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# Three essays on consumer choices on food

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**Three essays on consumer choices on food**

by

**Miyoung Oh**

A dissertation submitted to the graduate faculty  
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Economics

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## GENERAL ABSTRACT

The dissertation investigates how consumer choices on food are affected by habit forming behaviors of consumers, public policy and the uncertainty of the risk from food safety hazards and strategic interaction with food processors. Three stand-alone analyses on consumer choice consist of empirical frameworks to estimate parameters of dynamic demand, the treatment effects on program participation, and an analytical approach to modeling downstream consumer's and upstream firm's handling of food safety risk.

The first analysis focuses on dynamics in household demand. Incorporating dynamics such as habit formation in analysis of food demand can make estimation more reliable and help to explain the “stickiness” in consumer demand behavior. Capturing this response is important for evaluating consumers' response to new information about products – whether nutrition, food safety or other event. Scanner data allow many repeated observations of the same household so are ideal for analyzing the impact of habit on food demand. In addition to that, scanner data allow us to easily observe the presence of zero purchases. The presence of zero purchases is an important econometric issue in empirical modeling on food demand in the sense that ignoring the censoring issue can lead to biased estimation results. The first study investigates the impact of state dependence on dairy food demand using 2009 and 2010 Nielsen HomeScan data. In this analysis, we take into account the censored nature of food expenditure data and employ a Bayesian procedure to estimate the dynamic demand models on dairy products. By controlling the individual heterogeneity in the model the source of endogeneity for the lagged dependent variable is removed. The empirical evidence of habitual behaviors particularly in milk demand provides support for considering a model with dynamics in a study of food demand.

The second analysis examines the relationship between The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) participation and purchases of WIC related foods during the period shortly after introduction of changes in the WIC package. We use Nielsen Homescan data 2008 to 2010 to assess how participation in the WIC program relates to food expenditures by WIC eligible households. The research includes analysis of select food purchases by WIC eligible households – both of those reporting participation in the WIC program and those not participating in the program. In our analysis, we concentrate our attention on selected whole grain foods in the WIC food package as these foods are prominent in the revised WIC food package and grain products are purchased by most households. A propensity score matching estimator was used for estimating treatment effects and difference-in-difference method was conducted to control the policy change in the 2009 WIC package revision. The study contributes to current literature on WIC to confirm that the WIC package change in 2009 had a significant influence on WIC participating households to encourage greater whole grain expenditures relative to non-participating households.

The third analysis concerns the uncertainty of the risk from food safety hazards and strategic interaction with food processors. Domestic water consumers in many developing countries that boil water before use are presumably concerned about quality control on the part of upstream water authorities. In this third analysis, we investigate strategic incentives for food safety efforts by upstream food processors and downstream consumers. The strategic setting is where food processors move first and consumers react to perceptions about processor behavior. We consider two technological environments in which food safety is assured: i) weakest-link where both processor and consumer behavior must succeed; ii)

best-shot where it suffices for efforts by either party to succeed. We study privately optimal behavior under negligence and strict liability rules, and also investigate the role of consumer risk aversion.

## **CHAPTER 1. GENERAL INTRODUCTION**

### **1. Introduction**

Both public health workers as well as policymakers are concerned about the prevalence of obesity and other health problems associated with unhealthy dietary behaviors of consumers as well as the potential risk of food related illnesses. These health issues are substantially related to consumers' choices about food -- from the decision making of consumers over food purchases to food handling practices. The choices and policies related to the consumer choices have become a concern for all: government, agricultural industries and consumers. Thus, taking a closer look in the consumer's food related choices may be the starting point to approach these public health issues. The main objective of this dissertation is to explore the various factors that can influence consumer's decision-making related to food, to examine the economic impacts of those factors on consumers' food purchases and food practices and find the policy implications associated each analysis.

Eating patterns and choices are important in prevention of health problems and improving health status. Many of the choices can be explained by investigating market demand for food. Analysis of demand is of considerable interest not only for understanding consumer's food choices but also for informing public policies under consideration. The first topic of this dissertation, presented in Chapter 2, explores how habitual behaviors related to food purchases contribute to the consumer's responses to the food prices in food demand. We consider a demand model with dynamics to examine the association between past and current purchases of food as it is supported from the empirical evidence of habitual behaviors in

demand. Nielsen 2009 and 2010 HomeScan data are used in the estimation process of the dynamic food demand and selected food groups are dairy products.

In analysis of household level data, one of the main empirical challenges is the presence of zero purchases. Generally, households do not purchase or consume all goods available in the market in the time period observed, and this is often true for food products. Ignoring the censoring issue on food consumption data can lead to biased estimation results. Also accounting for dynamic aspects that arise from habit formation among other reasons can also make the demand analysis more reliable.

In this chapter, we take into account the censored nature of food expenditure data. The censoring arises when households do not purchase or consume all goods available in the market in the time period observed. This leads to censoring of the dependent variable in the estimation of demand or consumption equations. We also control for unobserved household heterogeneity to estimate dynamic demand for dairy products. Unobserved individual heterogeneity arises when estimating the effect of habit. By accounting for unobserved heterogeneity in micro data, we can avoid overestimation of the underlying habit formation. For estimating dynamic food demand, the chapter uses the dynamic Tobit panel model with unobserved household heterogeneity. The estimation results show that habit-forming effects on dairy demands exist conditional on unobserved household heterogeneity. In particular, the empirical evidence on milk expenditure shows the largest habit forming effect in milk demand.

Consumer choices on food purchases are influenced by also public policies through participation in food assistance programs. The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) is one of the largest food assistant programs in the

United States and is designed to enhance the foods eaten by target, at risk women, infants and young children. The program provides healthy food (WIC package food), nutrition counseling, and access to health services for low-income infants, children up to age five, and pregnant, breastfeeding, and postpartum women for improving health of people at nutritional risk. The second topic of this dissertation, presented in Chapter 3, addresses how participating in the WIC program affects household food purchases. We use scanner data in the analysis.

Investigating the effect of participating in the WIC program on food choices is an important aspect to understanding the role of the WIC in assuring improved long run health outcomes among program participants. As the WIC program aims to improve healthy eating behaviors of target people, the analysis of consumption patterns of WIC participants allows us to see whether the program leads to improved healthy food purchases. And this would be one way to measure the effectiveness of the program. There are relatively few recent studies about WIC effects on food consumption. Other studies have examined the impacts of WIC on health status and dietary conditions of the target population.

Existing literature on the WIC program finds that household decisions are important in evaluating the use of WIC provided foods, and suggests that there is a need for information about overall WIC household choices, expenditures and behaviors. In this sense, this paper contributes by providing an analysis of the impact of the WIC program on household food expenditures. The chapter includes: (1) analysis of the reliability of the WIC participation variable; (2) identification of subgroups of survey households by WIC income eligibility criteria and type of WIC individuals in the household; and (3) a comparison of select food purchases between eligible WIC reporting and eligible WIC not-reporting

households. The empirical analysis of food expenditures for WIC participating households is conducted by comparing the WIC participating households to eligible, non-participating households. We use a propensity score matching estimator to estimate the treatment effects on whole grain expenditures and the difference-in-difference method to control the policy change in the 2009 WIC package revision. The 2009 change in WIC package made a number of changes to the packing and included whole grain products. The results show that there was a significant impact of WIC participation on whole grain expenditure over three consecutive years and the WIC package change implemented in October 2009 was positively associated with this treatment effects in the year following its implementation.

Addressing the problem of the existence of food related risk presents another important factor that influences on consumers' decision making related to food. The risk of foodborne illnesses can be reduced by consumers' practice toward food safety based upon how the consumers perceive the risk. The decision on food safety efforts can be made together with food choices before consumers purchase food or considered as a separate decision after food choices had been made. In either way, consumers' protection incentives are heavily related to the food safety efforts by upstream food processors. Modeling the decision-making process of consumers on food safety has not received much attention in the literature.

The objective of the third topic of this dissertation, Chapter 4, is to examine how the interaction between downstream consumers and upstream firms influences the consumer's incentives to exert effort to reduce food safety risk, and to identify how policy rules may affect the interaction. Economic analysis through modeling of the consumers' protection

incentives on the risk of food-borne illnesses addresses an important option for food safety control and can provide a rigorous theoretical foundation for policy implications.

In Chapter 4, we construct a Stackelberg model with asymmetric timing in moves, allowing the upstream agents to move first and consumers make decisions later as second-movers. Our analysis is distinct from earlier work by allowing self-protective incentive to reduce the probability of a loss as we directly apply risk aversion on the consumer's part. The uncertainty that is an essential feature of food safety events has implications for consumer behavior. Finally the timing and risk aversion dimensions in our model give us the opportunity for policy analyses not available in earlier works.

In our analysis, we contrast food safety incentives and outcomes across two dimensions, technology and liability assignment. Food safety effort by each party can be either a success or a failure based on the assumption of statistical independence between the success probabilities. Two very different technologies between effort outcomes and food safety outcomes are considered: weakest link and best shot. In the weakest link, if one or both of two actions fails then the outcome is a failure, i.e., a food safety event occurs. In best shot if either or both of the actions is a success then the food is safe. We examine how the sort of technical interaction between upstream and downstream efforts affects the behavior strategies in response to food safety risk. In the second contrast set forth under different liability rules, two liability rules are considered: strict liability and negligence in a bilateral accident setting. Thus, the incentives under four settings (weakest link, best shot)  $\times$  (strict liability, negligence) are developed.

By backward induction, we solve the expected utility maximization problem for a downstream consumer in Stage II and for the upstream processor's Stage I cost minimization

problem to obtain the optimal levels of preventative effort. After solving for the Stackelberg equilibrium in each case, we provide comparative statics to ascertain strategic interactions between both efforts as well as how consumer risk aversion affects each effort type. The findings show that the strategic interactions under different technologies, the consumer reacts differently to an increase in processor food safety effort. Several of our findings might be viewed as counterintuitive and these stem partly from the self-protective nature of food safety efforts.

## **2. Organization of the dissertation**

This dissertation provides the economic analysis on consumers' decision making over food purchases and practices when they face internal and external factors that affect their choices. While each of these chapters can be a stand-alone study, they are all dedicated to an investigation of consumer choice on food. A brief overview of the remainder of this dissertation is outlined as follows:

- Chapter 2 examines the effects of habit-forming behaviors on demand for dairy products by incorporating dynamic aspects in the demand equations.
- Chapter 3 conducts the estimation for the treatment effect of the WIC program to investigate the relationship between WIC program participation and purchases of WIC related foods. The period investigated includes the period shortly after introduction of changes in the WIC package.
- Chapter 4 develops a Stackelberg model with self-protection motives to examine the interaction among downstream consumers and upstream firms in the presence of uncertainty of food safety risk, and explores how the food safety incentives and outcomes across

different dimensions of technology and liability rules are determined in a strategic model setting.

- Chapter 5 highlights the findings and implications of the three investigations addressed in this dissertation and outlines future directions.

## **CHAPTER 2. DYNAMIC FOOD DEMAND AND HABIT FORMING BEHAVIORS: BAYESIAN APPROACH TO A DYNAMIC TOBIT PANEL DATA MODEL WITH UNOBSERVED HETEROGENEITY<sup>1</sup>**

### **1. Introduction**

#### **Habit formation**

Eating behaviors and habits contribute to health outcomes and thus understanding factors associated with eating choices is important to efforts to protect and improve health status. Food habits are also important in explaining observed “stickiness” in food demand when consumers receive new information about food safety and risk. Food choices can be explained, in large part, by investigating market demand for food. The empirical evidence of habitual behaviors in demand provides support for considering a model with dynamics in a study of the food demand. Following Pollack (1970), habit forming goods are defined as goods associated with preferences for which current consumption behavior relies on the past consumption experience. Therefore, lagged dependent variables are used to show how habit formation influences the demand.

A number of empirical studies in food demand have analyzed habit formation using macro and micro level panel data. Habit forming behaviors are found in various categories of food products including products such as beverages, meats, cereal, cheese, ketchup and snacks, as well as food at home, food away from home and aggregate food (Zhen et al, 2010; Wohlgenant and Zhen, 2006; Thunström, 2009; Arnade et al., 2008; Seetharaman, 2004; Richards et al., 2007; Heien and Durham, 1991; Naik and Moore, 1996). Although food

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<sup>1</sup> An earlier version was prepared and presented as a Selected Paper at the Agricultural & Applied Economics Association’s 2013 AAEA & CAES Joint Annual Meeting, Washington, DC, August 4-6, 2013.

demand models generally exhibit habit formation, the evidence of habit formation varies over empirical methods used (Daunfeldt et al., 2011). For example, Naik and Moore (1996) use a single demand functions model and show habit formation in individual food consumption using aggregated food consumption of household panel data. In contrast, Dynan (2000) uses a life-cycle consumption model and finds no evidence of habit formation using the same data set. And, Browning and Collado (2007) find habit formation for consumption of ‘food outside the home’ while there is no state dependence for ‘food at home’. Other important example is found in studies of non-alcoholic beverages. Zhen et al. (2011) examine state dependence over beverage demand and find strong evidence for habit formation.

As an alternative to the traditional state dependence approach, recent work of Adamowicz and Swait (2012) evaluates a conceptual framework of decision strategy which would minimize cognitive effort using panel data. They find significant evidence of a habitual decision strategy particularly in the case of catsup which has a relatively longer inter-purchase period while they find evidence of variety-seeking preference in the case of yogurt.

Controlling for the unobserved individual heterogeneity is one distinct issue that arises when estimating the effect of habit. Often, the literature on habit formation is concerned with possible sources of persistence in consumer’s behavior and addresses whether the association between current and past consumption reflects state dependence or individual heterogeneity (Naik and Moore, 1996; Carrasco et al., 2005; Browning and Collado, 2007). Failure to control for unobserved heterogeneity in micro data may lead to overestimation of the underlying habit formation. In order to distinguish between heterogeneity among individuals and the effect of habit, researchers have estimated models

that include fixed effects to explain the time invariant unobserved heterogeneity across households and provide a strong tool for testing the habit formation hypothesis. Naik and Moore (1996) conclude that controlling for heterogeneity reduces estimated habit effects; the importance of accounting for time invariant unobserved individual effects has been shown in Carrasco et al. (2005).

Most of the literature referenced above on habit formation employs dynamic linear panel data models to estimate dynamic demand. In the linear models with unobserved individual effects, the unobserved effects can be eliminated by using an appropriate transformation such as differencing; instrumental variables (IV) can be implemented to estimate the transformed model in a generalized method of moments (GMM) framework. To date, significant progress has been achieved in estimating unbiased and consistent estimators and improving the efficiency of the estimators (Anderson and Hsiao, 1982; Arellano and Bond, 1991; Arellano and Bover, 1995; Baltagi, 1995; Bond and Hahn, 1999; Arellano and Honore, 2001; Hsiao, 2003).

### **Empirical challenges: Censoring**

Generally, households do not purchase or consume all goods available in the market in the time period observed. It is a well-known econometric issue in microdata based on surveys of household expenditures that households do not purchase all goods available but only some of them in the observed time period. This leads to censoring of the dependent variable in the estimation of demand or consumption equations. While this zero consumption issue can be represented as a corner solution in utility maximization (Perali and Chavas, 2000), we can also find various reasons for a household to make a decision to purchase none of the good (zero purchases). For example, people may simply avoid certain products or, if

they do make purchases, do so infrequently according to their lifestyles. Alternatively, the decision related to infrequent purchases which are observed as zero purchases in a given period of time, may be related to the capacity of storing products and use of inventories. Other non-purchase decisions may be associated with factors related to information about the safety of products or the dietary environment. This type of response would occur as a change in behavior from the previous responses. With any possible reason, if there is a significant fraction of the zero observations in the dependent variable, analysis that uses a conventional regression approach may lead to inappropriate biased and inconsistent estimators.

In order to deal with censored data, several approaches to demand systems have been taken in the econometric literature and include the Kuhn-Tucker model, Amemiya-Tobin model, Heckman's two-step method and a Bayesian approach (Wales and Woodland, 1983; Lee and Pitt, 1986; Tobin, 1958; Amemiya, 1974; Heien and Wessells, 1990; Shonkwiler and Yen, 1999; Tiffin and Arnoult, 2010; Ishdorj and Jensen, 2010; Kasteridis et al., 2011).

For estimating dynamic food demand, this paper uses the dynamic Tobit panel model with unobserved individual heterogeneity. The non-linear nature of treating censored panel data makes the estimation even more difficult along with some complexity that arises from the two main features of the dynamic panel data model: the individual specific effects and lagged dependent variables. The literature on nonlinear panel models, particularly in the case of censored regression, has been developed to overcome the difficulties of differencing away the unobserved effects and dealing with initial conditions (Honore, 1993; Hu, 2002, Hsiao, 2003; Honore and Hu, 2004; Wooldridge, 2005; Li and Zheng, 2008).

In this paper, we apply the Bayesian approach to estimate a dynamic censored dairy food demand. We selected the dairy and eggs food group because most households purchase

some of these products and it is a sector of interest in food and health programs. In micro panel data, the pairs of observations corresponding to a given individual are likely to be correlated and individual specific effect are introduced in the models to account for this fact. The form of the correctly specified likelihood function might be complex and this leads to computational difficulties. The Bayesian approach – inference from the parameters’ posterior distribution conditioned on the observations -- is our alternative to maximum likelihood estimation as it offers computational convenience through the simulation methods. One of the standard Markov Chain Monte Carlo (MCMC) algorithms that can be easily applied to high dimensional problems is the Gibbs sampler. This method is used in the iteration procedure for sampling the parameters from the conditional posterior distributions.

The main contribution of this paper is to estimate a dynamic demand model by using a Bayesian approach, accounting for censored data. We apply the estimation procedures to the dairy group, a group that has relatively well defined products. Gibbs sampling is conducted to deal with the censored data.

## 2. Empirical Model

The dynamic single demand equations are estimated as a dynamic Tobit panel data model. Following methods used in related studies, we consider a dynamic unobserved effects Tobit model in the form

$$y_{iht} = \max[0, z_{iht}\gamma + g(y_{ih,t-1})\rho + c_{ih} + u_{iht}], \quad i = 1, \dots, n, \quad h = 1, \dots, H, \quad t = 1, \dots, T \quad (1)$$

$$u_{iht} \mid y_{ih,t-1}, \dots, y_{ih,0}, z_{ih}, c_{ih} \sim^{iid} \text{Normal}(0, \sigma_{iu}^2)$$

where  $y_{iht}$  is the censored response variable of interest on the  $i^{th}$  good by the  $h^{th}$  household in time period  $t$  which depends on the explanatory variables  $z_{iht}$ , the lags of the dependent

variable  $y_{iht-1}$  and the unobserved individual heterogeneity  $c_{ih}$  (Hu, 2002; Wooldridge, 2005; Li and Zheng, 2008). As Heckman (1981) notes, in order to interpret observed persistence in consumption as the habit effect corresponding to the case of true state dependence, we allow the intercept in equation (1) to vary across households to control for omitted factors.

We assume that the error terms,  $u_{iht}$ , are i.i.d. normally distributed conditional on  $(y_{ih0}^*, \{z_{iht}\}_{t=1}^T, c_{ih})$  and not serially correlated in the model. By accounting for the unobserved individual effects and the assumptions on error terms, the model exhibits strict exogeneity on  $z_{iht}$ . In other words, the possible dynamic feedback from realizations  $z_{ih}$  on past and future time periods to the current realizations of the dependent variables is removed in the model so that the dynamic nature of the model is only from the presence of the lagged dependent variables (Hu, 2002).

The model in equation (1) is well suited to corner solution applications, however the model with lagged censored dependent variable is not applicable for data censoring applications (Wooldridge, 2002; 2005). As we are to account for a data censoring case, the lagged latent dependent variable will be placed in the function  $g(\cdot)$  as was done in Hu (2002) and we specify the model in the current paper as follows:

$$y_{iht}^* = z_{iht}\gamma + y_{ih,t-1}^*\rho + c_{ih} + u_{iht} \quad (2)$$

where  $y_{iht}^*$  represents the latent quantities of product  $i$  purchased by household  $h$  in  $t^{th}$  month,  $y_{ih,t-1}^*$  is the lagged latent quantities of product  $i$  purchased by household  $h$  in  $(t-1)^{th}$  month and  $z_{iht}$  represents the vector of covariates of interest: a set of own and cross prices, set of demographic variables along with total expenditures over all food categories (food at home) and seasonal effects.

As the unobserved individual heterogeneity  $c_{ih}$  is a nuisance parameter, specifying the distribution of  $c_{ih}$  and its relationship with  $z_{iht}$  is needed to complete the model setup. We follow the specification of the relationship between the individual effects and the initial conditions in Li and Zheng (2008). Li and Zheng make an assumption of the following conditional mean dependence of the  $c_{ih}$  on the initial conditions and observed strictly exogenous variables

$$E[c_{ih} | y_{ih,0}, z_{ih}] = a + h(y_{ih,0}, z_{ih})\delta \quad (3)$$

where  $a$  is a constant,  $h(\cdot)$  is a function of the vector of initial values of the dependent variable  $y_{ih0}$  and a matrix of time-invariant covariates  $z_{ih}$  which only vary over different households and  $\delta$  is a vector of corresponding parameters.<sup>2</sup> An independent relationship between  $y_{ih,0}$  and  $z_{ih}$  is assumed. We set  $z_{ih} = \bar{z}_{ih}$  where  $\bar{z}_{ih}$  is the average of  $z_{iht}$  over the entire time path as in Chib and Jeliazkov(2006).<sup>3</sup> Following the specification of

$h(y_{ih0}, z_{ih}) = y_{ih0}\delta_1 + z_{ih}\delta_2$  in Li and Zheng (2008), we rewrite (3) as

$$c_{ih} = y_{ih,0}\delta_1 + z_{ih}\delta_2 + \varepsilon_{ih}, \quad \varepsilon_{ih} | y_{ih0}, z_{ih} \sim^{iid} \text{Normal}(0, \sigma_i^2) \quad (4)$$

where  $\varepsilon_{ih}$  is an error term in the auxiliary equation.<sup>4</sup> This specification of the unobserved individual heterogeneity allows its linear correlation with the initial observations of the dependent variable and the set of exogenous explanatory variables.

