# ESSAYS ON MODELING LIMITED DEPENDENT VARIABLES APPLIED TO INDUSTRIAL ORAGINIZATION AND LABOR MARKETS

By

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## Abstract

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My dissertation research includes three essays that utilize limited dependent modeling applied to problems in industrial organization and labor markets. The first one asks what affects child care providers' duration of employment. The child care industry commonly experiences difficulties in retaining employees. The extremely high employee turnover rate is a threat to quality of care. The data used in this analysis is from surveys by participating child care center directors regarding both individual employees and child care center characteristics. Factors considered include an employee's wages, benefits, position description, age-group assignment, education, center characteristics, and other employee demographic variables.

The Second paper in this dissertation examines the retirement decisions of university faculty. Approximately one-half of all U.S. faculty in higher education are older than 50 years, and more than two-thirds of payrolls are tied up with these faculty. Since the removal of mandatory faculty retirement in 1994, it is difficult to make precise predictions of when an individual faculty member will retire. This study investigates the phased retirement decisions of faculty using survey data .The estimation results suggest that investment in social security

decreases the likelihood of acceptance of early phased retirement programs. This analysis has important implications for both individual faculty members and the University as an employer.

The third paper provides a new explanation for the existence of quantity surcharges that occur in some food products. Quantity surcharges occur when a larger sized package of a product has a higher per-unit price then its smaller-sized counterpart. I hypothesize that different size the same product are imperfect substitutes and thus are differentiated products. To test this hypothesis, I utilize grocery store scanner data with canned tuna of varying sizes. I estimate the demand for each type of tuna and the associated cross-price elasticities. A random coefficients logit demand approach to calculate elasticities. There is evidence to support the hypothesis that quantity surcharges in canned tuna are driven by firms catering to heterogeneous consumer preferences. All the three papers are presented as separate chapters in this dissertation.

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# Chapter 1

## A Latent Class Parametric Weibull Survival Model for Child Care Labor Market

Abstract

The child care industry commonly experiences difficulties in retaining employees. A concern is that the high employee turnover rate negatively affects the quality of care. Utilizing a large data set on child care providers, we estimate a model that accounts for unobserved heterogeneity that exits in the child care provider labor market. We identify three distinct classes of workers with varying means duration of employment. Wages affect all the three classes, but health benefits, accreditation, and high infant ratio are class specific.

*Keywords: child care, Latent class, survival analysis, unobserved heterogeneity*

## 1. Introduction

There has been a steady increase in the number of children being placed in child care during the day, primarily due in increases in maternal employment. Data from the U.S Bureau of Labor Statistics (BLS) indicates that the labor force participation rate (LFPR) for mothers with child in any age category has been increasing since 1975. Presently, close to 61% of mothers with children under age of 6 are in the labor force (BLS 2008).

The continued entry of mothers of preschool and school-age children into the labor force is directing attention to the subject of child care. From economists (Heckman & Masterov, 2007) to developmental psychologists (Hayes, Palmer and Zaslow, 1990), early childhood education and care has become an issue of national importance. Research has confirmed that the child care provider is one of the most important elements in quality child care (Blau and Mocan, 2002; Boschee and Jacobs, 1997). While the message of the importance of quality child care may have reached a new high point, a serious impediment continues to plague the field. The problem lies with the high level of turnover, most notably in teaching staff.

The child care industry commonly experiences difficulties in retaining employees. The high employee turnover rate is a threat to quality of care. If child care quality is compromised, it can negatively affect the child's cognitive and social-emotional development (Manlove and Guzell, 1997). Previous studies of turnover in the child care sector have identified low pay, poor benefits, lack of training, and poor quality standards as key factors resulting in turnover (Rolfe, 2005).

Several attempts to intervene on high turnover have focused on increasing wages with the hopes that wage-supplements will curb high turnover (Park-Jadotte, Golin and Gault, 2002; Boyd and Wandschneider, 2004; Gable et.al, 2007). However, turnover rates have remained fairly constant at 30% (Center for the Child Care Workforce, 2004; Whitebook and Sakai, 2004), indicating that wage is not only reason teachers leave their jobs.

The significance of the present study is the use of survival analysis to capture the interplay of the timing and predictors of turnover occurring. This is one of the few studies that utilize survival analysis to examine duration of employment in child care staff (Gable et.al., 2007; Manlove and Guzell, 1997).

In this study, we estimate a model that allows for unobserved heterogeneity of workers in day care labor market. The results indicate that child care workers can be classified into three classes viz., *long term workers*, *intermediate-term workers* and the *short-term workers.* Beyond wages, which affect the tenure of employment for all three classes, there are certain class-specific variables that give us insight into the decisions of each class.

## 2. Background

The inability to retain staff has long been recognized as a serious problem in child care programs (Hofferth, 1996). Reports indicate the percentage of employees that leave programs each year ranges from 25 to 40% (Center for the Child care Workforce, 2004). The National Child Care Staffing Study (NCCSS) examined centers over a nine year period and found the staff turnover to be 31% (Whitebook, Howes and Phillips, 1998) which is four times greater than the 7% turnover rate of elementary school teachers (Whitebook and Bellm, 1999). Even higher trends in turnover were found in Whitebook and Sakai's (2004) study measuring child care staff departures. In this study of 137 centers, over half (58%) of the staff had left their respective centers by the time of the final observations.

Teacher turnover is costly to child care programs. Actual costs increase with advertising for new positions, interviewing, implementing new employee orientations, and conducting background checks and the fingerprinting process (Hale-Jinks et.al, 2006). A study by Vandell and Wolfe (2000) showed just how much turnover affects program costs. They estimate the departure of 10% of all staff employees to increase the total costs by 6.8%.

In addition to being costly for business, staff retention in child care has often been concerns because of its implications for quality of care and resulting child development outcomes (Hale-Jinks et al., 2006). Among child care researchers, the established view is that child care quality contributes to children's developmental outcomes, higher quality care being associated with better developmental outcomes and poorer quality care being associated with poorer outcomes for children (Clark-Stewart and Fein, 1983). It is interesting to note that while concerns about quality of care and resulting child outcomes are a commonly cited factor in attempts to intervene on turnover, few studies have shown empirical connection between turnover and child outcomes.

Three studies have linked high turnover rates with lower quality of care (Whitebook and Sakai, 2004; Whitebook et al., 1990; Helburn, 1995). Helburn (1995) examined the relationship between global quality measured by early childhood environment rating scales and turnover. The study linked poor outcomes with low quality centers, which were characterized by high rates of teacher turnover, and better child outcomes with higher quality centers. In a similar study Whitebook et al. (1990) showed lower scores on language and vocabulary tests were obtained by children in centers marked with higher levels of teacher turnover in the preceding year.

The majority of research on child care turnover is theoretical. An exception is Gable et.al, (2007) who study turnover of staff in child care centers. They found that job commitment depends whether the employee feels satisfied, such that the rewards outweigh the costs. They used survival analysis and reported that teacher education and retention may be related. Within the labor turnover literature, wages, poor benefits, low level of educational requirements, and unsupportive workplace conditions are the variables most commonly examined.

The mean hourly wages for child care workers and preschool teachers are $9.05 and $12.45, respectively, compared to $22.62 for kindergarten teachers (U.S Bureau of Labor Statistics, 2006). The high turnover of child care staff is not surprising when child care wages are less compared to other comparable jobs. Several studies link wages with job satisfaction (Helburn, 1995; Stremmel, 1990). In a study conducted in 227 child care centers to assess predictors of job satisfaction by Phillips et al., (1991), wages received lowest levels of job satisfaction.

Another closely related extrinsic job factor is benefits. Helburn's (1995) and Boyd and Wandschneider's (2004) findings both revealed that health and retirement benefits are significant factors. Since employees at child care centers are predominately female, we hypothesize that maternity benefits (such as maternity leave) can also be important in staff retention. Although it seems reasonable to assume that increased educational qualification build a stronger workforce, empirical studies have failed to reveal a clear consensus on the relationship between education and retention. The literature generally falls into two categories: studies that demonstrate a relationship between increased education and increased retention (Boyd and Wandschneider, 2004; Whitebook and Sakai, 2004) or studies that report mixed or no relationship between employee education and retention (Early et. al. 2007).

The present study contributes to the literature on the economics of child care by examining which individuals and center-level variables are most predictive of staff turnover. The literature has recently recognized turnover as a multifaceted issue. However, the literature has not specified which factors are most influential to staff leaving. We use survival analysis to model duration of employment of child care workers. Additionally, we incorporate unobserved heterogeneity into the model in order to gain additional insights into the behavior of child care workers.

It is well known that unobserved heterogeneity can produce biased estimates in survival analysis (Lancaster, 1990; Allison, 1995). In estimating probabilistic models for duration of employment, one should allow for fact that individuals may be heterogeneous. The observed changes in population intensities (or hazard rates) over time are a mixed result of two influences viz., the actual changes in the individual hazards and the selection due to high-risk individuals leaving the risk group early. For example, it seems reasonable to assume that some child care workers are highly motivated by their job and want to spend their whole life in the same job. In contrast, others are less motivated and consider their current work activity as temporary. They stay in that position until something more appealing becomes available in other segments of the labor market. Lancaster (1990) pointed out that the failing to account for unobserved heterogeneity leads to biased coefficient estimates in duration dependence.

## 3. Data

The data used in this analysis was collected as part of the Washington State Child Care Career and Wage Ladder Pilot Project (Boyd and Wandschneider, 2004). The survey solicited information regarding both individual employees and child care center characteristics. The surveys were self-administered by participating child care center directors over three years. The data set includes 3,444 usable observations[1] from 137 participating centers. The variable descriptions, coding, and summary statistics for employee characteristics and benefit and child care center characteristics are presented in Tables 1 and 2, respectively.

The data includes employee characteristics such as age range, gender, wage per hour, wage increases over the employment duration, levels of education and training. The benefit data collected includes whether the child care center offers paid maternity/paternity leave, partially or fully paid health insurance and partially or fully paid retirement plans. The center characteristics data includes the ratio of children in each age group (infant, toddler, pre-school, kindergarten, and school age) at the center relative to center capacity, whether the center is National Association for the Education of Young Children (NAEYC) accredited, whether the center is Quality Child Center (QCC) accredited, the location of center (whether the center is in major city or town), and whether the employees are union members.

### 3.1. *Employee Characteristics*

The majority of individuals in study are female (94%). In regards to age ranges, 61% are in the 18-30 years range, 31% are in the 31-50 years of range; and 8% are 51 years or more. The individuals occupied various positions. Thirty-nine percent of respondents are assistant aides, 52% are lead instructors; 10% are site coordinators; and 8% are center directors or other positions. The cross tabulation (Figure 1) indicates that younger workers occupy most of the assistant aide or lead instructor positions. In regards to education, 18% have high school degree or less; 40% have completed State Training and Registry System (STARS); 23% have completed

[1] Note that this number is lower because of missing data. The original observation was 3575. None of the missing variables were more than 2% and little chi square MCAR test was not significant and hence we deleted the missing observations.

college courses in early childhood education (ECE) during employment; 8% have Bachelors or Masters degrees; and the remaining 11% have completed other education. Two variables capture wage effects; one is the wage per hour and second is average wage increment of increase over the period of employment. Some workers may focus on the hourly wage level, but others may value the raises they receive over the duration to judge their current employment value.

### *3.2. Benefits*

Three common benefits that employees expect from their employers are included in this analysis. Since our sample is predominantly female, maternity-related benefits may be important. Only 11% of centers offered maternity related benefits. Health insurance is a desirable and costly benefit, and 31% of centers provide some kind of health benefits. However, the majority of centers (72%) provide retirement benefits.

### *3.3. Center Characteristics*

The child care centers included in study varied by mix of children groups and locations. Four variables representing children's age groups are included: INFANT, TODDLERS, PRESCHOOL and KINDERGARTEN. These variables represent the ratio of children belonging to certain age groups relative to the overall center capacity. The majority of centers in the sample were located in rural settings (48%) followed by town/small cities (31%), and larger cities/ metropolitan areas (21%).

The two indicators of quality centers that are included are NAYEC and QCC accreditation. For example, the NAYEC promotes program accreditation (strong indicator of program quality) specifically in regards to teacher education. For NAYEC accreditation, seventy five percent (75%) of teaching staff must have at least a bachelor's degree in a child-related field. In our data 22% of centers are NAYEC accredited and 39% are QCC accredited.

## 4. Modeling Unobserved Heterogeneity in the Child Care Labor Market

If some observations are more likely to experience an event of interest and if the factors contributing to this propensity are not accounted for in the systematic portion of the model, then negative duration dependence will be observed (Lancaster 1990; Heckman 1991; and Omori and Johnson 1993). For example, consider a population in which the probability of the event of interest (quitting child care job) is constant over time, but consist of a mixture of high- and low-probability individuals (motivated and unmotivated child care workers). Over time, those individuals who are more likely to experience the event of interest will do so and be removed from the data. As a result, the data will increasingly consist of low-probability individuals, and estimates of the average hazard will decline over time. In economics, this type of duration dependence is known as "spurious" duration dependence (Elbers and Ridder, 1982).

The existence of spurious duration dependence suggests that a more accurate picture of the true distribution of the conditional hazard may be obtained through better model specification (Lancaster and Nickell 1980). The Weibull model is widely used and well developed to deal with unobserved heterogeneity (Kalbfleisch and Prentice, 1980). In the presence of unobserved, individual-specific heterogeneity, the most widely used modification to the Weibull has been a random-effects (or "frailty") approach in which the individual-specific effects are assumed to follow a gamma distribution (e.g., Butler and Worrall 1989; Lancaster 1979, 1985; Lancaster and Nickell 1980; McDonald and Butler 1987; see also Vaupel et al. 1979; Larsen and Vaupel 1993).

We propose to model duration of employment using parametric survival model. We first describe Weibull survival models, with and without heterogeneity. We then present a latent class Weibull hazard model.

