ADOPTION AND USE OF INTERNET AMONG AMERICAN ORGANIC FARMERS

by

DANIEL GEORGE NGUGI

(Under the Direction of XiangRong Yin and Luanne Lohr)

ABSTRACT

In this study, we examine adoption and intensity of use of the internet among organic farmers in the United States based on nationwide survey data. A logistic regression model is used to analyze internet adoption. A Poisson model is applied to the analysis of the portfolio of applications for marketing and production management. Organic farmers use the internet primarily for production information gathering. Higher education and prospects of increasing direct marketing of farm products are associated with increased adoption and the portfolio of internet applications. Increased share of horticultural acreage is associated with increased internet adoption. Larger farms have a larger portfolio of internet uses. It is expected that adoption and use of the internet will increase, and educating farmers in making the most efficient use of the internet as well as providing organic farming information online is recommended.

INDEX WORDS: Adoption, technology, Organic, farmers, internet, logistic, Poisson, management, portfolio, farms

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DANIEL GEORGE NGUGI

B.S., University of Nairobi, Kenya, 1993

M.S., University Of Malawi, Malawi, 1998

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DANIEL GEORGE NGUGI

Major Professor: XiangRong Yin
and Luanne Lohr

Committee: Paul Schliekelman
Michael Wetzstein

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
December 2007

DEDICATION

To my dear sister Leah “naisiae” Njeri, you are a true and faithful friend. For all your support to me you deserve the best in life. May the good Lord be ever so gracious and may he bless you “exceedingly abundantly above” your wildest dreams.

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CHAPTER I

INTRODUCTION

Problem Statement and Justification

Over the last decade, internet use has grown tremendously to become a significant source of information and a tool for marketing and production in agriculture. There are numerous studies on the use of computers and the internet outside agriculture, but economic research on use of these technologies on the farm is scarce.

The recent interest in direct marketing among farmers and consumers (United States Department of Agriculture (USDA), 1998) makes internet use in the farm business more attractive than ever before. There are many reasons for the growing popularity of direct marketing. Among consumers, many want support local farmers, establish a closer connection to agriculture, and access fresher, less processed, and organic foods (USDA, 1998). Farmers are interested in increasing market share, creating a niche closer to home away from more competitive distant markets (Adam, Balasubrahmanyam and Born,1999) and increasing profits through by-passing the wholesaler (USDA,1998).

As a portion of direct marketing, the number of Americans shopping online has increased drastically in recent years. Among 168 million internet users aged 16 and above, 56% shopped online in 2002, and consumer spending online continues to increase (Klotz, 2002). This trend is likely to continue as computer ownership and internet service become more affordable.

Computer ownership is often a prerequisite for internet adoption and internet adoption seems to track computer ownership, with rates of computer ownership being higher than rates of internet adoption (USDA, 2003). We define internet adoption as having convenient access to the internet either at home, at work (farm in agriculture) or away from home/work. We define internet use (in agriculture) as actual application of the internet to search, access, or distribute information pertinent to farm business operation.

Unlike computer ownership, the internet is a non-capital technology with minimal fixed equipment costs and a monthly internet charge. No replacement is required as service upgrades come from the internet service provider (ISP). The literature shows that rates of internet use for organic farm business are lower than rates of internet adoption (Waltz, 2004).

Internet Use Among Conventional Farmers

Farmers use the internet for diverse purposes including finding and tracking prices, finding commodity markets (Smith, et al. 2004), accessing agricultural information services, communicating with other farmers and farming advisors and maintaining and transmitting farm data (Hopkins and Morehart, 2002). Furthermore, government regulations governing direct marketing are changing to better serve the interests of farmers (USDA, 1998) spurring an increase in direct marketing in general and internet use for agribusiness in particular.

In the last decade, internet use has seen phenomenal growth the world over with innovative applications increasing by the day. The National Agricultural Statistics Service (USDA) report on “Farm Computer Usage and Ownership” indicates that the percentage of farms with access to a computer increased from about 38% in 1997 to about 58% in 2005 (USDA, 2005). The report also indicates that, the proportion of farms using computers for farm business increased from about 17% in 1997 to 29% in 2005.

Conversely, the percentage of US farms with internet access has been steadily increasing from 13% in 1997 to 51% in 2005; and about 9% of farms used the internet for farm business in 2005 compared to 6% in 2001 (USDA, 2005). The report documents that in 2003, farms with higher incomes had higher computer and internet adoption and use. Among farms with incomes of $250,000 and above, 79% had access to a computer, 66% used the computer for farm business and 72% had access to the internet. Among farms with incomes below $250,000, 56% had access computer, 27%

used the computer for farm business, and 49% had access to the internet (USDA, 2005).

Across the country the aforesaid USDA report indicates that within the US, the West census region had the highest rate of computer access (66%), followed by the Northeast (60%), the North-central (57%) and the South (49%). Access to the internet follows the same trend with 62% of farms in the West having the access, followed by the Northeast (55%), the North-central (51%) and the South (46%).

American farmers in general use the internet for various purposes. In 2005, among all US farmers with internet access, 9% used the internet to purchase inputs including seeds; 9% conducted marketing activities including selling products and tracking prices; 11% accessed USDA reports and services (USDA, 2005).

Internet Use among Organic Farmers

Results of the 2002 Organic Farming research Foundation's (OFRF) Fourth National Organic Farmer's Survey indicate that 78% of organic farmers had internet access, while 22% had no internet access(Waltz, 2004). Thus internet adoption among organic farmers was higher than that of the general population of US farmers by about 6%.

Among organic farmers with internet adoption, many hold a portfolio of internet applications instead of restricting themselves to a single use. In 2001, 50% of organic farmers used the internet at least once a month to check the weather; 39% look for farming news; 32% look for organic product information; 32% communicate with other farmers; 22% look for organic market information; 15% sell organic farm products; 7% purchase seeds; 9% purchase other inputs online (Waltz, 2004).

It seems that organic farmers use the internet more frequently and for a wider array of services than their counterparts in conventional farming. This difference may be due to the fact that, although organic farmers are a subset of US farmers and quite like the latter in many respects, the former differs from the latter in several important aspects. Organic farmers are more likely to produce outputs that require substantial farmer effort to locate a market outlet or negotiate a price; more likely to direct market their products to more geographically distant buyers; must often buy inputs from distant markets.

Of the total volume of organic farm livestock products sold in 2001, 74% was sold more than 100 miles away from the farm, as well as 67% of grains and field crops, 57% of fruits and nuts, and 21% of vegetables, herbs and floriculture (Waltz, 2004).

At least 31% of organic farmers buy inputs from sources more than 100 miles away from the farm (Waltz, 1999). Moreover, information on organic farming and farm management is not easy to come by. Farmers must often rely on other farmers, input suppliers, buyers, conferences and seminars, field days and farm demonstrations, and published sources for farming information (Waltz, 1999).

In addition to the aforesaid reasons, organic farmers face a number of production challenges, including production losses due to weather changes, pest and diseases, weed control, high costs of inputs and labor, and access to organic seeds and stock (Waltz, 2004).

Farmers also have to deal with numerous problems in marketing their products including finding information on prices, finding premium and stable product prices, lack of marketing networks, distance to markets, locating and accessing existing markets, finding new markets and dealing with unverified organic labeling. Farmers also have to deal with high organic certification costs and meeting certification requirements (Waltz, 2004). This situation holds huge potential for organic farmers to be more efficient and reduce transaction costs, if they used the internet as a source of information, a forum for exchange of ideas, and a platform for sale of products and purchase of inputs.

Using the Internet to Solve Farm Business problems

The internet could be a useful tool for finding solutions to marketing and production problems facing organic farmers.

Hopkins and Morehart (2002) examined the impact of adoption of Communication and Information Technology (CIT) on firm-level efficiency using data from a survey of conventional cash grain farms. They employed stochastic frontier analysis techniques and concluded that use of CIT significantly increased the efficiency of the farm business.

Weather reports and forecast are readily available online; many research findings on farm pests, diseases and soil fertility are published or referenced online; sellers of organic farm inputs and seeds can be located through web searches and farmers can sell their products online. Organic farmers can also use websites and internet discussions to brainstorm and share ideas on issue of interest including production and marketing issues.

Organic farmers operate in an environment that requires substantial specialized information. In 2001, organic farmers obtained their production and marketing information from diverse sources including, other farmers (52%); conferences workshops and seminars (26%); newsletters and magazines (31%); books(19%); buyers (36%);consumers (29%); growers associations (18%); internet based sources(19%), and other sources. Yet most of the information could be easily provided online with substantial efficiency gains. Survey data shows organic farmers have higher internet access than conventional farmers. Nevertheless there exists limited analysis of adoption and use of the internet among organic farmers. Understanding the factors that influence adoption and use of the internet among this special group of farmers would support the spread of the technology among farmers. It would help focus the efforts of government agencies and organic farmer groups on issues that have a significant bearing on internet adoption and use, ensuring better results. The information provided would also enhance development of software and database by the information industry.

Study Objectives

This study applies a logistic model to national survey data to examine factors that influence adoption of internet technology among organic farmers in the US, including demographic and farm environment factors. Beyond analyzing internet access we apply count data models (Poisson, negative binomial) to examine factors that influence the number of applications that farmers adopt to solve problems in two major areas of constraint in the organic farm business, production and marketing. Objectives of this study are:

1. To examine factors that influence internet adoption among US organic farmers;

2. To examine factors that influence the intensity of use of the internet and the portfolio of applications for marketing and production management.

In the chapter II, we present a review of literature on internet adoption and use among farm businesses. We discuss theoretical models of adoption and use by organic farmers in chapter III. In chapter IV we discuss estimation procedures and present results in chapter V. Chapter VI summarizes the findings, conclusions and recommendations.

CHAPTER II

LITERATURE REVIEW

Characteristics That Affect Adoption and Use of Internet

A number of studies have examined adoption of computer technology in agriculture. But there is not much literature on adoption of Internet services and access. The literature on the same in regard to organic farmers is even more limited, making this an area of research need. It is envisaged that factors that are important for adoption of computer technology should also be important for the adoption of the internet since the two are closely related. Given scarcity of literature on adoption of internet applications, this study will borrow a lot from studies on computer adoption.