---

<sup>2</sup> Alternatively,  $z_{ih}$  can be the set of all explanatory variables in all time periods,  $z_{ih} = (z_{ih1}, \dots, z_{ihT})$  with multidimensional  $z_{ih}$  as in Wooldridge (2005).

<sup>3</sup> Time-invariant variables such as race or ethnicity cannot be in both  $z_{iht}$  and  $\bar{z}_{ih}$  for identification purposes (Li and Zheng; 2008).

<sup>4</sup> For the estimation of the model, we assume that  $y_{ih0}^* = y_{ih0}$ , initial values of dependent variable to be uncensored following Hu (2002).

### 3. Estimation

We fit the following dynamic Tobit model with the unobserved individual heterogeneity

$$y_{iht}^* = x_{iht}\beta + c_{ih} + u_{iht} \quad (\text{or } Y^* = X\beta + C^e + u)$$

where  $x_{iht} = (z_{iht}, y_{ih,t-1}^*)$ ,  $\beta = (\gamma', \rho')'$  and  $u_{iht} | y_{ih,t-1}, \dots, y_{ih,0}, z_{ih}, c_{ih} \sim^{iid} \text{Normal}(0, \sigma_{iu}^2)$

$$c_{ih} = r_{ih}\delta + \varepsilon_{ih} \quad (\text{or } C = R\delta + \varepsilon)$$

where  $r_{ih} = (y_{ih0}, z_{ih}, 1)$ ,  $\delta = (\delta_1', \delta_2')'$  and  $\varepsilon_{ih} | y_{ih0}, z_{ih} \sim^{iid} \text{Normal}(0, \sigma_i^2)$

using a Bayesian approach by drawing samples from the posterior distribution of the parameters in the model.<sup>5</sup> One thing we are concerned about is that our latent variables  $\{y_{ih}^*\}_{t=1}^T$  and  $c_{ih}$  are not completely observable. So, we need to employ data augmentation suggested by Albert and Chib (1993) to replace the zero observations with fitted values for latent dependent variables and update nuisance parameters  $c_{ih}$  through Bayesian Markov Chain Monte Carlo algorithm (MCMC) iterations. We will discuss the data augmentation in the Gibbs sampling algorithm.

#### Sampling density and priors

Recall that the distribution of  $u_{iht}$  and equation (2) give us the sampling density of the dependent variables conditioned on the latent variables. In addition to other variables, we write the model as follows:

---

<sup>5</sup>  $C^e = (c_{i1}^{(t=1)}, \dots, c_{i1}^{(t=T)}, \dots, c_{iH}^{(t=1)}, \dots, c_{iH}^{(t=T)})'$

$$\begin{aligned}
f(y_{ih1}, y_{ih2}, \dots, y_{ihT} | y_{ih1}^*, y_{ih2}^*, \dots, y_{ihT}^*, y_{ih,0}, z_{ih}, c_{ih}, \gamma, \rho) \\
= \prod_{t=1}^T \{1(y_{iht} > 0)1(y_{iht} = y_{iht}^*) + 1(y_{iht} = 0)1(y_{iht}^* \leq 0)\} \\
* \frac{1}{(2\pi\sigma_{ui}^2)^{\frac{1}{2}}} \exp\left(-\frac{1}{2\sigma_{ui}^2}(y_{iht}^* - z_{iht}\gamma - y_{ih,t-1}^*\rho - c_{ih})^2\right)
\end{aligned} \tag{5}$$

Before we discuss how the model can be fit using the MCMC, we introduce the specifications on priors following Li and Zheng (2008):

$\beta = (\gamma', \rho')' \sim \text{improper flat prior}^6$

$$\frac{1}{\sigma_{iu}^2} \sim \text{gamma}\left(\frac{N_1}{2}, \frac{R_1}{2}\right) \text{ or } \frac{1}{\sigma_{iu}^2} \propto \left(\frac{1}{\sigma_{iu}^2}\right)^{\frac{N_1}{2}-1} e^{-R_1\left(\frac{1}{\sigma_{iu}^2}\right)} \tag{6}$$

### Gibbs sampling from the posterior

Combining the model given in (2) and the prior information in (6), we can determine what the posterior conditional distributions of the parameters look like. We use the Gibbs sampler - one simple and effective sampler in the MCMC algorithms - to generate samples from the posterior. We set initial values for  $\beta, \delta$  and  $\sigma_{iu}^2$ , and the Gibbs iteration algorithm proceeds in the following steps:

Step1: For each  $h = 1, \dots, H$  and  $t = 1, \dots, T$  such that  $y_{iht} = 0$ , generate  $y_{iht}^*$  from the truncated

normal distribution on the interval  $[-\infty, 0]$  with mean  $x_{iht}\beta + r_{ih}\delta$  and variance

$\sigma_{iu}^2 + \sigma_i^2$  conditional on  $y_{iht}, x_{iht}, r_{ih}, \beta, \delta, \sigma_i^2$  and  $\sigma_{iu}^2$ .

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<sup>6</sup> “For example, a uniform prior distribution on the real line,  $\pi(\theta) \propto 1$ , for  $-\infty < \theta < \infty$ , is an improper prior. Improper priors are often used in Bayesian inference since they usually yield noninformative priors and proper posterior distributions.” (SAS/STAT(R) 9.2 User's Guide, Second edition). Accessed at [http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug\\_introbayes\\_sect004.htm](http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_introbayes_sect004.htm)

Step2: Update  $\sigma_{iu}^2$  and  $\beta$  by drawing from the joint posterior distribution of  $\frac{1}{\sigma_{iu}^2}$  and

$\beta$  conditional on data and other parameters and marginalized over each other.

$$\frac{1}{\sigma_{iu}^2} \sim \text{gamma}\left(\frac{N_1 + nT}{2}, \frac{R_1 + (Y^* - X\hat{\beta} - C^e)'(Y^* - X\hat{\beta} - C^e)}{2}\right)$$

$$\beta \sim \text{Normal}\left(\hat{\beta}, \left(\frac{X'X}{\sigma_{iu}^2}\right)^{-1}\right) \text{ where } \hat{\beta} = (X'X)^{-1}(X'(Y^* - C^e))$$

Step3: For each  $h = 1, \dots, H$ , update  $c_{ih}$  from the normal distribution with mean

$$c_{ih}^* = \left(\frac{T}{\sigma_{iu}^2} + \frac{1}{\sigma_i^2}\right)^{-1} \times \left(\frac{1}{\sigma_{iu}^2} \sum_{t=1}^T (y_{iht}^* - x_{iht}\beta) + \frac{r_{ih}\delta}{\sigma_i^2}\right) \text{ and variance } \left(\frac{T}{\sigma_{iu}^2} + \frac{1}{\sigma_i^2}\right)^{-1}.$$

Step4: Update  $\delta$  by drawing from the posterior distribution conditional on  $r_{ih}, c_{ih}$  and  $\sigma_i^2$ .

$$\delta \sim \text{Normal}\left(\hat{\delta}, \left(\frac{R'R}{\sigma_i^2}\right)^{-1}\right) \text{ where } \hat{\delta} = \left(\frac{R'R}{\sigma_i^2}\right)^{-1} \left(\frac{R'C}{\sigma_i^2}\right).$$

#### 4. Data

The dynamic food demand model is estimated by using the Nielsen HomeScan data for the period 2009 and 2010. The data are based on a representative sample of U.S. households that report on all food purchase for each shopping trip. The food items are recorded by the unique Uniform Product Code (UPC) using a scanning device and the information is collected on weekly basis. The initial dataset consists of dry grocery purchases, dairy products purchases, UPC-produce, meat and frozen products purchases, and random weight purchase data. “Household expenditures on food at home” are generated by using the aggregated expenditures on dairy, dry grocery, frozen and random weight products

purchase data. The data files also contain information on household socio-economic and demographic characteristics and purchase information by purchase date, product module, UPC number, size, quantity, multipack, use of coupon and price paid. The demographic characteristics matched with the household purchases data include household income, age, education and employment of household head, race and ethnicity, marital status, and presence of children.

The total number of households reporting any food purchase in the 2009 and 2010 scanner data is over 60,000 households. Of those, more than 59,000 households report some food purchases at least 10 months of a year. Among those households, 36,256 households report dairy products both in 2009 and 2010. This was our sample of interest. The dairy file includes both dairy products and shell eggs. We refer to this as the “dairy” products group. In order to have a sample size that would simplify the estimation process we took a random sample of 3,626 households for our analytic sample, which is approximately 10% of 36,256 households.

In Table 2.1, the dairy products are categorized into four groups of products – milk, cheese, egg and other dairy products. Table 2.1 provides the number of households who purchase each group of products and the percentages of zero purchases of each group. The majority of the households who reported any grocery purchase information for at least 10 months have purchased each group of products at least once in 2009 and 2010. As we consider a month as a time unit out of 24 months’ time period based on the expected average shelf life of dairy products; the number of observations is the number of households times 24.<sup>7</sup> Of our final sample, 40 percent of observations on egg purchases and 29 percent of

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<sup>7</sup> Note that the shelf life of cheese might last longer than any other dairy products in the freezer. This may influence the results of estimation on cheese demand.

observations on cheese purchases had no expenditures on the respective products while 17 percent of observations of milk data were zero purchases. As we see some households that have zero purchase for each category of products, accounting for censoring in the estimation is a reasonable concern.

Table 2.2 provides information on the distribution of average quantities and imputed prices (unit values) for the four product groups. We calculated regional prices as the regions' households' prices after we accounted for the reported product units: ounces, fluid ounces and count measures. The price of each group of products for each region is imputed as the unit value defined as the sum of households' expenditure (\$) in each region for the group of products divided by quantity purchased in ounces. In Table 2.2, monthly average quantities purchased of each category and prices (unit values) are reported. As shown in the table, cheese and other dairy products are more expensive than milk and eggs on a per ounce basis.

Table 2.3 presents the descriptions of variables and provides the calculated means and standard deviations of the final sample. Demographic variables include the household's income, total food (at home) expenditures, household's age, presence of children (kids), employment status of female household head and race and ethnicity. The race and ethnicity are collected from the sample person, and may not reflect the race and ethnicity of all members of the household when race and ethnicity are mixed. The household's income is recorded as a categorical variable. In our estimation we use the household's monthly expenditure calculated over all food groceries as an explanatory variable, instead of reported income (Benson et al., 2002). In doing this, similar to Benson et al. (2002), the estimation results of the demand equations solve the second stage of a two-stage budgeting problem based upon weak separability over households' preferences. Households allocate the total

food expenditures monthly among purchases of dairy products and non-dairy food products after the first allocation of income among purchases of food at home and other goods or services. Using total food expenditure also reduces possible endogeneity posed from use of the dairy group expenditure as a measure of total expenditures or income. We use the information of household's income to compare the demand of low income households to the demand of high income households. The presence of children, race and ethnicity, and the employment status of female household head were considered as binary variables.

The estimation proceeded as follows: the numbers of observations for each data file were iterated 10,000 times; the first 5,000 iterations were set to be burn-in periods.

## 5. Results

Table 2.4 presents the results from the estimation of the dynamic Tobit model with individual heterogeneity on purchases of dairy products reporting the posterior means and standard deviations of parameters for the prices and demographic variables. The probabilities of being positive that is loosely comparable to the notion of “significance” are also reported for each set of parameters estimated for the demand model. The parameter estimates from the main equation and auxiliary equation are shown in Table 2.4. The effect of habit persistence is seen in the parameter value of  $Y_{t-1}$ . We find strong evidences that past purchases of each dairy category play an important role in current purchases of each group of products, as the estimates of all four demand equations present similar positive effects for the lagged dependent variable with probability of being positive 1.0. Even though we controlled for the effect of unobserved heterogeneity, we observe the presence of habit formation in the

purchases of dairy products. In particular, milk demand exhibits the strongest habit forming behavior; we find less effect from the lagged dependent variable on cheese demand.<sup>8</sup>

As shown in Table 2.4, the estimates of the own price responses for all dairy demands are negative signed; most of the own price response have probability of being positive near 0 except for eggs. The estimated response to total food expenditures is positive for all products as we expected, and with probability of being positive 1.0. The presence of children in all age ranges and total food expenditures have substantial positive impacts on milk demand. The effect of having kids on milk consumption is particularly large in the households that have children under 5 years of age. Some interesting result from the estimates for the auxiliary equation is that there is a positive correlation between the unobserved heterogeneity and Hispanic ethnicity in all dairy demands.

In order to avoid possible correlation expected between total expenditure and income, we conducted an additional analysis by separating the sample into two income groups of households and ran the same estimation process on milk products only. We converted midpoints of categorical income ranges into estimated income and computed poverty-income ratios. Low income household is defined if having income less than 200% of the poverty income level and high income household has income more than the cut-off level.<sup>9</sup> The results in Table 2.5 show that the price and total food expenditure responses of low income

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<sup>8</sup> When it comes to estimating habit effects of food demand, perishability and storage motives together with the length of lags may also matter to state dependence. As the length of lags was to be set to be consistent with the length of shelf life for dairy products except for cheese products, we are not overly concerned about controlling storage behaviors from state dependence. The weakest impact of the lagged variable is for cheese demand among dairy demands and this result may relate to the product's longer length of self life. That is, there may be possible storage behaviors in cheese purchases with the result that the habit formation factor may possibly be underestimated.

<sup>9</sup> The official cut-off applied in some nutrition programs (e.g., WIC) is 185%, although higher income households may qualify on the basis of Medicaid or other social assistance programs. We use 200% to include "potentially" eligible households.

households are more responsive than those of high income households. Also, the effect of the presence of children is larger among the low income households.

Uncompensated price and total food expenditure elasticities were calculated from the posterior parameters on prices and food expenditures and are provided in Table 2.6. Point estimates provided in each cell are the means of the Gibbs samples and the 95% credible intervals are given in parentheses. Corresponding to the probabilities of being positive in Table 2.4, most of the own-price elasticities and all the food expenditure elasticities are considered to be “significant” as 95% credible sets exclude zero. The own-price elasticities of each group are negative and inelastic which means that dairy products are necessary goods, as we expect. Demand for cheese is relatively more price responsive than the other products. In the case of egg demand, there is little evidence that most of the price elasticities are “significant” as the 95% credible sets include zero. Complementarity was found among the dairy products.<sup>10</sup> In addition, the food expenditure elasticity estimates for each group are positive. We find some evidence of larger food expenditure elasticities for cheese and other dairy products than for milk and eggs. Both the higher and lower income households have similar inelastic milk demand patterns (see Table 2.7). Low income households exhibit more elastic price and expenditure responses for milk demand compared to the responses of the higher income households.

## 6. Conclusions

This paper investigates the impact of state dependence on dairy demand using Nielsen 2009 and 2010 HomeScan data. The results of the estimation show that habit forming

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<sup>10</sup> Note that as we estimate single demand equations, no restrictions such adding-up, symmetry and homogeneity were imposed.

behaviors exist for these products and are conditional on unobserved individual heterogeneity. As expected in estimating demand for particular product categories, problems of censoring appear in the micro-data. In this paper, we take into account the censored nature of food expenditure data and employ a Bayesian procedure to estimate the dynamic demand models on dairy products. By controlling the individual heterogeneity in the model, the source of endogeneity for the lagged dependent variable has been removed. The Bayesian estimation approach used reduces the burdens of having complicated computations through simulation methods.

This research provides a unique contribution to a dynamic censored demand for food by applying Bayesian method to estimate habit effects using relatively recent household panel data. We examined the dairy foods group and find that most of the dairy products exhibit habit formation. These findings suggest that consumers of these products will be slower to adjust their purchase behavior. Subsequent analysis will expand the time period covered and examine responses to specific food safety recalls and product information. Additional product groups will be considered as well, including meats. Another area for extension of this work is to account for some correlation among the single equations by estimating demand as a demand system.

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**Table 2.1 The Dairy Product Categories and Distribution for Sampled Households<sup>a</sup>**

<b>Product Category/Product Group Description</b>	<b># of HHs</b>	<b>% of Zero Purchases*</b>
MILK	3565	17.7%
CHEESE	3595	29.1%
EGGS	3491	40.9%
OTHER		
BUTTER AND MARGARINE		
COT CHEESE, SOUR CREAM, TOPPINGS		
DOUGH PRODUCTS	3613	19.5%
PUDDING, DESSERTS-DAIRY		
SNACKS, SPREADS, DIPS-DAIRY		
YEAST		
YOGURT		
<b>Total Dairy</b>	<b>3626</b>	

<sup>a</sup> Note: Percentage of observed month with zero purchases over all households purchasing each category of product. Data are reported on the 10% randomly drawn sample of reporting households from Nielsen HomeScan household data 2009-2010.

**Table 2.2 Distributions of Monthly Average Quantities and Prices for Sampled Households<sup>a</sup>**

<b>Variable</b>	<b>Unit</b>	<b>Mean</b>	<b>Std.</b>	<b>Min.</b>	<b>Max.</b>
<b>Milk</b>	Ounce	94.20	77.24	0.00	1382.40
<b>Cheese</b>	Ounce	10.46	10.83	0.00	320.00
<b>Egg</b>	Ounce	17.18	18.82	0.00	761.92
<b>Other dairy</b>	Ounce	13.52	14.77	0.00	288.00
<b>P_milk</b>	\$/oz	0.03	0.01	0.02	0.06
<b>P_cheese</b>	\$/oz	0.28	0.03	0.20	0.45
<b>P_egg</b>	\$/oz	0.07	0.01	0.04	0.12
<b>P_other</b>	\$/oz	0.12	0.02	0.08	0.22

<sup>a</sup> Note: Data are reported on the 10% randomly drawn sample of reporting households from Nielsen HomeScan household data 2009-2010.

**Table 2.3 Definitions and Statistics on the Variables for Sampled Households<sup>a</sup>**

Variable		Mean	Std.Dev	Minimum	Maximum
Household income		59976	38795	5000	200000
Sum_expd	Monthly total food expenditure	155.73	189.24	0	3150.25
Household age	Maximum age of the two household's heads	59.67	12.58	25	110
<b>Binary Variables (equal 1 if following conditions met, and 0 otherwise)</b>					
Kids	Household has a kid under 5 year olds	0.037	0.19	0	1
Skids	Household has a kid between 5 and 11 year olds	0.08	0.27	0	1
Bkids	Household has a kid between 13 and 17 year olds	0.07	0.26	0	1
Emplf	Female household head is employed	0.56	0.50	0.00	1.00
Black	Household's sampled person's race is black	0.08	0.28	0	1
White	Household's sampled person's race is white	0.86	0.35	0	1
Hispanic	Household's sampled person's ethnicity is Hispanic	0.04	0.20	0	1
Summer	Purchasing month is in June to August	0.25	0.43	0	1
Winter	Purchasing month is in November to January	0.25	0.43	0	1

<sup>a</sup> Note: Data are reported on the 10% randomly drawn sample of reporting households from Nielsen HomeScan household data 2009-2010.