*4.1. Weibull Survival Model (Reference Model)*

Let $t_i$ and Y = $ln\ t_i$ be random variables representing a continuous activity duration and the natural logarithm of the activity duration, respectively. Following Greene (2003), a parametric accelerated hazard model for log-activity duration *Y*, given covariate vector *X*, can be specified as

$$w_i = (lnt_i - x_i^{\prime}\beta)/\sigma \qquad (1)$$

From equation (1), the observed random variable Y = $ln\ t_i$ can be written as

$$lnt_i = \sigma w_i + x_i^{\prime}\beta \qquad (2)$$

The difference between the accelerated hazard model and a typical regression model is that in the former the standard baseline distribution is not necessarily normal but may assume other distributional forms and can also handle censored observations.

The Jacobian transformation of the transformation from $w_i$ to $ln\ t_i$ is $dw_i\ /\ lnt_i = \frac{1}{\sigma}$, so the density and survival function for $ln\ t_i$ are

$$f(lnt_i \mid x_i, \beta, \sigma) = \frac{1}{\sigma} f\ (lnt_i - x_i^{\prime}\beta/\sigma\ ) \qquad (3)$$

$$S(lnt_i \mid x_i, \beta, \sigma) = \mathrm{S}\ (lnt_i - x_i^{\prime}\beta/\sigma\ ) \qquad (4)$$

If we consider the Weibull distribution, then equations (3) and (4) will be

$$f(lnt_i \mid x_i, \beta, \sigma) = \frac{1}{\sigma}\exp(w_i - e^{w_i}) \qquad (5)$$

$$S(lnt_i \mid x_i, \beta, \sigma) = \mathrm{S}\ \exp(-e^{w_i}) \qquad (6)$$

Let $\delta_i$=1 if the spell is completed and $\delta_i = 0$ if the spell is censored then the log-likelihood for the observed data will be

$$\ln L\,(\beta\,,\sigma\,|data) = \sum_{i=1}^{i=n}[\delta_i \ln f(lnt_i \mid x_i\,,\beta,\sigma) + \,(1-\delta_i)\ln S(lnt_i \mid x_i\,,\beta,\sigma)] \qquad (7)$$

This likelihood function can be solved by either Berndt, Hall, Hall, and Hausman (BHHH) estimation (Green, 1995a) or Newton's method (Kalbfleisch and Prentice, 1980). Equation (7) can be written in a more general form as

$$L_i = \left\{\frac{1}{\sigma}\ f(w_i)\right\}^{\delta_i} \{\,S(w_i)\}^{1-\delta_i} \qquad (8)$$

*4.2. Weibull Survival Model with Gamma Heterogeneity*

The parametric models discussed thus far are based on an assumption of homogeneity of the survival distribution across individuals. If one assumes the survival distribution is homogenous when it is not, then our parameter estimates will be inconsistent and inferences will be based on inappropriate standard errors (Keifer, 1988; Heckman and Singer, 1984). A familiar, traditional model of heterogeneity in parametric survival models is of Weibull survival model with gamma heterogeneity (Green, 2003).

The equation (1) $w_i = (lnt_i - x_i^{\prime}\beta)/\sigma$ is a parametric accelerated hazard model for log-activity duration Y given covariate vector X, where $\lambda = e^{-\beta}$ and $p = {}^{1}/_{\sigma}$ are location and scale parameters (Greene, 2003). A modification of Weibull model suggested by Hui (1991) is

$$S(t|v) = v\{exp\{\,(-\lambda t)\}^{p}\} \qquad (9)$$

The random variable $\upsilon$ is the heterogeneity effect. We assume that $\upsilon$ is distributed as gamma with parameters k and R. Then following Green (2003) and Hui (1991) the result for Weibull model with gamma heterogeneity is

$$S(t) = \{ 1 + \theta(\lambda t)^p \}^{-1/\theta} \qquad (10)$$

Where $\theta = 1/k$ and k = R. The variance of $\upsilon$ is 1/k, so $\theta = 0$ corresponds to the Weibull model. The further $\theta$ deviates from zero, the greater the effect of heterogeneity. If $\theta$ is significantly different from zero, then it would be worth to allow for latent classes.

### *4.3. Latent Class Weibull Survival Model*

The latent class formulation provides an attractive platform for modeling latent heterogeneity. To formulate the latent class model, we assume that there exist *K* different homogeneous latent classes in the heterogeneous population of the sample. Given that an individual belongs to latent class *k* (where *k = 1,. . . ,K)*, the latent class model for log-activity duration *Y* given covariate vector *X* can be obtained from equation (2): $lnt_i = \sigma_k w_{i/_k} + x_i^{\prime} \beta/_k$ ,

where $\beta_k$ is an unknown parameter vector and $\sigma_k$ is a scale parameter vector of each latent class *k*. We assume that the standard baseline distribution for has a finite mixture of the Weibull distribution. The conditional likelihood, given that individual *i* with covariates vector $x_i$ belongs to latent class *k*, has the following form:

$$L_{i/k} = \left\{\frac{1}{\sigma k}\, f\left(w_{i/k}\right)\right\}^{\delta_i} \left\{ S\left(w_{i/k}\right)\right\}^{1-\delta_i} \qquad (11).$$

Let $P_{ik}$ denote the prior probability that an individual *i* belongs to latent class *k*. To characterize unobserved heterogeneity of latent classes, we must utilize the observed variables. Following Bucklin and Gupta (1992) and Gupta and Chintagunta (1994), we draw on the vector of socio-demographic variables $D_i(\cdot)$. Various functional forms have been used to represent the prior probability. For this application, the most convenient form is the multinomial logit, which can be represented (Zenor and Srivastava, 1993; Swait and Sweeney, 2000) as

$$P_{ik} = \frac{\exp(\overline{\alpha_k} + \overline{\gamma_k} D_i)}{\sum_{k=1}^{K} \exp(\overline{\alpha_l} + \overline{\gamma_l} D_i)} \qquad (12)$$

Where $\overline{\alpha_k}$ is the intercept and $\overline{\gamma_k}$ ($k = 1,. . . ,K$) is an unknown parameter vector and represents the contribution of the socio-demographic variables to the probability of class membership. For ease of estimation and interpretation of the parameters, we normalize equation (10) with respect to the parameters of segment *K*:

$$P_{ik} = \frac{\exp(\alpha_k + \gamma_k D_i)}{1 + \sum_{k=1}^{K-1} \exp(\alpha_{k'} + \gamma_{k'} D_i)} \qquad (13) \quad Where\ k \neq k'$$

Given equation (11) and (13) the likelihood function for individual *i, Li,* is given by

$$L_i = \sum_{k=1}^{K} P_{ik} L_{\frac{i}{k}} \qquad (14)$$

and the log likelihood for all the individuals can be given as:

$$\ln L = \sum_{i=1}^{N} \ln\left\{\sum\nolimits_{k=1}^{K} P_{ik} \left[\left\{\frac{1}{\sigma k} f\left(w_{\frac{i}{k}}\right)\right\}^{\delta_i} \left\{S\left(w_{\frac{i}{k}}\right)\right\}^{1-\delta_i}\right]\right\} \qquad (15)$$

The latent class model is estimated using BHHH algorithm (Green, 2003).

## 5. Results

### *5.1. Weibull Model with and without Unobserved Heterogeneity*

As a first step, we compare the results of the Weibull survival model with and without heterogeneity in Table 3. The results indicate that unobserved heterogeneity is significant ($\theta$ for Weibull model with heterogeneity is significant). Not allowing for unobserved heterogeneity leads to overestimated (underestimated) coefficients for positive (negative) parameters in the reference model. All the parameters in both the models are significant at the 5% level with the exception of KINDERGARTEN parameter, which is now significant at the 10% in the Weibull survival model with unobserved heterogeneity.

First, before considering unobserved heterogeneity, we observe that the estimated coefficients of the worker's age variables (YOUNG and MIDDLE) are negative and statistically significant. This means that younger (18-30 years) and middle age (31-50 years) day care workers have higher hazard rates of mortality (lower survival) *ceteris paribus*. Further, in terms of positions they occupy at child care center, AIDE, LEAD and SITE variables have negative and statistically significant effect on duration of employment. Similarly less educated (HIGH) workers are more likely to resign, *ceteris paribus.* Finally, if a child care center does not provide health benefits (BENHY), then the workers are more likely to quit.

In contrast, higher wages and wage increments, as expected, increases the duration of employment of day care workers. Also workers at centers that are accredited by NAEYC and QCC have significantly longer duration of employment. Further, child care workers associated with day care where KINDERGARTNERS constitute a higher percentage of the children tend to significantly stay longer at the child care center. Another observation is that child care workers who have obtained STAR and ECE credits have significantly longer of employment durations, which suggests that those who engage in this training are investing in credentials for child care work.

Second, after considering unobserved heterogeneity, the estimated coefficients for the age groups YOUNG and MIDDLE are higher in magnitude compared to the corresponding coefficients in the reference model. This suggests that younger and middle-age child care workers might have greater unobserved heterogeneity. In contrast, the position variables AIDE, LEAD and SITE have lower magnitudes compared to their corresponding coefficients in the reference model, indicating that position might have a small unobserved heterogeneity effect on duration. Similar observations can be made about education parameters (HIGH, STAR and ECE). Also, it seems that wages and raise might have a smaller unobserved heterogeneity effect on estimated duration, indicating that wages alone may not be detrimental in longevity of employment of child care workers. A similar conclusion can be made about the effects of variables BENHY, NAEYC, QCC, and KINDERGARTEN.

The estimate for the Weibull distribution shape parameter after incorporating heterogeneity is 0.87, which is different from the estimate 0.86 from the reference model. As a result, we can see the difference in survival graphs (Figures 1 and 2) and hazard graphs (Figures 3 and 4). The survival (hazard) after incorporating unobserved heterogeneity decreased (increased) after incorporating heterogeneity. The mean duration (survival) obtained from both the models are 30.4 months (reference model) and 26.47 months. Next after understanding the effects of unobserved heterogeneity, we present the results of latent class Weibull survival analysis.

### *5.2. Latent Class Parametric Weibull Survival Model*

We estimated a three-class latent class model based on the lowest Bayesian information criterion **(**BIC) value presented in Table 4. The first class has the majority of individuals (48% of sample), and we name this class as the *long-term class* since it has the longest mean duration time (32.7 months). Next, the second class is named as the *intermediate class* and has 28% of individual with mean duration of 29.08 months. Finally, the third class is named as the *short-*

*term class* and has 24% individuals to that group with a mean duration of survival being 26.9 months. The comparative survival plots for the three classes are presented in Figure 5.

The estimation results of latent class analysis are presented in Table 5. Age of child care workers (YOUNG and MIDDLE) were significant across all the three classes, indicating that being young or middle-aged significantly increases the hazard (e.g. the probability of quitting). However the magnitude of YOUNG is highest for the *short-term class* and the magnitude for MIDDLE is highest for the *intermediate class*. Similarly, the variable RAISE is significant for all the three classes, indicating that higher wage increment increases the survival of members belonging to any of the classes. In this case, the magnitude was highest for the *long-term class*.

The variable WAGE significantly increases the employment duration of individuals of both the *long-term survivor class* and the *intermediate class*. It seems like individuals belonging to the *short-term class* care more about their wage increments than their current hourly wage. In addition, there were some class-specific variables too.

The variable BENHY is class-specific to only the *long-term class* and is positive and significant, indicating that health-related benefits offered by child care center has a significant effect on employment duration for individuals belonging to this class. For the *short-term class*, individuals working as an assistant aide or lead instructor significantly contribute to quitting. However, if the individual has STAR accreditation, then it significantly increases the employment duration for this group. Also, if the center is NAYEC and QCC accredited and has higher percentage of preschool children, then the employment duration increases for this class significantly. Similarly for the *intermediate class*, if the individuals are site coordinators or have bachelor's degree, then they are more likely to contribute to hazard significantly. An interesting observation regarding this class is that survival significantly increases if the center has higher percentage of infants.

## 6. Discussion and Conclusion

To the best of our knowledge, this paper reports the findings of first latent-class survival model for the child care labor market using of a large dataset. The Weibull parameter model with gamma heterogeneity indicates that younger and middle-aged workers who occupy the positions of assistant aid and lead instructor tend to have reduced employment duration. One good indicator of increased employment duration of child care workers is if they have STARS or ECE credits because by taking these credits, the worker signals a commitment to work in child care. The two most important factors that can have positive and significant impact on child care workers employment duration are wages (higher wages per hour and high wage increments) and health benefits provided to them by their centers. Also if the centers are QCC and NAYEC accredited, then it prolongs duration of employment, indicating good work environment conditions.

Further, the latent-class model provides insight into the heterogeneity of child care workers and how it affects employment duration. The *short-term class* has a significant presence of assistant aids and lead instructors. Within the same class, the employment duration increases if the center is NAYEC and QCC accredited. For the *intermediate class,* being site coordinators significantly reduces duration of employment. Similarly if the center provides health benefits, then employment duration increases significantly in the *long-term class.*

In general, younger and middle age workers contribute to turnover. Since the majority of these workers hold positions of assistant aids and lead teacher, then this may affect the quality of child care. Wages do affect the duration decision of these workers. Some workers who tend stay longer have higher hourly wages, but wage increment affect all the workers' duration of employment. For retention, higher wages and wage increments (raises) are important factors. The findings of present study have important implications for the current dialogue in public policy concerning child care standards. Day care workers wages should be comparable to similar profession of teachers as it relates to cognitive development of children. It is known fact that women traditionally receive lower wages and whether child care market which is dominated with female workers may be receiving lower wages leading workers to quit job? Whatever is the cause but the loss is for children.