In the literature, factors that positively influence the computer adoption include education, farm income, having dairy and/or cotton as major enterprises, complexity of the farm business, and exposure to computer technology such as through peer networks or school going children. Conversely, the farmer’s age, leasehold form of land tenure, and livestock ownership, reduce the odds of computer adoption.

A number of authors including, Jarvis (1990), Batte, Jones and Schnitkey (1990) and Amponsah (1995) have examined computer adoption in conventional agriculture using survey data. Jarvis (1990) observed that among rice farmers in Texas, farm size, business complexity, number of peers with computer knowledge and the influence of children with computer knowledge increased the probability of computer adoption. Among Ohio commercial farmers, Batte, Jones and Schnitkey (1990) observed higher probability of adoption and more complex uses among younger and more educated farmers. Amponsah (1995) indicated that farm size, level of education and farm income increased the probability of computer adoption and usefulness among North Carolina.

Hoag, Ascough and Frasier (1999) surveyed farmers in the Midwest. They found that farm size and off-farm employment tended to increase the odds of computer adoption while farming experience (related to age), ownership of livestock and leasehold farm tenure negatively influenced computer adoption. Gloy and Akridge (2000) examined adoption of computer and internet use among commercial farmers in the US based on mail-in survey data. The authors concluded that higher education, and sophistication of management (complexity of the farm business) increased the probability of internet use while this probability declined with age.

In regard to internet access and internet use for business, Smith, et al.,(2004), studied the adoption of computers and internet technology among farmers in the Great Plains, based on farm survey data. Their results indicate that farm acreage, off-farm employment, exposure to technology through college education and family and friends increased the probability of internet connectivity on the farm and use of the same for farm business. On the other hand the probability decreases with age and off-farm income. Additionally, they find that family farms were more likely to consider the internet less beneficial on the farm, while farmers who used the internet to gather information on input prices of find commodity markets were more likely to consider it beneficial.

Mishra and Park (2005), used data from a national survey to analyze the level of internet use (number of uses) among US farmers. The authors found that educational level of the farmer, farm size (value of sales), farm complexity (diversification), off-farm investments, and some regional location variables to be significant factors positively influencing the number of internet applications. They find off-farm wage, to negatively influence the number of internet uses.

Previous studies have examined mostly regional computer adoption among US farmers. Nevertheless, studies on use of the internet are few as are studies on intensity of computer adoption (number of uses/applications). Moreover, studies on intensity of internet adoption are even fewer and there are no documented studies on computer or internet adoption or intensity of adoption among US organic farmers. This study makes a contribution to existing research by focusing on access and use of the internet among organic farmers in the entire contiguous US. In the next section, we discuss some theoretical models of technology and internet adoption.

Models of Internet Adoption and Use

Organic farmers face a number of challenges particularly in their production and marketing processes, many of which are not encountered by conventional farmers. In regard to production organic farmers have to find innovative, organically acceptable and financially efficient ways of managing pest and diseases (including diversification), controlling weeds, meeting high costs of inputs and labor, accessing seeds and organic stock, and reducing production losses due to weather changes (Waltz, 2004). In the marketing arena, organic farmers unlike their counterparts in conventional agriculture, have to work harder (and often pay more) to find information on prices, premium and stable product prices and marketing networks. They also have a harder time locating and accessing existing markets, supplying longer distant markets, finding new markets and dealing with unverified organic labeling. Organic farmers have to deal with high organic certification costs and meeting certification requirements (Waltz, 2004). Organic farmers therefore stand to benefit more from efficiency and cost effectiveness that should come with increase internet use for information seeking, exchange of ideas, sale of products, and purchase of inputs.

Any attempt to understand internet access and use among organic farmers must follow the beaten path of adoption of innovation and outside agriculture. Adoption studies try to answer questions like: why do people choose, and continue to use a specific innovation over time; and, why would there be repeated choice and use of one innovation while another is selected (used) only a limited number of times?

Generally economists agree that the decision to adopt an innovation is based on underlying unobservable utility (benefits) of using the technology vis-à-vis the existing scenario. Adoption can be measured at the individual or aggregate/regional level. At the farm level, the farmer chooses the technology or set of technologies they perceive most likely to maximize the expected gains subject to certain factors or explanatory variables. Commonly used explanatory variables, include economic factors, physical factors and the demographics of the farm and socioeconomic characteristics of the farmer.

Traditional research on adoption on innovation focused on the discrete choice to use/not use a technological innovation. Ruttan (1996) argues for focusing on frequency of use and the complimentary nature of related innovations, to enhance understanding of adoption and diffusion of new technology.

Feder, Just, and Zilberman (1985), documented a literature survey of more than 70 studies on adoption and use of agricultural innovations. The authors observed key indicators of adoption to include: the discrete decision to use/not use an innovation, the duration of continued use (how long the technology has been used), and the intensity of use (proportion of farm on which input is applied, or amount of input applied per acre, etc).

A number of adoption studies have focused on adoption and intensity of adoption of individual technologies, often using the probability of adoption as the dependant variable, and trying to identify factors that significantly affect that probability. Probit, Tobit and logit models have been commonly used in this regard (Gloy and Akridge, 2000; Smith et al., 2004; Hogh, Ascough and Frasier, 1999; Putler and Zilberman, 1988).

Conversely, count data models have been applied in the more advanced aspect of measuring adoption - modeling the intensity of use. The negative binomial and the Poisson are the common types of models, being preferred because of their usefulness in measuring degree or intensity of use of a technology (Mishra and Park, 2005; Lohr and Park, 2002).

Smith et al. (2004) applied a multinomial logit (MNL) model to study the adoption of computers and the internet. The MNL model entailed a four alternative-outcomes dependant variable representing levels of adoption and use of the computer and the internet on the farm: no PC, PC but no internet, internet used but not for farm business, and internet used for farm business. Where there are a few but more than two alternatives/groups to choose from, the MNL is a common model of choice. But in situations where the decision maker is faced with more than a few alternatives, count data models like the negative binomial and the Poisson come in handy.

Lohr and Park (2002) used a negative binomial model to examine factors that influenced the number of insect pest management practices adopted by organic farmers, based on the 1997 OFRF national survey data. They found that farmers with college level of education, smaller farm size, larger proportion of farm in horticulture, and experience with organic production methods, were more likely to be adopters.

The application of count data models has made studying factors that determine intensify of use easier. Unlike binary variable models that are based on a yes/no scenario, count data models support estimation where there are degrees of use. In such cases, levels of adoption can be examined using such methods as the negative binomial or Poisson regression.

McWilliams, et al. (1998) used count data (Poisson, generalized negative binomial and the geometric) regression models to estimate the time to adoption of computer technologies in California.

Park and Mishra (2005) used data from a national survey and a negative binomial model to analyze the level of internet use (number of uses) among US farmers. The authors found educational level of the farmer, farm size, farm diversification, of-farm income, off-farm investments, and regional location of the farm to be significant factors influencing the number of internet applications. They found off-farm wage to reduce the number of uses adopted and suggested that farmers with larger off-farm wages were likely to be small and medium sized farmers majoring on less complex farming enterprises. This group of farmers would least benefit from the sophisticated management supported by computer and internet technology.

CHAPTER III

THEORETICAL MODELS OF INTERNET ADOPTION AND USE

From a theoretical perspective the decision to use an innovation or not; or to use one innovation (or level of innovation) as opposed to another, can be viewed as being driven by the desire to maximize marginal utility that a farm/farmer gains from the choice. Thus an innovation is adopted only if the adopter perceives it to add value. Utility can be viewed as an unobservable index determined by a set of explanatory variables that an individual uses to rank a set of decision alternatives. The set of explanatory variables includes farmer attributes (F), such as age, education, off-farm work and farm characteristics (H), such as farm size, farm income, and dummy variables for major farm enterprises among others.

Given the unobserved nature of utility, it can be treated as a random variable, and the choice decision involved can be analyzed using a “random utility model” (Green, 2000). An alternative and simpler way of looking at the problem is to bear in mind that the unobserved utility index (and by implication the decision to adopt an innovation) is dependant on the set of (explanatory) variables. Thus, we can (more directly), model the probability of adoption instead of the unobserved index. Because it is unobserved, utility is treated as a random variable, and the multi-choice decision involved is analyzed using a random utility model. To evaluate the probability that a farmer will decide on one alternative based on the set of explanatory variables, we envisage an indirect net benefit function where the net benefit depends on a vector of the farmer's personal attributes, F (age, education, off-farm work) and a vector of farm characteristics, H (farm size, farm income, major enterprise).

The Internet Adoption Model

Following Green (2000) the indirect utility function for a typical farm can be expressed as:

(0.1) $V_1 = \beta_1^{'} X + \varepsilon_1$ and $V_0 = \beta_0^{'} X + \varepsilon_0$,

where V_i is the unobserved net benefit for the ith choice (i=1 for adoption or i=0 for non adoption); X is a vector of characteristics of the farmer (H and F); β is a vector of parameters to be estimated; ε_i is a vector of error terms. A farmer chooses alternative 1 if it gives the most unobserved benefits. Equation 1.1 can be simplified as:

$$V = (V_1 - V_0) = (\beta_1^{'} X + \varepsilon_1 - \beta_0^{'} X + \varepsilon_0)$$

(0.2) $$V = (\beta^{'} X + \varepsilon)$$.