**Table 2.4 Bayesian Dynamic Tobit Estimation Results for each Dairy Group's Demand**

	<b>Milk</b>			<b>Cheese</b>			<b>Other Dairy</b>			<b>Eggs</b>		
<b>Main Equation</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>
Yt-1	0.538	0.002	1.000	0.177	0.005	1.000	0.284	0.003	1.000	0.246	0.003	1.000
log(P_milk)	-12.886	1.296	0.000	-0.824	0.286	0.002	-1.593	0.333	0.000	-0.222	0.445	0.307
log(P_other)	3.556	1.978	0.966	-0.459	0.411	0.134	-1.618	0.500	0.001	0.173	0.676	0.593
log(P_cheese)	4.264	2.176	0.975	-2.674	0.512	0.000	3.251	0.557	1.000	-1.399	0.763	0.034
log(P_egg)	4.018	1.628	0.992	1.101	0.390	0.997	0.612	0.423	0.929	-0.039	0.573	0.474
log(Sum_expd)	5.994	0.059	1.000	1.114	0.026	1.000	1.306	0.019	1.000	1.572	0.027	1.000
Kids	9.338	1.224	1.000	1.152	0.262	1.000	0.719	0.305	0.991	0.288	0.405	0.755
Skids	7.357	0.744	1.000	0.752	0.184	1.000	0.943	0.193	1.000	1.714	0.250	1.000
Bkids	7.084	0.722	1.000	0.939	0.149	1.000	0.390	0.198	0.977	1.277	0.248	1.000
Hhage	-0.183	0.016	0.000	-0.035	0.005	0.000	-0.015	0.004	0.000	0.038	0.006	1.000
Emplf	-3.572	0.400	0.000	-0.116	0.083	0.080	0.268	0.101	0.995	-1.016	0.138	0.000
Summer	0.048	0.462	0.544	-0.295	0.095	0.001	0.014	0.114	0.551	-0.576	0.156	0.000
Winter	-2.800	0.478	0.000	-0.040	0.097	0.345	-0.743	0.122	0.000	0.592	0.163	1.000
<b>Auxiliary Equation</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>
Yo	0.071	0.001	1.000	0.050	0.006	1.000	0.148	0.005	1.000	0.058	0.003	1.000
mean of log(P_milk)	0.303	0.110	1.000	-0.547	0.314	0.000	1.363	0.210	1.000	-0.443	0.096	0.000
mean of log(P_other)	-0.955	0.251	0.000	-1.184	0.536	0.000	0.166	0.123	0.928	-0.278	0.155	0.045
mean of log(P_cheese)	0.249	0.234	0.877	1.328	0.590	1.000	1.066	0.197	1.000	-0.834	0.359	0.000
mean of log(P_egg)	0.373	0.247	0.956	0.787	0.417	1.000	-1.416	0.215	0.000	0.659	0.195	1.000
mean of log(Sum_expd)	-0.113	0.037	0.000	0.309	0.122	1.000	-0.112	0.024	0.000	0.286	0.076	1.000

mean of kids	0.275	0.111	1.000	-0.297	0.151	0.048	-0.034	0.086	0.315	-0.079	0.073	0.145
mean of skids	-0.146	0.053	0.000	0.087	0.085	0.904	-0.114	0.061	0.006	-0.030	0.055	0.367
mean of bkids	-0.008	0.038	0.391	-0.060	0.048	0.147	0.109	0.071	0.828	-0.156	0.061	0.000
mean of hhage	0.016	0.001	1.000	0.021	0.006	1.000	0.009	0.001	1.000	0.015	0.001	1.000
mean of emplf	0.071	0.020	1.000	0.050	0.031	0.992	-0.050	0.019	0.000	0.058	0.012	1.000
Black	-0.034	0.046	0.245	-0.333	0.139	0.000	-0.317	0.101	0.000	0.356	0.068	1.000
White	0.075	0.048	0.988	-0.051	0.052	0.191	-0.094	0.045	0.005	-0.261	0.080	0.000
Hispanic	0.283	0.082	1.000	0.228	0.152	0.925	0.034	0.069	0.668	0.432	0.062	1.000
Constant	-0.064	0.264	0.520	-2.938	1.461	0.000	2.884	0.633	1.000	-3.401	0.479	0.000

**Table 2.5 Bayesian Dynamic Tobit Estimation for Milk Demand by Different Income Groups**

	Low income			High income		
<b>Main Equation</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>
Yt-1	0.510	0.006	1.000	0.542	0.003	1.000
log(P_milk)	-15.517	3.219	0.000	-12.560	1.436	0.000
log(P_other)	10.650	4.894	0.985	1.946	2.148	0.821
log(P_cheese)	9.850	5.584	0.962	4.131	2.329	0.960
log(P_egg)	-0.550	4.098	0.450	4.743	1.774	0.995
log(Sum_expd)	6.413	0.141	1.000	5.935	0.068	1.000
Kids	7.539	2.809	0.996	9.994	1.320	1.000
Skids	4.019	1.737	0.990	8.194	0.809	1.000
Bkids	5.970	1.616	1.000	7.172	0.811	1.000
Hhage	-0.140	0.036	0.000	-0.194	0.019	0.000
Emplf	-0.050	1.011	0.483	-3.992	0.452	0.000
Summer	-0.053	1.112	0.489	0.072	0.496	0.559
Winter	-3.300	1.155	0.002	-2.619	0.522	0.000
<b>Auxiliary Equation</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>	<b>Mean</b>	<b>Std</b>	<b>Prob&gt;0</b>
Yo	0.158	0.003	1.000	0.026	0.001	1.000
mean of log(P_milk)	0.303	1.021	0.621	-0.437	0.140	0.000
mean of log(P_other)	0.764	1.387	0.626	-1.001	0.182	0.000
mean of log(P_cheese)	-2.226	0.918	0.000	-1.173	0.109	0.000
mean of log(P_egg)	-0.158	0.667	0.476	1.208	0.124	1.000
mean of log(Sum_expd)	-0.706	0.214	0.000	-0.214	0.065	0.000
mean of kids	0.378	0.309	0.840	0.134	0.066	0.978
mean of skids	-0.713	0.173	0.000	-0.163	0.064	0.000
mean of bkids	1.442	0.361	1.000	-0.176	0.059	0.000
mean of hhage	0.009	0.004	1.000	0.011	0.001	1.000
mean of emplf	0.158	0.099	1.000	-0.042	0.025	0.073
Black	-0.894	0.245	0.000	0.535	0.202	1.000
White	-0.747	0.136	0.000	0.253	0.160	0.884
Hispanic	3.020	0.414	1.000	0.061	0.048	0.960
Constant	1.312	1.401	0.830	-1.839	0.412	0.000

**Table 2.6 Elasticities of Dairy Product Demand**

	<b>Milk</b>	<b>Cheese</b>	<b>Other Dairy</b>	<b>Eggs</b>
<b>P_milk</b>	-0.141 (-0.169, -0.112)	-0.089 (-0.148, -0.028)	-0.127 (-0.179, -0.075)	-0.014 (-0.070, 0.041)
<b>P_cheese</b>	0.047 (0.000, 0.094)	-0.287 (-0.393, -0.179)	0.259 (0.173, 0.345)	-0.088 (-0.183, -0.07)
<b>P_other</b>	0.039 (-0.003, 0.081)	-0.049 (-0.136, -0.036)	-0.129 (-0.206, -0.050)	0.011 (-0.071, 0.096)
<b>P_egg</b>	0.044 (0.009, 0.079)	0.118 (0.037, 0.202)	0.049 (-0.017, 0.115)	-0.002 (-0.070, 0.069)
<b>Sum_expd</b>	0.066 (0.065, 0.067)	0.120 (0.115, 0.125)	0.104 (0.101, 0.107)	0.099 (0.096, 0.102)

**Table 2.7 Elasticities of Milk Demand by Different Income Groups**

	<b>Low income</b>	<b>High income</b>
<b>P_milk</b>	-0.172 (-0.242, -0.102)	-0.138 (-0.168, -0.106)
<b>P_cheese</b>	0.109 (-0.012, 0.231)	0.045 (-0.005, 0.095)
<b>P_other</b>	0.118 (0.012, 0.222)	0.021 (-0.024, 0.067)
<b>P_egg</b>	-0.006 (-0.095, 0.008)	0.054 (0.014, 0.09)
<b>Sum_expd</b>	0.071 (0.068, 0.074)	0.065 (0.063, 0.066)

## **CHAPTER 3. IMPACT OF WIC PROGRAM PARTICIPATION ON FOOD EXPENDITURES<sup>11</sup>**

### **1. Introduction**

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) is one of the largest food assistance programs in the United States. WIC is a federally sponsored program administered by the Food and Nutrition Service (FNS) of United States Department of Agriculture (USDA) and implemented by 90 WIC State Agencies and 34 Indian Tribal Organizations (USDA, 2012). The program provides benefits in the form of healthy foods (WIC package food), nutrition counseling, and access to health services to qualifying low-income infants, children up to age five, pregnant, breastfeeding, and postpartum women in order to improve the health of those at nutritional risk. The program aims to serve the targeted individuals (women, infants and young children) by providing supplemental foods and additional nutrition education. To participate in the program, applicants need to meet the eligibility criteria of having low income, being in an at-risk subgroup (such as pregnant, postpartum, breastfeeding women, infants and children up to age five) and being at nutritional risk. The food package benefits are prescribed based on the age and status of the qualifying individual. The benefits include foods such as infant formula, infant cereal, juice, iron-fortified cereal, milk, eggs, and cheese – with the specific food package assigned by each local agency to be consistent with federal requirements and consistent with the eligibility of WIC participant. In October 2009, the U.S. Department of Agriculture revised the WIC food package. The revised package included the introduction of

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<sup>11</sup> An earlier version was prepared and presented as a Selected Poster at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

new whole-grain products, lower fat content of dairy foods, and reduced juice quantities, and provision of cash-value vouchers for fruits and vegetables among other changes (Federal Register, 2014).

In this paper, we seek to identify households participating in the WIC program and WIC-eligible households in order to evaluate the effect of WIC on the participating households. In the process of identifying participating and eligible households, we follow the work of Bitler, Currie and Scholz (2003) who analyze WIC eligibility and participation using different sources of information. Their paper matches the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP) to an administrative data and compares WIC reporting patterns among respondents. Their comparisons show that WIC participation is significantly under-reported in both the CPS and SIPP, and more so than other antipoverty programs.

We estimate the association between WIC program participation and food expenditures using the Nielsen Homescan data – national level household food purchase data. WIC program provides participating household with free food products that may augment or substitute for foods that might be acquired without the program benefits. Although benefits are prescribed at the individual level, household level data on food expenditure can provide useful information for evaluating the effects of WIC program participation.

Household-level scanner data provide detailed information on each shopping trip made over the span of several years. This level of detail allows a more precise measurement of WIC impact on food consumption compared to other survey data, such as the CPS or SIPP that provide more coarse information on food purchases. The Homescan data provides

detailed information on food prices, expenditures, demographics and information on WIC program participation starting from 1999 allowing tracking households across a period that includes the change in program regulations. Detailed demographic information allows us to identify households that are eligible but not participating the WIC program. Although WIC program participation is self-reported in the HomeScan data and subject to reporting errors, we address this problem by carefully developing a classification of WIC eligible. A formal account for the possibility of misclassification error on participation status is outside the scope of this research.

Self-selection can be a problem in estimating the treatment effect in the programs without random assignment. A self-selection problem arises if program participants systematically differ from non-participants for reasons other than program participating status per se. For example, eligible households that prefer healthier foods may be more interested in participating in the WIC program in order to obtain the foods they like for free. Thus, unobserved factors such as attitudes towards health and food and expected future food security may affect the decision of participation in the WIC program and food consumption. In this study, we assume that the self-selection is determined by observable covariate variables. This can thus be done by imposing an ignorability condition.

Our main objective is to examine how participating in the WIC program influences purchase patterns of households relative to non-participating but eligible households.<sup>12</sup> We assume that the WIC participants and their children are the primary beneficiaries of the WIC program and the change in the availability of foods in the household from WIC participation is a reasonable proxy for a change in the consumption of WIC participants. After detecting

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<sup>12</sup> As observed purchases, the effect could be through vouchers and also nutrition education. We do not account for the nutrition education effect.

and removing the overreporting of WIC participation, we estimate how participating in the WIC program affects food expenditures and the purchases of grain food products among WIC participants and WIC eligible non-participants using 2008-10 data from the Nielsen HomeScan. In addition, we account for WIC food package change implemented in the middle of the period. Although WIC state agencies were required to implement new program rules by October 2009, some states implemented the revised packages earlier (see listing in Appendix 3.1). We estimate WIC impacts before/after the WIC package changes and control potential impact of the policy change based on the implementation dates for each state. In our analysis, we focus on the purchases of grain products – whole grain. Whole grain products were included in the 2009 WIC package revision because whole grain products are under-consumed in the target population relative to the Dietary Guidelines for Americans (DGAs). We selected whole grain foods in the WIC food package as these foods are prominent in the WIC food package and grain products are purchased by most households. Under the new program rules, whole grain products were added to the food packages for women and the young children. At least half of the total number of breakfast cereals state agency food list must be whole grain. Whole-grain bread also added to the new food packages, with substitutions of other whole grain products allowed.<sup>13</sup> We categorize the whole grain products into four groups of products – breads, tortillas, ready-to-eat cereals, and brown rice.

Because the WIC program aims to encourage healthy eating among program participants, analysis of consumption patterns of WIC participating households relative to similar non-participants allows us to see whether participation in the program is associated with healthy food purchases. In particular, this study provides a unique contribution to

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<sup>13</sup> Possible options allowed as substitutes for whole-wheat bread are whole-grain bread, brown rice, bulgur, oatmeal, soft corn, barley, soft corn or whole-wheat tortillas.

literature on the WIC program by investigating the whole grain consumption of WIC participants both before and after the change of the WIC food package. Whole grain products had not been identified explicitly in the WIC package prior to the 2009 package revisions. To date, there has been relatively little research on the effect of the WIC program on whole grain consumption of program participants. As this study deals with evaluation of the WIC program in terms of purchases on WIC-approved packaged foods, it is an important component of program evaluation research and has implications for public health policy. This study provides a model for analysis of the food component changes introduced in 2009. In addition to that, as far as the authors are aware, this paper is the first study using national level scanner data to see WIC program effects on food expenditures. We take advantage of using scanner data which enables us to access detailed information on the food expenditure of households of both WIC participating and non-WIC but eligible households. Other sources of data often lack information on WIC status or of consistent expenditures on food. The research also contributes to better understanding of the potential use of scanner data for examining the reliability of reported WIC participation on food demand.

## **2. Background**

Existing literature on the WIC program finds that participation in WIC has a significant positive impact on the health status of the target population and a significant contribution to reducing food insecurity (Edmunds et al., 2014; Colman et al., 2012; Metallinos-Katsaras et al., 2010; Lee et al., 2006; Meyers et al., 2004; Herman et al., 2004; Carlson and Senauer, 2003). Research also supports positive association between WIC participation and infants' growth and health (Edmunds et al., 2014; Meyers et al., 2004).

Other studies show WIC participation of children to have a significant positive impact on the overall health of children and reduce the risk of several nutrition-related health problems, such as anemia and nutritional deficiency (Carlson and Senauer, 2003; Lee et al., 2006). The literature examining WIC participation's association with food security also finds a beneficial impact of WIC participation on household food security status among first-time program and (Metallinos-Katsaras et al., 2010; Herman et al., 2004)

The main mechanism for improving health outcomes for WIC program participants is through the free provision of healthful foods and therefore investigating the effect of WIC program participation on selection of specific foods is an important program outcome of interest. As the WIC program aims to improve healthy eating behaviors of target people, the analysis of consumption patterns of WIC participants allows us to see whether the program is associated with healthier food purchases. This is one way to measure the effectiveness of the program. There are relatively few studies about the effect of WIC on food consumption; most studies have considered the impacts of WIC on health status and dietary conditions of the target population. These studies have found evidence of a positive association between WIC participation and consumption for some WIC package foods and other related foods (Deming et al., 2014; Watowicz and Taylor, 2014; Oliveira and Chandran, 2005; Ponza et al., 2004). Ponza et al.(2004) examine the nutrient intakes and feeding patterns of participating infants and toddlers and conclude that WIC participants under 24 month old were more likely than nonparticipants to consume many of the foods that are provided in the WIC food package such as cow's milk, 100% juice and peanut butter.

The consumption patterns of WIC food packages for participating children under 5 year old compared with nonparticipants have been investigated and similar positive results

are observed prior to the package change in 2009 (Deming et al., 2014; Watowicz and Taylor, 2014; Oliveira and Chandran, 2005). Most of the studies concentrated on the question whether WIC participation is associated with the development of more healthful eating patterns, in particular, increased fruits and vegetables consumption and limiting intake of sugar-sweetened beverages (Deming et al., 2014; Watowicz and Taylor, 2014; Ponza et al., 2004). Findings from Watowicz and Taylor (2014) are based on data from the National Health and Nutrition Examination Survey (NHANES) 2005-2010.<sup>14</sup> Two studies support the results from the previous study of Ponza et al.,(2004) in which WIC participation was associated with higher intakes of sugar-sweetened beverages for children participating in WIC (Deming et al., 2014; Watowicz and Taylor, 2014). Deming et al. (2014), in their study of young children from the 2008 Feeding Infants and Toddlers Study (FITS) also find that fewer WIC toddlers and preschoolers consumed any fruit compared to nonparticipants and fewer infants of age 6 month-12 months old consumed any vegetables compared to nonparticipants.

In order to address the shortfalls in intake and to improve overall consumption of foods recommended by current Dietary Guidelines, USDA introduced the revision of WIC food packages with new food categories, revised maximum purchase quantities and new food substitution policy options for state agencies. The revisions were approved and implemented by most of states in October 2009 (Institute of Medicine, 2005; Andreyeva et al., 2011). Major changes included in the package revision were placing limitations on the amounts of caloric sweeteners allowed, reducing saturated fat, cholesterol and total fat, promoting the

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<sup>14</sup> NHANES data has only two day dietary recall to measure the food consumption, which can be very noisy, whereas in Homescan data we observe the food purchased for each shopping trip over the years.

consumption of fruits and vegetables through cash-value vouchers and introducing whole grain products in the breads and cereal food group. . There are many on-going studies of the WIC package revisions and assessing the potential effects of the new WIC package revisions on food selection is the main focus of this paper (See, for example, Hillier et al., 2012; Andreyeva and Luedicke, 2014; Bertmann et al., 2014; Thornton et al., 2014; Ritchie et al., 2014).

Along with the primary intent of improving the nutrition of targeted individuals, WIC participation may also affect the food consumption patterns of unintended individuals within the WIC household (Ishdorj, Jensen and Tobias, 2008; Arcia, Crouch and Kulka, 1990). The program food packages are “prescribed” to qualifying individual women, infants and young children. Since the benefits of WIC participation are aimed at specific groups of women and children, not a household, “leakage” of program benefits would occur if benefits go instead to others in the household and reduced for the intended individual. Related literature has found little evidence of possible “spillover” benefits on the household members who are not WIC participants (Ishdorj, Jensen and Tobias, 2008; Arcia, Crouch and Richard, 1990).

### **3. Empirical methodology**

#### **Defining problem: treatment effect**

Our approach to WIC program evaluation adopts the counterfactual (or potential outcomes) framework by Rubin (Rubin, 1974) to measure the effect of the treatment. The treatment variable,  $w_i \in \{0,1\}$  refers to whether household  $i$  participates in the WIC program or not. Let  $y_{1i}$  and  $y_{0i}$  be the outcomes with treatment and without treatment, i.e., food expenditures of WIC participating and non-participating households. The observed outcome

for household  $i$  is given by  $y_i = w_i y_{1i} + (1 - w_i) y_{0i}$ . The impact of a treatment for a household  $i$  is defined as the difference between the potential outcome with and without treatment,  $y_{1i} - y_{0i}$ , that is, the difference between an observed outcome and a counterfactual which we do not observe.

The main measure of interest for the treatment effect suggested in Rosenbaum and Rubin (1983) is known as Average Treatment Effect (ATE):

$$ATE = E[y_{1i} - y_{0i}],$$

which measures the mean difference across all the households including both treatment and control group. The average treatment effect on the treated (ATET) is another measure of interest:

$$ATET = E[y_{1i} - y_{0i} | w_i = 1] = E[y_{1i} | w_i = 1] - E[y_{0i} | w_i = 1]$$

which is obtained by averaging the impact of the treatment on those program participating households. Our objective is to identify the average treatment effect on the treated (ATET). Instead of requiring that all control units have a positive probability of treatment, we only need to keep propensity scores of the treated units to be less than 1 and to have at least some control units with positive propensity scores. We estimate ATET under relatively weaker conditions than the average treatment effect.

### **Propensity score: program participation model**

The fundamental problem of estimating causal effect is that it is impossible to observe the counterfactual when participants have not participated. Estimating the valid counterfactual outcome in a relevant comparison group might be one possible way to solve the problem. To this end, we need to make sure that the comparison group has statistically identical characteristics to the treatment group in order to be the counterfactual of the

treatment group. This process is referred to as “matching”. In a general, non-experimental setting, treatment without being randomized might result in self-selection bias. The basic idea of matching is to reduce the possible sources of self-selection bias by controlling for the set of observed covariates in order to have a group that is comparable to the treated group. In other words, the circumstances where the matching is most likely to work are restricted in selection on observables into the program.

Propensity score matching imputes counterfactual outcomes for program participants using the non-treated group with similar propensity scores. The propensity score (Rosenbaum and Rubin, 1983) is defined as the conditional probability of receiving the treatment. In order to implement the matching estimator, Rosenbaum and Rubin (1983) proposed two assumptions that underlie propensity score matching.<sup>15</sup> First, the potential outcomes are statistically identical after controlling a set of observable covariates. This assumption is known as conditional independence or unconfoundedness or the ignorability assumption. This assumption essentially restates the main requirement of selection on observables addressed above:

$$(Y_1, Y_0) \perp W | X.$$

Second, there is a positive probability of both being participants and not being participants for each value of  $X$ . That is, there is a common support to ensure a similar chance of being treated for proper matches with a sufficient overlap in the characteristics:

$$0 < \Pr(W = 1 | X) < 1.$$

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<sup>15</sup> Rosenbaum and Rubin (1983) note that the assignment of treatment is said to be strongly ignorable if there are two conditions satisfied.

The assumption of common support is testable by checking the distribution of estimated propensity scores for both the treatment group and the comparison group.

Based on the two main assumptions for adequate matching, we first conduct an estimation of the program participation model to characterize the propensity score using a Logit choice model (Rosenbaum and Rubin, 1983). The propensity score of program participation is estimated using various household characteristics such as household income, size, age, the presence of kids under 5, ethnicity and regional information and indicators of employment and the education level of household heads.

### **Matching procedure**

After we characterize the expected probability of program participation, the propensity score, the next step is to determine the matching estimator which will combine a treated group with a non-treated group with equal propensity score to estimate the counterfactual outcome. Note that the sample ATET we aim to estimate is given by:

$$ATET_{psm} = N^{-1} \sum_{i=1}^N \frac{[w_i - \hat{p}(x_i)]y_i}{\hat{p}[1 - \hat{p}(x_i)]},$$

where  $\hat{p} = N_1 / N$  denotes the fraction of treated units in the sample and  $\hat{p}(x_i)$  denotes the estimated probabilities of treatment.