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Table 1 Variable Descriptions

| Variables | Description |
|---|---|
| DURATION (Months) | Dependent variables; duration in months |
| ***<u>Workers characteristics</u>*** | |
| FEMALE | 1 if worker is female; 0 otherwise |
| YOUNG | 1 if worker is between 18-30 years; 0 otherwise |
| MIDDLE | 1 if worker is between 31-50 years; 0 otherwise |
| AIDE | 1 if worker is Assistant Aide 0; otherwise |
| LEAD | 1 if worker is Lead Instructor 0; otherwise |
| Site | 1 if worker is Site Coordinator 0; otherwise |
| HIGH | 1 if worker is high school or less educated 0; otherwise |
| STAR | 1 if worker has 20 hrs of STARS education 0 ;otherwise |
| EC | 1 if worker has 15 to 135 credits of Early Childhood Education 0 ;otherwise |
| BS/MS | 1 if worker was between 18-30 years 0 otherwise |
| ***<u>Wages</u>*** | |
| WAGE | Wage/hr at exit |
| RAISE | Percentage increase in wages |
| ***<u>Center characteristics</u>*** | |
| BENMAT | 1 if Center offers paid maternity/paternity leave; 0 otherwise |
| BENHY | 1 if Center offers partial/full health insurance; 0 otherwise |
| BENRET | 1 if Center offers partial/full retirement; 0 otherwise |
| NAEYC | 1 If child care is NAEYC accredited ; 0 otherwise |
| UNION | 1 If any employee at center is a union member; 0 otherwise |
| METRO | 1 if Center is in metro; 0 otherwise |
| TOWN | 1 if Center is in town or smaller city; 0 otherwise |
| QCC | 1 If the center is Quality Child care center accredited; 0 otherwise |
| INFANT | Percentage of Infants at center |
| TODDLERS | Percentage of Toddlers at center |
| PRESCHOOL | Percentage of Preschoolers at center |
| KINDERGARTEN | Percentage of Kindergarteners at center |

Table 2 Descriptive Statistics

| Variables | Mean | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|
| DURATION (Months) | 30.2286 | 42.6654 | 1.1 | 417 |
| ***Workers characteristics*** | | | | |
| FEMALE | 94% | | 0 | 1 |
| YOUNG | 63% | | 0 | 1 |
| MIDDLE | 31% | | 0 | 1 |
| AIDE | 39% | | 0 | 1 |
| LEAD | 52% | | 0 | 1 |
| Site | 1% | | 0 | 1 |
| HIGH | 18% | | 0 | 1 |
| STAR | 40% | | 0 | 1 |
| ECE | 23% | | 0 | 1 |
| BS/MS | 8% | | 0 | 1 |
| ***Wages*** | | | | |
| WAGE | 8.61368 | 1.84288 | 6.5 | 23.64 |
| RAISE | 8.43423 | 13.1238 | 0 | 135.67 |
| ***Center Characteristics*** | | | | |
| BENMAT | 11% | | 0 | 1 |
| BENHY | 31% | | 0 | 1 |
| BENRET | 72% | | 0 | 1 |
| NAEYC | 27% | | 0 | 1 |
| UNION | 97% | | 0 | 1 |
| METRO | 21% | | 0 | 1 |
| TOWN | 31% | | 0 | 1 |
| QCC | 39% | | 1 | 3 |
| INFANT | 3.72006 | 4.62946 | 0 | 20.23 |
| TODDLERS | 13.22 | 10.0941 | 0 | 41.89 |
| PRESCHOOL | 29.2459 | 16.7208 | 0 | 89.23 |
| KINDERGARTEN | 6.07378 | 5.40413 | 0 | 27.12 |

Table 3 Parameter Estimates from Weibull Survival Models

| | Weibull Survival Model | | | Weibull Survival Model with Gamma Heterogeneity | | |
|---|---|---|---|---|---|---|
| | Coeff. | Std.Err. | P-value | Coeff. | Std.Err. | P-value |
| Constant | 2.53* | 0.25 | 0.00 | 2.33* | 0.27 | 0.00 |
| FEMALE | 0.03 | 0.07 | 0.66 | 0.13 | 0.08 | 0.13 |
| YOUNG | -1.20* | 0.08 | 0.00 | -0.97* | 0.09 | 0.00 |
| MIDDLE | -0.76* | 0.08 | 0.00 | -0.67* | 0.09 | 0.00 |
| AIDE | -0.63* | 0.10 | 0.00 | -0.69* | 0.10 | 0.00 |
| LEAD | -0.42* | 0.10 | 0.00 | -0.53* | 0.09 | 0.00 |
| Site | -0.56* | 0.20 | 0.01 | -0.72* | 0.20 | 0.00 |
| HIGH | -0.26* | 0.08 | 0.00 | -0.33* | 0.09 | 0.00 |
| STAR | 0.31* | 0.07 | 0.00 | 0.29* | 0.08 | 0.00 |
| ECE | 0.31* | 0.07 | 0.00 | 0.25* | 0.07 | 0.00 |
| BS/MS | -0.10 | 0.08 | 0.23 | -0.13 | 0.09 | 0.14 |
| WAGE | 0.20* | 0.02 | 0.00 | 0.17* | 0.02 | 0.00 |
| RAISE | 0.07* | 0.00 | 0.00 | 0.06* | 0.00 | 0.00 |
| BENMAT | -0.06 | 0.06 | 0.32 | -0.09 | 0.07 | 0.20 |
| BENHY | 0.14* | 0.04 | 0.00 | 0.10* | 0.05 | 0.05 |
| BENRET | -0.03 | 0.05 | 0.47 | 0.00 | 0.06 | 0.97 |
| NAEYC | 0.38* | 0.08 | 0.00 | 0.32* | 0.08 | 0.00 |
| UNION | -0.06 | 0.12 | 0.58 | 0.01 | 0.13 | 0.92 |
| METRO | -0.06 | 0.05 | 0.24 | -0.07 | 0.06 | 0.20 |
| TOWN | -0.02 | 0.06 | 0.72 | -0.04 | 0.06 | 0.46 |
| QCC | 0.09* | 0.04 | 0.01 | 0.08 | 0.04 | 0.06 |
| INFANT | 0.00 | 0.01 | 0.91 | -0.01 | 0.01 | 0.37 |
| TODDLERS | 0.00 | 0.00 | 0.48 | 0.00 | 0.00 | 0.49 |
| PRESCHOOL | 0.00 | 0.00 | 0.24 | 0.00 | 0.00 | 0.81 |
| KINDERGARTEN | 0.01* | 0.00 | 0.02 | 0.01** | 0.00 | 0.10 |
| Sigma | 0.86* | 0.02 | 0.00 | 0.87* | 0.10 | 0.00 |
| Theta | X | X | X | 0.63* | 0.02 | 0.00 |
| Mean duration (months) | | 30.4 | | | 26.47 | |

*Significant at 5 %, **Significant at 10%

Table 4. Model Comparisons of Latent Class Weibull Survival Model

| Model type | Log likelihood | Parameters | BIC Value |
|---|---|---|---|
| 1 Latent Class | -3831.45 | 27 | -3941.34 |
| 2 Latent Class | -3655.56 | 54 | -3874.56 |
| 3 Latent Class | -3615.88 | 81 | -3944.88 |

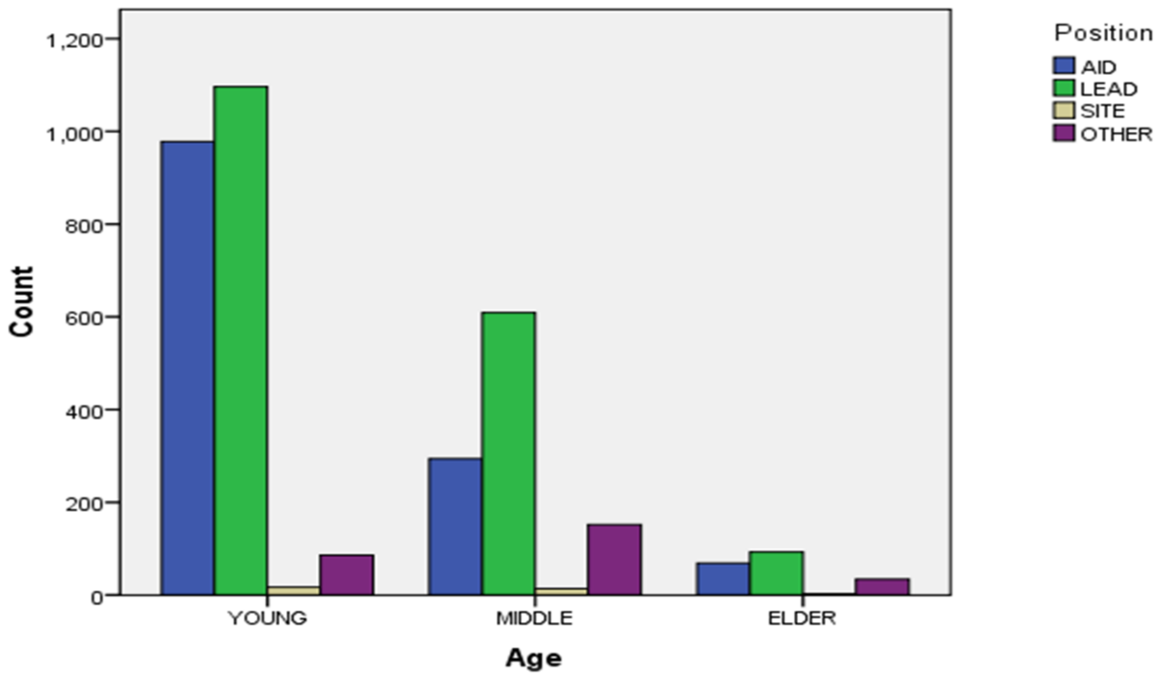
BIC value calculated using BIC = lnL-0.5*parameters*ln(N)

Table 5. Parameter Estimates of Latent Class Weibull Survival Model

| Variable | Latent Class | | |
| --- | --- | --- | --- |
| | Class 1 | Class 2 | Class 3 |
| Constant | 3.81* | 2.02* | 2.39* |
| FEMALE | | | |
| YOUNG | -2.51* | -0.63* | -0.58* |
| MIDDLE | -1.55* | -0.55* | -0.57* |
| AIDE | | | -1.23* |
| LEAD | | | -1.21* |
| Site | | -1.28* | |
| HIGH | | -0.79* | |
| STAR | | | 0.28** |
| EC | | | |
| BS/MS | | -0.55* | |
| WAGE | 0.22* | 0.22* | |
| RAISE | 0.19* | 0.02* | 0.11* |
| BENMAT | | | |
| BENHY | 0.28* | | |
| BENRET | | | |
| NAEYC | | -0.36* | 0.46* |
| UNION | | | |
| METRO | | | |
| TOWN | | | |
| QCC | | | 0.23* |
| INFANT | | 0.02** | |
| TODDLERS | | | |
| PRESCHOOL | | | 0.01** |
| KINDERGARTEN | | | |
| Sigma | 0.72* | 0.58* | 0.60* |
| Class Probability | 0.38* | 0.32* | 0.30* |
| Mean Duration | 32.7 | 29.08 | 26.9 |
| Number | 1645 (48%) | 924(28%) | 875 (24%) |

*Significant at 5%, **Significant only at 10%
Only significant variables are presented in the table.

Figure 1: Positions by Age Group*




*young (18-30 years) and middle (31-50 years), and elder (>50 years).