If we assume that ε has a logistic or normal distribution with mean 0 and variance 1, we can denote the observed choice variable y, such that:

(0.3) $y=0$ if $V\leq 0$ and $y=1$ if $V>0$

Then, the probability that the farmer will choose the innovation (Prob(y=1)) can be presented as:

$$
\begin{aligned}
\Pr ob(y=1) &= \Pr ob(V_1 > V_0) = \Pr ob(V>0) \\
&= \Pr ob(\beta_1^{'}X + \varepsilon_1 - \beta_0^{'}X - \varepsilon_0 > 0) \\
&= \Pr ob((\beta_1^{'}X - \beta_0^{'}X) + (\varepsilon_1 - \varepsilon_0) > 0) \\
&= \Pr ob(\beta^{'}X + \varepsilon > 0). \\
&= \Pr ob(\beta^{'}X > -\varepsilon) \\
&= \Pr ob(\varepsilon < \beta^{'}X)
\end{aligned} \tag{0.4}
$$

If the distribution is symmetric (e.g. normal), then,

$$\Pr ob(V>0) = G(\beta^{'}X) \tag{0.5}$$

Where $G(\beta^{'}X)$ is the cumulative distribution function (cdf) of the error term ε in equations 1.2 and 1.4. A linear probability model can be assumed but it has the shortcoming that the error terms are heteroscedastic, and the predictions from the model can not be constrained to the 0-1 interval. The common practice is to assume a standard normal distribution or a logistic model (Amponsah, 1995; Batte, Jones and Schnitkey, 1990, Jones and Schniketly, 1990; Jarvis, 1990); Hoag, Ascough and Frasier, (1999)). The normal distribution results in the probit model, but the logistic model is often preferred because of its mathematical convenience. If we follow the logistic model path, then:

$$P = \Pr ob(y = 1 | X) = \Lambda(\beta' X)$$
$$= \frac{1}{1 + e^{-\beta' X}} = \frac{e^{\beta' X}}{1 + e^{\beta' X}} \tag{0.6}$$

Where, P is the probability of adoption and $\Lambda(\beta' X)$is the cumulative density function. Equation 1.6 reduces to the:

$$\frac{P}{1 - p} = e^{\beta' X}, \tag{0.7}$$

where $\frac{P}{1-P}$ is the odds ratio in favor of adoption of the innovation. Since equation 1.6 and 1.7 are nonlinear, the parameters can be estimated by maximum likelihood.

The Internet Use Model

Survey data (Waltz, 2004) indicates that rates of internet access are higher than rates of internet use for business. Unlike computer adoption, the internet is a non-capital technology and not a fixed cost. The technology does not require replacement, as service upgrades are provided by the internet service provider (ISP). Once access has been realized, the marginal (additional) costs of using the internet for business are small. These costs are normally limited to the cost of learning how to access the relevant sites and any fees charged by those sites, most of which come free of charge. Equally, the marginal cost of adding an extra application to an existing package or portfolio of uses is also small. This suggests that internet adoption (access) and use are not joint decisions. We envisage that business uses are added to an existing portfolio only if they increase profitability/efficiency of the business. We hypothesize that internet applications are jointly chosen according to their contribution to the overall profitability of the farm business.

Once the decision to adopt a technology has been made, selection of a given application, of the technology, is related to others already adopted and others yet to be adopted (Park and Lohr, 2005). In the final analysis, the portfolio of applications selected is the choice set that maximises the net benefits. Analysis of intensity of use helps us explore factors (farmer/farm characteristics and environmental variables) that contribute to the level of intensity of internet use among American organic farmers.

Count data models can by design be useful in explaining determinants of the intensity/level of adoption (as measured by the number of applications) of technology. The Poisson and the negative binomial are count data models that have been used widely in modelling levels of events (Hausman, Hall and Griliches, 1984; McWilliams, et al., 1998; Park and Lohr, 2005; Mishra and Park, 2005).

We estimate the intensity of internet use for supporting marketing and production operations among organic farmers using a Seemingly Unrelated Poisson (SUP) model. Seemingly unrelated regression estimation (SUR) approach best fits the way we think organic farmers make decisions about the number and type of applications to use in the farm business. As hypothesized earlier, we view internet uses as being jointly chosen according to their contribution to the overall profitability. Using the SURE approach, we can treat the adoption decisions for marketing and production (management categories or types of uses) as interrelated. We can then examine the relationship among the two categories (marketing and production) by allowing some of the variables to vary across the categories.

The basic SUP model (Hausman, Hall and Griliches, 1984) derives from a multivariate Poisson with n_{ij} as the observed event count for individual (farm) i and use category j (j=1,…, J). From the moment generating function of a Poisson ($m(t) = e^{-\lambda} e^{\lambda e^{t}}$), each count is independently distributed with equal mean and variance, $En_{ij} = Var(n_{ij}) = e^{X_{ij}\beta} = \lambda_{ij}$, so that, $\log(\lambda_{ij}) = X_{ij}\beta$. The intensity parameter vector is λ_{ij} and X_{ij} is a vector of independent variables. It follows that the Poisson probability:

$$\Pr ob(n_{ij}) = \frac{e^{-\lambda ij} \lambda_{ij}{}^{nij}}{n_{ij\,!}} . \qquad (0.8)$$

In the event of over-dispersion, the variance could be larger than the mean, resulting in a Negative Binomial Distribution (NEGBIN) and estimation of a Seemingly Unrelated Negative Binomial (SUNB) model. Following Hausman, Hall and Griliches (1984) and Mishra and Park (2005), we introduce this possibility by assuming the intensity parameter λ_{ij} is follows a gamma distribution with parameters(γ, δ), where $\gamma = e^{Xij\beta}$ and δ is common across all farms and categories. The mean and variance of the parameter, λ_{ij} are $E\lambda_{ij} = e^{Xij\beta} / \delta$ and $Var(\lambda_{ij}) = e^{Xij\beta} / \delta^2$. Integrating the gamma distribution by parts, we get the NEGBIN with (γ_{ij}, δ) as parameters:

$$(0.9) \qquad \Pr ob(n_{ij}) = \int_0^{\infty} \frac{1}{n_{ij}!} e^{-\lambda ij} \lambda_{ij}{}^{nij} f(\lambda_{ij}) d\lambda_{ij} \,,$$

where $f(\lambda_{ij})$ is the probability density function (pdf) of the intensity parameter vector. The mean and variance of n_{ij} are now, $En_{ij} = e^{Xij\beta} / \delta$ and $Var(n_{ij}) = e^{Xij\beta}(1+\delta)/\delta^2$ respectively. It follows that the variance to mean ratio is $Var(n_{ij}) / E(n_{ij}) = 1 + \delta / \delta > 1$ which represents over dispersion of the NEGBIN with the Poisson as a space case (as $\delta \to \infty$). Equation 1.9 can be solved and the parameters estimated by maximum likelihood procedure. The next section we choose between the SUNB and the SUP and estimate the logistic regression and the count data model.

CHAPTER IV

EMPIRICAL ESTIMATION

Data and Methods

The research data we used are from the Organic Farming research Foundation's (OFRF) Fourth National Organic Farmer's Survey conducted in May 2002. The 22-page mail-in survey was the fourth among organic farmers, three others having been conducted in 1993, 1995 and 1997. The survey sought information about the farmers, their farms and farm farming operations in the 2001 production year. In the survey, 6,487 certified organic farmers throughout the US were asked for information on a wide variety of issues affecting organic farmers. Of the surveys that were sent out, 1,185 were returned, representing a response rate of about 18%. We found sufficient detail to test our models in about 745 of the surveys as many observations had missing values for one variable or another.

This was the first OFRF survey to focus on marketing information including internet access and use of internet services. The survey also collected data on farmer attributes and farm characteristics. Farm manager/operator attributes included age; education (years of schooling), off-farm employment. Farm characteristics included farm size, farm income, major farm enterprises, type of farm ownership, and region among others. Other questions related to production, marketing, information services and future plans. The survey results indicated that about 22% of all respondents had no internet access compared to 78% who had access either at home or farm and 6% who had a convenient access to the internet away from the home or farm.

In regard to the internet, respondents were asked about the frequency of use for nine services including checking the weather, reading/looking for farming news, looking for organic product information, communicating with other farmers, looking for market information, buying farm inputs and seeds, and selling organic produce. We used responses to these questions to construct dependant variables for our models. The use decision was defined as the number of services chosen adjusted for frequency of use. The wide geographical coverage of the survey (reaching over 90% of organic farmers in US), and the range of issued addressed is such that it provides a valuable database for research. Table 4.1 presents a summary of the variables and their descriptive statistics.

Table 4.1: Variable Description and Summary Statistics

Variable	Description	Mean	SD
ADOPT	1 if internet access available at home, work or elsewhere	0.82	0.38
NUMAPPS	Total number of internet applications for business	2.81	2.31
MAKDEX	Number of internet applications related to marketing	1.01	1.07
PRODEX	Number of internet applications related to production	1.80	1.48
FARMSIZE	Farm six (acres)	311.09	1031.60
HORTDIS	Share (%) of horticultural crops fruits and vegetables sold outside local area (>100 miles from home)	8.55	18.00
DIR_MKT	1, if direct marketing is set to increase in future	0.27	0.45
DIS_MKT	1, if distant marketing (at least 100 miles) is set to increase in future	0.45	0.50
HORTLAND	Share(%) organic acres put to fruits and vegetables	54.88	47.11
MKTPROB	Extent of Marketing Problems (sum of Q41)	0.70	1.20
	Finding any market		
	Finding organic markets		
	Finding access to existing markets		
	Lack of organic price information		
	Distance to available organic market/point of delivery		
PRODPROB	Extent of Production Problems (sum of Q41)	0.82	0.97
	Weather related production losses		
	Pest related production losses		
	Weed related production losses		
	Fertility related production losses		
	Finding organic production seed stock		
SOLEPR	1 if farm ownership is “single family-sole proprietor”	0.72	0.45
EDUCOL1	Education: 1 if operator has Junior College/Some College /Trade school education and above	0.66	0.47
GORINC	Gross Organic Farming Income, 4 if $15000 to $29999	4.39	2.10
YRSORFAM	Years of organic farming	12.22	9.54
FARFULT	Off-farm employment: 1, if fulltime farmer	0.66	0.47
ONAGSCO	Online Agriculture Score; percentage of farmers with Internet access and who use computers for business.	3.45	0.74
DIVINDEX	Theil’s diversity index based on farm sales	0.03	0.06

Note: N=745

The Dependant Variables

The dependant variable for adoption, ADOPT, was created based on Question 47 of the survey, “Do you currently have access to the internet? If so, is this access at home or farm, or do you have convenient access elsewhere?” All farmers that indicated having access to the internet (at home or away) were labeled “adopters” (ADOPT=1) while the rest were labeled “non-adopters”(ADOPT=0). In the survey, 78% of the respondents had access while 22% did not. The final dataset we used for analysis had slightly different ratings, with adopters forming 82% of the sample – this was due to the presence of missing values in the data and subsequent reduction of the sample size.