There are several approaches to find good matches. The choice of the matching procedure is important in terms of the size of samples (Heckman, et al., 1997). In this paper, we employ three different matching algorithms to our analysis based on the estimated propensity scores: nearest neighbor matching (NNM), kernel matching and Radius matching. NNM is one of the most straightforward matching estimators. It is conducted by simply comparing every treatment unit with one or more units of the non-treated group in terms of the closest propensity score. By imposing a tolerance level on the maximum propensity score

difference –or caliper – an analyst can improve NNM to have better matches. Radius matching is a variation of caliper matching, which specifies a caliper and chooses not only the nearest neighbor but all units whose differences lie within the caliper’s radius. While NNM uses only a few units from the non-participation group, the Kernel matching estimator uses weighted averages of all units in the non-treated group to construct the counterfactual outcome of the treatment group in a non-parametric way. One might see a trade-off going on between two different matching algorithms in the sense that KM achieves more efficiency having the lower variance with more information but it also is at risk of possible poor matching for some units. In contrast, while NNM reduces bias by selecting only the nearest neighbors which characteristics are very similar, in general, to the treated it has higher variance with less information ignoring many untreated units for the estimation.

We also performed the inverse-probability weighted regression adjustment(IPWRA) for our analytic dataset as an alternative to propensity matching estimators as the sample size for WIC participating households are relatively small for obtaining reliable coefficients. We use the inverse of the predicted probabilities obtained from the propensity score regression as weights and run regressions on the outcome variable -the food expenditures for each group of the treated and the control (Hirano and Imbens, 2001). IPWRA is considered to be a robust estimator as it allows for potential misspecifications in the propensity model and it still provides a consistent estimate of the treatment effect even under misspecifications.

#### **4. Data**

The treatment effect of WIC program participation is estimated by using the Nielsen HomeScan data for the period 2008 to 2010. The Homescan data are originally collected

from a nationally representative sample of households. Identifying WIC participation was based on the self-reported WIC participation variable.

The Homescan data report on expenditures on food items purchased for each shopping trip during the reporting period. The household records all food items by the unique Uniform Product Code (UPC) using a scanning device. Information is collected by Nielsen on weekly basis. Only dollar expenditures for aggregated categories of random weight items are reported.<sup>16</sup> For these random-weight categories, there is no information on prices and quantities. Despite the lack of detail for these items, because the total expenditure on is reported the deficiency does not affect the report on all food purchases for each shopping trip. In this paper, we aggregate food expenditure by month in order to limit the number of zeros.

The Homescan dataset consist of three UPC-coded modules: dry grocery purchases, dairy products purchases, meat and frozen products, and a non-UPC random weight module. For 2008-2010, almost all whole grain items reported by the households have a UPC code. The data also contain information on purchase date, product category, UPC, size, quantity, multipack, use of coupon and the price paid. Socio-economic and demographic characteristics include WIC program participation status, household income, age, education and employment of household head, race and ethnicity, marital status, and presence of children. After narrowing down our analytic sample to WIC eligible households, we match the demographic information including WIC program participation with the food expenditure data to obtain the sample for analysis.

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<sup>16</sup> Random weight items are the items which do not have a UPC codes, they may be sold by weight or by quantity. Most of the fresh fruit and vegetables are sold this way. Some breads baked in the supermarkets are sold as random weight, but they are relatively uncommon.

### **i. Identification of WIC participation households**

The Homescan data were initially screened to classify households as WIC-eligible and ineligible households on the basis of income and demographics. We found a number of possible misreporting errors on current WIC status (e.g., a household reporting WIC participation with no women and no children present). Initial analysis of the data suggested that 3%~21% of households reporting on WIC status may have been in error (either underreporting or over-reporting of WIC participation). From reported demographic characteristics and reported income (200% of poverty or below), we worked to distinguish eligible and ineligible households or as over-reporting. We eliminated potential over-reporting errors (observed as WIC reporting by ineligible households). The underreporting issue is more difficult to deal with.

We identified WIC reporting households for each year (2008, 2009 and 2010) based on the variable: *Currently enrolled in WIC*. Although the total number of households in each year is a bit different from each other, the patterns that emerge in the datasets are similar. Table 3.1 shows unweighted and weighted distributions of households reporting that they are *currently enrolled in WIC* in each year.<sup>17</sup> In unweighted distribution, there were 674 households in 2008, 372 households in 2009 and 439 households in 2010 that reported current WIC enrollment. We observe that the percentage of the WIC reporting households in each year of the Homescan data was a bit under 2% of the total number of households based

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<sup>17</sup> “Household universe weights are available at the county level for all demographic targets. These numbers are kept updated at the beginning of each year and population growth is forecasted each month to allow for population growth. Projection factors for the data are basically computed using these numbers. The projection factors reflect the sample design and each factor reflects the representation of each household in the U.S. population,  $\text{Projection factor} = \text{universe of households} / \text{sample households}$ . The projection factor produces demographic weighting as well as household population projection. The projection system also takes into account the correlation between household demographics and item purchases. Additional weighting is also included in the case of lower income households because of slight under-sampling due to the difficulty of recruiting households in this group. The values of the weights range from small to large and reflect the differential probabilities of household selection.” (Harris, 2005)

on weighted distributions of households.<sup>18</sup> Connor et al. (2011) report that in April 2010, 10,021,136 women, infants, and children were enrolled in the WIC program and this number represents an increase of 5 percent over WIC enrollment reported in 2008. As the supplemental data set by state agencies in Connor et al. (2011) includes the number of household members receiving WIC benefits by each state, the weighted average number of people in the participant's household was calculated as 2.35 based on the projection weights in 2010 Homescan data. By using this average number of household's members we can convert the number of WIC households in Table 3.1 to the number of total WIC participants, 1.9 million to 4.6 million. This estimate which is still less than the half of the total WIC reporting individuals in Connor et al.(2011), and the results from the data analysis in Table 3.1 indicate that the households' report of WIC participation is likely to be under-reported (Bitler, Currie and Scholz: 2003). Under-reporting in WIC can be partially explained by the finding in Bitler, Currie and Scholz (2003) that male respondents are less likely to report WIC participation in the household than female respondents other things being equal.

The general WIC eligibility criteria include income, categorical and nutrition risk requirements. Individuals in households with income 185% of poverty income meet the income requirements. Infants, children up to age five, pregnant, breastfeeding, and postpartum women are categorically eligible for WIC and they should be considered to be in low income households and at nutritional risk. In the data we cannot observe pregnancy, lactation, and nutritional risk status. Individuals may be automatically eligible if they are

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<sup>18</sup> In separate analysis we find that nearly 10% of all households in the NHANES data report receiving WIC benefits in the last 12 months (9.06% in 2007-08 and 2009-10 based on weighted data from the NHANES) and while 2.8% ~ 3.2% of all individuals including children and women report "currently receiving benefits" in the WIC program. Based on the NHANES weights, 3.2% of current WIC participants in 2009-2010 NHANES data reflect nearly 9.6 million number of people which is close to 10,021,136, the number of WIC participants in 2010 (Connor et al., 2011).

eligible to receive SNAP benefits, Medicaid, or benefits from the Temporary Assistance for Needy Families (TANF, formerly known as AFDC, Aid to Families with Dependent Children) program. Because eligibility for these programs is often higher than 185% poverty income, individual may qualify for WIC even though their income is above the 185% level. Therefore, we identify households that are potentially eligible for WIC by including households that have members in a WIC qualifying age group, and have income less than and equal to 200% poverty income ratio. To this end, we examined whether those households reporting WIC do, in fact, meet the eligibility requirements of WIC based on having an eligible household member and having low income level (200% poverty income).

We establish three measurements to use in identifying WIC eligible households: (a) low income level, (b) children under 5 years-old, and (c) having a woman of childbearing age. We estimate poverty income (PIR) as a ratio of the income received (using the mid-point of the income category) to the poverty income level for that size household, multiplied by 100. Low income households are defined as having income less than 200% of the poverty level. All individuals in the household are reported by age, including children. In order to identify the WIC reporting households that include pregnant, breastfeeding or postpartum women, we screen for households that report any female age 14-44 years old (the age range used in the IOM WIC report). Based on the three measurements described above, the screening for WIC eligible households was applied to those low income households with children under 5 years-old and those low income households with a woman of child bearing age. Thus, all eligible households need to be “poor” and have either children under 5 years-old or woman of child bearing age.

In Table 3.2, we check the number of households that are determined to be “eligible” against those reporting WIC enrollment during each year. We would expect the number to be the same as the total WIC reporting households if all eligible households also reported participation. However, as we see in the unweighted distribution of the reported data, in 2008 only 398 of the 654 total households reporting WIC enrollment (61% of the WIC households), satisfy the loosened eligibility criteria and 57% - a slightly smaller percentage – of the households in 2009 were determined WIC eligible. In 2010, there are 287 households identified as “eligible”, or 65% of the WIC participating households. Table 3.2 also shows more detail on the households that reported WIC but are likely ineligible. We observe 35% - 43% of WIC reporting households do not satisfy the eligibility requirements (based on income and demographics) for each year. Most households that we consider erroneously reported WIC status were disqualified on the basis of high income levels. It is possible that some of these households will not qualify during the next program recertification, or may in fact qualify based on participation in another program (e.g., Medicaid).

After removing the 35-43% of WIC-participating but not eligible households, we use the remaining households that satisfy WIC eligibility criteria in the subsequent analysis. Table 3.3 represents the distribution of WIC participation among eligible households in each year. For panel analysis, we are interested in looking at the households that are in three consecutive years. Of all the households that remained in the sample during the three years (39,834), almost half of the total sample of eligible households in each year, stayed in the data system. The second part of Table 3.3 shows the distribution of WIC reporting and eligible households among households with any purchases over three years. Once we apply the additional filter of reporting three consecutive years of WIC participation, the number of

WIC reporting and eligible households in each year gets smaller. For example, only 223 households of 398 households that reported on WIC participation and were eligible in 2008 also were in the data system during the three years. Some of these 223 households participated in WIC in 2009 or in 2010 while some portion would have dropped out of the program during the next two years. Likewise, eligibility status may also vary over the three years.

Appendix 3.2 shows a more detailed distribution of WIC status and eligibility status in 2008, 2009 and 2010. As shown in Appendix 3.2, we are able to check how many households changed their WIC participation status and eligibility status during the years. For example, 119 households of the 223 WIC reporting households in 2008 were not on WIC for the next two years and 31 households returned to the program in 2010 while 73 households continued on the program in 2009; 38 households of those 73 households retained WIC status in 2010. For the analysis, we define treatment in the model to be participation in the WIC program at least once during three consecutive years for simplicity; the control is defined as households that were never on WIC but eligible at least one year during the 3 years.

## **ii. Identification of WIC related food expenditures**

Our tentative target food of interest is “grain” foods, a group of foods that are widely prescribed in the WIC foods package. There are four categories of grain products in the WIC packages: bread, ready-to-eat cereal, rice and tortillas. The Final Rule defines whole grain products as: whole grain or whole wheat bread must conform to FDA standard of identity (21 CFR 136.110), must be the primary ingredient by weight in all whole grain bread products and must meet FDA labeling requirements for making a health claim as a “whole grain food with moderate fat content”. Among the new WIC package requirements were to require that

at least one half of breakfast cereals be identified as whole grain and that whole-grain bread was introduced with allowable substitutions of other whole grains (rice, tortillas) allowed.

In this paper, we constructed a dataset of grain products that consist of four categories as in the WIC packages: bread, read-to-eat cereal, rice and tortillas. We do not consider buns, rolls, bagels, or muffins as bread but only take bakery bread type; rice includes packaged and bulk, canned, mixes and instant forms. In order to focus on the expenditures of grain products allowed in WIC packages, we exclude any other grain products that are not relevant to the WIC program, such as snack, bread mixes, canned bread, granola or hot cereals etc. For the treatment effect analysis, we identify whole grain products by separating grain products into two parts, refined grain products and whole grain products based on UPC description, grain type and product category (product module) variables in the scanner data.

For our analysis of data from 2008 to 2010, we restricted our final analytic sample to 3,198 WIC eligible households that reported grain expenditures in all three years as shown in Table 3.4. There are 3,198 households with grain expenditure in three consecutive years that are eligible some time during the years and 312 households report WIC at least once during three years. Similar to previous analysis in Appendix 3.1, we can indicate WIC identification and eligibility status for those with three years of grain purchases in Appendix 3.3. By comparing Appendix 3.3 with the previous table of distributions (Appendix 3.2), we note that all of households who were on the WIC program at least a year over the three year period purchased some grain products during the time period while very few of households never on the WIC program did not purchase grain product.

## 5. Results

Based on our analytic dataset from the previous section, we estimate the treatment effect of the WIC program on grain product expenditure through the propensity score matching procedure. Note that as our treatment group is eligible WIC participating households, the comparison group is restricted to eligible households not participating in WIC. To clarify the terms we use from now on in the estimation, ‘eligible’ means ‘eligible at least a year during three consecutive years’ and ‘participating’ refers to ‘participating in the program at least a year during the time period’. In the estimation of the propensity score, the set of covariates includes household income, size, maximum age of the household's heads, the presence of kids under 5, and indicators of employment and education level of household heads, race/ethnicity, and regional location. The description of variables and summary statistics are shown in Table 3.5.<sup>19</sup> Several WIC participation indicators including WIC participation at least once during three years and participation in each year are also given. We would expect that household income and the presence of kids under 5 might be correlated with participation in the WIC program and food expenditure as those variables are not perfectly controlled from the analytic steps for our final sample. We would expect that the household size and the employment status of either household head (male, female) might affect the decision to participate in the program. Note that it is still possible to have an income higher than the maximum income for eligibility in one of the years and still be in the final sample. For example, a household might have been eligible in the first two years (2008, 2009) and not be eligible in 2010 because of earning high income in 2010. We include this

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<sup>19</sup> We calculated summary statistics with the weighted distributions of households in the scanner data.

household in our analytic sample according to our definition of eligibility in the estimation because the household was eligible at least one year during the three years.

Summary statistics for purchases on grain products are reported in Table 3.6. We calculate monthly average of whole and refined grain expenditures and weights over the 3 years of pooled data, before and after the implementation of the WIC package change. Although October 2009 was the date approved for implementing the package changes, some states implemented the new rules earlier (see Appendix 3.1). We matched the information on implementation dates to each household's location to calculate monthly average expenditures and weights before and after the change in policy. Table 3.6 shows that both whole grain and refined grain expenditures and weights of WIC participating households are greater than those of non-WIC households across the 3 years, before the change and after the change. In addition, whole grain expenditures and weights of WIC households increased after the package change and this fact suggests that there may be a potential impact of the WIC change in boosting expenditures and weights by WIC participating households relative to non-participating households. In order to have better understanding of the changes, we conduct a difference-in-difference analysis to estimate the WIC impact excluding the possible influence of the policy change in the estimation.

The propensity score is estimated through a logit participation model. We are interested in the decision to participate in WIC for at least one year during the three years. Table 3.7 presents the results of the estimation of the probability of the household's participation in the WIC program at least once in the 3 years. The results with significant levels show that household size and the presence of kids under 5 are highly correlated with WIC participation in the model and that the employment of a household's female head is

negatively correlated with WIC program participation. The households with relatively older male or female head are less likely to participate in the program. We also observe some locational effects on the participation: households in west or south in the United States are less likely to join the program.

In order to have a relevant estimator for program evaluation, one might be interested in testing if there is a proper imposition of the common support condition in the estimation of propensity scores through the distribution of propensity scores for each group. For the assumption to hold true there must be an overlap of the propensity scores of the treatment group and control group. In Figure 1, as an example we report the distribution of predicted propensity scores of both treatment and comparison groups in our main model evaluated under the case of at least one-year participation. Most of propensity scores in both treatment and comparison groups fall into the range of  $[0, 0.79]$ . Thus, it is not unreasonable to impose an assumption of common support to ensure that there are sufficient overlaps of the probability of the program participation in the characteristics. It satisfies the first requirement of using matching for estimating the treatment effect of WIC program participation.

We matched WIC treated and untreated observations based on the estimated propensity score. In order to check if the matching improved the balance of the covariates among two groups, we conduct balancing tests comparing the mean of each covariate before (unmatched) and after matching (matched) and report the results of the main model in Table 3.8. The average values of each covariate, the percentage difference in means (percentage bias) and p-values for t-statistics of the mean differences are reported. Table 3.8 shows that most of variables have more balanced values after the matching as the percentage bias of

each covariate were reduced except for few variables such as male and female education.<sup>20</sup> The reduction of overall bias through the matching can be seen from the difference in mean bias between two samples in unmatched and matched. With two different tests above, we can conclude the propensity score matching process is relevant and successful for our study on WIC participation.

Table 3.9 represents the matching results of average treatment effect on treated (ATET) using estimated propensity scores for the WIC participation indicator. We also report the results of inverse-probability weighted regression adjustment (IPWRA) as an alternative to propensity matching estimators. We estimate at least one year of WIC participation on whole grain product purchases. We are interested in looking at how the experience of WIC participation during the three consecutive years affected whole grain consumption over the three years.

As the new WIC package was implemented during 2009, one might also be interested in seeing the treatment effects before and after the introduction of the package change.<sup>21</sup> In addition to that, merely examining treatment effects without the impact of WIC package changes as a positive demand shock is useful. Therefore, we have four outcome measures in the analysis between the treatment (WIC program participation) and control: (1) the difference in monthly average expenditure of whole grain products in 2008-2010, (2) the difference in average whole grain expenditure before package change, (3) the difference in average whole grain expenditure after package change and (4) the difference in difference in

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<sup>20</sup> Table 3.8 and Figure 3.1 are based on the estimation of NNM(n=10) as the method gives us smaller bias and no off support observation.

<sup>21</sup> We created a variable that indicates whether each transaction of purchasing grain products occurred before or after the particular date of the policy implementation. All WIC agencies should have changed the package by October 2009. In appendix 3, there is information of implementation dates for WIC food packages by state agencies.

average whole grain expenditure over WIC package changes. We compare the results of different matching methods such as Nearest neighbor matching, Kernel matching and Radius matching to check the robustness of the estimation results of average treatment effects. We use 10 neighbors in the non-participating households to match each participating households comparing with one-to-one matching. We use 0.06 bandwidth for Kernel estimator and 0.05 radius for Radius estimator which fit well with the data.

In Table 3.9, the significant differences of monthly average whole grain expenditures during three years between treatment and control group are shown over all four matching mechanisms. Results on households with at least one-year WIC participation (Outcome A) indicate that WIC participating households purchased more whole grain products over the three years, on average. One interesting observation is that the differences of expenditures made after the WIC package changes are generally higher than the differences over the periods that include times before the changes (Outcomes C and B). The treatment effect of WIC participation on whole grain expenditures after the policy change seems to be stronger than the effects over all three years. However, there should be positive impact of WIC package changes promoting whole grain consumption so we need to control the impact of the change on whole grain expenditures.

For the last outcome measure (Outcome D), we first took differences between average expenditures before and after the policy changes for each group and compared these differences by different groups. Applying difference-in-difference to propensity score matching estimation reduces the treatment effect by decreasing the size of estimates from the first outcome to the fourth outcome. From this observation, it might be possible to show indirectly the potential impact of the implementation of the WIC package change as being

positive shock for whole grain purchases. Most of matching procedures except one-to-one NNM give us the consistent result that there is no significant treatment effect of WIC participation on whole grain expenditures after we control for the positive effect of the policy change on demand. We can interpret the results presented here as showing a significant and positive effect of the WIC package revision on increasing whole grain expenditures.

The estimation results under our main specification are based on the loosened eligibility criteria including all potentially eligible households that have either children under 5 years-old or woman of child bearing age. However, there are many women in the age range 14-44 years old who do not have children under 5 or are not pregnant. In order to check the robustness of our main findings, we discard the observations for households with women of child bearing age and no children under 5. By limiting to households with children under 5, we are likely to only miss pregnant women without other children at home. We expect this number to be small. We can control for pregnancy by looking at which households added infants in the next year's survey; there were no additional infants reported over 2009-2010 in the data. Table 3.10 and 3.11 show that dropping households with no children reduced the number of total eligible households for each year and the number of observations ultimately declined to 448 from 3198.<sup>22</sup>

The estimation results with the new subsample are shown in the Table 3.12.<sup>23</sup> By comparing the results in Table 3.9, we observe a similar order of magnitude in the estimates with less statistical significance over most of the methods due to a decline of statistical significance with the smaller sample size. There are no substantial, significant differences in

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<sup>22</sup> This sample has almost 40% of eligible women on WIC, which is a better match to the national statistics.

<sup>23</sup> Table 3.10, Table 3.11 and Table 3.12 with the new subsample are comparable to Table 3.3, Table 3.4, and Table 3.9 with the main specification.

the monthly average whole grain expenditures during the three years (outcome A). The period before the package change (outcome B) between treatment and control group are shown over all mechanisms. Most of matching procedures except NNM provide some significant effect associated with WIC participation on whole grain expenditures after the package change – outcome C - while there is no significant treatment effect for outcome D on the difference in difference estimation. Thus, we conclude that the significant effects on outcome C were more likely attributed to the policy change and not from the WIC participation itself. Estimating with two different samples allows us to show that the results in this paper are consistent and robust.

