel it is important to maintain farm income levels, those who believe farmers should engage in sustainable production practices, people who have previously purchased alternative food products, primary food shoppers, high income households and single respondents are most likely to purchase PFP food products.

The WTP model results indicate there is a high probability that respondents are willing-to-pay low to moderate premiums for PFP food products. There is a small, but significant probability that respondents are willing-to-pay high premiums for PFP food products. Respondents who are most likely to be willing-to-pay high premiums are: Those from Calgary and Toronto, those who shop regularly at health food stores, those who are environmentally conscious and those who have previously purchased alternative food products. These results indicate that health and environmental concerns are important factors influencing WTP high premiums for PFP food products, while socio-demographic characteristics are relatively unimportant.

The results of this study fit with the findings of previous studies examining consumer preferences for reduced input food products in the respect that health, environmental and food safety concerns were found to be important factors influencing consumer preferences for PFP food products. Previous studies have concluded that socio-demographic characteristics played a significant role in consumer preferences for reduced input food products, although with no clear consensus among studies as to the effects of these characteristics. Here the effects of socio-demographic characteristics are somewhat muted, as they do have significant effects in some binary models of PFP food product demand but are not really a factor in the WTP model. Other variables such as those representing the five attitude statements and previous purchasing habits have greater influence on consumer interest in, and WTP for PFP food products.[1]

Assuming the sample is representative of the population, then conclusions regarding respondents' interest in and willingness-to-pay for PFP food products can be mapped to the population. A comparison of sample and population demographic data was presented in Chapter 3 and it was concluded that, while differences do exist, the sample is a reasonable representation of the population. Therefore, the conclusions drawn in this study are considered to be a good approximation of consumer preferences for PFP food products.

6.3 Limitations of Study

A limitation of studying consumer interest in products not yet on the market is that consumers' actual market behaviour cannot be observed. To deal with this limitation a consumer survey was implemented to gather consumers' stated preferences regarding PFP food products. Contingent Valuation (CV) methodology was used to elicit respondents' WTP valuations. CV techniques have been criticized due to their hypothetical nature. However, studies such as Shogren *et al.* 1999 have indicated that CV

[1] The attitude variables are: Environment (ENV), Concerned about Pesticide Residues (CPR), Label (LABEL), Farm Income (FINC), Sustainable Agricultural Practices (SAP). The important purchasing habit variables are: Occasionally shop at health food stores (HEALTH2), Usually/always shop at health food stores (HEALTH3), previously purchased IPM or organic food products (PALT).

methods yield quite accurate estimates of consumer WTP. Buzby, Ready and Skees (1995) state that CV methodology has the highest validity when the hypothetical scenario is closely related to a familiar market choice situation. The WTP scenario is close to a real market choice situation, as consumers make this type of decision every time they go shopping. Other authors studying consumer food safety preferences indicate that CV is a common methodology used in measuring consumer food safety preferences (Baker 1999: Boccaletti and Nardella 2000).

A second limitation of this study is that it is difficult to generalize the effects of the explanatory variables across all of the potential PFP food product models. Many variables have different effects on different product models. This could be due to the fact that the potential PFP product list includes a wide variety of products and consumers quite likely do not regularly purchase all of these products. However, information regarding what products respondents currently purchase was not collected and this limits the analysis into why some products have a lower predicted probability of purchase.

6.4 Future Research Opportunities

This study makes a valuable contribution to the literature regarding consumer preferences for reduced input food products. The results provide information on the likelihood of consumer acceptance of and willingness-to-pay for PFP food products. The results provide insight into the characteristics of consumers most likely to purchase PFP food products and most likely to be willing-to-pay a premium for PFP food products. There are however, some questions that could be investigated further to get a more complete understanding of the potential market for PFP food products.

The results of the WTP model indicate that a distinction exists between consumers willing-to-pay no or low premiums and those willing-to-pay moderate or high premiums. This suggests scope for segmentation research to explore this distinction in greater detail. Such research could focus on determining what differentiates these groups and what motivates their willingness-to-pay.