For the “intensity of use” model, the variable NUMAPPS was used as the dependant variable. Once internet adoption has been realized, the marginal cost of adding an application is equal to the cost of learning how to access the sites and any fees charged by those sites. This indicates that on average (except where the cost of adding an application is zero), business uses are added only if they are perceived to be useful to the farm profitability or efficiency. Thus internet adoption and internet use are considered different, not joint, decisions. We hypothesize that internet uses are jointly chosen according to their contribution to the overall utility.

Organic farmers who used the internet for a specific application at least once a month were identified as “users” and given a score of one, while the rest were identified as “non-user” and given a score of zero. Based on the responses to question 48 of the survey, we created an index (variable NUMAPPS), to represent the number of frequently used applications per farm. There were three marketing related applications namely, “sell your organic farm product(s)”, “check conventional market information”, “look for organic market information”. Four production related applications were listed namely, that is, “check weather”, “purchase seed”, “purchase other farming inputs”, and “look for production information”. The maximum score (value of NUMAPPS) a farm could attain is seven and the minimum is zero. Table 4.1 shows that organic farmers frequently used about 3 applications; about 2 related to production management and about 1 related to marketing. Comparing, at face value, the number of marketing and production related uses reported by the farmers may be misleading since this may depend on the number of applications listed in the questionnaire for either category (four for production and three for marketing).

Independent Variables

The wide range of farmer and farm data provided by the survey enabled us to examine the effects of a relatively wide range of characteristics on adoption and use of internet technology. As observed earlier, organic farmers operate under circumstances that seem more constrained than their conventional agriculture counterparts. This makes them more likely candidates for adoption and more intensive use of the internet.

Although there is scarcity of literature on internet adoption even among conventional farmers, we imagine that in general farm environment characteristics and farmer attributes that impact on adoption of one farm technologies are likely to impact on another at least to some extent. We also imagine that factors which have been shown to affect adoption of PC technology among farmers are most likely to impact on farm internet adoption.

In literature, key factors affecting technological adoption include income, farm size, and farmer/farm operator education level, and the ability to network and share knowledge and experience with other adopters. In the 2001 production year, the average organic farmer’s gross organic farm income (GORINC) was between $15,000 and $29,999, which compares them with small conventional farmers (Lohr and Park, 2002; USDA, 2005).

Generally, larger (higher income) farmers have been shown to adopt computer and internet technology ahead of their lower income counterparts (USDA, 2005). Higher revenues minimize impact of risk as the farmer experiments with new innovation

(Park and Lohr, 2005) and also probably because larger (richer) farmers have more discretionary income to allocate to internet service provider (ISP) fees. Once adoption has taken place however, factors other than income may become more important in expanding the farmer's internet application portfolio as monetary costs become more or less constant irrespective of the size of the portfolio.

Farm complexity as evidenced by, say, diversity of enterprises is likely to drive up the need for internet technology adoption (Jarvis (1990); Gloy and Akridge, 2000; Mishra and Park, 2005) in order to increase efficiency and reduce operation costs. We applied an entropy index (Theil, 1972, cited by Mishra and Park, 2005) to measure diversification, and by implication the complexity, of the farm. The index (DIVIDEX) takes a value of 1 when the farm is highly diversified and 0 when it is a single enterprise.

A simple measure of complexity would be the share of farm business taken by enterprises requiring intensive management such as horticultural crops. These high value, management intensive commodities often require more complex information, faster decision making and ready markets, areas in which the internet would come in handy. The variable, HORTLAND, measures the share of organic farm acres put to fruits and vegetables. We anticipate that horticulture farmers are likely to have higher adoption rates.

The average size of farms in the survey is about 311 acres. In line with the literature, we expect the effect of farm acreage (FARMSIZE) to be similar to that of diversity and income and therefore increase the probability of adoption (Amponsah, 1995; Jarvis, 1990; Hoag, Ascough, and Frasier, 1999; Mishra and Park, 2005) as well as the size of the portfolio of applications.

It is generally understood that education provides the human capital element that is required for comprehension and adoption of new technology. We postulate that higher levels of education are likely to increase adoption and intensity of use (Batte, Jones and Schnitkey, 1990) and use the variable, EDUCOL1 (1 if operator has Junior College/Some College/Trade school education and above), to represent education in our model.

The extent of exposure to a technology as may come through a network of friends, family, colleagues, etc, should also drive up adoption and use of the internet (Jarvis, 1990; Gloy and Akridge, 2000). We include in our models the variable, ONAGSCO, a state by state index that measures the “State New Economy” (Atkinson, 2002). The index is a good measure of the internet use, access among farmers and networking effects. The literature shows that regional variables are often significant in their effect on technology adoption (Lohr and Park, 2002; USDA, 2005), with some regions doing better than others. This variable ONAGSCO should perform better, than, and may be correlated with, regional dummy variables that have been used in the literature to capture similar effects.

Farmers with off–farm employment may be more likely to adopt the internet away from the farm (Hoag, Ascough, and Frasier, 1999), since off-farm work offers them access to the internet. Conversely, farmers with off-farm work may be less likely to adopt the internet at the farm, but more likely to adopt internet technology nevertheless. Considering the conflicting evidence in regard to computer and internet adoption (Mishra and Park, 2005), it will be interesting to see what our analysis reveals. Our variable, FARFULT takes a value of 1 if the farm operator is a fulltime farmer, and zero otherwise.

It is conceivable that age could have a decreasing effect on the odds of technology adoption (Gloy and Akridge, 2000). Older farmers may not find it profitable to learn enough on internet use to be able to derive the potential benefits. They may also not be as exposed or as quick to learn so that their cost of learning new innovations may be higher than those of younger farmers. Besides, younger people are more likely to have more exposure to the internet at school or at work, so that age may be inversely related to adoption. One attribute that may conflict with age is experience. Farming experience often comes with time spent on the farm which older farmers (less likely to adopt) are more likely to have (more likely to adopt). We use a variable related to age, YRSORFAM (years of organic farming), and although we expect it to be positively related to internet adoption, we would not be surprised if it turned out to be negatively related.

The nature/form of business ownership is likely to hinder or enhance internet adoption. Leasehold farms for example have been found to experience lower likelihood of adoption of the computer (Hoag, Ascough, and Frasier, 1999). As is the case with leasehold farms, we envisage a priori that “single family –sole proprietorship” (SOLEPR) would negatively influence internet adoption and use, as this form of ownership may signal lack of complexity, small size of the farm and therefore the likelihood of underestimating the usefulness of the internet technology or underutilising the same.

Organic farmers surveyed by OFRF were asked about problems they encounter in their farming endeavors. The variable that captures their responses is MKTPROB, which is the sum of score of marketing problems in one of the questions (Q41) of the survey. In the survey specific issues facing organic farmers (such as obtaining organic price premium), were ranked in order of severity of problem from 1 to 5, with 1 denoting “not a problem” and 5 denoting “severe problem”. We re-ranked the entries thus, 0 if the farmer’s answer was “not a problem”, or “slight problem”; and 1 if it was, “moderate problem”. We then summed up to create an index of the perceived marketing problem. We followed the same procedure to create, PRODPROB, a measure of sum of score of production problems in survey Q41. We envisage that farmers a higher score (greater marketing or production problem) are more likely to use the internet to find solutions to their problems, which would increase adoption.

In addition to the aforesaid variables we have included the percentage variables to measure “if direct marketing is likely to increase in future” (DIR_MKT) and a variable to measure “if distance (100 miles from farm and above) marketing is likely to increase in future”.

The variable HORTDIS, measures the share of horticultural produce sold at least 100 miles from the farm. Together with DIR_MKT and DIS_MKT, This measure of the geographical extent of farm markets is important since one of the problems cited by organic farmers is lack of product markets close to the farm and their use of the internet to find distant markets. We postulate that farmers serving a larger share of long distant markets, and farmers that are likely to increase distant and direct marketing are more likely adopters of the internet.

Empirical Model of Adoption

Most studies on adoption and use of technological innovation have viewed the decision to adopt innovations as a dichotomous choice. The most common practice has been to examine the basic question of whether technologies are adopted or not. But in order to fully understand adoption and diffusion of the innovation, research needs to focus on additional aspects including intensity of use and the extent to which closely related innovations are complementary. This research addresses these questions in regard to adoption and use of the internet among US organIC farmers. An important contribution is to examine factors that contribute to internet adoption at the farm/farm operator level. The effect of policy and investment changes on adoption can then be predicted.

In estimation, equation 1.7 can be linearized (in X’s and the parameters) by taking the log of the odds ratio (the logit):

(4.1) $$L = \ln\left(\frac{P}{1-P}\right) = \alpha_0 + \sum_i \alpha_i X_i$$

where L is the logit, the αs are parameters to be estimated; X is the set of explanatory variables, including Farm and farmer (F) and environmental (H). The variables included FARMSIZE, HORTDIS, DIR_MKT, DIS_MKT, HORTLAND, MKTPROB, PRODPROB, SOLEPR, EDUCOL1, GORINC, YRSORFAM, FARFULT, ONAGSCO, and DIVINDEX. The aforesaid equation was estimated by maximum likelihood, using LIMDEP software (Green 2002).