Figure 2. Survival from Model without Heterogeneity

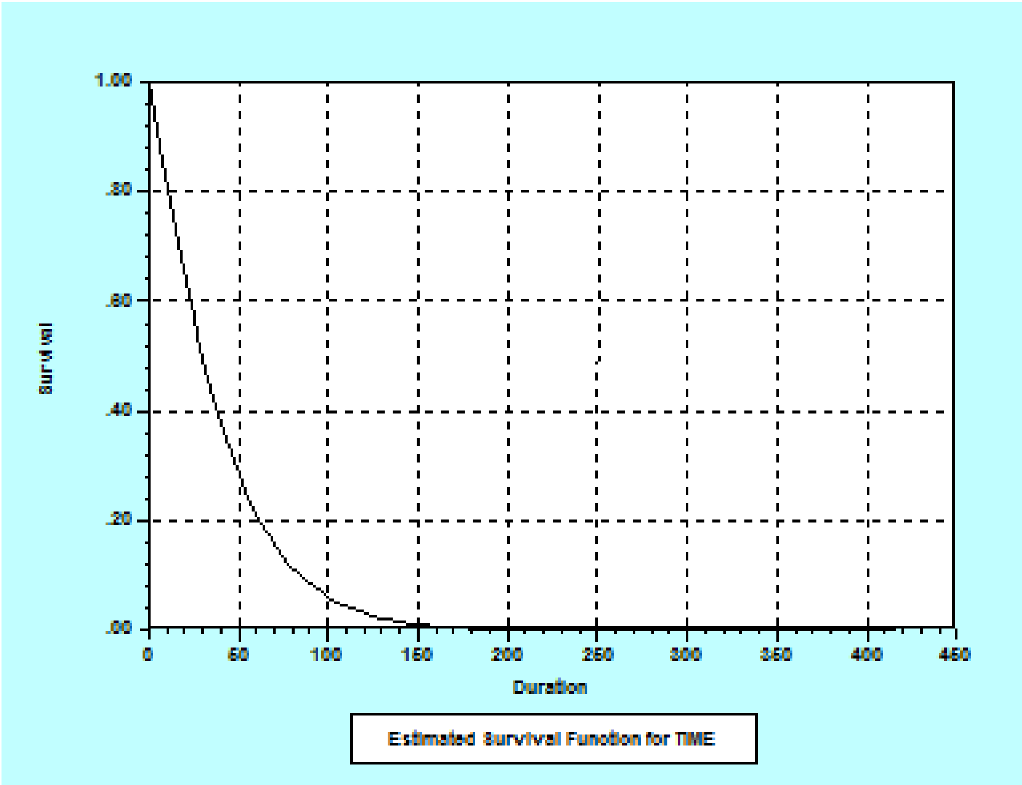


Figure 3. Survival from Model with Gamma Heterogeneity

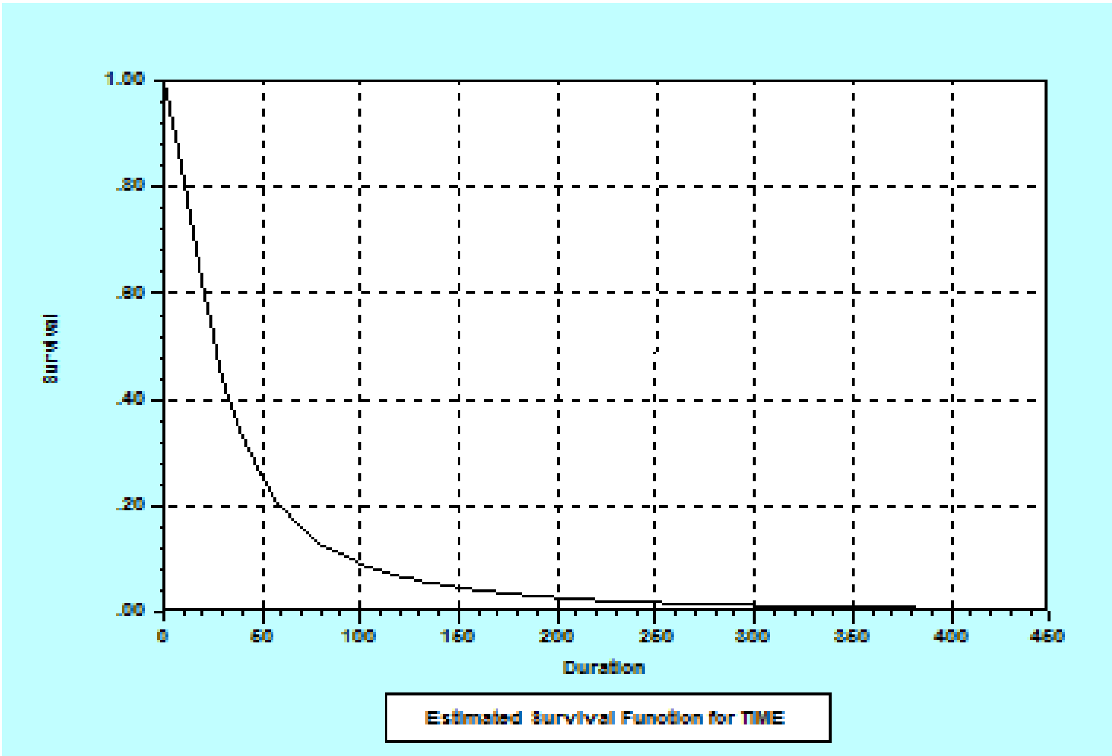


Figure 4 Probability of Quitting for Child Care Workers without Heterogeneity

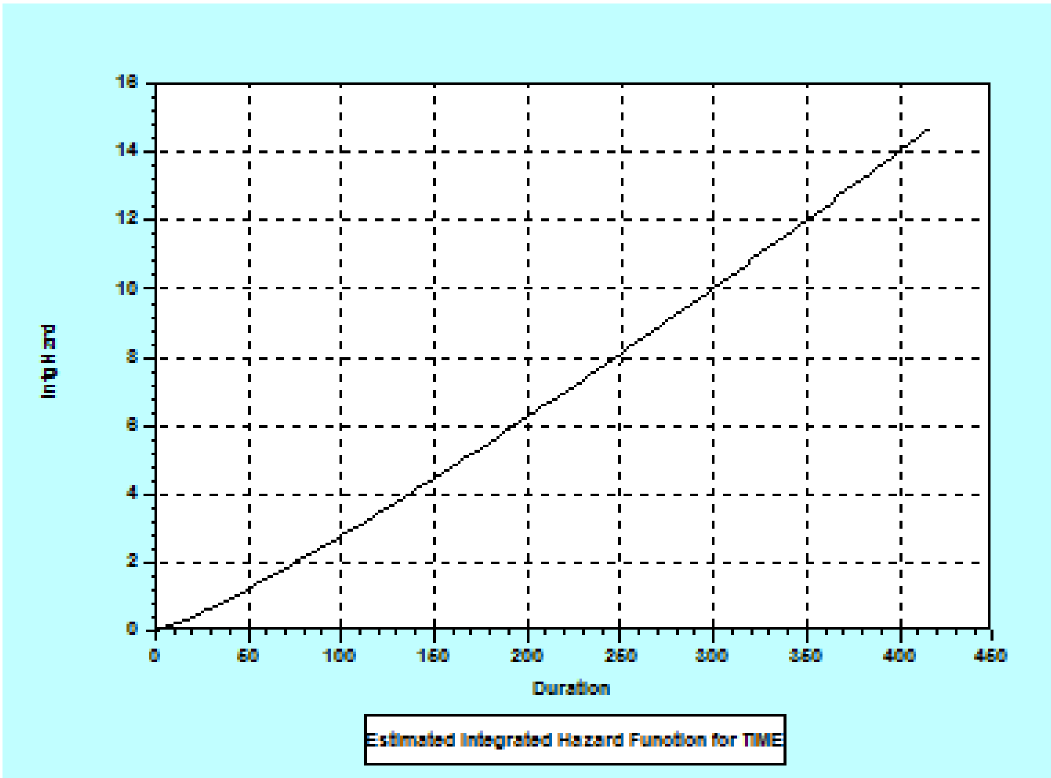


Figure 5. Probability of Quitting From Model with Heterogeneity

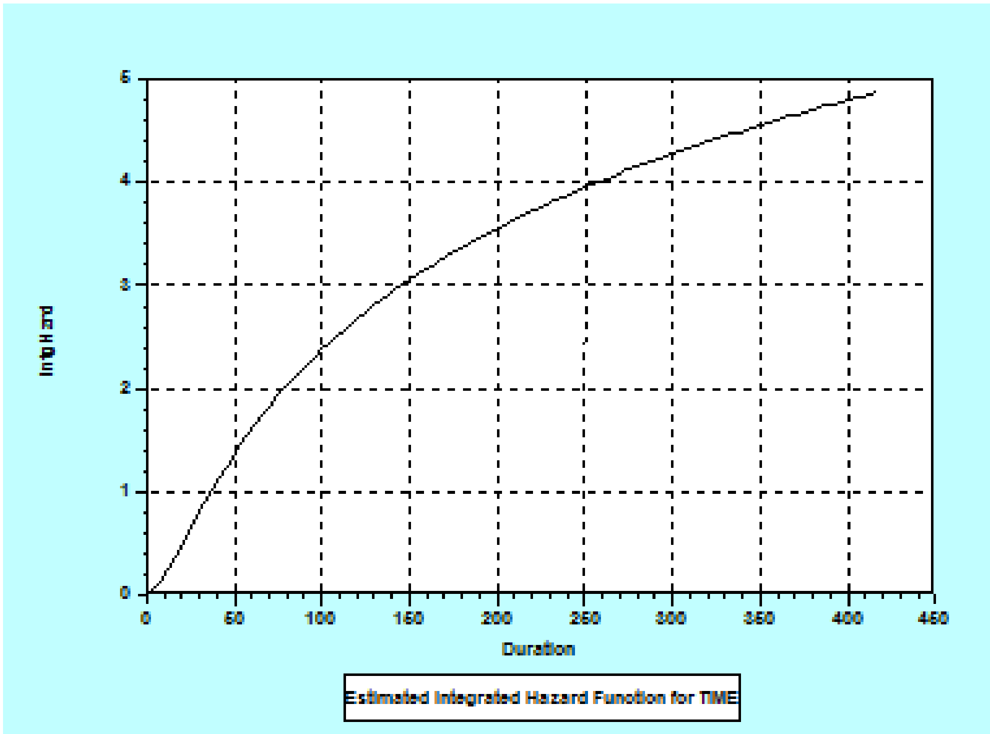
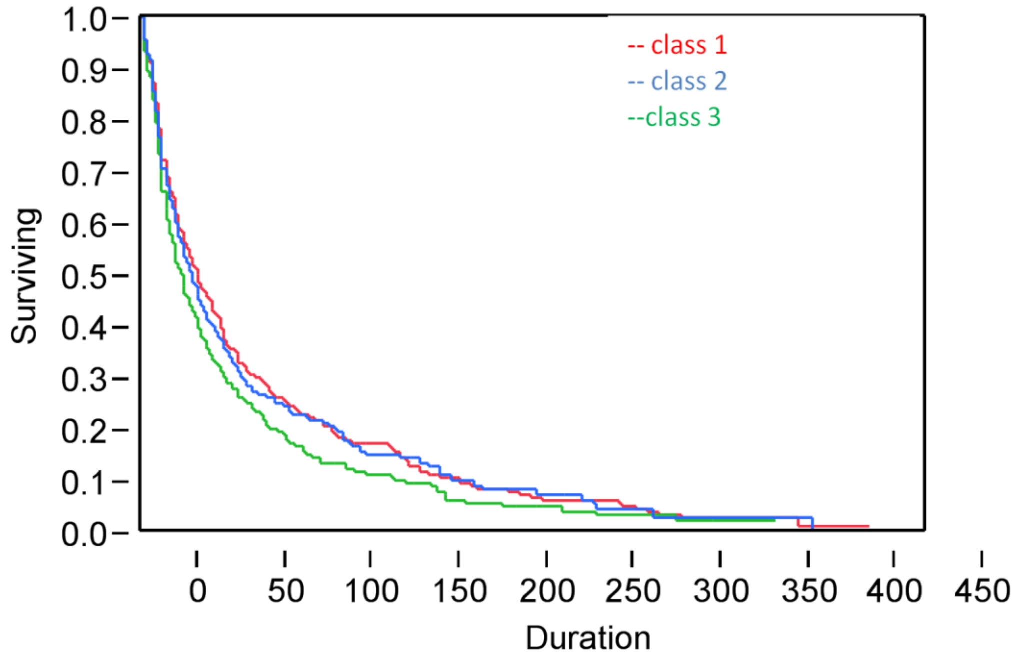


Figure 6. Estimated Survival curves for different Latent Classes



# Chapter 2

# Do All Faculty Prefer Phased Retirement


## Abstract

The retirement decisions of faculty have important implications for both individual faculty members and the University as an employer. The uncapping of mandatory faculty retirement in 1989, institutional policies, personal choices, and the nation's economy make precise predictions of faculty retirement trends difficult. The need for this study grew out of a recognition that approximately one-half of all faculty in American higher education are age 50 and older, that colleges and universities have more than two-thirds of their payrolls invested in these faculty, and that a "generation turnover" of these faculty members will occur over the next decade as they retire in large numbers. If this turnover were experienced at Washington State University then little is known about either the retirement plans of these faculty members or the impact that their retirement will have on this institution and to students. One of the ways to tackle abrupt retirement is phase retirement programs adopted by many universities including Washington state university. This study investigates faculty preference for phase retirement. Our results indicate those high salaried and female faculty have preference for phase retirement. Early phase retirement is not preferred by faculty who has invested his/her retirement income towards social security.



*Keywords: phased retirement, university, nested logit*

## 1. Introduction

Mandatory retirement of college and university tenured faculty based on age was abolished by Federal statute (Public law 99-592, 1986). Faced with the loss of this prerogative, school administrators immediately began to speculate about its potential impact. If viewed strictly from within a business model, a rapidly growing number and proportion of senior faculty could seriously alter both the cost and productivity of educational institutions (Lewis, 1996). However, unlike the usual labor markets, professors receive tenure. How senior faculty might react, when no longer restricted, is largely unknown. How and to what extent the retirement behavior of impacted faculty would change is subject to speculation, but little is known and verifiable (Ashenfelter and Card, 2002).

Throughout the 1990's, researchers attempted to measure this cause/effect behavior, but the results often were in conflict (Holden and Hansen, 1989; Ashenfelter and Card, 2002). Recent studies have found that the abolishment of mandatory retirement has had little, if any effect on retirement behavior of faculty. In a study of Kansas faculty, Rickman and Terry (2002) found that the persistent fear that large numbers of senior faculty would choose to significantly extend their retirement age has not been borne out.

Other related fears that institutional flexibility and research productivity would be adversely impacted by an ever-growing senior faculty cohort have also produced mixed research results. For example, Keefe's (2001) results suggest that while a growing number of faculties have increased their retirement expectations to the age of 70, those who act on their intentions remain productive relative to their colleagues. The desire to maintain (manage via retirement) a reasonable faculty turnover and mixture by rank is still subject to debate, particularly as each institution's specific environment and needs differ.

As noted above, replacing faculty in a timely and orderly manner over the next decade may easily become one of the most significant issues confronting institutional administrators in the future. Any attempt at evaluation or comparison of alternative retirement systems requires a set of normative standard against which individual plans may be measured (Pfeffer, 1956). Incentive-based early retirement programs such as phased retirement programs are increasingly used by institutions as a tool to manage the mix of faculty. However, the general impact of such programs on university faculty is largely unknown.

Policies providing for phased retirement for faculty have been in place for as many as thirty years or more. Historically, many colleges and universities allow faculty to phase into retirement with reduced workloads (Chronister and Trainer, 1985). In some cases, individuals had fully retired and then agreed to teach a course or two at some agreed-on rate of pay. In other institutions, existing policies or individual agreements had allowed older faculty to renegotiate their work assignments to accommodate declining health or changing interests.

Psychologically, faculty often define themselves by their fields of study. They are not just "professors." Rather, they are chemists or mathematicians or economists. Retirement suggests that they will no longer be able to rely on the professional identity they have cultivated for thirty or forty years. The prospective psychological devastation this presents to some faculty may prevent them from considering retirement, notwithstanding its inevitability (Janson, 2005). Janson (2005) argued that phasing is a healthy way to avoid the trauma of sudden retirement.

Phasing usually means working half time and receiving half salary. The benefits to individuals of phase retirement are largely intangible. Phasing makes life easier, less stressful, and more tolerable, and it provides flexibility to handle a complicated major life transition (Leslie, 2005). Although phasing can mean less current income, time and money are fungible to some extent, especially for those at or near retirement age (Clark, 2007).

Phased retirement plans may not be always financially attractive especially for faculty who are not yet eligible for social security or Medicare and who also elect the option to phase retire before they can receive annuities from their provider. This loss of income may be perceived by faculty as an unattractive aspect of phasing. Another issue in the case of public university faculty is that they may participate in either private or public pension plans. The terms and conditions of these plans may differ substantially, making a phased retirement policy attractive to one group but unattractive to others.

There have been only a few studies on the preferences for phased retirement plans in higher education. Allen (2006) and Allen, Clark and Ghent (2004) found that probability of retiring using phased retirement depends on the type of institution, the type of pension plan chosen by the faculty, and other individual characteristics. Rickman and Parker (2005) found that poor health status reduces the probability of a faculty member to enter into a phased retirement program.

In this article, we evaluate faculty preferences for phased retirement at a major land grant university. We expect for the findings to be useful in developing phased retirement programs and provide the basis for more accurate expectations for how these programs will be utilized by faculty members.