Another question that could be addressed, as it cannot be inferred from this study, is why consumers are *not* interested in PFP food products? Gaining further insight into why consumers would *not* purchase PFP food products could help in developing products and marketing strategies that enhance the appeal of PFP food products.

This study analyzes consumer interest in PFP food products for households in three Canadian cities. Previous literature has found that pesticide residue concerns are prevalent in many regions of the world. As Canadian producers export the majority of their products, consumer preferences in other regions of the world have ramifications on the market for Canadian agricultural products. Analysis of consumer preferences for PFP food products in foreign countries could provide additional information about the market potential for PFP food products.

This study has shown that there is strong interest in PFP food products, that there is a high probability that consumers will pay low or moderate premiums and a small but significant probability that consumers will pay high premiums. A question that needs to be addressed is; what size premium is enough for producers, processors or retailers to pursue the development and marketing of PFP food products? Further analysis of how much of any premium will be seen at the various levels of the supply chain would help all involved decide if the market for PFP food products is strong enough to warrant pursuing the development of PFP food products.

Health and environmental concerns were shown to be important factors influencing consumer WTP high premiums. An opportunity for further study would be to analyze the factors that influence health or environmental concerns among consumers. Understanding the characteristics of health and environmentally conscious consumers may provide more insight into consumer interest in reduced input food products.

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APPENDIX 1 - PFP CONSUMER SURVEY AND ACCOMPANYING COVER LETTER

In a continuing effort to ensure the sustainability of Canadian agriculture, researchers at the University of Manitoba, Manitoba Agriculture and Food, and Agriculture and Agri-Food Canada have begun research on a new production system that may revolutionise agriculture. Pesticide Free Production, or PFP, crops are grown using conventional techniques but no pesticides are applied from the time the crop is planted through to harvest, storage, and sale.

Part of this research, which is funded by the Manitoba Rural Adaptation Council, focuses on developing a better understanding of consumer perceptions and attitudes towards the PFP concept and gathering input regarding food products consumers would purchase if available in a PFP form. We ask for your co-operation in having the principal grocery shopper in your household complete the enclosed survey. Responses are anonymous and confidential, but will help farmers better understand the marketplace. The completed survey can be mailed back in the enclosed stamped, self-addressed envelope.

If you have any question, please feel free to contact me at (204) 474-9713, or through e-mail at john_cranfield@umanitoba.ca. Your co-operation is very important to the development of this new agricultural production system and sincerely appreciated.

Sincerely,

John Cranfield
Assistant Professor

To be completed by the principal grocery shopper of the household

1. Which of the following is your ***primary*** source for information regarding food safety?
   - ❑ Radio, television,
   - ❑ Newspapers, popular magazines
   - ❑ University academic reports
   - ❑ Government food safety programs (*e.g.*, The Canadian Food Inspection Agency)
   - ❑ Friend's word of mouth
   - ❑ Other ______________________________

2. Which of the following best describes you in terms of purchasing and trying a newly introduced food product in the grocery store?
   - ❑ Among the first to try
   - ❑ Among the last to try
   - ❑ In between
   - ❑ Never try

3. Do you shop at health food stores or nutrition centres?
   - ❑ Never
   - ❑ Occasionally
   - ❑ Usually
   - ❑ Always

4. Do you regularly purchase private label food products? (Private label food products are those sold under a grocery store's brand name.)

   ❑ Yes ❑ No

   If *Yes*, please proceed to question 5
   If *No*, please proceed to question 6

5. What is the ***primary*** reason you regularly purchase private label food products?
   - ❑ Private label brands are of better quality compared to national brands
   - ❑ Private label brands offer a broader selection compared to national brands
   - ❑ Private label food products are a better value compared to national brands
   - ❑ Other (please use the space below to indicate your reason)