The goodness of fit of the model can be tested using a number of R^2 measures including the Pseudo-R^2, McFadden R^2 and the Likelihood ratio test (Green, 2002; Green 2000; Gujarati, 2003). Empirical studies indicate the statistic normally lies between 0.2 and 0.4(Sonka, Hornbaker and Hudson, 1989; cited by Jarvis, 1999). The McFadden R^2 can be represented as:

(4.2) $$R^2_{MF} = 1 - \frac{L_{ML}}{L_0}$$

Where R^2_{MF} is the McFadden R^2, L_{ML} is the maximum value log likelihood function, and L_0 is the value of the log likelihood function when all coefficients (except the constant)are set to zero.

The Likelihood ratio chi-square examines if the model performs better than an alternative with the constant as the only independent variable. A value of 0.05 or less causes rejection of the null hypothesis that there is no difference between the observed and predicted values of the dependent variable. With a value greater than 0.05, we fail to reject the null hypothesis, and conclude the model estimates fit the data at an acceptable level.

Probably the simplest yet quite important measure of goodness of fit is the percentage of correct predictions that the model is able to make about.

One way of interpreting the coefficients of the logit model is simply in terms of the sign on the variable. Thus a positive sign would imply that increasing the level of the independent variable would likely have and increasing effect on the probability of adoption and vis versa. A more technical way is to calculate the “marginal effects”, that is, change in probability of adoption given a change in the characteristic (independent variable) in question. Marginal effects or probabilities are normally calculated at the means, and for continuous X variables. For discrete independent variables, what is more appropriate is the “probability difference” between the scenario with the variable and one without the variable (Green, 2002).

Empirical Intensity of Internet Use Model

The SUP adoption portfolio model was estimated by maximum likelihood using LIMDEP software. We applied the same as independent variables - farm and farmer characteristics and farm environmental factors - as the adoption model. We envisage that a number of farm and farmer attributes including farm size, income, education and state online agriculture score would be the same for both categories (marketing and production). We expect that the remaining characteristics would vary across the categories. Empirically the equation estimated was of the form:

(4.3) $$\ln(NUMAPPS_i) = \alpha + \beta' F_i + \phi' H_i \,.$$

Where, $NUMAPPS_i$ represents the number of frequently used internet applications for farmer i for a given category of use (production or marketing), F_i represents farm/farmer attribute variables, H_i represents variables related to the environment of the farm, and α, β and ϕ are parameters to be estimated.

The second step was to test for over-dispersion, so as to determine the appropriate model between the SUP and SUNB. Following Winkelmann (2000) and Cameron and Trivedi(1990), the test for mean-variance equality is:

(4.4) $$\begin{aligned} H_0 &: Var(n_{ij}) = \lambda_{ij} \\ H_1 &: Var(n_{ij}) = \lambda_{ij} + \alpha.g(\lambda_{ij}) \end{aligned}$$

Where, $g(\lambda_{ij})$ is a specified function that maps from R^- to R^+. The test for over/under-dispersion is essentially a test for $\alpha = 0$. Rejecting the null hypothesis implies the Poisson is an inadequate fit for the data. Another way of testing for the relevance of the Poisson is to use the deviance and Pearson Chi-square statistics outputted by “SAS” software. A value of either statistic, divided by the degrees of freedom, greater than 1 indicates over dispersion, while values less than 1 indicates under dispersion. Either scenario suggests the Poisson is an inadequate fit for the data.

If the mean-variance equality hypothesis fails, one has to estimate the SUNB or the robust SUP. Either of these takes to account of any deviation of the mean from the variance (over/under-dispersion). The robust Poisson is particularly useful when the NEGBIN becomes inestimable, and the iterations converge without finding a satisfactory solution as it occasionally happens (Green, 2002).

The Wald statistics is used to test whether the coefficients are the same across the two management categories. We hypothesize that a number of variables have The hypothesis that that the variable has a similar influence on the number of internet applications across the two management categories is rejected if the Wald static exceeds the 5% chi-square critical value of 3.84.

CHAPTER V

RESULTS AND DISCUSSION

Results of the Adoption Model

The adoption decision was analyzed using a binomial logit model with farm/farmer characteristics and environmental variables outlined earlier as independent variables. The results are as provided in Table 5.1. The model diagnostics are reasonable for a discrete dependant variable model with McFadden R^2 of 14%, a likelihood ratio of 98.687, and 82% correct predictions.

The results of the adoption model indicate positive and significant (at 5%) signs on education at or above junior college (EDUCOL1), direct marketing (DIR_MKT) and acreage share of horticulture (HORTLAND). They indicate negative and significant signs on farming experience (YRSORFAM), full time farming (FARFULT), and sole proprietorship of the farm (SOLEPR). The other factors did not have significant signs, implying they did not significantly influence internet adoption.

Table 5.1: Logistic Regression Model for Internet Adoption

Variable	Coefficient	Wald Statitic (Coefficient)	marginal effects	t-value (marginal effects)
Constant	0.278	0.453	0.035	0.454
FARMSIZE	0.000	0.063	0.000	0.063
EDUCOL1	1.082**	5.195	0.154**	4.793
YRSORFAM	-0.027**	-2.623	-0.003**	-2.604
FARFULT	-0.607*	-2.418	-0.072**	-2.591
SOLEPR	-0.611*	-2.355	-0.070**	-2.614
GORINC	0.115	1.888	0.015	1.899
ONAGSCO	0.164	1.197	0.021	1.201
DIVINDEX	1.293	0.774	0.163	0.773
LOCHVMKT	0.004	0.538	0.000	0.538
DISMKTI	0.397	1.519	0.047	1.628
DIRMKTI	0.628**	2.790	0.078**	2.850
HORTLAND	0.008**	3.422	0.001**	3.470
MKTPROB	-0.135	-1.570	-0.017	-1.575
PRODPROB	0.017	0.154	0.002	0.154
McFadden R^2	0.138			
Likelihood Ratio			98.697[p-value 0.000]	
Proportion of correct predictions			0.821	

Note: N=745; **, implies significant at 1% level; *, implies significant at 5% level

All other factors yield positive but not significant signs except the extent of marketing problems (MAKTPROB) which carries a negative sign.

In regard to education, our results are in line with those of past studies on adoption of new innovations in general including computers (Batte, Jones and Schnitkey, 1990; Lohr and Park, 2002) and internet technology in particular (Mishra and Park, 2005) and suggest that the farmers with higher levels of education are likely to adopt internet technology than those with lower levels of education, holding other factors constant. This underscores the importance of a certain level of human capital development be open to new innovations and to take advantage of what the internet has to offer. It may probably also display the positive introductory effect that exposure to information technology at school has on internet adoption.

The positive and significant sign on DIR_MKT is as expected. If a farmer is planning on increasing direct marketing in the near future, they are likely to be on the lookout information on how to better serve their clientele – the internet is one place to find that kind of information. Moreover, by definition these category of farmers are more likely to be open to new ways of doing things including using the internet.

The positive and significant sign on HORTLAND suggests that farmers with increased share of farmland allocated to horticultural crops are more likely to adopt internet technology than non-horticultural enterprises. These results agree with Lohr and Park (2002) in their study on adoption of pest management practises. The complexity of horticultural production underscores the need for more intense management; the internet is a tool that may provide a bridge to acquisition of this knowledge.

The complexity of horticultural production underscores the need for more intense management; the internet is a tool that may provide a bridge to acquisition of this knowledge.

The negative effect of full time farming (FARFULT) on internet adoption was not entirely unexpected – this is in line with Hoag, Ascough, and Frasier (1999) and Batte, Jones and Schnitkey(1990), who found off-farm employment likely to increase adoption. Full time farmers may have less exposure to the internet than their counterparts with off-farm employment as the latter are likely to get more exposure to the internet and therefore opt for adoption, holding other things constant.

People who have been doing organic farming longer are less likely to adopt the internet as evidenced by the negative and significant sign on YRSORFAM. The literature seems to support the view that people with longer term farming experience are more likely to adopt new innovations (Lohr and Park, 2002). It may be that YRSORFAM in our data is quite like age (Gloy and Akridge, 2000), so that farmers with more farming experience are entrenched in their ways and not as open to try new innovations.

The negative and significant (at 5%) sign on SOLEPR implies that farms under sole proprietorships are less likely to adopt the internet, holding other factors constant. This is unlike some studies (Lohr and Park, 2002; Park and Lohr, 2005) where sole proprietorship was not found to significantly affect the number of applications of innovative pest management practices.

Results of the Internet Use Model

In regard to the internet use model, the deviation and Pearson chi-square statistics (divided by degrees of freedom) are 2.32 and 1.86 respectively. The value of alpha (equation 4.4) is 4.834 which is significant at the 5% level. The results of all three tests suggest we should reject the null hypothesis of mean-variance equality and take the SUNB or the robust SUP as the more appropriate approaches to analyzing our data. We opted for the robust SUP model because of ease of attaining convergence in computation compare to the SUNB and the fact that a robust SUP would be just as efficient as a SUNB.

We specified the model to test whether the coefficients differed across the management categories, production and marketing. We allowed a number of variables (DIVINDEX, HORTLAND, DIS_MKT, DIR_MKT, HORTDIS, MKTPROB and PRODPROB)to differ across the two categories and used the Wald test to test the hypothesis the variable has a similar influence on the number of internet applications used in the categories. The Wald static exceeds the 5% chi-square critical value of 3.84 for all the aforesaid variables except DIS_MKT and MKTPROB. This causes us to reject the hypothesis that the variable has a similar influence across the categories for all but these two variables. We fail to reject the hypothesis of similar impact for DIS_MKT and MKTPROB. Coefficient estimates and asymptotic t-values for the models of the two management categories namely marketing and production are presented in table 5.2.

Among the uniform components of the internet use model, independent variables FARMSIZE and EDUCOL1 yield positive and signs, while YRSORFAM and SOLEPR yield negative and significant signs at 5% level. The variable FARFULT yield a positive an not significant sign, while GORINC and ONAGSCO yield negative but not significant sign.

Increasing farm acreage (FARMSIZE) increases the number of internet applications, all things equal. This is in line with other studies on computer (Amponsah, 1995) and internet use (Smith, et al., 2004; Mishra and Park, 2005; and USDA, 2005).