## **6. Conclusion**

This paper investigates the impact of participating in the WIC program on food purchasing patterns of households. Using Nielsen HomeScan data for 2008-2010, we compare expenditures on whole grain products of WIC participating households to those of non-participating but eligible households using propensity score matching methods. The results of the average treatment effect estimation show that the monthly average whole grain expenditures of households with at least one-year WIC participation are significantly higher than the control (eligible but not participating in WIC). The finding that WIC participating households purchase more whole grain products than non-participating eligible households is useful for evaluating the effectiveness of WIC program participation. A major objective of the WIC program is to increase consumption of healthy foods. Furthermore, in terms of whole grain expenditures, this study may address the issue of recent policy change to the WIC food package which included the introduction of whole grain products to the WIC

packages. In order to see the WIC participation effect over the package changes, we use difference-in-difference propensity matching estimator and this provides us the result of the potential impact of the food package changes, implemented as a positive policy shock. In all three matching methods, we observed consistently that it was the policy shock that played an important role relative to purchasing whole grains rather than the treatment effect of WIC participation itself. A possible extension of the work is to examine the influence of the WIC package changes on the expenditure of the other relevant food groups such as fruit and vegetable might in the similar analysis.

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**Table 3.1 The number of WC reporting households (HHs) in Homescan data**

WIC-currently reporting	Scanner 2008	Scanner 2009	Scanner 2010
<b><i>Unweighted</i></b>			
WIC reporting HHs	654(1.06%)	372(0.61%)	439(0.72%)
Blank (Missing)	60786(98.94%)	60134 (99.39%)	60209 (99.28%)
Total	61440(100%)	60506(100%)	60648 (100%)
<b><i>Weighted</i></b>			
WIC reporting HHs	2,322,106(1.97%)	1,476,452(1.25%)	1,901,481(1.60%)
Blank (Missing)	115,380,000(98.03%)	117,020,000(98.75%)	116,920,000(98.40%)
Total	117,702,106	118,496,452	118,821,481

Source: Nielsen Homescan 2008-2010

**Table 3.2 WIC eligible and non-eligible HHs in reporting HHs**

	Scanner 2008	Scanner 2009	Scanner 2010
<b>WIC reporting HHs</b>	654(100%)	372(100%)	439(100%)
<b>WIC eligible</b>	398(60.86%)	212(56.99%)	287(65.38%)
<i>kids and no chbr women</i>	19(2.91%)	9(2.42%)	8(1.82%)
<i>no kids and chbr women</i>	85(13.00%)	52(13.98%)	71(16.17%)
<i>kids and chbr women</i>	294(44.95%)	151(40.59%)	208(47.38%)
<b>WIC non-eligible</b>	256(39.14%)	160(43.01%)	152(34.62%)
<i>high income</i>	230(35.17%)	141(37.90%)	138(31.33%)
<i>no kids and no chbr women</i>	26(3.98%)	19(5.11%)	14(3.19%)

Source: Nielsen Homescan 2008-2010

**Table 3.3 WIC reporting HHs in eligible HHs (pir <=200 and children or chbr women)**

	Scanner 2008	Scanner 2009	Scanner 2010
<b>WIC reporting and eligible HHs in each year</b>			
WIC reporting HHs	398(8.50%)	212 (4.75%)	287 (6.49%)
Blank (Missing)	4286(91.50%)	4377 (95.25%)	4137 (93.51%)
Total WIC eligible HHs	4694(100%)	4459 (100%)	4424 (100%)
<b>WIC reporting and eligible HHs among 39834 HHs with any purchases of three consecutive years</b>			
WIC reporting HHs	223(9.84%)	128 (5.79%)	123 (5.62%)
Blank (Missing)	2039(90.16%)	2081(94.21%)	2067(94.38%)
Total WIC eligible HHs	2266(100%)	2209(100%)	2190 (100%)

Source: Nielsen Homescan 2008-2010

**Table 3.4 WIC reporting HHs in eligible HHs with grain purchases in three consecutive years**

	Scanner 2008-2010
WIC reporting and eligible HHs*	312
Non-WIC but eligible HHs	2886
<b>Total eligible HHs with any grain purchases</b>	<b>3198</b>
Total HHs with any grain purchases in three years	36477
<i>HHs with any grain purchases in each year</i>	
in 2008	60981
in 2009	60043
In 2010	60177

Source: Nielsen Homescan 2008-2010

\* At least one year of WIC reporting with at least one year of WIC eligible.

**Table 3.5 Definitions and Statistics on the Variables for Sampled Households**

Variable		Mean	Std.Dev	Minimum	Maximum
N	Number of final analytic sample <sup>24</sup>	3198			
HHinc	Household income (\$)	30220.89	17598.04	5000.00	200000.00
HHage	Maximum age of the two household's heads	48.41	12.46	2.00	98.00
Fhage	Age of the household's female head <sup>25</sup>	46.15	12.60	2.00	93.00
HHsize	Household size	3.74	1.66	1.00	9.00
<b>Binary Variables (equal 1 if following conditions met, and 0 otherwise)</b>					
WIC_id	Household reports WIC participation at least once during 2008-2010	0.140	0.347	0.000	1.000
WIC08	Household reports WIC participation in 2009	0.094	0.291	0.000	1.000
WIC09	Household reports WIC participation in 2009	0.060	0.238	0.000	1.000
WIC10	Household reports WIC participation in 2010	0.066	0.247	0.000	1.000
Kids	Household has a kid under 5 year olds	0.192	0.394	0.000	1.000
Edmscol	Male household head's education is collage level	0.304	0.460	0.000	1.000
Edfscol	Female household head's education is collage level	0.329	0.470	0.000	1.000
Emplf	Female household head is employed	0.521	0.500	0.000	1.000
Emplm	Male household head is employed	0.665	0.472	0.000	1.000
Black	Household's sampled person's race is Black	0.156	0.363	0.000	1.000
Hispanic	Household's sampled person's ethnicity is Hispanic	0.140	0.347	0.000	1.000
West	Region is west	0.200	0.400	0.000	1.000
South	Region is south	0.397	0.489	0.000	1.000
Central	Region is central	0.243	0.429	0.000	1.000

Source: Nielsen Homescan 2008-2010

<sup>24</sup> The number reflects the total number of eligible households with any grain purchases in three consecutive years.<sup>25</sup> 61 households do not have information of female head age.

**Table 3.6 Summary Statistics on Monthly Average Grain Expenditures (\$) and Weights (OZ)**

		<b>3 year pooled data</b>	<b>Before package change</b>	<b>After package change</b>
<b>WIC</b>	Whole Grain Exp.(N=309)	7.33	6.79	7.31
(N=312)	Refined Grain Exp.(N=312)	14.20	14.26	13.47
	Total Grain Exp.	21.46	21.05	20.78
<b>Non WIC</b>	Whole Grain Exp.(N=2853)	6.00	5.80	5.57
(N=2886)	Refined Grain Exp.(N=2885)	11.84	11.94	11.18
	Total Grain Exp.	17.76	17.74	16.75
	Diff. in Whole Grain Exp. Between WIC and Non-WIC HHs	1.34	0.99	1.74
<b>WIC</b>	Whole Grain Weight(OZ) (N=309)	50.93	44.98	51.05
(N=312)	Refined Grain Weight(OZ) (N=312)	126.93	130.4	116.83
	Total Grain Weight(OZ)	177.48	175.38	167.88
<b>Non WIC</b>	Whole Grain Weight(OZ) (N=2853)	45.86	44.03	42.57
(N=2886)	Refined Grain Weight(OZ) (N=2885)	106.95	108.9	99.94
	Total Grain Weight(OZ)	152.19	152.93	142.51
	Diff. in Whole Grain Weight(OZ) Between WIC and Non-WIC HHs	5.07	0.95	8.48

Source: Nielsen Homescan 2008-2010

**Table 3.7 Participation model**

	WIC participation at least once over three years	
	Coef.	Std. Err.
<i>Inc=hhinc/1000</i>	-0.011	0.013
<i>hhsiz</i> <i>e</i>	0.375***	0.099
<i>hhsiz</i> <i>e</i> * <i>inc</i>	-0.002	0.003
<i>kids</i>	3.554***	0.476
<i>inc</i> * <i>kids</i>	-0.015	0.010
<i>hsiz</i> <i>e</i> * <i>kids</i>	-0.195	0.096
<i>hhage</i>	-0.099**	0.043
<i>hhage</i> <sup>2</sup>	0.001	0.000
<i>edmscol</i>	0.107	0.153
<i>emplf</i>	-0.355**	0.142
<i>edfscol</i>	-0.007	0.151
<i>emplm</i>	-0.280	0.171
<i>black</i>	0.278	0.218
<i>hispanic</i>	0.299	0.255
<i>west</i>	-0.531**	0.246
<i>south</i>	-0.525**	0.202
<i>central</i>	0.007	0.197
<i>_cons</i>	-0.105	1.131
Number of obs.	3198	
Log likelihood	-7895.11	
LR chi2(17)	466.52	
Pseudo R2	0.228	

Source: Nielsen Homescan 2008- 2010

**Table 3.8 Balancing test**

Variable	Unmatched Matched	Mean		%reduct		t-test	
		Treated	Control	%bias	bias	t	p>t
inc	Unmatched	30.831	33.171	-14.3		-2.21	0.027
	Matched	30.831	31.96	-6.9	51.8	-0.94	0.346
hhsize	Unmatched	4.5288	3.5908	57.7		9.65	0.000
	Matched	4.5288	4.5112	1.1	98.1	0.14	0.891
kids	Unmatched	.56731	.09667	115.2		24.63	0.000
	Matched	.56731	.57724	-2.4	97.9	-0.25	0.802
hhage	Unmatched	46.25	51.19	-43.5		-7.42	0.000
	Matched	46.25	46.125	1.1	97.5	0.14	0.890
edmscol	Unmatched	.32372	.30873	3.2		0.54	0.587
	Matched	.32372	.34776	-5.2	-60.4	-0.63	0.526
emplf	Unmatched	.41987	.54712	-25.7		-4.29	0.000
	Matched	.41987	.45096	-6.3	75.6	-0.78	0.434
edfscol	Unmatched	.33333	.33229	0.2		0.04	0.970
	Matched	.33333	.35128	-3.8	-1626.7	-0.47	0.637
emplm	Unmatched	.69872	.68919	2.1		0.35	0.730
	Matched	.69872	.70417	-1.2	42.8	-0.15	0.882
black	Unmatched	.10577	.11573	-3.2		-0.52	0.600
	Matched	.10577	.09167	4.5	-41.6	0.59	0.556
hispanic	Unmatched	.08013	.06584	5.5		0.96	0.338
	Matched	.08013	.08686	-2.6	52.9	-0.30	0.762
west	Unmatched	.13782	.15835	-5.8		-0.95	0.343
	Matched	.13782	.13494	0.8	85.9	0.10	0.917
south	Unmatched	.32372	.3815	-12.1		-2.00	0.045
	Matched	.32372	.31699	1.4	88.4	0.18	0.857
central	Unmatched	.36538	.28933	16.2		2.80	0.005
	Matched	.36538	.3734	-1.7	89.5	-0.21	0.836
<b>Sample</b>	<b>p&gt;chi2</b>	<b>MeanBias</b>		<b>MedBias</b>			
Raw	0	23.4		12.1			
Matched	0.999	3		2.4			

Source: Nielsen Homescan 2008-2010

**Table 3.9 Treatment effects of WIC participation on whole grain expenditures (\$)**

<b>Treatment: Participation during three consecutive years</b>					
Nearest Neighbor (N=1)	Nearest Neighbor (N=10)	Kernel Matching (BW=0.06)	Radius (r=0.05)	IPWRA	Unmatched
<b><i>Outcome A = Dif in Average Expenditure of Whole Grain in 2008-2010 (Monthly )</i></b>					
1.135** (0.3610)	1.100*** (0.3431)	1.092*** (0.3130)	1.066*** (0.3021)	0.968*** (0.2951)	1.333*** (0.2202)
<b><i>Outcome B = Dif in Average Whole Grain Expenditure before package change</i></b>					
0.715 (0.3580)	0.816 (0.3457)	0.793 (0.3230)	0.930*** (0.2753)	0.678 (0.2947)	0.987*** (0.2331)
<b><i>Outcome C = Dif in Average Whole Grain Expenditure after package change</i></b>					
1.578*** (0.3705)	1.442*** (0.3776)	1.450*** (0.3406)	1.660*** (0.2979)	1.268*** (0.3251)	1.738*** (0.2483)
<b><i>Outcome D = Dif in Dif in Average Whole Grain Expenditure over WIC package changes</i></b>					
0.862** (0.3055)	0.626 (0.2840)	0.657 (0.2843)	0.703 (0.2973)	0.589 (0.2712)	0.751*** (0.197)
<b>Number of observations</b>					
3198	3198	3198	3198	3198	3198
<b>Number of treated(WIC ever) used</b>					
312	312	307	305	312	312
<b>Number of untreated(never WIC) used</b>					
231	1221	2881	2874	2886	2886

Source: Nielsen Homescan 2008- 2010

The standard errors in parenthesis are calculated from bootstrapping with 500 repetitions.

\*\*\* significant at the 1 percent level, \*\* significant at the 5 percent level, \* significant at the 10 percent level.

**Table 3.10 WIC reporting HHs in eligible HHs with Subsample (for Robustness check)**

	Scanner 2008	Scanner 2009	Scanner 2010
<b>WIC reporting and eligible HHs in each year</b>			
WIC reporting HHs	313(27.38%)	160 (15.72%)	216 (22.27%)
Blank (Missing)	830(72.62%)	858 (84.28%)	754 (77.73%)
Total WIC eligible HHs	1143(100%)	1018(100%)	970(100%)
<b>WIC reporting and eligible HHs among 39834 HHs with any purchases of three consecutive years</b>			
WIC reporting HHs	141(29.38%)	74(16.41%)	85(20.38%)
Blank (Missing)	339(70.63%)	388(83.59%)	332(79.62%)
Total WIC eligible HHs	480(100%)	451(100%)	417(100%)

Source: Nielsen Homescan 2008- 2010

**Table 3.11 WIC reporting HHs in eligible HHs with grain purchases in three consecutive years with Subsample (for Robustness check)**

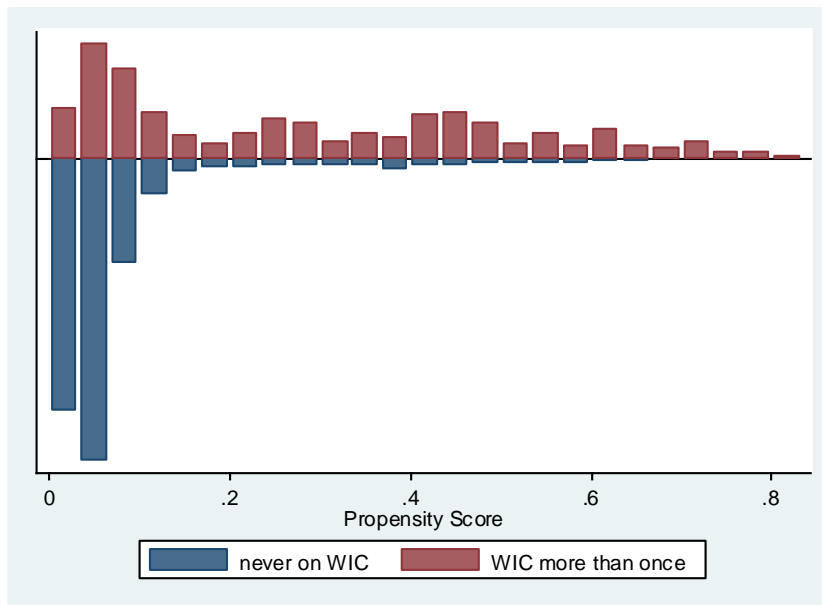
	Scanner 2008-2010
WIC reporting and eligible HHs*	177
Non-WIC but eligible HHs	271
<b>Total eligible HHs with any grain purchases</b>	<b>448</b>
Total HHs with any grain purchases in three years	36477
<i>HHs with any grain purchases in each year</i>	
in 2008	60981
in 2009	60043
In 2010	60177

Source: Nielsen Homescan 2008- 2010

**Table 3.12 Treatment effects of WIC participation on whole grain expenditures (\$) in Subsample (for Robustness check)**

<b>Treatment: Participation during three consecutive years</b>					
Nearest Neighbor (N=1)	Nearest Neighbor (N=10)	Kernel Matching (BW=0.06)	Radius (r=0.05)	IPWRA	Unmatched
<b><i>Outcome A = Dif in Average Expenditure of Whole Grain in 2008-2010 (Monthly)</i></b>					
0.933	0.984	1.105	1.124*	1.118*	1.313***
-0.4695	-0.5801	-0.4369	-0.4211	-0.4103	-0.3801
<b><i>Outcome B = Dif in Average Whole Grain Expenditure before package change</i></b>					
0.734	0.634	0.808	0.827	0.794	0.935
-0.5258	-0.4823	-0.5263	-0.4322	-0.4507	-0.4213
<b><i>Outcome C = Dif in Average Whole Grain Expenditure after package change</i></b>					
1.23	1.399*	1.486**	1.493**	1.543***	1.695***
-0.5966	-0.5423	-0.4831	-0.4967	-0.4587	-0.4196
<b><i>Outcome D = Dif in Dif in Average Whole Grain Expenditure over WIC package changes</i></b>					
0.496	0.735	0.678	0.666	0.748	0.76
-0.4292	-0.4492	-0.3895	-0.3893	-0.4027	-0.341
<b>Number of observations</b>					
448	448	448	448	448	448
<b>Number of treated(WIC ever) matched</b>					
175	177	177	177	177	177
<b>Number of untreated(never WIC) matched</b>					
173	262	268	271	271	271

Source: Nielsen Homescan 2008- 2010



**Figure 1 The distribution of the estimated propensity scores**  
Source: Nielsen Homescan 2008-2010

## APPENDIX A. ADDITIONAL MATERIAL FOR CHAPTER 3

Appendix 3.1 Policy Implementation Dates: Month in 2009 when State WIC Agencies implemented the food package revisions

<b>State</b>	<b>Month in 2009</b>
Delaware, New York	January
Kentucky, South Carolina	May
Colorado	June
Utah	July
Illinois, Kansas, Michigan, Oklahoma, Oregon, Wisconsin	August
Minnesota, South Dakota	September
Alabama, Alaska, Arizona, Arkansas, California, Connecticut, Florida, Georgia, Hawaii, Idaho, Indiana, Iowa, Louisiana, Maine, Maryland, Massachusetts, Mississippi, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, North Carolina, North Dakota, Ohio, Pennsylvania, Rhode Island, Tennessee, Texas, Vermont, Virginia, Washington, West Virginia, Wyoming, District of Columbia	October
Montana	November

Note: List does not include Indian Tribal Organizations (ITO).

Appendix 3.2 The distribution of WIC reporting and eligible HHs with three-year reporting

Table of Elig status by WIC status										
Frequency Percent	Elig status	WIC status								Total
		never	08only	09only	10only	08 & 09	08 & 10	09 & 10	08,09 & 10	
	<b>08only</b>	445	10	2	1	2	0	0	1	461
		13.89	0.31	0.06	0.03	0.06	0	0	0.03	14.39
	<b>09only</b>	223	4	0	1	0	0	1	0	229
		6.96	0.12	0	0.03	0	0	0.03	0	7.15
	<b>10only</b>	367	7	9	9	4	3	4	3	406
		11.46	0.22	0.28	0.28	0.12	0.09	0.12	0.09	12.68
	<b>08 &amp; 09</b>	306	7	0	0	5	1	1	3	323
		9.55	0.22	0	0	0.16	0.03	0.03	0.09	10.08
	<b>08 &amp; 10</b>	116	4	1	2	1	0	2	1	127
		3.62	0.12	0.03	0.06	0.03	0	0.06	0.03	3.97
	<b>09 &amp; 10</b>	272	10	5	2	5	5	1	2	302
		8.49	0.31	0.16	0.06	0.16	0.16	0.03	0.06	9.43
	<b>08,09 &amp; 10</b>	1162	77	18	19	18	22	11	28	1355
		36.28	2.4	0.56	0.59	0.56	0.69	0.34	0.87	42.3
	<b>Total</b>	2891	119	35	34	35	31	20	38	3203
		90.26	3.72	1.09	1.06	1.09	0.97	0.62	1.19	100

Source: Nielsen Homescan 2008- 2010

Appendix 3.3 The distribution of WIC reporting and eligible HHs with three-year grain purchases

Frequency Percent	Elig status	Table of Elig status by WIC status								
		WIC status								
		never	08only	09only	10only	08 & 09	08 & 10	09 & 10	08,09 & 10	Total
	08only	444	10	2	1	2	0	0	1	460
		13.88	0.31	0.06	0.03	0.06	0	0	0.03	14.38
	09only	222	4	0	1	0	0	1	0	228
		6.94	0.13	0	0.03	0	0	0.03	0	7.13
	10only	367	7	9	9	4	3	4	3	406
		11.48	0.22	0.28	0.28	0.13	0.09	0.13	0.09	12.7
	08 & 09	306	7	0	0	5	1	1	3	323
		9.57	0.22	0	0	0.16	0.03	0.03	0.09	10.1
	08 & 10	116	4	1	2	1	0	2	1	127
		3.63	0.13	0.03	0.06	0.03	0	0.06	0.03	3.97
	09 & 10	272	10	5	2	5	5	1	2	302
		8.51	0.31	0.16	0.06	0.16	0.16	0.03	0.06	9.44
	08,09 & 10	1159	77	18	19	18	22	11	28	1352
		36.24	2.41	0.56	0.59	0.56	0.69	0.34	0.88	42.28
	Total	2886	119	35	34	35	31	20	38	3198
		90.24	3.72	1.09	1.06	1.09	0.97	0.63	1.19	100

Source: Nielsen Homescan 2008-2010

## CHAPTER 4. UPSTREAM AND DOWNSTREAM STRATEGIC FOOD SAFETY INTERACTIONS<sup>26</sup>

### 1. Introduction

When making final preparations for home meals, the preparers' views on ingredient wholesomeness matter. These views determine effort at the last defense for preventing foodborne illnesses. For example, the risk of cross-contamination can be reduced by washing hands and cutting boards in meal preparation, and by keeping food at the right temperature. Thoroughly cooking meats and raw eggs might be one good way to reduce the risk of infection by pathogens such as *E. coli* O157:H7.