## 2. WSU phase retirement program

Most of the major public university have similar phase retirement program but they may differ in terms of requirements and process. Below we describe some of the important features of WSU phase retirement program

*Eligibility Requirements:* Eligibility for phase retirement is usually based on a combination of age and years of service. For example, UNC has established fifty five as the minimum age of eligibility and required that an individual achieve some combination of age and years of service totaling to seventy five (Allen, Clark and Ghent, 2003).WSU's policy also mandates that a faculty member be 55 years of age with at least 10 years of cumulative service to WSU.

*Tenure Status:* Eligibility for phased retirement is usually, although not always, conditioned on a waiver of tenure rights (e.g., Texas State University System's) or on formal notice of retirement or intent to retire on a certain date. However, there are exceptions, as in the California State University System's and WSU's policy that preserve tenure rights for those electing to phase.

*Length of Notice:* Eligibility to phase usually requires either notice of intent to retire at a certain time or a formal declaration of retirement. WSU requires that "…. ..several months ahead of the formal request, persons considering Washington State University's Phased Retirement Plan should informally discuss with their administrative unit head, the professional staff in benefit services, and other appropriate persons about the advantages and implications of a reduced appointment,"

*Participation Period*: Faculty members who choose the phased retirement option can expect to phase out within a fixed period. At WSU faculty may choose from 1 to 5 years to phase out.

*Work Assignment***:** Phased retirees are often technically assigned a set of responsibilities amounting to less than a full-time workload as customarily defined. The most common assignment is a 50 percent workload as defined by the institution, (An individual teaching four courses a term may be assigned to teach two courses on entering phased retirement,)

*Salary:* Pay for phased retirees are usually prorated: half pay for half time, for example, at WSU the policy notes that, the salary during phased retirement is calculated at the appropriate percentage of the full-time base salary of the employee's position held just prior to entering phased retirement.

*Raises:* Phased retirees are eligible for merit increases or supplemental pay for summer sessions under some plans but not under others.

*Insurance:* Premiums paid by the institution for health, life, and disability insurance are generally continued for the faculty member at the same rate as for full-time faculty. However, eligibility is often conditioned on some minimum level of work, such as the half-time requirement at WSU).

*Social Security and Pensions:* Eligibility for retirement plan payouts and social security depend on the age of the individual, terms and conditions of the employment agreement, the structure of the retirement plan, and the individual's own relationship to these sources of income, The resulting financial implications may determine the degrees of freedom an individual was in electing (or not) to phase, WSU's policy advises that "those participants qualifying for Social Security retirement benefits may be eligible to draw those benefits while on phased retirement beginning at age 62 or any later date".

*Financial Planning:* Financial planning for retirement was generally considered to be the individual's (and not the institution's) responsibility. WSU recommends that in planning for income needs during phased retirement, it is important to review all sources of retirement income to determine eligibility for receiving payments, the taxability of the payments, and when it would be most advantageous to begin drawing these payments. This can be done with the assistance of University officials, TIAA-CREF representatives, or independent financial advisors,"

## 3. The Economics of Phased Retirement

We consider a one period labor-leisure choice model in order to understand the phased retirement decision of faculty. We assume that a professor accepts a phase retirement at the age of 62 that makes him/her eligible for social security benefits also. In the presence of phased retirement program a faculty has one of these three choices: (1) work full-time for $H$ hours in a career job and earn income $Y$ with zero pension income, (2) work half-time 0.5H hours and earn half the income 0.5Y with full pension income $P$, and (3) retire from the career job and receive $P$.

Let worker utility be represented by $U = U(y, T - h)$, where $y$ = income, $T$ = time endowment, and $h$ = labor hours. Workers compare $U_1(Y, T - h)$ to $U_2(0.5Y + P, T - 0.5H)$ and $U_3(P, T)$ and select the option that maximizes utility. The desirability of phase retirement work depends on how much labor income must be sacrificed to obtain a half-time hours reduction. For most workers, we expect $0.5Y+P > Y`$ where Y` is income from a different part-time job. This occurs because (1) specific human capital at the original job would not be valued at the new job and (2) wage rates on part-time jobs tend to be lower than on full-time jobs. The greater the income sacrifice needed to obtain a part-time work schedule ($Y - Y'$), the lower the odds of working part-time.

## 4. Empirical model

Since the entire faculty in our study indicated that they will retire at some point of time so we rule out no retirement scenario developed earlier. Now a faculty has three options: (1) accept full retirement (2) Early phased retirement (before 62 years) (3) Late phased retirement (at/after 62 years) to be eligible for social security benefits. Some of the early retirement studies (Allen, Clark and Ghent, 2003; Bratberg, Holmas and Thogersen 2000) have used multinomial logit model (MNL) to formulate choice decision related to early retirement. Although MNL models are widely used for discrete choice modeling but it suffers from independence of irrelevant alternative (IIA).

The independence of irrelevant alternative (IIA) condition assumption in the standard logit forces the model to have a homoscedastic covariance matrix. This is a strong assumption that has received several criticisms in the literature. The nested logit model recognizes the possibility that each alternative may have information in the unobserved influences of each alternative, which in turn has a role to play in determining a choice outcome that is different across the alternative branches (Louviere, 2000). This implies that the variance might be different (i.e., specific alternatives do not have the same distributions for the unobserved effects). The information content could also be similar amongst subsets of alternatives and hence some amount of correlation could exist among these subsets. The presence of these possibilities is equivalent to relaxing the IIA assumption. That is the appeal of the nested logit model. It has the ability to accommodate correlation between subsets of alternatives in a choice set (Greene, 2000).

The nested logit model is the most advanced of the closed form models, particularly for unordered outcomes (Hensher, 2005). The main benefit of using the nested logit model is that parameters and probability outcomes in the model are easier to estimate and interpret, especially as the number of attributes and alternatives increases (Hensher, 2005). An opportunity therefore exists to identify and illustrate interaction amongst faculty at WSU upon their decision to retire. The decision to retire can be modeled in a random utility framework. A utility function can be specified, expressing the hypothesis about the way in which respondents combine their part utilities into an overall evaluation or preference. Following Ben-Akiva and Lerman (1987), and Louviere, Hensher, and Swait (2000), a general random utility function, in terms of attributes can be expressed as

$$U_{in} = V(X_{in}) + \varepsilon(X_{in}) \qquad (1)$$

where $U_{in}$ is respondent $n$'s utility of choosing alternative $i$, $V$ is indirect utility, $X_{in}$ is a vector of attribute values for alternative $i$, and $\varepsilon$ is a random element. Total utility, $U_{in}$, is a sum of observable and unobservable components that can also be expressed as $V_{in}$ and $\varepsilon_{in}$, respectively. The utilities are not known with certainty and are treated as random variables. From this perspective, the choice probability of alternative $i$, is equal to the probability that the utility of alternative $i$, $U_{in}$, is greater than or equal to the utilities of all other alternatives in the choice set. This can be written as follows

$$\pi_n(i) = Pr\,[V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn};\ \ all\ \ j \in C_n\,] \qquad (2)$$

where $C_n$ is choice set. Assuming that $V_{in}$ is linear-in-parameters, the functional form can be expressed as:

$$V_{in} = \beta_1 + \beta_2 x_{in2} + ... + \beta_k x_{ink} \qquad (3)$$

where, $V_{in}$ is respondent $n$'s utility of choosing alternative $i$, $x_{ink}$ is attributes, and the $\beta$s are coefficients to be estimated. Assuming that utility is linear-in-parameters, the probability of a decision option is expressed as:

$$\pi_n(i) = \frac{\exp[\beta' X_{in}]}{\sum_j \exp[\beta' X_{jn}]} \qquad (4)$$

where, $\pi_n\,(i)$ is a respondent's decision option $i$. All other variables are as described above.

The nested logit model for faculty decision to retire is built upon the decision tree shown in Figure.1. The decision tree starts with a branch based on whether the respondent will accept phased retirement program. If he or she responds positively, then next level is whether he or she will accept early phased retirement program (before 62 years) or late phased retirement program (at or after 62 years). The variables used at branch level are socio-demographic variables (Hensher et.al, 2005). Since one of the branches of this nested model is degenerate; the inclusive value (IV) for that branch is constrained to one (Hensher et.al, 2005). Details of all the independent variable used at branch and attributes levels are given in Table 1. We describe the selected variables below.

*HEALTH*: The effects of bad health on retirement are ambiguous. A change in health status may intervene in workers retirement decision. In general poor health will result in earlier retirement (Sammartino, 1987; Dwyer & Mitchell, 1999).

*SALARY:* Current salary is a proxy for the financial ability to enter into phased retirement. An increase in salary increases the opportunity cost of leisure and hence reduces the consumption of leisure (substitution effect). However increase in salary may also lead to increase wealth that leads to greater consumption of normal goods including leisure (an income effect). Therefore, the effect of earnings on retirement may be unclear and depends upon the net effect.

*RESWEAL:* This variable is created to capture the effect of reservation wealth. Reservation wealth is the level of wealth where an individual is indifferent between work and retirement and it depends upon the marginal rate of substitution between consumption and leisure and real wages. However, we do not observe reservation wealth so we created *RESWEAL* as a proxy for reservation wage. It is the ratio of expected retirement wealth and estimated earnings at retirement which is calculated by growing current academic salary by 3% each year until expected retirement age (Rickman & Parker, 2005).

We also included variables for gender (MALE) and expected longevity (LIFE). If a faculty expect to live longer then it may result in consumption of less leisure currently (more work) and hence late retirement *ceteris paribus*. We also included variables UNILAR, SSLAR, UNISEC and SSSEC. These variables relates to faculty retirement investment. If a faculty member has invested more in social security then they may not accept early phased retirement programs.

## 5. Data:

The study utilizes primary cross sectional data obtained from a web-based survey of WSU faculties. All instructional faculty of WSU were encouraged to participate in this survey. They were twice sent reminders to increase the response rate. A total of 177 responses are recorded from a population of approximately 850. The questionnaire was based on a similar document used in study by Kansas State University (Rickman and Terry, 2002) with little modification to suit WSU conditions. Questionnaire sought information on varieties of issues viz., socio-demographic, satisfaction level, retirement planning actions, stock market expectations, financial support of others, Taxes, phased retirement plan, spouse information, and investment allocation.

A total of 177 survey responses were generated amounting to 20% response rate. The expected retirement age as indicated by faculty was 65.3 years. Fifty eight percent (58%) of faculty respondents indicated financial ability to retire as the single most important factor to their retirement decision; 17% indicated more leisure time for family; 11% indicated health status; 5% indicated they will qualify for retirement benefits; 2% indicated dissatisfaction with job/superiors; and 6% indicated other reasons.

When asked about their satisfaction with their overall academic career to this point 41% indicated they are very satisfied; 36% indicated somewhat satisfied; 9% indicated neutral satisfaction; 11% indicated somewhat dissatisfied; and 3% indicated very dissatisfied. With regards to satisfaction over salary increase they have received from university 13% indicated they are very satisfied; 25% indicated somewhat satisfied; 15% indicated neutral satisfaction; 24% indicated somewhat dissatisfied; and 23% indicated very dissatisfied.

The respondents were asked for their responses if WSU Board of Regents offered a phased retirement plan for faculty aged 55 or older that continues to pay into the state basic retirement program based on 100% of salary and no reduction in medical contributions by the state. To this, 67% faculty indicated they would consider it, and 33% indicated that they would not consider it. Of the faculty who are willing to accept phase retirement, the mean of preferred age that faculty would consider beginning a phased retirement option was 61 years.

The mean of minimum amount of “cash severance payment” that would induce retirement following year once a faculty reaches 62 was found $ 210774.4. When asked if upon retirement, the university would continue to provide them office space in close proximity to their department, secretarial assistance, access to computer, or other support services, would those benefits affect their retirement decision to which 52% indicated that it would not have any effect on age of retirement; 27% indicated they were uncertain; 11% indicated they would retire more than one year earlier; 4% indicated they would retire one year earlier; and 4% indicated they would retire more than one year later. Sixty-one percent (61%) respondents indicated that they would consider retiring at an earlier age if the university would continue to pay their health insurance until eligible for Medicare; 27% indicated it would have no effect; and 12% indicated they were not certain.

Majority of faculty that responded have 9 months contract with university (48%) followed by faculty that have 12 months contract (43%). Ninety six percent (96%) of these faculty indicated that they are employed full time followed by faculty that indicated employed part time (4%). Of those entire faculty that replied to the survey the mean age for working in WSU was found 16.2 years and 20 years for total number of years employed in any university. Majority of faculty indicated that they were on tenure track (72%). The mean age of faculty that responded was 52 years. Of these 62% were male. Seventy-seven percent (77%) of faculty indicated that they were married; 11% indicated that they were separated or divorced; 10% indicated they were never married; and 2% indicated they were widowed.

## 6. Results and Discussion

The decision process for retirement was examined in two stages. The first stage is whether faculty member accepts phased retirement, and the second stage groups those who indicated accepting phased retirement into early acceptance and late acceptance of phased retirement.

Those that indicated will not accept phase retirement remain as the same branch (degenerate branch). The nesting increased the log likelihood function value. The computed chi-square value is 47.76 with 12 degrees of freedom and is statistically significant. Thus, nesting improves the model over the non-nesting model.

Table 2 presents the estimated coefficients and p-value for the independent variables within and between branches. In the first stage, the decision to accept the phased retirement program significantly decreased if faculty indicated having poor health (HEALTH). This may be because poor health requires increased consumption of health care related goods and service. The marginal utility of health services may increase with poor health status which, in turn, may delay retirement or choice of phased retirement.

The variable SALARY was also statistically significant, indicating that higher salary leads to acceptance of phased retirement. This may be caused by a dominant income effect. This is, faculty with higher salaries wants to consume more leisure.

We also found that male faculty (MALE) are less likely to accept the phased retirement program. A similar result was reported by the consulting firm Watson Wyatt Worldwide (2005). Possible explanations include that female faculty are often in lower paid fields with higher teaching loads, such as the humanities and education.

When it comes to choosing earlier (before 62 years) or later (at or after 62 years) retirement, we found that faculty whose second largest retirement income contribution goes to social security are more likely to accept phased retirement at or after 62 years. These faculty may receive a higher overall income by waiting until 62 years.