   ____

   ____

   ⇒ **Please proceed to question 6**

6. Please indicate how you feel about the following statements.

	Select one response per statement				
I feel the use of synthetic chemicals in agriculture has a negative effect on the environment.	1. Strongly agree	2. Agree	3. Neutral	4. Disagree	5. Strongly disagree
I am concerned about pesticide residues in our food supply.	1. Strongly agree	2. Agree	3. Neutral	4. Disagree	5. Strongly disagree
The labeling of food ingredients on food packaging is important to me.	1. Strongly agree	2. Agree	3. Neutral	4. Disagree	5. Strongly disagree
I feel it is important to maintain farm income at a level that keeps the family farm viable.	1. Strongly agree	2. Agree	3. Neutral	4. Disagree	5. Strongly disagree
I believe farmers should engage in sustainable agricultural production practices. That is, practices which adopt the goal of ensuring the productive future of agriculture, the environment and the economy of rural communities.	1. Strongly agree	2. Agree	3. Neutral	4. Disagree	5. Strongly disagree

7. Have you ever heard of Integrated Pest Management (IPM)?
   - ❑ Yes ❑ No

   If *Yes*, please proceed to question 8
   If *No*, please proceed to question 11

8. Do you regularly purchase food that is labelled as being produced in an Integrated Pest Management (IPM) system?
   - ❑ Yes ❑ No

   If *Yes*, please proceed to question 9
   If *No*, please proceed to question 10

9. How often do you purchase IPM grown food?
   - ❑ Once or twice a year
   - ❑ Once a month
   - ❑ Twice a month
   - ❑ Once a week
   - ❑ More than once a week

10. What is the ***primary*** reason you do not regularly purchase IPM labelled food?
- ❑ I am content with conventionally produced food
- ❑ IPM labelled food is too expensive
- ❑ My usual grocery store does not carry IPM labelled products
- ❑ Appearance
- ❑ Other (please use the space below to indicate your reason)

____

____

11. Have you ever heard of organic food?

❑ Yes ❑ No

If *Yes*, please proceed to question 12
If *No*, please proceed to page 4 of the survey

12. Do you regularly purchase food labelled as organic?

❑ Yes ❑ No

If *Yes*, please proceed to question 13
If *No*, please proceed to question 14

13. How often do you purchase food labelled as organic?
- ❑ Once or twice a year
- ❑ Once a month
- ❑ Twice a month
- ❑ Once a week
- ❑ More than once a week

⇒ **Please proceed to page 4 of the survey**

14. What is the ***primary*** reason you do not regularly purchase organic food?
- ❑ I am content with conventionally produced food
- ❑ Food labelled organic is too expensive
- ❑ My usual grocery store does not carry organic food products
- ❑ Appearance
- ❑ Other (please use the space below to indicate your reason)

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Please read the following definitions before moving on:

Pesticide Free Production crops are grown using conventional techniques but they have not been treated with pesticides during the growing season and while in storage. Other pest control methods are used, such as competitive crop varieties, natural pest enemies, and crop rotation. No pesticides are applied from the time the crop is planted through to harvest, storage, and sale of the crop. In addition, such crops cannot be grown where previous pesticide applications are considered to still be active.

*A **PFP alternative** is a food product in which the main ingredient(s) have been produced in a pesticide free production system, but other ingredients may have been produced with pesticides.*

15. Have you previously heard of or read any news reports about Pesticide Free Production (PFP)?
    - ❑ Yes ❑ No

16. If you saw two similar products beside each other at the grocery store, but one is labelled PFP and the other has no such label, what would that say to you about the food product with no label? (Select more than one response if appropriate)
    - ❑ The product with no label is equally safe
    - ❑ The product with no label has been produced with pesticides
    - ❑ The product with no label is of inferior quality
    - ❑ The product with no label is not as healthy for me
    - ❑ The product with no label was produced at a greater expense to the environment
    - ❑ None of the above
    - ❑ I do not know

17. Would you prefer to buy a PFP food product over a conventionally produced food product if they were of comparable taste, price, availability and nutritional content?
    - ❑ Yes, I would buy a PFP food Product
    - ❑ No, I would not buy a PFP food product
    - ❑ I do not know/not sure
    - ❑ I would need more information/experience with the PFP food product

If you answered "No, I would not buy a PFP food product" please skip to question 22, otherwise please continue.

18. Consider the following list of food products. Suppose that a PFP alternative were available for each item, at the same price and with no difference in taste. Please indicate which of the food products you would purchases in the PFP form.