That consumer's practice toward food safety plays an important role in reducing food-related risk has been firmly established across a wide variety of practices. The scope of analyses on consumer food handling is varied. Literature specific to food safety behaviors considers practices such as cleaning the kitchen area, transporting and storing of selected foods, keeping food temperatures, and cooking hamburgers (Fein et al., 2011; Mattick et al., 2003; Godwin and Coppings, 2005; Hudson and Walley, 2009; Ralston et al., 2001).

Meanwhile, much of the economics literature on food safety presumes that the household, and specifically the main meal preparer, practices safe food handling and studies concentrate more on controls at the food producer sectors. In the literature related to consumer responses to food safety signals, studies mainly focus on the effects of information and quality of food, food safety risk, the effects of food safety incidents and shocks, and the value that consumers place on food safety (Piggott et al., 2007; Jensen and Choi, 1991;

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<sup>26</sup> An earlier version was prepared and presented as a Selected Paper at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

Grunert, 2005; Arnade et al., 2008; Kivi and Shogren, 2010).

A gap exists in the literature in regard to economic analyses of how the consumer's protection incentives affect the risk of food-borne illnesses. Little is known about modeling the consumer's decision-making process in regard to own food safety efforts. The oversight is important because the benefit to be derived from policies that seek to influence on-farm and processor food safety efforts will depend upon how consumer efforts adjust to these policies.

In this study, we investigate strategic interactions among food safety efforts by upstream food processors and downstream consumers in the presence of uncertainty. One of the few studies to examine such interactions is Elbasha and Riggs (2003). They investigate a simultaneous-move game solving Nash equilibrium for food safety efforts when losses are incident on both parties. While their model presumes simultaneous moves, in reality consumers make decisions later and have reason to take producer actions as given so that a natural alternative is to posit an upstream firm as first mover and consumers as second-movers. Our Stackelberg model setting is more similar to Roe (2004). Roe (2004) compares liability assignment rules for a consumer and producer, both risk neutral, in a two-stage decision setting and provides an in-depth investigation of damage function non-convexities. He contrasts the impacts of strict liability with negligence liability rules. We will also make this comparison.

Our analysis is distinct in several ways. The model considers asymmetric timing in moves, thus allowing the upstream agent to move first. By contrast with earlier work we allow for risk aversion on the consumer's part so that the uncertainty that is an essential feature of food safety events has implications for consumer behavior. Finally the timing and

risk aversion dimensions in our model allow for policy analyses not available in earlier works, and we follow through on these opportunities.

Our analysis contrasts food safety incentives and outcomes across two dimensions, technology and liability assignment. In the technology contrast, food safety effort by each party can be either a success or a failure and we assume statistical independence between the success probabilities. Given this, however, two very different maps between effort outcomes and food safety outcomes are considered: weakest link and best shot (Hirshleifer, 1983). In weakest link if one or both of two actions fails then the outcome is a failure, i.e., a food safety event occurs. This relationship is an instance of complementary interactions between efforts because the marginal value of one entity's effort increases with the other entity's effort level. In best shot if either or both of the actions is a success then the food is safe. In this case efforts are substitutes in that one party's effort has less impact at the margin when the other party increases effort. We examine how the sort of technical interaction between upstream and downstream efforts affects behavior strategies when responded to food safety risk.

The second contrast is between incentives under different liability rules. Accommodating the liability rules for food safety has received attention in the food safety literature (Rouvière and Caswell, 2012; Pouliot and Sumner, 2008; Buzby and Frenzen, 1999; Roe, 2004). Roe (2004) is the closest in spirit to our work in that it also considers two liability rules- strict liability and negligence in a bilateral accident setting. However, the current study differs in having a richer technological structure, including risk aversion and allowing for conjectures other than nash.

The analysis in this paper is founded on the framework of self-protection and self-

insurance facing food safety risk. As probability and severity are the two elements that define risk, decreasing either element, privately or collectively, can reduce risk (Shogren, 1990; Ehrlich and Becker, 1972). Ehrlich and Becker (1972) defined and systematically illustrated self-protection, a reduction in loss probability, and self-insurance, a reduction in loss size.

We explicitly examine the self-protection incentives of both consumer and producer to decrease the probability of food safety risk with the fixed severity of a loss under the assumption that there is no self-insurance motive to decrease the size of loss. The relevant example of an undesirable environmental externality in the self-selection literature is investigated in Shogren and Crocker (1991). Shogren and Crocker (1991) analyze self-protection investments by cooperative and noncooperative agents for transferable externality and extend the model to a Stackelberg two-stage game to examine the effects of strategic commitment upon self-protection. However, the association between self-protection and risk aversion is absent in their study.

The relationship between self-protection incentive and risk aversion is an intriguing issue (Lee, 2012; Briys and Schlesinger, 1990; Dionne and Eeckhoudt, 1985). For example, Dionne and Eeckhoudt (1985) and Briys and Schlesinger (1990) demonstrate that self-insurance efforts increases as risk aversion increases, but this is not necessarily true for self-protection efforts (Jullien et al., 1999). In this paper, we explore how risk aversion affects consumer and upstream behavior, where it is known that more risk-averse agents may possibly protect less. As far as we know, none of the extant literature on self-protection incentives considers strategic issues.

The paper is organized as follows. We first explain our general two-stage model set-up, which allows for different technologies as well as for different liability rules. The first-

best choices are identified. Turning to strategic settings, we develop incentives under four settings (weakest link, best shot)  $\times$  (strict liability, negligence). We use backward induction to solve the expected utility maximization problem for a downstream consumer in Stage II. Then we solve for the upstream processor's Stage I cost minimization problem to obtain the optimal levels of preventative effort. After solving for the Stackelberg equilibrium in each case, comparative statics are provided to ascertain strategic interactions between both efforts as well as how consumer risk aversion affects each effort type. We close with a summary and discussions of policy implications.

## 2. Model Set-up

We model a single upstream food processor and a representative downstream food user. The user could be a restaurant or an at-home consumer. Actions are taken at two time points, or stages. At Stage I the upstream firm takes action  $f$  at cost  $x_f$ . At later Stage II the consumer takes action  $c$  costing  $x_c$ . The consumer moves in full knowledge of the firm's earlier action. Food price is fixed throughout the analysis and will be ignored. Two liability rules are considered, strict liability and negligence. One intent in this inquiry is to relate these rules to technical settings. Under strict liability, which we label as SL, the upstream firm is liable whenever a food incident occurs. Under negligence, labeled as N, the firm is liable whenever the firm is negligent even if the consumer's action does not succeed. Let  $G(x_c)$  and  $H(x_f)$  be the respective probabilities that the consumer and firm succeed in their part when securing safe food. Respective first derivatives are given by  $g(x_c)$  and  $h(x_f)$ . Probabilities of failure in either task are written with a bar on top, i.e.,  $\bar{G}(x_c)$  and  $\bar{H}(x_f)$ .

We assume that these events are independent, but how success in these activities maps into safe food is another matter.

In the manner of a copula (Sklar, 1959), these success probabilities combine to form the cumulative probability of having safe food to eat as  $J[G(x_c), H(x_f)]$ . Where convenient, to simplify notation we will write  $J(x_c, x_f)$  for short. Each action has positive but declining marginal impact on this outcome, i.e.,  $J_c(\cdot) > 0$ ,  $J_f(\cdot) > 0$ ,  $J_{cc}(\cdot) < 0$  and  $J_{ff}(\cdot) < 0$ . Actions involve self-protection in the sense of Ehrlich and Becker (1972), i.e., they affect state probabilities and not state outcomes. It remains to state and then motivate the structure of  $J(\cdot, \cdot)$ .

#### *Weakest Link Assumption*

The weakest link, or WL, technology setting is when  $J(x_c, x_f) = G(x_c)H(x_f)$ , i.e., both firm and consumer must succeed if the food is to be safe. Notice that  $J_{cf}(\cdot) \geq 0$ , i.e., efforts are technical complements in the most direct sense. As the weakest link terminology suggests, efforts are likely to complement when the intent of both is to keep a pathogen out. An instance is washing activities, which occurs on packing lines and in kitchens. A contamination event will occur if either a processor or at home user allows produce to be contaminated. In this case,  $\Pr(\text{fse: ff}) = 1$  and  $\Pr(\text{fse: fs}) = \bar{G}(x_c)$  where we use ‘fse’ for ‘food safety event,’ ‘ff’ for ‘firm fails,’ and ‘fs’ for ‘firm succeeds.’ Thus,  $\Pr(\text{fse}) = \bar{J}(x_c, x_f) = 1 - G(x_c)H(x_f)$  in the case of weakest link.

#### *Best Shot Assumption*

The best shot, or BS, technology setting is when  $J(x_c, x_f) = 1 - \bar{G}(x_c)\bar{H}(x_f)$ , i.e., it is only necessary that one or other party succeeds for the food to be safe. Here,  $J_{cf}(\cdot) \leq 0$  so

that efforts are technical substitutes in this very direct sense. Efforts are likely to substitute when the intent of both is to kill a pathogen that is already in, so that cooking and irradiation (microwave) are examples. If either effort succeeds then the problem has been addressed. In this case,  $\Pr(\text{fse: ff}) = \bar{G}(x_c)$  and  $\Pr(\text{fse: fs}) = 0$ .

We model the impact of damage through scaling factor  $e^D$  on consumer utility. Quantity  $L$  is the monetary liability faced by the upstream firm, while  $\tau \in [0,1]$  indicates extent of traceability/transparency which we take to be the fraction of liability that is collected. Damage and traceability parameters allow us to consider policy interventions through government penalties, court imposed fines and public investments in tracing technologies. The model can be adapted to accommodate alternative forms of policy intervention. Roe (2004) and Pouliot and Sumner (2008) study related, but distinct problems, absent risk aversion and strategic dimensions. Elbasha and Riggs (2003) do consider the strategic dimensions but absent risk aversion and presuming simultaneous moves.

The consumer is held to have initial wealth  $w$ , CARA risk preferences  $-e^{-\lambda(\text{wealth})}$  and risk aversion parameter  $\lambda > 0$ , so that utility in the healthy state is  $-e^{-\lambda(w-x_c)}$  and utility in the unhealthy state is  $-e^D e^{-\lambda(w-x_c+\tau L)} = -e^{D-\lambda(w-x_c+\tau L)}$ . Note here that damage and income considerations enter the utility function in distinct ways, where income/wealth effects are mediated by the degree of risk aversion but damage is not. In this way we separate monetary risk preferences from preferences over adverse health events. We assume that  $D > \lambda\tau L$  so that compensation does not exceed damage. As liability and the traceability/transparency index enter in a multiplicative manner throughout, for the sake of simplicity we will write  $P = \tau L$  from this juncture on. We intend for  $P$  to be interpreted broadly, to include marketplace penalty for damage to reputation as well as any direct regulatory penalty. Also, due to the CARA utility structure, wealth  $w$  may be ignored and we will do so from this

point on.

The upstream firm is risk-neutral and seeks to minimize the expected sum of preventive and liability costs while recognizing the consumer's reaction. The four (WL, BS)  $\times$  (SL, N) settings lead to the following four objective functions for the firm's Stage I problem;

$$(1) \quad \begin{aligned} \text{WL} \quad \min_{x_f} C(x_f, x_c^{*\bullet}(x_f)) &= \begin{cases} \text{SL:} & \min_{x_f} x_f + [1 - G(x_c^{*,\text{WL,SL}}(x_f))H(x_f)]P, \\ \text{N:} & \min_{x_f} x_f + \bar{H}(x_f)P, \end{cases} \\ \text{BS} \quad \min_{x_f} C(x_f, x_c^{*\bullet}(x_f)) &= \begin{cases} \text{SL:} & \min_{x_f} x_f + \bar{G}(x_c^{*,\text{BS}}(x_f))\bar{H}(x_f)P, \\ \text{N:} & \min_{x_f} x_f + \bar{G}(x_c^{*,\text{BS}}(x_f))\bar{H}(x_f)P. \end{cases} \end{aligned}$$

with generic solution  $x_f^{*\bullet}$ . The determination of  $x_c^{*,\text{WL,SL}}(x_f)$  and  $x_c^{*,\text{BS}}(x_f)$  will be explained shortly.

Several comments are in order concerning (1) above. One is that under BS the Stage I incentive structures are the same for the firm regardless of liability rule. Were the firm to succeed in its task then the liability rule does not matter. Were the firm to fail then the events of strict liability and negligence are synonymous. The second is that for either rule expected costs are weakly larger under WL than under BS as there are more ways to fail under WL. Under WL too, expected costs are larger when the strict liability rule applies than when the negligence rule applies as the firm's probability of incurring a fine is larger when subject to the strict liability rule. In addition, for WL the expected cost reduces to the same expression under either rule when  $G(x_c^{*\bullet}(x_f)) = 1$ . If the consumer always succeeds then the distinction between liability rules is moot regardless of technology form. Finally, the negligence rule possesses an interesting strategic consequence when the technology is WL. Then the firm is always found to be negligent when it fails because success in its task is essential. This essentiality separates the firm's choice from the consumer's choice and the firm has no

strategic motive to act, where by strategic motive we mean an intent to influence choice  $x_c$ .

By contrast, when the technology is BS then the firm may seek to underinvest in effort and force the consumer to incur the food safety cost.

Corresponding to (1), there are three Stage II consumer problems. For WL and SL the consumer's problem is to

$$(2) \quad \max_{x_c} U^{\text{WL,SL}}(x_c, x_f) = \max_{x_c} -[1 - G(x_c)H(x_f)]e^{D+\lambda(x_c-P)} - G(x_c)H(x_f)e^{\lambda x_c},$$

with generic solution  $x_c^{*,\text{WL,SL}}(x_f)$ . Here there are two possible outcomes;

i) where there is not a fse (occurring with probability  $G(x_c)H(x_f)$ ), and

ii) where there is a fse so that the firm pays  $P$  (occurring with probability  $1 - G(x_c)H(x_f)$ ).

For WL and N the problem is

$$(3) \quad \max_{x_c} U^{\text{WL,N}}(x_c, x_f) = \max_{x_c} -\bar{G}(x_c)H(x_f)e^{D+\lambda x_c} - \bar{H}(x_f)e^{D+\lambda(x_c-P)} - G(x_c)H(x_f)e^{\lambda x_c},$$

with generic solution  $x_c^{*,\text{WL,N}}(x_f)$ . Here there are three possible outcomes;

i) as above, where there is not a fse (occurring with probability  $G(x_c)H(x_f)$ ),

ii) where there is a fse, the firm failed and pays  $P$  (occurring with probability  $G(x_c)\bar{H}(x_f) + \bar{G}(x_c)\bar{H}(x_f) \equiv \bar{H}(x_f)$  where the first left-hand term represents failure by the firm only and the second left-hand term represents failure by both firm and consumer), and

iii) where there is a fse, the firm did not fail and  $P$  is not paid (occurring with probability  $\bar{G}(x_c)H(x_f)$ ).

For BS and either liability rule the problem is

$$(4) \quad \max_{x_c} U^{\text{BS}}(x_c, x_f) = \max_{x_c} -\bar{G}(x_c)\bar{H}(x_f)e^{D+\lambda(x_c-P)} - [1 - \bar{G}(x_c)\bar{H}(x_f)]e^{\lambda x_c}.$$

with generic solution  $x_c^{*,BS}(x_f)$ . Here there are two possible outcomes;

- i) where there is not a fse (occurring with probability  $1 - \bar{G}(x_c)\bar{H}(x_f)$ ), and
- ii) where there is a fse so that the firm must have failed and consequently the firm pays  $P$ .

We seek to understand the nature of the different reaction function  $x_c^{*,\bullet}(x_f)$  that arise in the consumer problem, including conditions under which  $x_c^{*,\bullet}(x_f)$  is monotone. This will allow us to understand the nature of incentives facing the upstream firm. Were  $x_c^{*,\bullet}(x_f)$  increasing then the upstream firm will be incentivized to encourage consumer protection by applying high effort itself. Were the function decreasing then the upstream firm will have incentives to free-ride, placing the burden on the consumer. We also seek to understand how  $x_f^{*,\bullet}$  is affected by policy and related parameters. Finally, we seek to understand how risk aversion parameter  $\lambda$  affects consumer and upstream behavior, where it is known that more risk averse agents may be incentivized to protect less, see, e.g., Jullien et al. (1999). Given the problem's temporal structure the approach taken is, of course, to first solve Stage II and then allow the firm to use imputed reaction functions when acting in Stage I.

### 3. First-Best Outcomes

#### Weakest Link Assumption

Under the weakest-link technology, the consumer's expected utility may be written as

$$(5) \quad U^{WL,SL}(x_c, x_f) = \hat{u} \equiv -e^{-\lambda r(x_c, x_f)} \equiv -[1 - G(x_c)H(x_f)]e^{D+\lambda x_c} - G(x_c)H(x_f)e^{\lambda x_c},$$

so that certainty equivalent is

$$(6) \quad \begin{aligned} r(x_c, x_f) &\equiv -\lambda^{-1} \ln \left[ (1-p)e^{D+\lambda x_c} + pe^{\lambda x_c} \right] \\ &= -\lambda^{-1} \ln \left[ [1 - G(x_c)H(x_f)]e^D + G(x_c)H(x_f) \right] - x_c. \end{aligned}$$

Therefore we may write aggregate certainty equivalent return as the difference between consumer certainty equivalent and firm effort;<sup>27</sup>

$$(7) \quad r(x_c, x_f) - x_f = -\lambda^{-1} \ln \left[ [1 - G(x_c)H(x_f)]e^D + G(x_c)H(x_f) \right] - x_c - x_f.$$

This reveals that the welfare maximization problem may be posed as

$$(8) \quad \max_{x_c, x_f} -[1 - G(x_c)H(x_f)]e^{D+\lambda(x_c+x_f)} - G(x_c)H(x_f)e^{\lambda(x_c+x_f)},$$

and optimality conditions are

$$(9) \quad \begin{aligned} \lambda G(x_c)H(x_f) + g(x_c)H(x_f) &= \rho; & \rho &= \frac{\lambda e^D}{e^D - 1}; \\ \lambda G(x_c)H(x_f) + G(x_c)h(x_f) &= \rho. \end{aligned}$$

Some manipulation then delivers

$$(10) \quad \begin{aligned} \frac{g(x_c)}{G(x_c)} &= \frac{h(x_f)}{H(x_f)}; \\ \lambda G(x_c)H(x_f) + g(x_c)H(x_f) &= \rho. \end{aligned}$$

The first of these two optimality conditions shows that, whenever  $G(\cdot)$  and  $H(\cdot)$  are both logconcave (Bagnoli and Bergstrom, 2005), higher first-best values of  $x_c$  and  $x_f$  will rise or fall together. Consequently it is readily apparent that an increase in risk aversion parameter  $\lambda$  will lead to an increase in first-best levels of both effort choices.

### Best Shot Assumption

Under the best-shot technology, the consumer's expected utility is given as

$$(11) \quad U^{\text{BS,SL}}(x_c, x_f) = \hat{u} \equiv -e^{-\lambda r(x_c, x_f)} \equiv -(1-p)e^{D+\lambda x_c} - pe^{\lambda x_c}; \quad p \equiv 1 - \bar{G}(x_c)\bar{H}(x_f),$$

so that aggregate certainty equivalent return can be written as

$$(12) \quad r(x_c, x_f) - x_f = -\lambda^{-1} \ln \left[ \bar{G}(x_c)\bar{H}(x_f)e^D + (1 - \bar{G}(x_c)\bar{H}(x_f)) \right] - x_c - x_f.$$

The welfare maximization problem may be posed as

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<sup>27</sup> Notice that penalty is a transfer and so would not enter the calculation.

$$(13) \quad \max_{x_c, x_f} -\bar{G}(x_c)\bar{H}(x_f)e^{D+\lambda(x_c+x_f)} - [1-\bar{G}(x_c)\bar{H}(x_f)]e^{\lambda(x_c+x_f)}.$$

First-order conditions are

$$(14) \quad \begin{aligned} \lambda\bar{G}(x_c)\bar{H}(x_f) - g(x_c)\bar{H}(x_f) &= \frac{-\lambda}{(e^D - 1)} = \frac{-\rho}{e^D}; \\ \lambda\bar{G}(x_c)\bar{H}(x_f) - \bar{G}(x_c)h(x_f) &= \frac{-\lambda}{(e^D - 1)} = \frac{-\rho}{e^D}. \end{aligned}$$

If we set  $G(x_c) = 1 - e^{-\phi x_c}$  and  $H(x_f) = 1 - e^{-\kappa x_f}$  then the optimality conditions become and first-order conditions are

$$(15) \quad \begin{aligned} (\phi - \lambda)e^{-\phi x_c - \kappa x_f} &= \frac{\lambda}{e^D - 1}; \\ (\kappa - \lambda)e^{-\phi x_c - \kappa x_f} &= \frac{\lambda}{e^D - 1}. \end{aligned}$$

The conditions reveal that, with the given technologies the efforts are perfect substitutes up to a productivity scaling factor, the socially optimal solution is to use only the more cost effective effort. Use only consumer effort whenever  $\phi > \kappa$ , only upstream effort whenever  $\phi < \kappa$ , and be indifferent whenever they are equally productive. When  $\phi > \kappa$  then the socially optimal effort levels are  $x_c^{so} = -\phi^{-1} \ln[\lambda / (\phi - \lambda)] - \phi^{-1} \ln[1 / (e^D - 1)]$  and  $x_f^{so} = 0$ .