Table 5.2: Determinants of Internet Use, Seeming Unrelated Poisson Model Results

Variable	Same for both equations	Marketing Applications	Production Applications	Wald Statistic[a]
DIVINDEX		-0.035(-0.063)	1.453(4.055)**	5.31*
HORTLAND		-0.002(-3.046)**	0.002(3.410)**	25.73**
DIS_MKT		0.069(0.869)	0.058(0.848)	0.010
DIR_MKT		0.156(2.148)*	0.293(4.762)**	2.210
HORTDIS		0.006(2.960)**	0.002(1.417)	2.150
MKTPROB		-0.006(-0.193)	0.013(0.547)	0.250
PRODPROB		0.001(0.023)	0.107(4.057)**	6.43*
FARMSIZE	0.000(2.543)*			
EDUCOL1	0.273(5.006)**			
YRSORFAM	-0.007(-2.435)*			
FARFULT	0.051(0.900)			
SOLEPR	-0.181(-3.623)**			
GORINC	-0.002(-0.164)			
ONAGSCO	-0.033(-1.150)			
Constant	0.174(1.237)			

Likelihood Ratio	288.777(p-value 0.00)**
Deviation/df	1.86
Pearson Chi-square/df	2.32
Dispersion parameter alpha	0.2056(4.834)**

Note: N=745; Asymptotic t-values are in parenthesis; *, implies significant at 5%, **- implies significant at 1%; [c]critical value for Chi-square at 5% significance level (1 df) is 3.84.

As with the adoption model increased education (EDUCOL1) is expected to enhance the appreciation of the usefulness of the internet in farm management and increase the comprehension and use of information provided by the technology, hence result in increased use. These results agree with others such as Amponsah, (1995); Gloy and Akridge (2000) in regard to computer use and Mishra and Park (2005), and Smith et al. (2004) in regard to internet use.

On the other hand, farmers with longer organic farming experience (YRSORFAM) were likely to stick to a smaller portfolio of internet uses compared to their counterparts with fewer years of experience. The farmers in the sample had on average about 12 years of organic farming experience. This variable may reflect age as mentioned earlier. Farms managed by their owners are likely to be less complex and therefore less likely to underrate the usefulness of the internet hence adopting fewer applications. This may explain the negative and significant (at 5%) sign on SOLEPR, which agrees with Hoag, Ascough, and Frasier (1999) in a computer adoption study.

In regard to variables that were allowed to vary across management categories, marketing and production, the share of farmland planted with horticultural crops (HORTLAND) is significantly positively related to production management internet applications. The average farmer had about 55% of the farm under horticultural crops. Horticultural production is quite management intensive and innovative organic farmers may find the internet to useful in providing answers to daily operation questions like pest management and weed control.

On the other hand the share of farmland planted with horticultural crops (HORTLAND) is significantly negatively related to marketing management internet applications. This may suggest that farmers are quite efficient and find whatever marketing information they need with only a few applications.

Diversification of farm enterprises (DIVINDEX) is significantly positively related to production management internet applications. This agrees with the findings of Mishra and Park (2005). Organic farmers often need to diversity with intercropping and crop rotation being common strategies for pest and weed management. The more complex the farm the more likely farmers are to seek innovative solutions to production problems including on the internet.

The significantly positive sign on both production and marketing management applications on the likelihood of increasing direct marketing (DIR_MKT) is as explained earlier. Farmers looking into increased direct marketing are likely to be either planning on expanding their farm size or their scope of the market. Either way expanding the portfolio of internet applications seems the intuitive thing for such farmers.

The share of horticultural produce sold outside the local area (HORTDIS) is significantly positive, indicating as expected that distance marketing farmers use more internet applications for marketing management. Although the proportion of farmers engaged in distance marketing is small (only about 9%), this group of farmers will need more marketing information than their counterparts hence their use of more internet applications.

The extent of production problems the farmer is experiencing (PRODPROB) is significantly positive, which suggests as expected that the higher the level of production problems experience by the farmer the greater the number of production management internet applications they would use. Quite like complexity of the farm, production problems force farmers to become innovative and use all means at their disposal to safeguard their investment; the internet is one of these means.

Other factors variables such as DIR_MKT yield a non-significantly positive sign in both categories; MKTPROB yields a non-significantly negative sign in both categories; DIVINDEX and PRODPROB yield a non-significantly negative sign in the marketing management category; HORTDIS yields a non-significantly positive sign in the production management category.

CHAPTER VI

SUMMARY CONCLUSIONS AND RECOMMENDATIONS

Direct marketing has experienced tremendous growth among US organic farmers in the last decade making internet use in the farm business increasingly attractive. Nevertheless there exists limited analysis of adoption and use of the internet among organic farmers.

In this study we sought to examine factors that influenced internet adoption among US organic farmers and factors that influenced the intensity of use and the portfolio of internet applications for marketing and production management purposes. We applied a logistic model to national survey data of organic farmers to analyze adoption of internet technology. Additionally we applied count data (Poisson) models in the analysis of the intensity of internet use and the portfolio for production and marketing management among organic farmers. This study is unique in the use of national level data covering the 48 contiguous states, and application of count data models to analyze intensity of internet use.

The logistic model results indicate the level of education, the share of organic farmland allocated to horticulture, and the having plans to increase direct marketing of farm produce are associated with increased adoption of the internet among organic farmers. Conversely, full time farmers, farmers with greater organic farming experience, and farmers with sole ownership/ single family tenure are less likely to adopt the internet.

Findings of the analysis of the internet portfolio/intensity of internet use are similar to those of internet adoption. They indicate that the number of internet applications is positively and significantly associated with larger farms (acreage), future prospects of increasing direct marketing, and higher education of farm owners/managers.

Internet use portfolio includes both production and marketing applications for information seeking. Nevertheless organic farmers use the internet primarily for production information gathering. The results the Wald tests indicate that coefficient of most factors that influence internet use may not be the same across marketing and production management categories. The influence of the extent of marketing problems and the expectation of increasing direct marketing differ across the production and marketing categories. These results seem to support the SUR approach to analysis of the data.

In regard to production management farmers with more complex (diversified) operations, greater share of organic farmland under horticulture and facing greater production problems will seek to use more internet applications. On the other hand, in regard to marketing management, where a larger share of horticultural sales goes to distant markets, the farmer is more likely to increase the number of internet applications.

As organic farm acreage increases, it is expected that adoption and use of the internet will increase. This calls for organic farmer support groups including government agencies to increase availability and access of organic production and marketing information on the web as well as farmer awareness of these services. Marketing information such as organic price information remains difficult to find on the internet.

Organic farmers work under greater information constraints than those facing conventional farmers. Given the innovative nature of organic farmers, the higher levels of internet adoption and use among them, the cost effectiveness of providing and accessing information online, and the existing constrained environment under which organic farmers operate, there is room for increased efficiency and profitability through the use of the internet use for organic farm business.

The relevance of college level education to increasing internet adoption and intensity of use underscores the need for public agencies and non-profit organizations to provide continuing education to organic farmers particularly those with below college education to ensure that they benefit fully from the information available online. Future public research could focus on finding out how best to make the internet serve organic farmers including effective and affordable ways of providing them with on-time online information in support of organic farm business.