❑	Pasta	❑	Multi grain bread
❑	Whole wheat bread	❑	White bread
❑	Crackers	❑	Bagels
❑	Muffins	❑	Cookies
❑	Breakfast cereal	❑	Oatmeal
❑	Granola	❑	Canola oil
❑	Corn oil	❑	Margarine
❑	Dry beans	❑	Dry lentils
❑	Dry peas	❑	Baked beans
❑	Canned chickpeas	❑	Lentil, pea, or bean soups
❑	Corn chips	❑	Granola bars
❑	Sunflower seeds	❑	Buckwheat noodles
❑	Beer	❑	Other (please list below)

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19. If a PFP food product were available at the same price and with no difference in taste would your consumption of the conventionally produced food product be reduced?
   ❑ Yes ❑ No

20. Would you switch grocery stores in order to buy a PFP food product?
   ❑ Yes ❑ No

21. Suppose your favorite food product regularly costs $2.00 for each unit you purchase. Assuming no difference in taste and nutritional content, would you pay slightly more for a PFP version of the same food product?
   - ❑ No
   - ❑ Yes, I would pay between 1 cent and 10 cents more for the PFP version
   - ❑ Yes, I would pay between 11 cent and 20 cents more for the PFP version
   - ❑ Yes, I would pay between 21 cent and 40 cents more for the PFP version
   - ❑ Yes, I would pay more than 40 cents for the PFP version

Your answers to the following questions will help us interpret the results of the questionnaire. This information is will be kept strictly confidential.

22. How many people live in your household? ____________

23. How many people in your household are below the age of 17? ____________

24. Are you the primary shopper for food? Yes ___ No ___

25. Please indicate your gender. Male ___ Female ___

26. Please select the range in which your age falls (in years).
❑ Under 20 ❑ 20 - 35 ❑ 36 - 50
❑ 51 - 65 ❑ More than 65

27. Please select the highest level of education you have completed.
❑ Some Grade School ❑ Some High School
❑ High School Graduate ❑ Some University/College
❑ University/College Graduate ❑ Some Graduate School
❑ Masters Degree ❑ Doctoral Degree

28. What is your **household's** average monthly expenditure on food products?
❑ Under $199 ❑ $200 - $399 ❑ $400 - $499 ❑ $500 - $599
❑ $600 - $699 ❑ $700 - $799 ❑ More than $800

29. In what range does your annual **household** income fall?
❑ Under $19,999 ❑ $20,000 - $39,999 ❑ $40,000 - $59,999
❑ $60,000 - $79,999 ❑ $80,000 - $99,999 ❑ $100,000 - $119,999
❑ $120,000 - $149,999 ❑ More than $150,000

30. Please select the category that describes your current marital status.
❑ Single ❑ Married ❑ Separated
❑ Divorced ❑ Widowed/Widower ❑ Other

If you have any additional comments please feel free to express them below.

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Your participation in this survey is very important and much appreciated. Thank you <u>very</u> much for your time!

APPENDIX 2: PREDICTIVE ABILITY TABLES – SELECTED PFP FOOD PRODUCT MODELS

Predictive Ability Table – Table 7.1

Dependent Variable: Pr[*BuyPFP(**Pasta**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	21	9	30	0	0	0
P(Dep=1)>C	22	234	256	43	243	286
Total	43	243	286	43	243	286
Correct	21	234	255	0	243	243
% Correct	48.84	96.3	89.16	0	100	84.97
% Incorrect	51.16	3.7	10.84	100	0	15.03
Total Gain*	48.84	-3.7	4.2			
Percent Gain**	48.84	NA	27.91			

Expected Value Evaluation

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	18.7	23.97	42.67	6.47	36.53	43
E(# of Dep=1)	24.3	219.03	243.33	36.53	206.47	243
Total	43	243	286	43	243	286
Correct	18.7	219.03	237.73	6.47	206.47	212.93
% Correct	43.49	90.14	83.12	15.03	84.97	74.45
% Incorrect	56.51	9.86	16.88	84.97	15.03	25.55
Total Gain*	28.45	5.17	8.67			
Percent Gain**	33.49	34.4	33.94			