When  $\phi < \kappa$  then the socially optimal effort levels are  $x_c^{so} = 0$  and

$$x_f^{so} = -\kappa^{-1} \ln[\lambda / (\kappa - \lambda)] - \kappa^{-1} \ln[1 / (e^D - 1)].$$

Notice that in either case first-best effort declines with an increase in risk aversion. The reason for this peculiarity is the input's self-protective nature.

#### 4. Backward Induction

##### Stage II, when Firm Moves First

In this section we seek to understand the consumer's optimal choice in light of the

firm's decision so as to understand consumer reactions that the firm acting at Stage I can seek to manipulate. We assume that the cost function is convex, but will return to the issue when considering specific examples. Throughout we set  $G(x_c) = 1 - e^{-\phi x_c}$  and  $H(x_f) = 1 - e^{-\kappa x_f}$ . It is assumed throughout that  $\phi > \lambda$ , i.e., that the effort sensitive of consumer's probability of task failure  $-d \ln[\bar{G}(x_c)]/dx_c = \phi$  is large when compared with degree of risk aversion. Why this assumption is needed is explained in the appendix, where Stackelberg second-order conditions are established. Were risk aversion the larger of the two then corner solutions would be supported in that consumers would have unlimited incentive to protect and so reduce risk exposure.

#### *Weakest Link and Strict Liability*

In the case of objective function (2), the first-order optimality condition resolves to

$$(16) \quad \frac{\lambda \Phi}{1 - e^{-\kappa x_f}} = (\phi - \lambda)e^{-\phi x_c} + \lambda; \quad \Phi = \frac{M}{M - 1}; \quad M = e^{D - \lambda P} > 1.$$

where we write the solution as  $x_c^{*, \text{WL,SL}}(x_f)$ . Letting  $\Phi = \lambda / (\lambda - \phi)$ , some algebra establishes

$$(17) \quad x_c^{*, \text{WL,SL}}(x_f) = \frac{1}{\phi} \ln(e^{D - \lambda P} - 1) + \frac{1}{\phi} \ln(1 - e^{-\kappa x_f}) - \frac{1}{\phi} \ln(\Phi) - \frac{1}{\phi} \ln(1 + e^{D - \lambda P - \kappa x_f} - e^{-\kappa x_f}).$$

Notice here that the term  $-\phi^{-1} \ln(\Phi)$  is decreasing in  $\lambda$  so that the value of  $x_c^{*, \text{WL,SL}}(x_f)$  may well decrease in the degree of risk aversion even absent any consideration on how firm effort is impacted by risk aversion. As to why this is possibility arises, bear in mind that  $x_c$  is a self-protection input impacting probability of loss and not state-conditioned extent of loss, see eqn. (2).

### Weakest Link and Negligence

In the case of objective function (3) the optimality condition resolves to

$$(18) \quad (\phi - \lambda)(e^D - 1)(1 - e^{-\kappa x_f})e^{-\phi x_c} = \lambda(e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f} + 1).$$

Consequently,

$$(19) \quad \begin{aligned} x_c^{*,WL,N}(x_f) &= \frac{1}{\phi} \ln(1 - e^{-\kappa x_f}) - \frac{1}{\phi} \ln(e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f} + 1) - \frac{1}{\phi} \ln(\Phi) + \frac{1}{\phi} \ln(e^D - 1) \\ &= x_c^{*,WL,SL}(x_f) + \frac{1}{\phi} \ln\left(\frac{e^D - 1}{e^{D-\lambda P} - 1}\right). \end{aligned}$$

and

$$(20) \quad \frac{dx_c^{*,WL,N}(x_f)}{dx_f} = \frac{dx_c^{*,WL,SL}(x_f)}{dx_f} = \frac{\kappa e^{D-\lambda P} e^{-\kappa x_f}}{\phi(e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f} + 1)(1 - e^{-\kappa x_f})} > 0.$$

So under the weakest-link technology and either, actions are complementary in the sense of technological inputs.

**Remark 1:** Under the weakest-link technology and either liability structure, the consumer's reaction to an increase in processor food safety effort is to also increase effort.

It follows that any policy intervention intent on increasing firm effort should have a positive strategic impact on consumer effort.

### Best Shot

In the case of BS, the first-order condition arising from (4) resolves to

$$(21) \quad e^{-\phi x_c^*} = \frac{\Phi e^{\kappa x_f}}{e^{D-\lambda P} - 1};$$

with solution  $x_c^{*,BS}(x_f)$ . Solving explicitly, we have

$$(22) \quad x_c^{*,BS}(x_f) = \frac{1}{\phi} \ln(e^{D-\lambda P} - 1) - \frac{1}{\phi} \ln(\Phi) - \frac{\kappa}{\phi} x_f,$$

revealing that efforts are perfect substitutes. The consumer's reaction function is characterized by derivative  $dx_c^{*,BS}(x_f)/dx_f = -\kappa/\phi < 0$  so that we may assert;

**Remark 2:** Under the best-shot technology and either liability structure, the consumer's reaction is to decrease effort (and in linear manner) in response to an increase in processor food safety.

A comparison of remarks 1 and 2 shows that the qualitative nature of consumer reactions to firm choices will depend upon the technology setting, where our view is that both weakest link and best shot technologies are plausible approximations to reality.

### Stage I

We turn now to firm choice. In addition to managing direct effects of effort on effort costs and any liabilities, the firm can take advantage of strategic opportunities to guide the consumer's behavior. (Fudenberg and Tirole, 1984). These strategic opportunities are the matter of this section.

#### *Weakest-Link and Strict Liability*

Insert expression (17) for  $x_c^{*,WL,SL}(x_f)$  into  $G(x_c) = 1 - e^{-\phi x_c}$  to obtain

$$(23) \quad G(x_c^{*,WL,SL}(x_f)) = 1 - \Phi - \frac{\Phi e^{D-\lambda P}}{(e^{D-\lambda P} - 1)(1 - e^{-\kappa x_f})}.$$

so that the appropriate objective function is

$$(24) \quad \min_{x_f} C(x_f, x_c^{*,WL,SL}(x_f)) = \min_{x_f} x_f - \Phi P + (1 - \Phi)e^{-\kappa x_f} P + \frac{\Phi e^{D-\lambda P} P}{e^{D-\lambda P} - 1}.$$

Thus, the optimality condition is  $(1 - \Phi)\kappa P = e^{\kappa x_f^{*,WL,SL}}$  with explicit solution

$x_f^{*,WL,SL} = \kappa^{-1} \ln[(1 - \Phi)\kappa P]$ . The expression is independent of  $D$  but not of  $\lambda$ . Figure 4.1

depicts how  $x_f^{*,WL,SL}$  is determined. As  $x_f^{*,WL,SL} > 0$  if and only if  $e^{\kappa x_f^{*,WL,SL}} > 1$ , it follows that, for weakest-link and strict liability,  $x_f > 0$  if and only if  $(1 - \Phi)\kappa P > 1$ . This observation will prove to be useful when interpreting expressions to follow. Differentiate the optimality condition to obtain

$$(25) \quad \frac{dx_f^{*,WL,SL}}{dP} = \frac{1}{\kappa P} > 0; \quad \frac{dx_f^{*,WL,SL}}{d\lambda} = \frac{1}{\kappa(\phi - \lambda)} > 0;$$

comparative statics that are readily discerned from Figure 4.1.

**Remark 3:** Under the weakest-link technology and strict liability structure, the firm increases effort as the penalty increases and also as the consumer's level of risk aversion increases.

The origin of the response to a penalty is clear, that of the response to risk aversion less so. As already noted, the consumer's response to risk aversion is compromised due to the self-protective nature of effort. Given the complementarity embedded in the weakest-link technology (see Remark 1) and strict liability, and to the extent that consumer response to risk aversion is muted, the firm has a strong self interest in stepping up its protective effort to limit probability of liability. Perhaps counterintuitively, the firm's action may conceivably be more sensitive to consumer risk aversion than the consumer's own effort.

For interior solutions,  $H(x_f^*) = 1 - e^{-\kappa x_f^{*,WL,SL}} = (\phi\kappa P - \phi + \lambda) / (\phi\kappa P)$ . From (17) then we have

$$(26) \quad x_c^{*,WL,SL} = \frac{1}{\phi} \ln(e^{D-\lambda P} - 1) - \frac{1}{\phi} \ln\left(\frac{(\phi - \lambda)e^{D-\lambda P} + \phi\kappa P - \phi + \lambda}{\phi\kappa P - \phi + \lambda}\right) - \frac{1}{\phi} \ln(\Phi).$$

Next, from (26),

$$(27) \quad \frac{dx_c^{*,WL,SL}}{d\lambda} = \frac{(e^{D-\lambda P} - 1)^2 - \phi\kappa P^2 e^{D-\lambda P}}{\phi[(\phi - \lambda)(e^{D-\lambda P} - 1) + \phi\kappa P](e^{D-\lambda P} - 1)} + \frac{1}{\phi} \frac{\phi^2 - \lambda^2 - \phi^2 \kappa P}{(\phi\kappa P - \phi + \lambda)\lambda(\phi - \lambda)}.$$

To ascertain that this response can be negative, let  $P \rightarrow D/\lambda$  so that  $dx_c^{*,WL,SL}/d\lambda \rightarrow -\infty$ .

On the other hand, when  $P \approx (\phi - \lambda)/(\phi\kappa)$  then the first right hand term is finite but the second right hand term converges on value  $\phi^{-1} \lim_{\varepsilon \downarrow 0} 1/\varepsilon \rightarrow \infty$ . As the penalty facing the firm grows the consumer sees the probability and cost of loss decrease and so risk aversion ceases to be a motivation for effort.

Now differentiate with respect to the penalty:

$$(28) \quad \frac{dx_c^{*,WL,SL}}{dP} = \left\{ \frac{(\phi - \lambda)(e^{D-\lambda P} - 1) - \lambda P(\phi\kappa P - \phi + \lambda)}{(e^{D-\lambda P} - 1)(\phi\kappa P - \phi + \lambda)} \right\} \left[ \frac{\kappa e^{D-\lambda P}}{(\phi - \lambda)(e^{D-\lambda P} - 1) + \phi\kappa P} \right]$$

$$\stackrel{\text{sign}}{=} e^{D-\lambda P} - 1 - \frac{\lambda}{\phi - \lambda} P(\phi\kappa P - \phi + \lambda).$$

The sign is undetermined without further assumptions. Two forces are at play.

Complementarity suggests that an increase in penalty that elicits more processor effort should also elicit more consumer effort. On the other hand, strict liability creates a form of moral hazard such that the consumer may seek to lean on firm efforts. It is clear from (28) that if both the penalty and the coefficient of risk aversion are low then consumer effort will respond positively to a penalty. We saw above that when the penalty is low then consumer effort increases strongly to an increase in degree of risk aversion, because level of effort is very low. However, as the coefficient of risk aversion increases then consumer effort becomes less responsive to the penalty. When risk aversion is strong then the consumer is likely already applying much effort. Given strict liability, when the penalty increases then the consumer sees advantage in handing over food safety responsibilities to the firm and cutting effort costs.

*WL and Negligence*

From (1), the goal is to  $\min_{x_f} x_f + e^{-\kappa x_f} P$ , so the first-order condition is  $1 = \kappa e^{-\kappa x_f} P$  and the optimal solution is  $x_f^{*,WL,N} = \kappa^{-1} \ln(\kappa P)$  where  $\kappa P > 1$  is required to ensure an interior solution, i.e., if  $\kappa P \leq 1$  then  $x_f^{*,WL,N} = 0$  so that the firm accepts penalty  $P$  with certainty.

Three contrasts are apparent with  $x_f^{*,WL,SL}$  as arrived at from (24). One is that, as the objective function makes transparent, the firm's optimal choice under the negligence rule is independent of  $D$  and  $\lambda$ . Firm incentives are not coupled with consumer incentives. Another is that strict liability provides stronger incentives to the firm, i.e.,

$$(29) \quad x_f^{*,WL,SL} - x_f^{*,WL,N} = \frac{1}{\kappa} \ln(\Phi) > 0.$$

The third is that this difference is independent of the penalty's magnitude,  $P$ , which, as in (19) for consumer efforts, has a common effect on each effort level and nets out.

**Remark 4:** Under the weakest-link technology, optimal firm effort when subject to strict liability exceeds optimal effort when subject to the negligence rule and the difference is increasing in the consumer's level of risk aversion.

Risk aversion matters only under strict liability because then the firm can be liable when failure occurs on the consumer side. As a consequence, and in light of the technical complementarity pointed out in Remark 1, the firm possesses a strategic motive that does not exist under the negligence legal rule.

Insert  $x_f^{*,WL,N} = \kappa^{-1} \ln(\kappa P)$  into the Stage II optimality condition for WL and N, or (19), to obtain

$$(30) \quad x_c^{*,WL,N} = \frac{1}{\phi} \ln(\kappa P - 1) - \frac{1}{\phi} \ln(e^{D-\lambda P} + \kappa P - 1) + \frac{1}{\phi} \ln(e^D - 1) - \frac{1}{\phi} \ln(\Phi).$$

It follows that

$$(31) \quad \frac{dx_c^{*,WL,N}}{d\lambda} = \frac{e^{D-\lambda P}(P\phi\lambda - P\lambda^2 - \phi) - (\kappa P - 1)\phi}{(e^{D-\lambda P} + \kappa P - 1)(\phi - \lambda)\lambda\phi},$$

and

$$(32) \quad \frac{dx_c^{*,WL,N}}{dP} = \frac{[\kappa + \lambda(\kappa P - 1)]e^{D-\lambda P}}{\phi(\kappa P - 1)(e^{D-\lambda P} + \kappa P - 1)} > 0,$$

given the assumption that  $\kappa P > 1$ . Regarding (31), the denominator is certainly positive. If  $P\phi\lambda - P\lambda^2 - \phi < 0$  then the numerator is negative and  $dx_c^{*,WL,N} / d\lambda < 0$ . The quadratic's maximum value is when  $\lambda = \phi / 2$  so that it suffices to know whether  $P\phi < 4$ . Thus in the negligence setting,  $dx_c^{*,WL,N} / d\lambda < 0$  whenever  $4 / \phi > P > 1 / \kappa$ . So, assuming that penalty  $P$  is low and firm effort is interior, the comparatively more risk averse consumer takes less effort. Again, the effort's self-protective nature is manifest.

**Remark 5:** Under the weakest-link technology, the negligence liability rule, and interior firm effort, the privately optimal level of consumer effort is *i*) increasing in the level of penalty, and *ii*) decreasing in the level of risk aversion whenever  $4 / \phi > P > 1 / \kappa$ .

We turn now to a direct comparison of consumer effort across liability rules. From differencing (26) and (30) we have

$$(33) \quad x_c^{*,WL,SL} - x_c^{*,WL,N} = \frac{1}{\phi} \ln \left[ \frac{(e^{D-\lambda P} - 1)(\phi\kappa P - \phi + \lambda)}{(e^D - 1)[(\phi - \lambda)e^{D-\lambda P} + \phi\kappa P - \phi + \lambda]} \right] + \frac{1}{\phi} \ln \left( \frac{e^{D-\lambda P} + \kappa P - 1}{\kappa P - 1} \right).$$

Without further information we cannot establish whether the consumer facing the weakest link technology when under the strict liability rule takes more effort than when under the negligence rule. We know from Remark 4 that the firm takes more effort when under the strict liability rule. Given complementarity, this should promote comparatively more consumer effort under the strict liability rule. On the other hand, the user's loss under strict

liability are comparatively lower and so moral hazard effects will be comparatively stronger under the strict liability rule.

To probe the matter further, suppose that the penalty is as large as we will allow it to be, specifically when  $P \rightarrow D / \lambda$ . Then

$$(34) \quad x_c^{*,WL,SL} - x_c^{*,WL,N} \rightarrow \frac{1}{\phi} \ln \left[ \frac{(1-\lambda)(\phi \kappa D - \phi \lambda + \lambda^2)}{(e^D - 1)\phi(\kappa D - \lambda)} \right] < 0.$$

Alternatively, suppose that the penalty is low, such that  $\kappa P \rightarrow 1$ . Then

$$(35) \quad x_c^{*,WL,SL} - x_c^{*,WL,N} = \frac{1}{\phi} \ln \left[ \overbrace{\frac{(e^{D-\lambda/\kappa} - 1)\lambda}{(e^D - 1)[(\phi - \lambda)e^{D-\lambda/\kappa} + \lambda]}}^{\text{negative and finite}} \right] + \frac{1}{\phi} \ln \left( \overbrace{\frac{e^{D-\lambda/\kappa}}{\kappa P - 1}}^{\rightarrow \infty} \right).$$

**Remark 6:** In weakest link, when the penalty is sufficiently

- i) low then consumer effort under strict liability exceeds that under negligence;
- ii) high then consumer effort under strict liability is lower than under negligence.

As to why these outcomes arise, when the penalty is high and the rule is strict liability then the consumer is better able to free-ride off the firm. When the penalty is low then the firm takes little effort and is likely to be deemed negligent. There is little incentive to free-ride off firm effort but the strategic motive to respond positively to any firm effort remains.

### Best Shot

From (1), the goal is to  $\min_{x_f} x_f + \bar{G}(x_c^*(x_f))\bar{H}(x_f)P$ . From (21), we have

$$(36) \quad \bar{G}(x_c^{*,BS}(x_f)) = \frac{\Phi e^{\kappa x_f^{*,BS}}}{e^{D-\lambda P} - 1}.$$

Therefore,  $\bar{G}(x_c^{*,BS}(x_f))\bar{H}(x_f) = 1 / (e^{D-\lambda P} - 1)$  and the goal becomes

$$(37) \quad \min_{x_f} x_f + \frac{\Phi P}{e^{D-\lambda P} - 1},$$

with solution  $x_f^{*,BS} = 0$ . The firm, having the first-move, exploits the opportunity to impose the cost of food safety effort on the consumer. From (22) then we have

$$(38) \quad x_c^{*,BS} = \frac{1}{\phi} \ln(e^{D-\lambda P} - 1) - \frac{1}{\phi} \ln(\Phi),$$

so that

$$(39) \quad \begin{aligned} \frac{dx_c^{*,BS}}{d\lambda} &= -\frac{Pe^{D-\lambda P}}{\phi(e^{D-\lambda P} - 1)} - \frac{1}{(\phi - \lambda)\lambda} < 0; \\ \frac{dx_c^{*,BS}}{dP} &= -\frac{\lambda e^{D-\lambda P}}{\phi(e^{D-\lambda P} - 1)} < 0. \end{aligned}$$

**Remark 7:** Under best-shot, the consumer's effort declines as the consumer's level of risk aversion increases and also as the penalty increases.

As under weakest-link, the response to degree of risk aversion arises from the input's self-protective nature. Turning to the adverse penalty response, this is most disturbing from the policy viewpoint. Due to moral hazard effects, under either liability rule an increase in penalty reduces consumer incentive to care while the firm's concern about the penalty is dominated by its desire to foist caretaking responsibility on the consumer. The penalty does not encourage the firm to take effort, but the prospect of compensation discourages the consumer from taking effort. The policy intervention is ineffective.

**Remark 8:** Under best-shot and either liability rule, the probability of a food safety event increases as the penalty imposed for a failure increases.

We turn now to a comparison with outcomes under simultaneous moves.

## 5. Simultaneous Moves

In this section we modify firm and consumer objective functions to the simultaneous

moves context. Notice from (1) that the

$$(40) \quad \frac{d^2 C(x_f, x_c)}{dx_f dx_c} \begin{cases} < 0 \text{ for WL and SL,} \\ = 0 \text{ for N,} \\ > 0 \text{ for BS.} \end{cases}$$

Thus, the firm facing a weakest-link technology and strict liability has marginal cost that is decreasing in consumer effort while the firm facing a best-shot technology has a marginal cost that is increasing in consumer effort.

From (1), it is also noteworthy that

$$(41) \quad \begin{aligned} \frac{d^2 C(x_f, x_c)}{dx_f dP} & \begin{cases} < 0 \text{ for WL and SL,} \\ < 0 \text{ for N,} \\ < 0 \text{ for BS;} \end{cases} \\ \frac{d^2 C(x_f, x_c)}{dx_c dP} & \begin{cases} < 0 \text{ for WL and SL,} \\ = 0 \text{ for N,} \\ < 0 \text{ for BS.} \end{cases} \end{aligned}$$

So, regardless of context, the marginal cost of firm effort decreases as the penalty increases and the same is weakly true for the cross impact of penalty and consumer effort on marginal cost.