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APPENDIX

A1. The Logit Model Results

```
--> sample; All$
--> skip
--> LOGIT; Lhs = ADOPT2; Rhs = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT,
SOL...
    DIVINDEX, LOCHVMKT, DISMKTI, DIRMKTI, HORTLAND, MKTPROB, PRODPROB; Margin$

 *********************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now    745 *
 *********************************************************************

Normal exit from iterations. Exit status=0.

+---------------------------------------------+
| Multinomial Logit Model                     |
| Maximum Likelihood Estimates                |
| Model estimated: Nov 30, 2007 at 04:28:28AM.|
| Dependent variable              ADOPT2      |
| Weighting variable                None      |
| Number of observations             745      |
| Iterations completed                 6      |
| Log likelihood function      -309.1615      |
| Restricted log likelihood    -358.5101      |
| Chi squared                   98.69715      |
| Degrees of freedom                  14      |
| Prob[ChiSqd > value] =        .0000000      |
| Hosmer-Lemeshow chi-squared =   5.44277     |
| P-value=  .70937 with deg.fr. =      8      |
+---------------------------------------------+
+---------+--------------+----------------+--------+---------+----------+
|Variable | Coefficient  | Standard Error |b/St.Er.|P[|Z|>z] | Mean of X|
+---------+--------------+----------------+--------+---------+----------+
          Characteristics in numerator of Prob[Y = 1]
 Constant     .2779557084       .61319694     .453   .6503
 FARMSIZE  .8125316771E-05  .12852873E-03     .063   .9496     311.53534
 EDUCOL1      1.082380479       .20833102    5.195   .0000     .66040268
 YRSORFAM -.2652153626E-01  .10109995E-01   -2.623   .0087     12.125503
 FARFULT     -.6072933829       .25110880   -2.418   .0156     .66442953
 SOLEPR      -.6112790729       .25951570   -2.355   .0185     .72080537
 GORINC       .1153224837   .61073940E-01    1.888   .0590     4.3932886
 ONAGSCO      .1637589623       .13681401    1.197   .2313     3.4495302
 DIVINDEX     1.292697027       1.6711119     .774   .4392  .33936956E-01
 HORTDIS.3718666470E-02  .69180354E-02     .538   .5909     8.5892349
 DISMKTI      .3969304086       .26126603    1.519   .1287     .27248322
 DIRMKTI      .6284643971       .22526294    2.790   .0053     .45771812
 HORTLAND   .8416163377E-02  .24593021E-02    3.422   .0006     54.661120
 MKTPROB     -.1347809368   .85859476E-01   -1.570   .1165     .70067114
 PRODPROB  .1675060208E-01      .10882906     .154   .8777     .82281879
 (Note: E+nn or E-nn means multiply by 10 to + or -nn power.)


+---------------------------------------------------------------------+
```

```
| Information Statistics for Discrete Choice Model.                      |
|                           M=Model MC=Constants Only   M0=No Model      |
| Criterion F (log L)     -309.16152       -358.51009    -516.39465      |
| LR Statistic vs. MC       98.69715           .00000        .00000      |
| Degrees of Freedom        14.00000           .00000        .00000      |
| Prob. Value for LR          .00000           .00000        .00000      |
| Entropy for probs.       309.16152        358.51009     516.39465      |
| Normalized Entropy          .59869           .69426       1.00000      |
| Entropy Ratio Stat.      414.46626        315.76911        .00000      |
| Bayes Info Criterion     710.91042        809.60757    1125.37668      |
| BIC - BIC(no model)      414.46626        315.76911        .00000      |
| Pseudo R-squared            .13765           .00000        .00000      |
| Pct. Correct Prec.        82.14765           .00000      50.00000      |
| Means:       y=0    y=1    y=2    y=3    yu=4   y=5,    y=6   y>=7     |
| Outcome     .1866  .8134  .0000  .0000  .0000  .0000  .0000  .0000     |
| Pred.Pr     .1866  .8134  .0000  .0000  .0000  .0000  .0000  .0000     |
| Notes: Entropy computed as Sum(i)Sum(j)Pfit(i,j)*logPfit(i,j).         |
|        Normalized entropy is computed against M0.                      |
|        Entropy ratio statistic is computed against M0.                 |
|        BIC = 2*criterion - log(N)*degrees of freedom.                  |
|        If the model has only constants or if it has no constants,      |
|        the statistics reported here are not useable.                   |
+------------------------------------------------------------------------+

+--------------------------------------------+
| Partial derivatives of probabilities with  |
| respect to the vector of characteristics.  |
| They are computed at the means of the Xs.  |
+--------------------------------------------+
+---------+--------------+----------------+--------+---------+----------+
|Variable | Coefficient  | Standard Error |b/St.Er.|P[|Z|>z] | Mean of X|
+---------+--------------+----------------+--------+---------+----------+
         Characteristics in numerator of Prob[Y = 1]
 Constant  .3500564088E-01  .77171316E-01     .454   .6501
 FARMSIZE  .1023299441E-05  .16187112E-04     .063   .9496     311.53534
         Marginal effect for dummy variable is P|1 - P|0.
 EDUCOL1      .1544697999  .32227657E-01    4.793   .0000     .66040268
 YRSORFAM -.3340112636E-02  .12829152E-02   -2.604   .0092     12.125503
         Marginal effect for dummy variable is P|1 - P|0.
 FARFULT  -.7151984215E-01  .27606054E-01   -2.591   .0096     .66442953
         Marginal effect for dummy variable is P|1 - P|0.
 SOLEPR   -.7018385894E-01  .26844371E-01   -2.614   .0089     .72080537
 GORINC    .1452367168E-01  .76499644E-02    1.899   .0576     4.3932886
 ONAGSCO   .2062374419E-01  .17176478E-01    1.201   .2299     3.4495302
 DIVINDEX     .1628017936      .21054664     .773   .4394  .33936956E-01
 HORTDIS.4683275035E-03  .87078223E-03     .538   .5907     8.5892349
         Marginal effect for dummy variable is P|1 - P|0.
 DISMKTI   .4695019249E-01  .28844716E-01    1.628   .1036     .27248322
         Marginal effect for dummy variable is P|1 - P|0.
 DIRMKTI   .7799877776E-01  .27370632E-01    2.850   .0044     .45771812
 HORTLAND   .1059928557E-02  .30542141E-03    3.470   .0005     54.661120
 MKTPROB  -.1697426219E-01  .10779435E-01   -1.575   .1153     .70067114
 PRODPROB  .2109564738E-02  .13707046E-01     .154   .8777     .82281879
 (Note: E+nn or E-nn means multiply by 10 to + or -nn power.)

+----------------------------------------+
| Fit Measures for Binomial Choice Model |
| Logit    model for variable ADOPT2     |
+----------------------------------------+
| Proportions P0= .186577   P1= .813423  |
| N =     745 N0=     139   N1=     606  |
| LogL =  -309.16152 LogL0 =  -358.5101  |
| Estrella = 1-(L/L0)^(-2L0/n) = .13284  |
+----------------------------------------+
```

```
|      Efron |  McFadden  |  Ben./Lerman  |
|     .14977 |    .13765  |       .74090  |
|     Cramer | Veall/Zim. |     Rsqrd_ML  |
|     .14640 |    .23853  |       .12408  |
+-----------------------------------------+
| Information  Akaike I.C. Schwarz I.C.   |
| Criteria         .87023     717.52380   |
+-----------------------------------------+
Frequencies of actual & predicted outcomes
Predicted outcome has maximum probability.
Threshold value for predicting Y=1 = .5000
            Predicted
------  ----------  +  -----
Actual       0    1 |  Total
------  ----------  +  -----
  0         21  118 |    139
  1         15  591 |    606
------  ----------  +  -----
Total       36  709 |    745
```

A2. The Poisson Model Results:

A2.1 The Overall Sur Model

```
--> STOP
--> SAMPLE; ALL $
--> SKIP
--> POISSON  ;  LHS     = NUMAPPS
    ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR, GORINC,
...
                      DIVM, DIVP,
                      PCTHM, PCTHP,
                      DISM, DISP,
                      DIRM, DIRP,
                      HORTDISM, HORTDISP,
                      MAKPM, MAKPP,
                      PRODPM, PRODPP
    ;ROBUST$
```

```
 ***********************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now   745 *
 ***********************************************************************


+---------------------------------------------+
| Poisson Regression                          |
| Maximum Likelihood Estimates                |
| Model estimated: June 30, 2007 at 03:04:20AM.|
| Dependent variable              NUMAPPS     |
| Weighting variable                 None     |
| Number of observations             745     |
| Iterations completed                  7     |
| Log likelihood function       -2278.568     |
| Restricted log likelihood     -2422.956     |
| Chi squared                    288.7774     |
| Degrees of freedom                   21     |
| Prob[ChiSqd > value] =         .0000000     |
| Chi- squared =  1702.40858  RsqP=   .1100   |
| G  - squared =  2082.88380  RsqD=   .1218   |
| Overdispersion tests: g=mu(i)  :  4.834     |
| Overdispersion tests: g=mu(i)^2:  2.711     |
| Robust (sandwich) estimator used for VC     |
+---------------------------------------------+
+---------+--------------+----------------+--------+---------+----------+
|Variable | Coefficient  | Standard Error |b/St.Er.|P[|Z|>z] | Mean of X|
+---------+--------------+----------------+--------+---------+----------+
 Constant      .1742576200       .14086410    1.237   .2161
 FARMSIZE  .3934999031E-04  .15445457E-04    2.548   .0108     311.53534
 EDUCOL1      .2733671258   .54605165E-01    5.006   .0000     .66040268
 YRSORFAM -.7086887534E-02  .29103703E-02   -2.435   .0149     12.125503
 FARFULT   .5050661206E-01  .56123043E-01     .900   .3682     .66442953
 SOLEPR     -.1813595722    .50055614E-01   -3.623   .0003     .72080537
 GORINC   -.2183004079E-02  .13303797E-01   -.164    .8697     4.3932886
 ONAGSCO  -.3301940637E-01  .28721140E-01  -1.150    .2503     3.4495302
 DIVM     -.3466402518E-01      .55247211   -.063    .9500  .16968478E-01
 DIVP        1.453081269        .35830349    4.055   .0001  .16968478E-01
 PCTHM    -.2392054464E-02  .78520123E-03  -3.046    .0023     27.330560
 PCTHP     .2250274226E-02  .65987016E-03   3.410    .0006     27.330560
 DISM      .6919914519E-01  .79621112E-01    .869    .3848     .13624161
 DISP      .5753162636E-01  .67832624E-01    .848    .3964     .13624161
 DIRM         .1557579976   .72496794E-01   2.148    .0317     .22885906
```

```
DIRP         .2928353098   .61497824E-01    4.762   .0000     .22885906
HORTDISM      .2894405008E-02  .19544782E-02    2.960   .0031     4.2946174
HORTDISP      .2179077861E-02  .15379298E-02    1.417   .1565     4.2946174
MAKPM    -.6017501058E-02  .31245500E-01    -.193   .8473     .35033557
MAKPP     .1341692245E-01  .24532018E-01     .547   .5844     .35033557
PRODPM    .8082804482E-03  .35372906E-01     .023   .9818     .41140940
PRODPP       .1071794311   .26420005E-01    4.057   .0000     .41140940
(Note: E+nn or E-nn means multiply by 10 to + or -nn power.)
```

A2.2 Testing the Restrictions

#1. WALD TEST FOR DIVERSITY OF SALES - **DIVM, DIVP,**

```
--> SAMPLE  ; ALL   $
--> SKIP
--> POISSON  ;  LHS     = NUMAPPS
   ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR, GORINC,
...
                     ONAGSCO,
                     DIVM, DIVP,
                     PCTHM, PCTHP,
                     DISM, DISP,
                     DIRM, DIRP,
                     HORTDISM, HORTDISP,
                     MAKPM, MAKPP,
                     PRODPM, PRODPP
           ;TEST = B(9) - B(10) = 0
           ;ROBUST$
```

```
**********************************************************************
* NOTE: Deleted    289 observations with missing data. N is now   745 *
**********************************************************************


+---------------------------------------------+
| Poisson Regression                          |
| Maximum Likelihood Estimates                |
| Model estimated: June 30, 2007 at 03:10:03AM.|
| Dependent variable              NUMAPPS     |
| Weighting variable                 None     |
| Number of observations             745      |
| Iterations completed                 7      |
| Log likelihood function      -2278.568      |
| Restricted log likelihood    -2422.956      |
| Chi squared                   288.7774      |
| Degrees of freedom                  21      |
| Prob[ChiSqd > value] =        .0000000      |
| Chi- squared =  1702.40858  RsqP=   .1100   |
| G  - squared =  2082.88380  RsqD=   .1218   |
| Overdispersion tests: g=mu(i)  :  4.834     |
| Overdispersion tests: g=mu(i)^2:  2.711     |
| Robust (sandwich) estimator used for VC     |
| Wald test of  1 linear restrictions         |
| Chi-squared =    5.31, Sig. level =  .02120 |
+---------------------------------------------+
```