## 7. Conclusion

The typical university in the United States provides a retirement program that when combined with social Security can be expected to provide a level of income at age 65 that is comparable to individual's current net working income. If the institution seeks to encourage retirement at normal retirement age of 65 or earlier, it should understand its faculty's preference for phased retirement. Faculty with poor health may not be willing to accept a phase retirement program. Incentives in the form of increased medical support from the university may lead them to consider phase retirement programs. Again faculty with higher salaries are more likely to accept a phase retirement program. Higher salary is also related to age and field of study.

If the entire faculty belonging to the same field retires the same time, then it could impose a huge loss on university in terms of expertise and hiring cost. The willingness to accept phase retirement by high salaried faculty can be capitalized by university in terms of reducing cost (the university will have to pay half salary) and at the same time these individuals will be mentoring and pass their expertise to young faculty. Female faculty are more likely to accept phase retirement program. The institution can provide them more knowledge about benefits of phase retirement. Phase retirement if implemented correctly will have win-win situation for both university and faculty. University can save their cost and recruit newer faculty and also retain their gifted old faculty whereas individual faculty can slowly acclimatize to retirement life.

**Future direction:**

The limitation of this study is the data, which is a cross section from one university. This study can be replicated at other and some additional variables can be used for analysis. For example, are there differences across the faculty in different fields (humanities compared to engineering) in their preference for phase retirement? There may be salary, burn outs and gender aspects related to different fields within the university. Another important variable that can be incorporated is the effect of stock market returns in faculty decisions for phase retirement. This study was conducted before the current stock market crisis and many faculty invest in stock markets. Does a fall in the stock market affect faculty preferences for phase retirement?

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Table 1 Independent variables selected for retirement nested logit model

| Variables | Description |
|---|---|
| HEALTH | 1 if a faculty reports poor health; 0 otherwise |
| SALARY | Annual Salary of faculty |
| RESWEAL | Reservation wealth |
| TWELVE | 1 if a faculty works whole year; 0 otherwise |
| MALE | 1 if male; 0 otherwise |
| LIFE | Expected longevity in years |
| UNILAR | 1 if University Retirement plan will be the largest source of retirement income; 0 otherwise |
| SSLAR | 1 if Social Security will be the largest source of retirement income; 0 otherwise |
| UNISEC | 1 if University Retirement plan will be the second largest source of retirement income; 0 otherwise |
| SSSEC | 1 if Social Security will be the second largest source of retirement income; 0 otherwise |

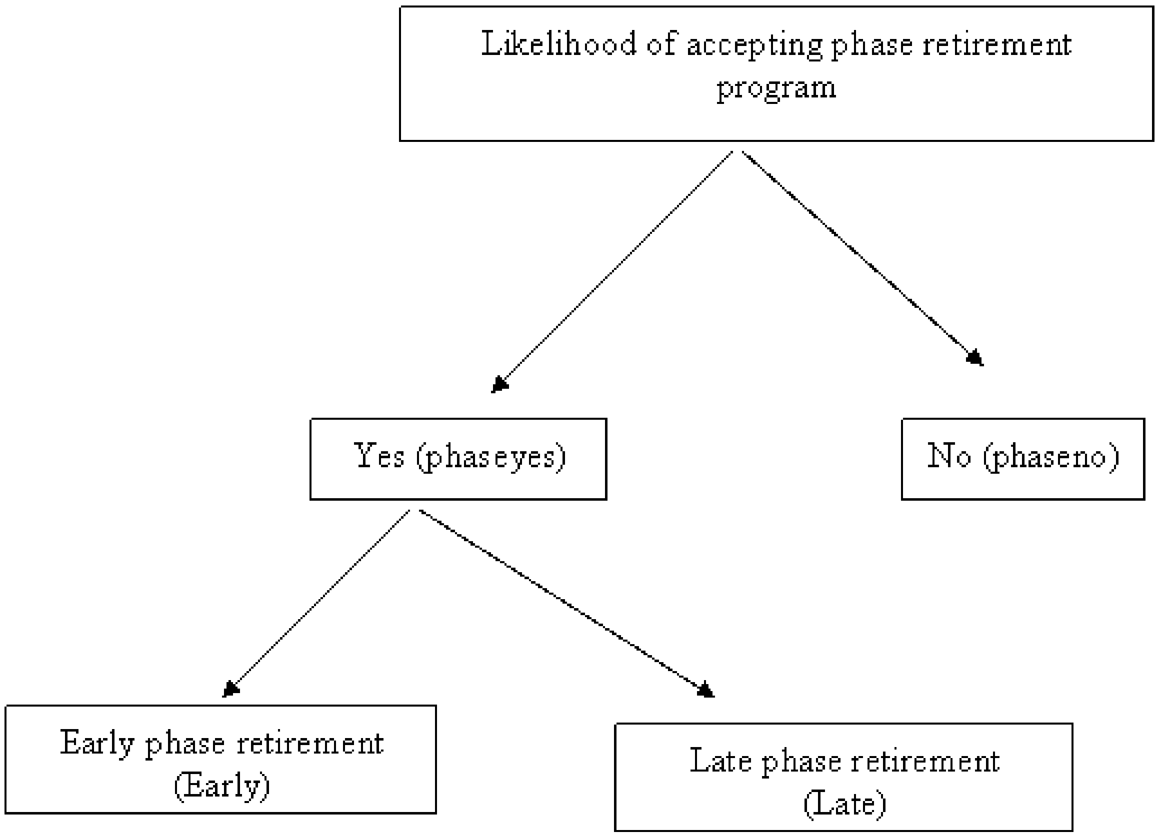
Table 2 Nested logit estimates for phased retirement decision

| Variables | Coefficient | Standard error | P-value |
|---|---|---|---|
| *Branch-Phaseyes/Phaseno* | | | |
| HEALTH | -1.34 | 0.69 | 0.05** |
| SALARY | 1.03 | 0.47 | 0.03** |
| RESWEAL | -0.01 | 0.01 | 0.40 |
| TWELVE | 0.04 | 0.37 | 0.91 |
| MALE | -0.69 | 0.41 | 0.09* |
| LIFE | -0.03 | 0.03 | 0.32 |
| *Choice-Early/Late* | | | |
| CONSTANT | -7.65 | 8.52 | 0.37 |
| UNILAR | 0.55 | 0.84 | 0.51 |
| SSLAR | -0.21 | 1.32 | 0.87 |
| UNISEC | -0.24 | 0.77 | 0.76 |
| SSSEC | -0.74 | 0.28 | 0.01** |
| N | 175.00 | | |
| LL | -177.45 | | |

** Significant at 95 % confidence interval

*Significant at 90% confidence interval

Figure 1.Decision tree for WSU phase retirement program



# Chapter 3

## A Product Differentiation Explanation for the Existence of Quantity Surcharges


### Abstract

*Quantity surcharges exist when a larger-sized package has a higher per-unit price than its smaller-sized counterpart. This article provides a new explanation for the existence of quantity surcharges based on the hypothesis that different sizes of the same product are imperfect substitutes and thus are differentiated products. To test this hypothesis, we utilize grocery store scanner data to estimate a demand system and the associated cross-price elasticities. We focus our empirical investigation on canned tuna, which often exhibits quantity surcharges. A random coefficients logit demand approach is used to calculate elasticities. There is evidence to support the hypothesis that quantity surcharges in canned tuna are driven by firms catering to heterogeneous consumer preferences.*

## 1. Introduction

Consumers often have strong expectations about the relative prices of products found in different sized packages. Many compare the per-unit price of products in hopes of finding a quantity discount (Granger and Billson, 1972; Manning, Sprott and Miyazaki, 1998; Nason and Della Bitta, 1983). Quantity discounts occur when the price per unit of a brand's larger-sized package is less than the price per unit of the same brand's smaller-sized package. In contrast, quantity surcharges exist when a larger-sized package of a product has a higher per unit price then its otherwise equivalent smaller-sized counterpart. Various studies in the marketing literature suggest between 16 and 34 percent of products available in two or more package sizes found in retail grocery outlets exhibit a quantity surcharge (Sprott, Manning and Miyazaki, 2003).

Consumers often react negatively to quantity surcharges. Previous research finds that when consumers discover quantity surcharges, they often feel that the retailer has engaged in deceptive pricing practices or has eliminated a preferred course of action (e.g. purchasing the larger package) for the consumer and this may decrease the likelihood of purchasing the surcharged brand or shopping in that retail outlet (Manning, Sprott, and Miyazaki, 1998). Consumers may feel exploited as they begin to associate a brand or store with quantity surcharges (Widrick, 1979).

Cost differentials and price-setting practices have been offered as justification for quantity surcharges. It may be more expensive to refrigerate larger packages of some goods, which can cause cost-based quantity surcharges. In the marketing literature, some suggest (without empirical support) that retailers may be exploiting consumers who do not notice quantity surcharges (Agrawal, Grimm and Srinivasan, 1993; Gupta and Rominger, 1996). Alternatively, retailers may not intentionally set prices that result in quantity surcharges. These retailers may actively compete with other retailers on specific sizes of fast-moving items and drive the price of that package size down, which can result in a quantity surcharge for the larger-sized product (Sprott, Manning and Miyazaki 2003).

We offer an alternative explanation for the existence of quantity surcharges. Goods sold in different package sizes may represent differentiated products to consumers. If this is the case, then consumers should not expect an additive price relationship between these products. We focus our empirical investigation on canned tuna, which often exhibits quantity surcharges (Agrawal, Grimm, and Srinivasan, 1993; Manning, Sprott, and Miyazaki, 1998). Tuna surcharge pricing earned the dubious distinction of being photographically featured in a *Consumer Reports* article on "sneaky consumer product tricks," (*Consumer Reports*, 2000).

Product attributes differentiate many products. Canned tuna products are differentiated with respect to a number of characteristics, including the meat type and canning medium. We hypothesize that package size also differentiates many products. Two six-ounce cans of tuna may not be viewed as equivalent to a single twelve-ounce can. In other words, from the consumer perspective, they are imperfect substitutes. Motivations for product differentiation based on package size include that different-sized packages may require different usage and storage options, both before and after the package is opened, or the use of the product may differ for a given quantity of the good. Another possible explanation comes from the convenience of opening and using a larger package. Also, different sizes of tuna may have different product quality. For example, small cans of tuna may have less meat and more broth compared to larger cans of tuna, or larger cans have larger pieces of tuna that may be in shorter supply. Thus, quality may be another attribute associated with size. Under these scenarios, it is realistic to assume that product size may form a basis to differentiate canned tuna products in addition to other product characteristics.

Given product differentiation based on size, consumers should not expect the price per unit of various sizes to be the same or less for larger packages in the same way as they do not expect price per unit of "albacore" tuna and "chunk light" tuna to be the same. Different sizes of the same products may have different demand curves, and firms should make their pricing decisions based on these different demand elasticities. This can result in different sized packages of the same product with unequal unit prices. We find evidence in support of the hypothesis that different sizes of canned tuna are imperfect substitutes, which can result in quantity surcharges.

The remainder of this paper is organized as follows. In section 2, we present a model of product differentiation based on product size using product characteristic space and explain how we measure product differentiation empirically. In section 3, we describe the retail-level scanner data that is used in this analysis. In section 4, we discuss the estimation procedures. In Section 5, we present the empirical results. We conclude in section 6

## 2. **The Model**

In this section, we apply the theory of product differentiation in a new way. We consider package size to be a product attribute, and this provides a new justification for the existence of quantity surcharges. As Lancaster (1966) established, products can be viewed as bundles of characteristics. Consumer preferences are defined over the characteristics space, rather than the products themselves and thus, consumers are willing to pay more for variants that are better suited to their own tastes. For example, some consumers may have preference for albacore tuna if they like white meat, and hence they will be willing to pay more for this product.

Furthermore, calorie conscious consumers may prefer their albacore tuna to be packed in water rather than oil. We propose that consumers have preferences for package size also.

Since we hypothesize that different sizes of canned tuna satisfy the idiosyncratic tastes of consumers, we place canned tuna with different attributes, including package size, in a multi-dimensional characteristic spaces. An example is provided in Figure 1. In Figure 1, there are three products “A”, “B” and “C,” which are differentiated based on three product characteristic dimensions, including size of package. Products “B” and “C” have similar size and the meat type “albacore,” but they differ with each other with respect to canning medium. Product “A” is differentiated with “C” with respect to both size and canning medium and differentiated with product “B” with respect to just size. All of these products cater to diverse consumer preferences and provide utility based on their characteristics.

The degree of product differentiation of all products in a market can be assessed by examining cross price elasticities (Bresnahan, 1981; Trajtenberg, 1990; Berry, 1994; and Feenstra and Levinsohn, 1995). If different sized products are used by consumers differently, then they may have different demand curves with different elasticities. Therefore, it is imperative to correctly estimate demand for differentiated products in order to compare their elasticities and elicit information regarding product differentiation. A prevalent utility-theoretic approach that is used in modeling demand in product differentiation is the representative consumer model (Spence, 1976 and Dixit and Stiglitz, 1977). However, a concern when using individual consumer data is whether the consumers selected in the sample are the true representative of the population. Another approach to study demand is to utilize market-level data. All types of individuals make purchases, and hence the representative consumer problem can be ignored.

In the current study, the objective is to estimate demand elasticities for differentiated products using market scanner data. A straightforward structural approach is to use a model of consumer preferences over the various products and estimate interconnected demand curves, as in a linear expenditure model (Stone, 1954). A problem with this approach is that if there are numerous demand curves and the demand for each product depends on the prices of the others, there will be a large number of parameters to estimate, which is infeasible for limited data sets. Thus, we take a different approach, making consumer utility a function of product characteristics instead of the product themselves. Further, we consider the individual consumer's problem of buying a particular product rather than how much to buy.

The combination of discrete choice modeling based on McFadden (1973) and Lancaster's (1979) characteristics model can be used to compute elasticities by projecting products on to their characteristics space. This resolves the dimensionality problem, and at the same time consumer preferences are defined over the characteristics space, rather than the products themselves. When analyzing product differentiation, one can view products as bundles of characteristics from which consumer derive their utility (Lancaster 1966, 1975, 1979). Products with similar characteristics will be close to each other in characteristic space, and their cross-price elasticities will be high, indicating more substitution between them and less differentiation perceived by consumers.