*Change in "% Correct" from default (constant only) specification

**Percent of incorrect (default) prediction corrected by equation

Predictive Ability Table – Table 7.2

Dependent Variable: Pr[*BuyPFP(**Breakfast cereal**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	13	8	21	0	0	0
P(Dep=1)>C	36	229	265	49	237	286
Total	49	237	286	49	237	286
Correct	13	229	242	0	237	237
% Correct	26.53	96.62	84.62	0	100	82.87
% Incorrect	73.47	3.38	15.38	100	0	17.13
Total Gain*	26.53	-3.38	1.75			
Percent Gain**	26.53	NA	10.2			

Expected Value Evaluation

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	17.36	31.73	49.09	8.4	40.6	49
E(# of Dep=1)	31.64	205.27	236.91	40.6	196.4	237
Total	49	237	286	49	237	286
Correct	17.36	205.27	222.64	8.4	196.4	204.79
% Correct	35.43	86.61	77.85	17.13	82.87	71.6
% Incorrect	64.57	13.39	22.15	82.87	17.13	28.4
Total Gain*	18.3	3.75	6.24			
Percent Gain**	22.08	21.87	21.98			

*Change in "% Correct" from default (constant only) specification

**Percent of incorrect (default) prediction corrected by equation

Predictive Ability Table – Table 7.3

Dependent Variable: Pr[*BuyPFP(**Dry peas**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	94	40	134	0	0	0
P(Dep=1)>C	40	112	152	134	152	286
Total	134	152	286	134	152	286
Correct	94	112	206	0	152	152
% Correct	70.15	73.68	72.03	0	100	53.15
% Incorrect	29.85	26.32	27.97	100	0	46.85
Total Gain*	70.15	-26.32	18.88			
Percent Gain**	70.15	NA	40.3			

Expected Value Evaluation

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	79.07	54.45	133.52	62.78	71.22	134
E(# of Dep=1)	54.93	97.55	152.48	71.22	80.78	152
Total	134	152	286	134	152	286
Correct	79.07	97.55	176.62	62.78	80.78	143.57
% Correct	59.01	64.18	61.75	46.85	53.15	50.2
% Incorrect	40.99	35.82	38.25	53.15	46.85	49.8
Total Gain*	12.15	11.03	11.56			
Percent Gain**	22.87	23.54	23.2			

*Change in "% Correct" from default (constant only) specification

**Percent of incorrect (default) prediction corrected by equation

Predictive Ability Table – Table 7.4

Dependent Variable: Pr[*BuyPFP(**Sunflower seeds**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	51	36	87	0	0	0
P(Dep=1)>C	70	129	199	121	165	286
Total	121	165	286	121	165	286
Correct	51	129	180	0	165	165
% Correct	42.15	78.18	62.94	0	100	57.69
% Incorrect	57.85	21.82	37.06	100	0	42.31
Total Gain*	42.15	-21.82	5.24			
Percent Gain**	42.15	NA	12.4			

Expected Value Evaluation

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	60.7	60.34	121.04	51.19	69.81	121
E(# of Dep=1)	60.3	104.66	164.96	69.81	95.19	165
Total	121	165	286	121	165	286
Correct	60.7	104.66	165.36	51.19	95.19	146.38
% Correct	50.16	63.43	57.82	42.31	57.69	51.18
% Incorrect	49.84	36.57	42.18	57.69	42.31	48.82
Total Gain*	7.85	5.74	6.63			
Percent Gain**	13.61	13.56	13.59			

*Change in "% Correct" from default (constant only) specification

**Percent of incorrect (default) prediction corrected by equation

Predictive Ability Table – Table 7.5

Dependent Variable: Pr[*BuyPFP(**Beer**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	94	43	137	0	0	0
P(Dep=1)>C	46	103	149	140	146	286
Total	140	146	286	140	146	286
Correct	94	103	197	0	146	146
% Correct	67.14	70.55	68.88	0	100	51.05
% Incorrect	32.86	29.45	31.12	100	0	48.95
Total Gain*	67.14	-29.45	17.83			
Percent Gain**	67.14	NA	36.43			