#2. WALD TEST FOR PERCENT OF ORGANIC THAT IS HORTICULTURE - PCTHM, PCTHP

```
--> STOP
--> SAMPLE  ; ALL   $
--> SKIP
--> POISSON  ;  LHS     = NUMAPPS
    ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR, GORINC,
...
                      ONAGSCO,
                      DIVM, DIVP,
                      PCTHM, PCTHP,
                      DISM, DISP,
                      DIRM, DIRP,
                      HORTDISM, HORTDISP,
                      MAKPM, MAKPP,
                      PRODPM, PRODPP
           ;TEST = B(11) - B(12) = 0
           ;ROBUST$

 ***********************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now   745 *
 ***********************************************************************


+----------------------------------------------+
| Poisson Regression                           |
| Maximum Likelihood Estimates                 |
| Model estimated: June 30, 2007 at 03:31:33AM.|
| Dependent variable               NUMAPPS     |
| Weighting variable                  None     |
| Number of observations               745     |
| Iterations completed                   7     |
| Log likelihood function       -2278.568      |
| Restricted log likelihood     -2422.956      |
| Chi squared                    288.7774      |
| Degrees of freedom                   21      |
| Prob[ChiSqd > value] =         .0000000      |
| Chi- squared =  1702.40858  RsqP=   .1100    |
| G  - squared =  2082.88380  RsqD=   .1218    |
| Overdispersion tests: g=mu(i)  :  4.834      |
| Overdispersion tests: g=mu(i)^2:  2.711      |
| Robust (sandwich) estimator used for VC      |
| Wald test of  1 linear restrictions          |
| Chi-squared =   25.73, Sig. level =  .00000  |
+----------------------------------------------+
```

```
?**#3. WALD TEST FOR DISTANCE MARKETING INCREASE - DISM, DISP,

--> STOP
--> SAMPLE  ; ALL   $
--> SKIP
--> POISSON  ;  LHS     = NUMAPPS
    ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR, GORINC,
...
                      ONAGSCO,
                      DIVM, DIVP,
                      PCTHM, PCTHP,
                      DISM, DISP,
                      DIRM, DIRP,
                      HORTDISM, HORTDISP,
                      MAKPM, MAKPP,
                      PRODPM, PRODPP
           ;TEST = B(13) - B(14) = 0
           ;ROBUST$

 ************************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now   745 *
 ************************************************************************


+----------------------------------------------+
| Poisson Regression                           |
| Maximum Likelihood Estimates                 |
| Model estimated: June 30, 2007 at 03:32:31AM.|
| Dependent variable               NUMAPPS     |
| Weighting variable                  None     |
| Number of observations              745      |
| Iterations completed                  7      |
| Log likelihood function       -2278.568      |
| Restricted log likelihood     -2422.956      |
| Chi squared                    288.7774      |
| Degrees of freedom                   21      |
| Prob[ChiSqd > value] =         .0000000      |
| Chi- squared =  1702.40858  RsqP=   .1100    |
| G  - squared =  2082.88380  RsqD=   .1218    |
| Overdispersion tests: g=mu(i)  :  4.834      |
| Overdispersion tests: g=mu(i)^2:  2.711      |
| Robust (sandwich) estimator used for VC      |
| Wald test of  1 linear restrictions          |
| Chi-squared =     .01, Sig. level =  .90930  |
+----------------------------------------------+
```

```
?*#4. WALD TEST FOR DIRECT MARKETING INCREASE - DIRM, DIRP,


SAMPLE  ; ALL   $
SKIP
POISSON  ;  LHS     = NUMAPPS
         ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR,
GORINC,
            ONAGSCO,
            DIVM, DIVP,
            PCTHM, PCTHP,
            DISM, DISP,
            DIRM, DIRP,
            HORTDISM, HORTDISP,
            MAKPM, MAKPP,
            PRODPM, PRODPP
      ;TEST = B(15) - B(16) = 0
      ;ROBUST$

STOP
***********************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now   745 *
 ***********************************************************************


+----------------------------------------------+
| Poisson Regression                           |
| Maximum Likelihood Estimates                 |
| Model estimated: June 30, 2007 at 03:35:51AM.|
| Dependent variable              NUMAPPS      |
| Weighting variable                 None      |
| Number of observations             745      |
| Iterations completed                 7       |
| Log likelihood function       -2278.568      |
| Restricted log likelihood     -2422.956      |
| Chi squared                    288.7774      |
| Degrees of freedom                   21      |
| Prob[ChiSqd > value] =         .0000000      |
| Chi- squared =  1702.40858  RsqP=   .1100    |
| G  - squared =  2082.88380  RsqD=   .1218    |
| Overdispersion tests: g=mu(i)  :  4.834      |
| Overdispersion tests: g=mu(i)^2:  2.711      |
| Robust (sandwich) estimator used for VC      |
| Wald test of  1 linear restrictions          |
| Chi-squared =    2.21, Sig. level =  .13675  |
+----------------------------------------------+
```

```
?*#5. WALD TEST FOR LOCATION OF HORTICULTRAL MARKETS - HORTDISM, HORTDISP,

SAMPLE  ; ALL   $
SKIP

POISSON  ;  LHS     = NUMAPPS
         ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR,
GORINC,
            ONAGSCO,
            DIVM, DIVP,
            PCTHM, PCTHP,
            DISM, DISP,
            DIRM, DIRP,
            HORTDISM, HORTDISP,
            MAKPM, MAKPP,
            PRODPM, PRODPP
      ;TEST = B(17) - B(18) = 0
      ;ROBUST$

STOP

************************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now   745 *
 ************************************************************************


+----------------------------------------------+
| Poisson Regression                           |
| Maximum Likelihood Estimates                 |
| Model estimated: June 30, 2007 at 03:36:34AM.|
| Dependent variable              NUMAPPS      |
| Weighting variable                 None      |
| Number of observations             745      |
| Iterations completed                  7      |
| Log likelihood function       -2278.568      |
| Restricted log likelihood     -2422.956      |
| Chi squared                    288.7774      |
| Degrees of freedom                   21      |
| Prob[ChiSqd > value] =         .0000000      |
| Chi- squared =  1702.40858  RsqP=   .1100    |
| G  - squared =  2082.88380  RsqD=   .1218    |
| Overdispersion tests: g=mu(i)  :  4.834      |
| Overdispersion tests: g=mu(i)^2:  2.711      |
| Robust (sandwich) estimator used for VC      |
| Wald test of  1 linear restrictions          |
| Chi-squared =    2.15, Sig. level =  .14245  |
+----------------------------------------------+
```

```
?**#6. WALD TEST FOR MARKETING PROBLEMS - MAKPM, MAKPP,

SAMPLE  ; ALL   $
SKIP

POISSON  ;  LHS     = NUMAPPS
         ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR,
GORINC,
            ONAGSCO,
            DIVM, DIVP,
            PCTHM, PCTHP,
            DISM, DISP,
            DIRM, DIRP,
            HORTDISM, HORTDISP,
            MAKPM, MAKPP,
            PRODPM, PRODPP
      ;TEST = B(19) - B(20) = 0
      ;ROBUST$

STOP

************************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now   745 *
 ************************************************************************


+----------------------------------------------+
| Poisson Regression                           |
| Maximum Likelihood Estimates                 |
| Model estimated: June 30, 2007 at 03:37:21AM.|
| Dependent variable              NUMAPPS      |
| Weighting variable                 None      |
| Number of observations              745      |
| Iterations completed                  7      |
| Log likelihood function       -2278.568      |
| Restricted log likelihood     -2422.956      |
| Chi squared                    288.7774      |
| Degrees of freedom                   21      |
| Prob[ChiSqd > value] =         .0000000      |
| Chi- squared =  1702.40858  RsqP=   .1100    |
| G  - squared =  2082.88380  RsqD=   .1218    |
| Overdispersion tests: g=mu(i)  :  4.834      |
| Overdispersion tests: g=mu(i)^2:  2.711      |
| Robust (sandwich) estimator used for VC      |
| Wald test of  1 linear restrictions          |
| Chi-squared =     .25, Sig. level =  .61560  |
+----------------------------------------------+
```

```
?**#7. WALD TEST FOR PRODUCTION PROBLEMS - PRODPM, PRODPP,

SAMPLE  ; ALL   $
SKIP

POISSON  ;  LHS     = NUMAPPS
         ;  RHS     = ONE, FARMSIZE, EDUCOL1, YRSORFAM, FARFULT, SOLEPR,
GORINC,
            ONAGSCO,
            DIVM, DIVP,
            PCTHM, PCTHP,
            DISM, DISP,
            DIRM, DIRP,
            HORTDISM, HORTDISP,
            MAKPM, MAKPP,
            PRODPM, PRODPP
      ;TEST = B(21) - B(22) = 0
      ;ROBUST$

STOP

************************************************************************
 * NOTE: Deleted    289 observations with missing data. N is now   745 *
 ************************************************************************


+-----------------------------------------------+
| Poisson Regression                            |
| Maximum Likelihood Estimates                  |
| Model estimated: June 30, 2007 at 03:38:06AM.|
| Dependent variable              NUMAPPS       |
| Weighting variable                 None       |
| Number of observations              745      |
| Iterations completed                  7       |
| Log likelihood function       -2278.568       |
| Restricted log likelihood     -2422.956       |
| Chi squared                    288.7774       |
| Degrees of freedom                   21       |
| Prob[ChiSqd > value] =         .0000000       |
| Chi- squared =  1702.40858  RsqP=   .1100     |
| G  - squared =  2082.88380  RsqD=   .1218     |
| Overdispersion tests: g=mu(i)  :  4.834       |
| Overdispersion tests: g=mu(i)^2:  2.711       |
| Robust (sandwich) estimator used for VC       |
| Wald test of  1 linear restrictions           |
| Chi-squared =    6.43, Sig. level =  .01124   |
+-----------------------------------------------+
```