Discrete choice models are often used to provide estimates of elasticities in differentiated products. Conditional logit models, based on McFadden (1973), have been applied to several of these problems (Shaked and Sutton, 1982; Perloff and Salop, 1985; and Anderson, Palma and Thisse, 1989). Many logit models include a restrictive assumption in which the substitution between products depends exclusively on market shares and not the similarity of the products.

This occurs because all the regressors, including price, are assumed to be exogenous. This endogeneity results in substantial biases and inconsistencies in elasticity estimates using ordinary least squares (Berry 1994; Villas-Boas and Winer, 1999).

Recent research in random coefficient models has focused on how to account for this endogeneity while investigating market power, innovation, and product differentiation. These models begin with random utility models where utility is composed of a mean level of utility from consuming a product and a deviation from the mean. The deviation from the mean depends on the interaction between consumer preferences and product characteristics. Some of the product characteristics are unknown to the researcher. Thus, from the researcher's point of view, prices are endogenous. Berry (1994) examines such a model of discrete choice of product differentiation. He uses instrumental variables to account for the endogeneity of prices. Berry, Levinsohn and Pakes (1995, hereinafter BLP) apply this technique to the automobile industry. They generate own- and cross-price elasticities for several models of automobiles. They find that substitution is more likely for vehicles with similar characteristics.

BLP's approach has also been applied at the city level and the national levels to food products, including breakfast cereals (Nevo, 2000 and 2001; Chidmi and Lopez, 2007), yogurts (Villas-Boas, 2007), frozen foods (Mojduszka, Caswell, and Harris, 2001), ketchup (Rennhoff, 2004) and Margarine (Kim, 2008). Nevo (2001) uses a random-coefficients logit model to estimate the price-cost margins for ready-to eat cereal. He estimates a brand-level demand system to obtain demand elasticities and then uses these to identify market power from product differentiation, multi-product pricing, and price collusion. Villas-Boas (2007) uses BLP's approach to calculate elasticities for yogurts at three individual grocery stores to explore alternative vertical relationships between retailers and manufacturers. Chidmi and Lopez (2007) use elasticities calculated using BLP's approach in their study of ready-to-eat breakfast cereals and find that retail markups increase and marginal costs decrease as grocery market shares increase, attesting to oligopoly power with efficiencies.

Following BLP, when choosing a product, the consumer maximizes utility driven by the brand characteristics, including product size, as well as his/her own characteristics. Here, we incorporate size as one of the product characteristics. The indirect utility of consumer *i* from buying the product *j* in market *m* is given by

$$U_{ijm} = \beta_i X_{jm} + \alpha_i p_{jm} + \xi_{jm} + \varepsilon_{ijm}, \text{ for } i = 1,\dots n;\ j = 1,\dots, J;\ m = 1,\dots\dots M \qquad (1)$$

Where $X_{jm}$ is a vector of the *observed* characteristics of brand *j* (excluding price) in market *m*, $p_{jm}$ is the price of the product *j* in market *m*, $\xi_{jm}$ denotes the *unobserved* (to the researcher) product characteristics, $\alpha_i$ and $\beta_i$ are parameters that depend on individual *i*'s tastes, and $\varepsilon_{ijm}$ represents the distribution of consumer preferences around the unobserved product characteristics with a probability density function $f(\varepsilon)$. Following BLP, let

$$\alpha_i = \alpha + \lambda D_i + \gamma V_i \qquad (2)$$

$$\beta_i = \beta + \phi D_i + \rho V_i \qquad (3)$$

where $D_i$ denotes observed consumer characteristics with probability density function $h(D)$, $v_i$ denotes the unobserved consumer characteristics with probability density function $g(v)$. Substituting (2) and (3) into (1) yields:

$$U_{ijm} = \beta X_{jm} + \alpha p_{jm} + \zeta_{jm} + \phi D_i X_{jm} + \rho V_i X_{jm} + \lambda D_i p_{jm} + \gamma V_i P_{jm} \qquad (4)$$

The indirect utility given in equation (4) can be decomposed into two parts:

$$\delta_{jm} = \beta X_{jm} + \alpha p_{jm} \qquad (5)$$

$$\mu_{ijm} = \zeta_{jm} + \phi D_i X_{jm} + \rho V_i X_{jm} + \lambda D_i p_{jm} + \gamma V_i P_{jm} \qquad (6)$$

Using (5) and (6), we can write (4) as following:

$$U_{ijm} = \delta_{jm} + \mu_{ijm} + \varepsilon_{ijm} \tag{7}$$

The first term $\delta_{jm}$ represents the mean utility level of product $j$ in market $m$. It is a product-specific term common to all consumers. The other terms $\mu_{ijm} + \varepsilon_{ijm}$ represent the deviation from the mean-level utility, which captures the effects of the random coefficients. If we assume that $\mu_{ijm}$ in (7) is zero, then we will have traditional logit model. In the logit model, consumers' tastes enter only through the additive error term $\varepsilon_{ijm}$, and the product characteristics and price parameters are the same for all consumers. The problem with the own- and cross-price elasticities implied by the logit model has been well documented (McFadden, 1981; BLP).

To complete the model and to define the market (and, hence, market shares), an outside good is included to complete the specification of demand system. Consumers may decide not to purchase any of the products. The indirect utility of the outside good is normalized to $U_{i0m} = \varepsilon_{i0m}$. This assumes it has a zero price and zero characteristic values. The share of the outside good is defined as the total size of the market less the shares of the market goods (Nevo, 2001).

Let $k$ = 0 denote an outside good if the consumer decides not to buy any of the $J$ products in the set of products ($j=1, \ldots, J$). As each consumer purchases a unit of the product that yields the highest utility or the outside good, aggregating over consumers, the market share of the $j^{th}$ brand corresponds to the probability the $j^{th}$ brand is chosen. That is,

$$S_j(\delta, x, p, \theta) = \int I\{ D_i, v_i, \varepsilon_{ij} : U_{ij} \geq U_{ik} \forall k = 0, \ldots. j \} dH(D) dG(v) dF(\varepsilon) \tag{8}$$

Where $\theta$ determines the impact of preferences on utility, and $H(D)$, $G(v)$ and $F(\varepsilon)$ are cumulative density functions for the indicated variables and are assumed to be independent. The price elasticities of the market shares for individual products are:

$$\eta_{jkm} = \frac{\partial s_{jm} p_{km}}{\partial p_{km} s_{jm}} = \begin{cases} -\dfrac{p_{jm}}{s_{jm}} \int \alpha_i s_{ijm}(1 - s_{ijm}) d \hat{p}^*_D(D) dP^*_v(v) & \text{if } j = k, \\ \dfrac{p_{jm}}{s_{jm}} \int \alpha_i s_{ijm} s_{ijm} d \hat{p}^*_D(D) dP^*_v(v) & \text{otherwise,} \end{cases} \tag{9}$$

Where $s_{ijt} = \dfrac{\exp(\delta_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{k} \exp(\delta_{kt} + \mu_{jkt})}$ is the probability of individual *i* purchasing product *j*. These patterns of substitution depend on price sensitivity, not functional form, and substitution between brands will depend on product characteristics, not market shares. The flexibility of this model provides accurate measures of the cross-elasticity between products. However this model does not have an analytic closed form solution. In the full random-coefficients model, the demand system is solved numerically.

## 3. Data

We utilize data from Dominick's Finer Food grocery store chain located in the Chicago area. The data was collected in cooperation between Dominick's and the Kilts Center for Marketing in the Graduate School of Business at the University of Chicago. For this analysis, a market is defined as activity in a specific store in a specific week. We examine ten stores over four weeks, and thus we consider forty markets. The ten stores are located in various neighborhoods across Chicago. The four weeks cover the period of May 31, 1990 through June 27, 1990. The products examined included canned tuna from three brands: Chicken of the Sea (COS), Star-Kist (SK), and Bumble Bee (BB). They offer canned tuna in various sizes and various types of packing characteristics. Eleven products are utilized in this analysis. We created a twelfth product as an outside good if the purchase was not made from eleven products selected. Approximately 18% of the products exhibit quantity surcharges in our data.

We include three product attributes that can be observed by consumers. The first attribute is canning medium (oil or water). Oil is observed for three out of eleven products in the data. The second observable attribute is meat type (albacore or chuck light). Albacore is observed in three products. The third attribute is “size”. All products came in two sizes of either 12.5 ounces or 6.12 ounces.

The dependent variable in the estimation is the market share of the product. To determine the market share, we consider that in 1990 the U.S per-capita consumption of canned tuna was 3.7 pounds. This equates to 1.14 ounces of canned tuna consumption per person, per week. The total available market for canned tuna in each store in each week is the number of customers in the store each week multiplied by 1.14. The market share for each product equals the total ounces of the product sold divided by the total available market. The price of the products is recorded for each store per week and is measured per ounce. Although each market consists of the same grocery chain, there is considerable variation of prices by market across stores and across weeks.

The demographics are based on the store specific information. The data comes from the U.S. Government 1990 census for the Chicago metropolitan area. The firm Market Metrics processed the data to generate demographic profiles for each store. The demographic variables include: single household (share of demographics that are single household), no car (share of demographics with no car), and logarithm of standard deviation of income. The descriptive statistics for our data are presented in Table 1.

We select the proportion of single households to examine whether being single affects the purchasing decisions for canned tuna. Most single people are expected to purchase small canned tuna. Similarly people with no car are restricted in their mobility which may impact their ability to search for their desired products.

To obtain consistent estimates, instrumental variables must be used to account for the endogeneity of prices. We use prices of the products at other Dominick stores in the Chicago area during different weeks. These prices are correlated with the original prices but will not include the unobserved characteristics that lead to the endogeneity.

**4. Estimation**

The characterization of the demand system and the choice of estimation techniques are especially important as more restrictive logit models impose structure on the cross-price elasticities. The restrictive models include the assumption that substitution between brands occurs in proportion to market shares, regardless of brand characteristics. For example, if six ounce cans of COS chunk light tuna packed in water and six ounce cans of SK tuna packed in oil have similar market shares, then substitution from six ounce cans of BB chunk light tuna packed in water will be the same for the COS and SK tuna.

The random-coefficient logit model does not force substitution patterns to be functions of market share by allowing prices to be correlated with the econometric term. In this model, products are defined by a set of characteristics that influence demand. Producers and consumers observe all the product characteristics. However, the econometrician only observes some of the characteristics. From this point of view, the econometric error term captures the unobserved characteristics. The unobserved characteristics influence the price of the product, and prices are endogenous. Therefore, it is desirable to model a system in which choices are correlated. Ideally, this correlation should be a function of product and consumer characteristics. Substitution patterns between products will then be similar for similar products, and consumers with similar demographics will exhibit similar choice behavior. Such a system more accurately describes selection behavior and generates better estimates of cross-price elasticities. The estimation strategy employed in the present study is a straightforward application of BLP's estimation technique.

The first step involves the estimation of predicted market shares using equation (8). Since the integral in equation (8) does not have a closed-form solution, it must be solved numerically. Once we have obtained the predicted and original market shares, then the criterion is to minimize the distance between them. The estimation objective is the following

$$\underset{\theta}{Min}\left\| S(p,x,\theta)-s \right\|, \tag{10}$$

where *S(.)* denotes predicted market shares (from equation 8) and *S* denotes observed market shares. However, this approach requires a non-linear minimization procedure that is difficult to perform, as most parameters enter (8) in non-linear manner. Berry (1994) suggests inverting the market share function, which yields the mean utility valuation $\delta$ (from equation 5) that equates the predicted market shares with observed market shares. We use a standard logit model to obtain mean utility value $\delta$.

The next step is to define the error term as the deviation from that mean. That is,

$$\omega_j = \delta_j(S_j;\theta)-(\beta X_{jm}+\alpha p_{jm}). \tag{11}$$

The error obtained in (11) is then interacted with instrument Z (prices of the products at other stores and during different weeks) to form the Generalized Methods of Moments (GMM) objective function.

$$f = \omega(\theta)^{'} Z A^{-1} Z^{'} \omega(\theta) \qquad (12)$$

Where $A$ is a consistent estimate of $E\left[Z^{'}\omega\omega^{'}Z\right]$. Minimization of (12) provides the solution, which yields the demand parameters.

## 5. Results

The demand parameter estimates are presented in Table 2. For comparison purposes, we present the results of both the random-coefficient (RC) model and the multinomial logit (MNL) model. The MNL model has a closed-form solution but does not allow for free substitution across the products. The parameter estimates of the mean utility are all statistically significant for both the RC model and the MNL model. As expected, price has a negative coefficient in both the models. When we compare the mean utility estimates of the RC procedure and the MNL, we find that all coefficients have similar signs with the exception of albacore. In the RC model, the albacore coefficient indicates that solid albacore tuna is a positive attribute for canned tuna. The oil coefficient is negative, indicating that it is a negative attribute for canned tuna. While albacore is considered to be a premium attribute, it is in short supply. On the other hand, oil is perceived as unhealthy. Thus consumers' tastes for canned tuna depend on the balance between brand, meat type (albacore preferred to chunk light), and canning medium type (packed in water is preferred to packed in oil).

Taking into account consumer heterogeneity, taste parameter for oil as a canning medium is not preferred by consumers who reside in single households, and oil is preferred by consumers who do not have a car. The taste parameter for albacore is less preferable for consumers who reside in single households but preferable for consumers who do not have a car.

The estimated elasticities are presented in Table 3. The diagonal elements in the table represent own-price elasticities and off-diagonal elements represent cross-price elasticities of products. The standard deviations were estimated with a bootstrapping approach. The means of all the own-price and the cross-price elasticities are significantly different from zero. As expected, all the own-price elasticities are negative, and all cross-price elasticities are positive and finite. The own-price elasticities range from -0.678 to -2.057, and the cross-price elasticities range from 0.000 to 0.334.