Expected Value Evaluation

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	85.52	53.9	139.42	68.53	71.47	140
E(# of Dep=1)	54.48	92.1	146.58	71.47	74.53	146
Total	140	146	286	140	146	286
Correct	85.52	92.1	177.62	68.53	74.53	143.06
% Correct	61.08	63.08	62.11	48.95	51.05	50.02
% Incorrect	38.92	36.92	37.89	51.05	48.95	49.98
Total Gain*	12.13	12.03	12.08			
Percent Gain**	23.77	24.59	24.18			

*Change in "% Correct" from default (constant only) specification
**Percent of incorrect (default) prediction corrected by equation

Predictive Ability Table – Table 7.6

Dependent Variable: Pr[*BuyPFP(**Multigrain bread**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	21	10	31	0	0	0
P(Dep=1)>C	45	210	255	66	220	286
Total	66	220	286	66	220	286
Correct	21	210	231	0	220	220
% Correct	31.82	95.45	80.77	0	100	76.92
% Incorrect	68.18	4.55	19.23	100	0	23.08
Total Gain*	31.82	-4.55	3.85			
Percent Gain**	31.82	NA	16.67			

Expected Value Evaluation

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	24.89	41.23	66.12	15.23	50.77	66
E(# of Dep=1)	41.11	178.77	219.88	50.77	169.23	220
Total	66	220	286	66	220	286
Correct	24.89	178.77	203.66	15.23	169.23	184.46
% Correct	37.71	81.26	71.21	23.08	76.92	64.5
% Incorrect	62.29	18.74	28.79	76.92	23.08	35.5
Total Gain*	14.64	4.34	6.71			
Percent Gain**	19.03	18.79	18.91			

*Change in "% Correct" from default (constant only) specification

**Percent of incorrect (default) prediction corrected by equation

Predictive Ability Table – Table 7.7

Dependent Variable: Pr[*BuyPFP(**Canola oil**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	40	19	59	0	0	0
P(Dep=1)>C	53	174	227	93	193	286
Total	93	193	286	93	193	286
Correct	40	174	214	0	193	193
% Correct	43.01	90.16	74.83	0	100	67.48
% Incorrect	56.99	9.84	25.17	100	0	32.52
Total Gain*	43.01	-9.84	7.34			
Percent Gain**	43.01	NA	22.58			

Expected Value Evaluation

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	44.37	48.75	93.12	30.24	62.76	93
E(# of Dep=1)	48.63	144.25	192.88	62.76	130.24	193
Total	93	193	286	93	193	286
Correct	44.37	144.25	188.62	30.24	130.24	160.48
% Correct	47.71	74.74	65.95	32.52	67.48	56.11
% Incorrect	52.29	25.26	34.05	67.48	32.52	43.89
Total Gain*	15.2	7.26	9.84			
Percent Gain**	22.52	22.32	22.42			

*Change in "% Correct" from default (constant only) specification

**Percent of incorrect (default) prediction corrected by equation

Predictive Ability Table – Table 7.8

Dependent Variable: Pr[*BuyPFP(**Dry lentils**)*=1]

Prediction Evaluation (success cutoff C = 0.5)

	Estimated Equation			Constant Only		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	96	37	133	0	0	0
P(Dep=1)>C	43	110	153	139	147	286
Total	139	147	286	139	147	286
Correct	96	110	206	0	147	147
% Correct	69.06	74.83	72.03	0	100	51.4
% Incorrect	30.94	25.17	27.97	100	0	48.6
Total Gain*	69.06	-25.17	20.63			
Percent Gain**	69.06	NA	42.45			

Expected Value Evaluation

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
E(# of Dep=0)	84.2	54.62	138.82	67.56	71.44	139
E(# of Dep=1)	54.8	92.38	147.18	71.44	75.56	147
Total	139	147	286	139	147	286
Correct	84.2	92.38	176.59	67.56	75.56	143.11
% Correct	60.58	62.85	61.74	48.6	51.4	50.04
% Incorrect	39.42	37.15	38.26	51.4	48.6	49.96
Total Gain*	11.98	11.45	11.7			
Percent Gain**	23.3	23.55	23.43			

*Change in "% Correct" from default (constant only) specification
**Percent of incorrect (default) prediction corrected by equation