We turn now to consumer incentives in nash equilibrium. As in (2), for WL and SL the consumer's problem is to

$$(42) \quad \max_{x_c} U^{\text{WL,SL}}(x_c, x_f) = \max_{x_c} -[1 - G(x_c)H(x_f)]e^{D+\lambda(x_c-P)} - G(x_c)H(x_f)e^{\lambda x_c},$$

with cross-derivative

$$(43) \quad \frac{d^2 U^{\text{WL,SL}}(x_c, x_f)}{dx_c dx_f} = h(x_f)[g(x_c) + \lambda G(x_c)](e^{D-\lambda P} - 1)e^{\lambda x_c}.$$

Now with  $G(x_c) = 1 - e^{-\phi x_c}$  and  $\phi > \lambda$ , the latter inequality to ensure problem convexity, then

$$(44) \quad \frac{d^2 U^{\text{WL,SL}}(x_c, x_f)}{dx_c dx_f} = h(x_f)[(\phi - \lambda)e^{-\phi x_c} + \lambda](e^{D-\lambda P} - 1)e^{\lambda x_c} > 0.$$

The inputs complement so that any exogenous increase in firm effort reinforces consumer incentives.

For WL and N the consumer's problem is to

(45)

$$\max_{x_c} U^{\text{WL,N}}(x_c, x_f) = \max_{x_c} -\bar{G}(x_c)H(x_f)e^{D+\lambda x_c} - \bar{H}(x_f)e^{D+\lambda(x_c-P)} - G(x_c)H(x_f)e^{\lambda x_c},$$

and the own-effort derivative is

(46)

$$\frac{dU^{\text{WL,N}}(\cdot)}{dx_c} = \overbrace{\left\{ \lambda e^{D-\lambda P} - \lambda \bar{G}(x_c)e^D - \lambda G(x_c) + g(x_c)(e^D - 1) \right\}}^{\geq 0} e^{\lambda x_c} H(x_f) - \lambda e^{D+\lambda(x_c-P)} = 0,$$

so that

$$(47) \quad \frac{d^2 U^{\text{WL,N}}(\cdot)}{dx_c dx_f} = \overbrace{\left\{ \lambda e^{D-\lambda P} - \lambda \bar{G}(x_c)e^D - \lambda G(x_c) + g(x_c)(e^D - 1) \right\}}^{>0} e^{\lambda x_c} h(x_f) > 0.$$

For BS the consumer's problem is to

$$(48) \quad \max_{x_c} U^{\text{BS}}(x_c, x_f) = \max_{x_c} -\bar{G}(x_c)\bar{H}(x_f)e^{D+\lambda(x_c-P)} - [1 - \bar{G}(x_c)\bar{H}(x_f)]e^{\lambda x_c}.$$

The first-order condition can be written as

$$(49) \quad \frac{dU^{\text{BS}}(\cdot)}{dx_c} = -\lambda e^{\lambda x_c} + \overbrace{\left\{ [g(x_c) - \lambda \bar{G}(x_c)](e^{D-\lambda P} - 1) \right\}}^{>0} e^{\lambda x_c} \bar{H}(x_f) = 0,$$

so that

$$(50) \quad \frac{d^2 U^{\text{BS}}(\cdot)}{dx_c dx_f} = -\overbrace{\left\{ [g(x_c) - \lambda \bar{G}(x_c)](e^{D-\lambda P} - 1) \right\}}^{>0} e^{\lambda x_c} h(x_f) < 0.$$

Figure 4.2 depicts how the consumer's optimality condition changes in response to an increase in firm effort under weakest-link and either liability rule.

**Remark 9:** Under

*i*) weakest-link and either strict liability or negligence rule, nash equilibrium firm and consumer choices will be lower than under stackelberg;

*ii*) best-shot and either rule, we cannot compare without further information.

The reasoning for *i*) is that in stackelberg the firm has the opportunity to foster coordination through first movement.<sup>28</sup> All are better off as in neither case are incentives sufficient to support first-best. This point has been made before by Hennessy, Roosen and Miranowski (2001) but in a cooperative game where surplus is shared via the Shapley value. The policy implications of *i*) are several, where three are provided below.

Communication between the firm and the consumer is a form of first movement where Ellingsen and Östling (2010) have shown that communication facilitates coordination given positive spillover payoffs similar to those in our model. Examples of such behavior are not hard to find. As with other commodity organizations, the National Turkey Federation of the United States seeks to link with consumers through recipe books, at home food safety recommendations and evidence of its members' commitment to food safety, see, e.g., <http://www.eatturkey.com/>. To be effective, communication must reach receptive ears. Information is more likely to have the intended effect when the message is clearly interpreted. Education matters, as in a basic understanding of microbiology and the chemistry of cooking among the general population.

Also, in reality pre-consumer production and processing typically involve many agents. Concerns about suboptimal effort are likely to grow in systems that involve many autonomous agents processing and then trading on, see, e.g., Collins (1993). Vertical integration can signal to the consumer that beggar thy neighbor food safety interactions in the

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<sup>28</sup> A proof can be established by arguments analogous to the proof of Proposition 1 in Hennessy, Roosen and Miranowski (2001).

marketing channel are being addressed. Chinese government concerns about loss of consumer confidence in its domestic production is a case in point. Commencing a decade or more ago, its government has sought to foster coordination through promotion of larger, more integrated processing firms (Gale and Hu, 2012).

Enforced minimum processing standards are also a means of imposing first-mover status on the processor, though these standards will only matter if binding. The implications of minimum standards are most interesting for the best shot technology, bringing us to part *ii*) and more generally to policy when efforts substitute. Minimum standards will force the processor not to free-ride but will allow the consumer to do so. Whether the resulting equilibrium is socially preferred is unclear. By contrast, the case for minimum standards under weakest link technologies is clearer. Although processors will be better motivated in stackelberg than in nash, they are unlikely to apply sufficient effort. As a result, consumers are also unlikely to apply sufficient effort. A standard above the stackelberg level for processor effort is likely to improve social welfare.

## 6. Discussion

Food safety decisions are not made in isolation and food systems are linked in complex ways. The growth of downstream value added and increased specialization in the food chain has led to an increase in the number of chain participants. A seminal insight from Coase (1937) is that the boundaries of the firm matter, in part because of tradeoffs between agency and technical costs. These agency costs can arise from private incentives that are poorly aligned with social welfare and coordination failures even when incentive alignment is good. This paper has considered a very simple problem of strategic interaction between a single upstream food processor and a representative food consumer. We show how the food safety production technology can matter, paying particular attention to penalties and extent of

consumer risk aversion in determining equilibrium outcomes. We also compare with first-best and nash equilibrium to demonstrate that a role exists for leadership in policy interventions.

Several of our findings might be viewed as counterintuitive and these stem partly from the self-protective nature of food safety efforts. Examples are where a penalty and a minimum effort standard may do more harm than good while consumers may take less effort when they are more risk averse. The extent to which these possible outcomes arise depend on several factors. One is the actual technology, as in whether weakest-link and keep food safety problems out nature or best-shot and get rid of existing food safety problems best depicts the situation. Another is whether processors and consumers understand the technology that they are dealing with. These are matters for further investigation.

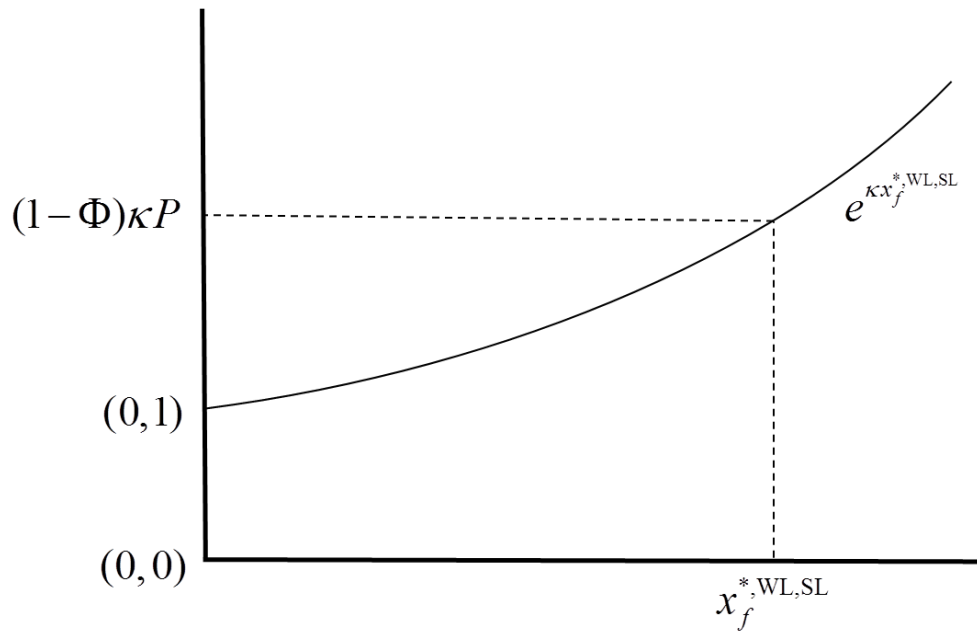
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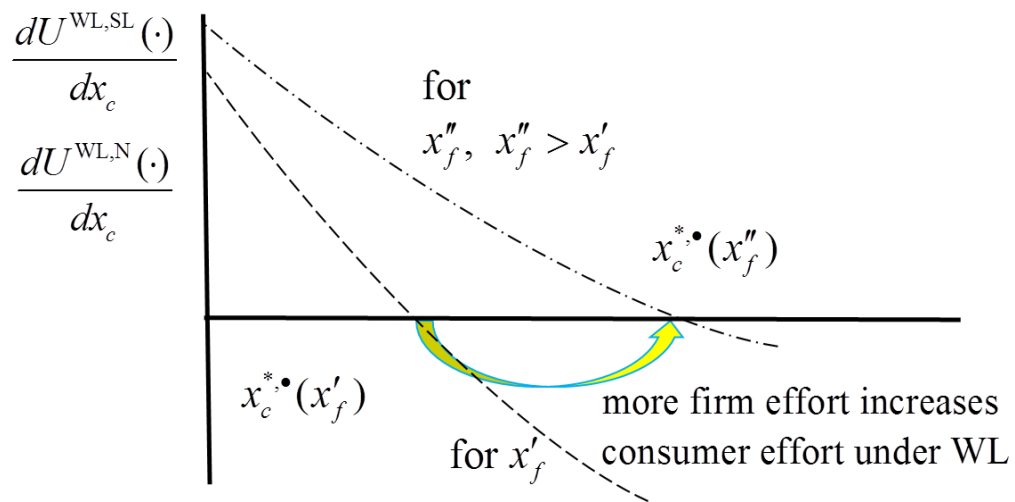
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**Figure 4.1** Firm's effort under weakest link technology and strict liability, as incentives change.



**Figure 4.2** Consumer's private optimality condition, as firm effort changes.

## APPENDIX B. ADDITIONAL MATERIAL FOR CHAPTER 4

*Second-order Conditions for the second mover consumer under stackelberg*

For WL and SL the consumer's problem is, as in (2), to

$$(A1) \quad \max_{x_c} U(x_c, x_f) = -[1 - G(x_c)H(x_f)]e^{D+\lambda(x_c-P)} - G(x_c)H(x_f)e^{\lambda x_c}.$$

The first-order condition is

(A2)

$$g(x_c)H(x_f)(e^{D-\lambda P} - 1)e^{\lambda x_c} - \lambda[1 - G(x_c)H(x_f)]e^{D+\lambda(x_c-P)} - \lambda G(x_c)H(x_f)e^{\lambda x_c} = 0.$$

At a solution to this equation, the second-order condition resolves to

$$(A3) \quad [g'(x_c) + \lambda g(x_c)](e^{D-\lambda P} - 1) < 0;$$

or  $\lambda < -g'(x_c) / g(x_c)$ . That is the consumer's success probability function should be more

concave than her utility function. When  $G(x_c) = 1 - e^{-\phi x_c}$  then the relationship resolves to

$$\phi > \lambda.$$

For WL and N the problem is

$$(A4) \quad \max_{x_c} U(x_c, x_f) = -\bar{G}(x_c)H(x_f)e^{D+\lambda x_c} - \bar{H}(x_f)e^{D+\lambda(x_c-P)} - G(x_c)H(x_f)e^{\lambda x_c},$$

The first-order condition is

(A5)

$$g(x_c)H(x_f)(e^D - 1)e^{\lambda x_c} - \lambda[\bar{G}(x_c)H(x_f)e^D + \bar{H}(x_f)e^{D-\lambda P} + G(x_c)H(x_f)]e^{\lambda x_c} = 0.$$

As before the second-order condition, when evaluated at a solution to the above, resolves to

$$(A6) \quad [g'(x_c) + \lambda g(x_c)](e^{D-\lambda P} - 1) < 0.$$

For BS and either liability rule the problem is

$$(A7) \quad \max_{x_c} U(x_c, x_f) = -\bar{G}(x_c)\bar{H}(x_f)e^{D+\lambda(x_c-P)} - [1 - \bar{G}(x_c)\bar{H}(x_f)]e^{\lambda x_c}.$$

The first-order condition is

$$(A8) \quad g(x_c)\bar{H}(x_f)(e^{D-\lambda P}-1)e^{\lambda x_c}-\lambda\left[\bar{G}(x_c)\bar{H}(x_f)e^{D-\lambda P}+1-\bar{G}(x_c)\bar{H}(x_f)\right]e^{\lambda x_c}=0.$$

As before the second-order condition, when evaluated at a solution to the above, resolves to (A6). So the second-order conditions sufficient for any consumer effort solution to be interior are common across technology and liability structure.

*Second-order Conditions for the first-mover firm under stackelberg*

For WL and SL the firm's problem is, as in (1), to

$$(A9) \quad \min_{x_f} x_f + [1 - G(x_c^{*,WL,SL}(x_f))H(x_f)]P$$

The first-order condition is

$$(A10) \quad 1 - G(x_c^{*,WL,SL}(x_f))h(x_f)P - g(x_c^{*,WL,SL}(x_f))H(x_f)P \frac{dx_c^{*,WL,SL}(x_f)}{dx_f} = 0.$$

A second-order sufficient condition is

$$(A11) \quad \begin{aligned} & 2g(x_c^{*,WL,SL}(x_f))h(x_f)\frac{dx_c^{*,WL,SL}(x_f)}{dx_f} + G(x_c^{*,WL,SL}(x_f))h'(x_f) \\ & + g'(x_c^{*,WL,SL}(x_f))H(x_f)\left(\frac{dx_c^{*,WL,SL}(x_f)}{dx_f}\right)^2 + g(x_c^{*,WL,SL}(x_f))H(x_f)\frac{d^2x_c^{*,WL,SL}(x_f)}{dx_f^2} < 0. \end{aligned}$$

When  $G(x_c) = 1 - e^{-\phi x_c}$  and  $H(x_f) = 1 - e^{-\kappa x_f}$  then the relationship may be written as

$$(A12)$$

$$\begin{aligned}
& 2\phi\kappa e^{-\phi x_c^{*,\text{WL,SL}}(x_f)} e^{-\kappa x_f} \frac{dx_c^{*,\text{WL,SL}}(x_f)}{dx_f} - \kappa^2 \left[ 1 - e^{-\phi x_c^{*,\text{WL,SL}}(x_f)} \right] e^{-\kappa x_f} \\
& - \phi^2 e^{-\phi x_c^{*,\text{WL,SL}}(x_f)} [1 - e^{-\kappa x_f}] \left( \frac{dx_c^{*,\text{WL,SL}}(x_f)}{dx_f} \right)^2 + \phi e^{-\phi x_c^{*,\text{WL,SL}}(x_f)} [1 - e^{-\kappa x_f}] \frac{d^2 x_c^{*,\text{WL,SL}}(x_f)}{dx_f^2} < 0,
\end{aligned}$$

or

(A13)

$$\begin{aligned}
& 2\phi\kappa \frac{\Phi(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})}{(e^{D-\lambda P} - 1)(1 - e^{-\kappa x_f})} e^{-\kappa x_f} \frac{dx_c^{*,\text{WL,SL}}(x_f)}{dx_f} - \kappa^2 \left[ 1 - \frac{\Phi(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})}{(e^{D-\lambda P} - 1)(1 - e^{-\kappa x_f})} \right] e^{-\kappa x_f} \\
& - \phi^2 \frac{\Phi(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})}{(e^{D-\lambda P} - 1)} \left( \frac{dx_c^{*,\text{WL,SL}}(x_f)}{dx_f} \right)^2 + \phi \frac{\Phi(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})}{(e^{D-\lambda P} - 1)} \frac{d^2 x_c^{*,\text{WL,SL}}(x_f)}{dx_f^2} < 0, \\
& e^{-\phi x_c^{*,\text{WL,SL}}(x_f)} = \frac{\Phi(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})}{(e^{D-\lambda P} - 1)(1 - e^{-\kappa x_f})}.
\end{aligned}$$

As

(A14)

$$x_c^{*,\text{WL,SL}}(x_f) = \frac{1}{\phi} \ln(e^{D-\lambda P} - 1) + \frac{1}{\phi} \ln(1 - e^{-\kappa x_f}) - \frac{1}{\phi} \ln(\Phi) - \frac{1}{\phi} \ln(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f}),$$

we may write

$$\begin{aligned}
& \frac{dx_c^{*,\text{WL,SL}}(x_f)}{dx_f} = \frac{\kappa e^{-\kappa x_f}}{\phi(1 - e^{-\kappa x_f})} + \frac{\kappa(e^{D-\lambda P} - 1)e^{-\kappa x_f}}{\phi(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})} \\
& = \left[ \frac{(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f}) + (1 - e^{-\kappa x_f})(e^{D-\lambda P} - 1)}{(1 - e^{-\kappa x_f})(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})} \right] \frac{\kappa e^{-\kappa x_f}}{\phi} \\
& = \frac{\kappa e^{D-\lambda P - \kappa x_f}}{\phi(1 - e^{-\kappa x_f})(1 + e^{D-\lambda P - \kappa x_f} - e^{-\kappa x_f})}.
\end{aligned}$$

Presently we cannot establish whether (A11) applies, but this is not very surprising as

complementary technologies can often involve nonconvexities.

For WL and N the firm's problem is, as in (1), to

$$(A16) \quad \min_{x_f} x_f + \bar{H}(x_f)P.$$

The first-order condition is

$$(A17) \quad 1 - h(x_f)P = 0.$$

A second-order sufficient condition is  $h'(x_f) < 0$ , which is valid when  $H(x_f) = 1 - e^{-Kx_f}$ .

$$(A18) \quad \min_{x_f} x_f + \bar{G}(x_c^{*,BS}(x_f))\bar{H}(x_f)P.$$

From (37) we already know that  $x_f^{*,BS} = 0$ .

## CHAPTER 5. GENERAL CONCLUSIONS

The dissertation examines the impacts of various economic factors on consumers' food related choices. The economic factors on consumer's choices that we consider in this dissertation are habit forming behaviors of consumers, supplemental food policies and the uncertainty of food safety risk and strategic interaction with food processors. The dissertation is organized to include three stand-alone analyses, each investigating an independent subject on the consumer's decision making process on food. Three topics are integrated in their common interest for understanding the influence of the consumer's choices on food expenditures and efforts to improve food safety along with food processors.

The first topic of this dissertation, presented in Chapter 2, investigates the effects of habit-forming behaviors on demand for dairy products using Nielsen 2009 and 2010 HomeScan data. The largest effect of habit formation is shown in milk demand; cheese demand rarely exhibits habit-forming behaviors. The own-price elasticities of each group are negative and smaller than unity which means that dairy products are necessary goods, just as we would expect. Having children and the total dairy expenditures both have substantial positive impacts on milk demand. According to my extensive reading of the literature, providing a dynamic uncensored demand on food applying a Bayesian method is one of the innovative and unique contributions of this study. In addition, this study can be a springboard for further discussion on the use of scanner data to analyze food demand and the empirical challenges faced from the censored nature of scanner data when dealing with dynamics in demand.

In Chapter 3, the second topic of this dissertation, an empirical analysis is developed to evaluate the impact of participating WIC food program on whole grain products

expenditures at the household level. Using Nielsen 2008, 2009 and 2010 HomeScan data, we compare expenditures on whole grain products of WIC participating households to those of non-participating but eligible households. The results of the average treatment effect estimation show that the monthly average whole grain expenditures of households with at least one-year of WIC participation are significantly higher. The finding that WIC participating households purchase more whole grain products than non-participating eligible households is useful for evaluating the effectiveness of WIC program participation for developing healthful eating patterns. Furthermore, in terms of whole grain expenditures, this study may address the issue of recent policy change to the WIC food package which included the introduction of whole grain products to the packages. In order to see the WIC participation effect over the package changes, we use difference-in-difference propensity matching estimator and this provides us the result of the potential impact of the food package changes, as a positive policy shock. Using nearest neighbor matching, we observed the policy shock played an important role on purchasing whole grain rather than the treatment effect of WIC participation itself. On the other hand, the WIC participation effect was shown to be very strong even after getting rid of the shock impact when we adopted the Kernel and Radius matching procedure.

The third topic of this dissertation, presented in Chapter 4, investigates the interaction between consumers' effort and producers' effort under the food safety risk. Food safety decisions are not made in isolation and food systems are linked in complex ways. This paper has considered a simple problem of strategic interaction between a single upstream food processor and a representative food consumer. We make use of the traditional modeling of expected utility maximization with self-protection incentive combining Stackelberg leader-

follower competition setting under two legal compensation rules and two technologies on the occurrence of the food safety hazard event. We show how the food safety production technology and can matter, paying particular attention to penalties and extent of consumer risk aversion in determining equilibrium outcomes. We also compare with first-best and nash equilibrium to demonstrate that a role exists for leadership in policy interventions. We have several counterintuitive findings which have stemmed partly from the self-protective nature of food safety efforts. For example, a penalty and a minimum effort standard may do more harm than good while consumers may take less effort when they are more risk averse.

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