If the cross-price elasticities between larger-sized cans (12.5 ounces) and smaller-sized cans (6.12 ounces) are close to zero, then the results provide empirical support for our hypothesis. The results (see Table 3) indicate that there is evidence of product differentiation across different sized packages. For example, SK (6.12 ounces, solid albacore, packed in water) has low cross-price elasticities with all three 12.5-ounce products with values 0.001, 0.026 and 0.026, respectively, indicating almost no substitution. On the other hand, there are higher cross-price elasticities between similar sized products, such as BB (6.12 ounces, solid albacore, packed in water) and BB (6.12 ounces, chunk light, packed in water) with values 0.334 for both, indicating higher substitution. A similar observation can be made with respect to product BB (6.12 ounces, solid albacore, packed in water). It has higher cross-price elasticities with similar sized products, such as SK (6.12 ounces, solid albacore, packed in water) and BB (6.12 ounces, chunk light, packed in water), and lower cross-price elasticities with all three similar products that are the 12.5 ounces size. These results provide evidence of little-to-no substitution between 6.12 ounce cans and 12.5 ounce cans in tuna.

The evidence for our hypothesis is further strengthened if we take into account substitution with the outside good. Table 4 presents cross-price elasticities of all products with the outside good for both the MNL and the RC estimation. From Table 4, BB (6.12 ounces, solid albacore, packed in oil) shows no substitution with the outside good (indicating that all substitution is going within the selected products). The cross-price elasticities are close to zero with all the three 12.5-ounce cans of tuna. This provides further empirical support for the hypothesis that different sizes of canned tuna are imperfect substitutes and differentiated products.

We also find evidence of substitution amongst canned tuna products based on characteristics other than size. For example, COS (12.5 ounces, chunk light, packed in oil) has low cross-price elasticities with the other two 12.5-ounce cans of tuna. However, it has higher cross-price elasticities (0.314) with SK (6.12 ounces, chunk light, packed in oil) and BB (6.12 ounces, chunk light, packed in oil). In this case, the oil characteristic appears to be the dominant characteristic in substitution.

We also conducted simulations using the RC model to test how changes in attributes and price impact the choice probabilities for each of alternatives. The simulation results are presented in Table 5. The base share provides the original market shares of each products predicted by the model. The scenario share demonstrates how the changes specified by hypothetical scenarios impact the base choice market shares. We test how the increase in the per-unit price of a small-sized canned tuna affects market shares of other small-sized canned tuna and large-sized canned tuna. Finally, we use the difference of the scenario share and the base share to calculate the change in the choice shares. Table 5a demonstrates the scenario in which the per-unit price of BB (6.12 ounces, solid albacore, packed in water) is increased by 50 cents.

As expected, the market share for this product went down by –1.87%. On the other hand, the market share for SK (6.12 ounces, solid albacore, packed in water) went up by 0.53%. Similarly, when prices per unit of COS (12.5 ounces, chunk light, packed in water) and SK (12.5 ounces, chunk light, packed in water) were increased by 75 cents, both these products experienced losses in market shares of 17.05% and 16.43%, respectively (see Table 5b). Under same scenario, the market shares for COS (12.5 ounces, chunk light, packed in oil) went up by 20.65%. Results from Tables 5a and 5b indicate that increases in price for either small-sized or large-sized cans of tuna lead to decreases in the market share of the product in question and an increase in the market shares of products that are of similar sized.

Similar results are obtained when we increase the per-unit prices of COS (12.5 ounces, chunk light, packed in water) and SK (6.12 ounces, chunk light, packed in water) by 25 cents and 50 cents, respectively (Tables 5c and 5d). Under both scenarios, the market share of similar sized products increases. The four simulations indicate substitution amongst the same-sized cans of tuna and smaller-to-no substitution between different-sized cans of tuna, indicating size-based product differentiation in canned tuna.

## 6. **Conclusions**

This article offers a new explanation for the existence of quantity surcharges based on *package size* as a product characteristic. Goods sold in different package sizes may represent differentiated products to consumers, and consumers should not expect an additive price relationship between these products. We find evidence in support of package size as one of the product characteristics that can differentiate products. This work demonstrates that a large can of tuna should not be considered equivalent to two small cans of tuna, in the same way as albacore tuna is differentiated from chuck light tuna. Quantity surcharges in canned tuna then can be viewed as stemming from product differentiation.

From the firm's standpoint, product differentiation is profit maximizing and can result in divergence from marginal-cost pricing. Hence, product differentiation can be useful from both consumer utility and firm's profit point of view. From this point of view, retailers are not engaging in "tricky" pricing techniques. Rather, they are choosing package sizes and prices to maximize profits. Therefore, consumers should not expect to find a consistent decline in per-unit prices when package size increases. Of course, we qualify our results as they may not apply to all incidences of quantity surcharges. There are some products for which package size does not affect convenience or quality, and thus, multiple smaller units are equivalent to a larger unit. Also, there are consumers for whom package size is not a significant product characteristic.

An interesting issue for future research is the relative impacts that specific characteristics have on differentiation. Although we find evidence in support of similar size substitution, we also find evidence of substitution across different sizes along the same characteristics. It would be interesting to test for product differentiation by size in other more homogeneous products that exhibit quantity surcharges, such as ketchup and cooking oil. In other future research, we would like to obtain individual-level data and assign a random parameter to the price variable.

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FIGURE 1 Product Differentiation Based on Three Characteristics

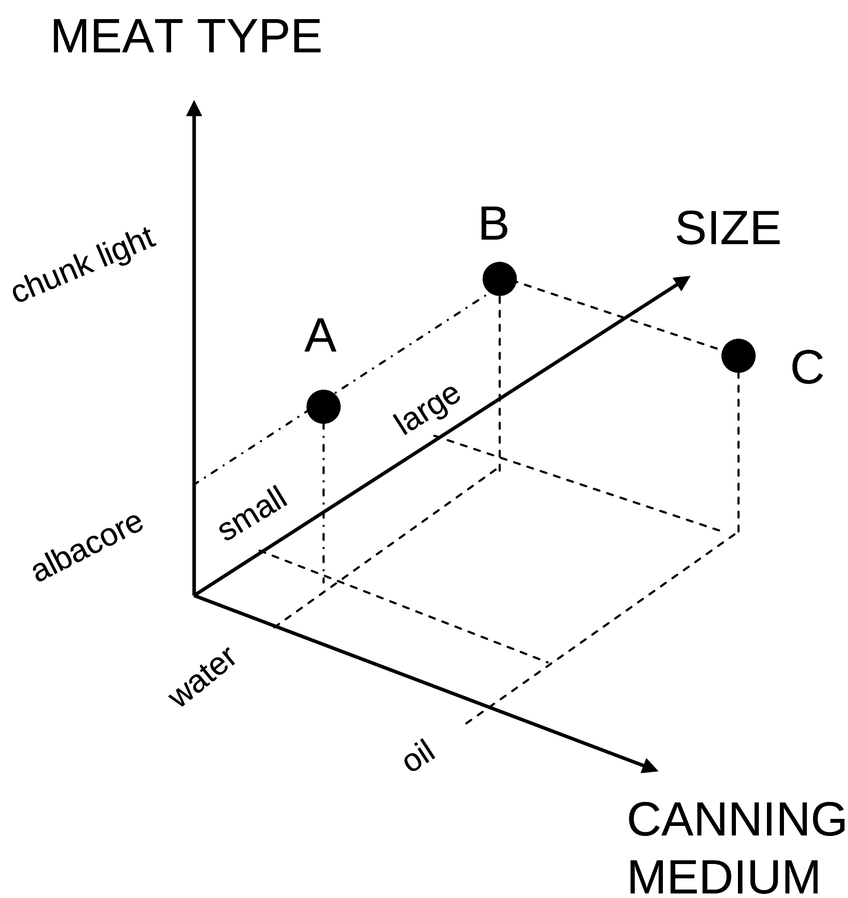

TABLE 1 Description and Summary Statistics of Variables

| **Variable** | **Description** | **Mean** | **Standard Deviation** | **Min** | **Max** |
|---|---|---|---|---|---|
| Market share | Observed market share of canned tuna | 0.083 | 0.166 | 0.001 | 0.847 |
| Oil | 1 if packed in oil; 0 otherwise | 0.333 | 0.471 | 0.000 | 1.000 |
| Albacore | 1 if solid white tuna; 0 otherwise | 0.333 | 0.471 | 0.000 | 1.000 |
| Price | $ per ounce | 0.187 | 0.088 | 0.000 | 0.310 |
| Std Dev of income | Log of standard deviation of income | 10.083 | 0.101 | 9.920 | 10.25 |
| Single household | Share that are single household | 0.289 | 0.076 | 0.220 | 0.550 |
| No car | Share with no car | 0.146 | 0.174 | 0.020 | 0.550 |

TABLE 2 Demand Parameter Estimates

| **Variables** | RC Estimate | RC Std. Error | MNL Estimate | MNL Std. Error |
|---|---|---|---|---|
| *Mean Utility* | | | | |
| Price (F) | -1.707 | 0.081** | -7.313 | 1.795** |
| Oil (U) | -0.031 | 0.008** | -1.529 | 0.531** |
| Albacore (U) | 0.184 | 0.014** | -1.169 | 0.678** |
| *Deviation from the Mean Utility* | | | | |
| Oil | 1.997 | 9.582 | | |
| Albacore | 0.571 | 5.329 | | |
| *Interaction with demographics* | | | | |
| *Oil X Standard deviation of income* | -3.631 | 15.662 | | |
| *Oil X Proportion of single household* | -8.075 | 45.385 | | |
| *Oil X People with no car* | 4.029 | 16.193 | | |
| *Albacore X Standard deviation of Income* | 1.458 | 12.595 | | |
| *Albacore X Proportion of single household* | -13.242 | 46.423 | | |
| *Albacore X People with no car* | 5.702 | 16.509 | | |
| Constant (from GMM) | 0.290 | 0.010** | | |
| Log Likelihood Value | -99.340 | | -74.410 | |

[1]Price (F) is fixed parameter. Oil (U) and Albacore (U) are random parameters with Uniform distribution.
[2]The Constant term is obtained from GMM minimization procedure.
[3]** indicates statistically significant

TABLE 3 Estimates of Own-Price and Cross-Price Elasticities*

| Products** | | 12.5 oz | | | 6.12 oz | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | COS (CLO) | COS (CLW) | STK (CLW) | STK (SWW) | STK (CLW) | STK (CLO) | BB (SWW) | BB (SWO) | BB (CLW ) | BB (CLO) | COS (CLW) |
| **12.5 oz** | COS (CLO) | **-0.678** **(0.058)** | 0.006 (0.000) | 0.005 (0.000) | 0.001 (0.000) | 0.004 (0.001) | 0.312 (0.027) | 0.001 (0.000) | 0.052 (0.008) | 0.001 (0.000) | 0.309 (0.027) | 0.005 (0.001) |
| | COS (CLW) | 0.001 (0.000) | **-0.818** **(0.075)** | 0.173 (0.010) | 0.026 (0.007) | 0.117 (0.004) | 0.001 (0.000) | 0.026 (0.007) | 0.000 (0.000) | 0.019 (0.005) | 0.001 (0.000) | 0.142 (0.001) |
| | STK (CLW) | 0.001 (0.000) | 0.174 (0.011) | **-0.877** **(0.053)** | 0.026 (0.007) | 0.117 (0.004) | 0.001 (0.000) | 0.026 (0.007) | 0. 000 (0.000) | 0.019 (0.005) | 0.001 (0.000) | 0.142 (0.001) |
| **6.12 oz** | STK (SWW) | 0.001 (0.000) | 0.095 (0.021) | 0.094 (0.021) | **-1.042** **(0.065)** | 0.065 (0.018) | 0.001 (0.000) | 0.254 (0.085) | 0.002 (0.001) | 0.233 (0.075) | 0.000 (0.000) | 0.078 (0.020) |
| | STK (CLW) | 0.001 (0.000) | 0.174 (0.011) | 0.173 (0.010) | 0.026 (0.007) | **-2.065** **(0.187)** | 0.001 (0.000) | 0.026 (0.007) | 0.000 (0.000) | 0.019 (0.005) | 0.001 (0.000) | 0.141 (0.001) |
| | STK (CLO) | 0.314 (0.029) | 0.005 (0.000) | 0.006 (0.001) | 0.001 (0.000) | 0.004 (0.001) | **-0.737** **(0.035)** | 0.001 (0.000) | 0.052 (0.008) | 0.001 (0.000) | 0.309 (0.027) | 0.005 (0.001) |
| | BB (SWW) | 0.000 (0.000) | 0.095 (0.021) | 0.094 (0.021) | 0.334 (0.125) | 0.065 (0.018) | 0.000 (0.000) | **-1.769** **(0.115)** | 0.002 (0.001) | 0.233 (0.075) | 0.000 (0.000) | 0.078 (0.020) |
| | BB (SWO) | 0.220 (0.033) | 0.004 (0.001) | 0.003 (0.001) | 0.011 (0.003) | 0.002 (0.000) | 0.220 (0.034) | 0.009 (0.002) | **-1.521** **(0.217)** | 0.008 (0.002) | 0.219 (0.034) | 0.003 (0.001) |
| | BB (CLW ) | 0.000 (0.000) | 0.096 (0.21) | 0.094 (0.021) | 0.334 (0.125) | 0.065 (0.018) | 0.000 (0.000) | 0.254 (0.085) | 0.002 (0.001) | **-1.95** **(0.131)** | 0.000 (0.000) | 0.078 (0.020) |
| | BB (CLO) | 0.313 (0.029) | 0.006 (0.001) | 0.006 (0.001) | 0.001 (0.000) | 0.004 (0.001) | 0.312 (0.027) | 0.001 (0.000) | 0.052 (0.008) | 0.001 (0.000) | **-0.675** **(0.061)** | 0.005 (0.001) |
| | COS (CLW) | 0.001 (0.000) | 0.174 (0.110) | 0.173 (0.010) | 0.026 (0.007) | 0.117 (0.004) | 0.001 (0.000) | 0.026 (0.007) | 0.000 (0.000) | 0.019 (0.005) | 0.001 (0.000) | **-1.641** **(0.142)** |

*( ) Values in Parenthesis are Standard Deviations

** CLO-Chunk Light Oil, CLW-Chunk Light Water, SWW-Solid White Water, SWO-Solid White Oil

TABLE 4 Cross-Price Elasticities between Tuna and Outside Good

| Product type | RC | MNL |
|---|---|---|
| COS (12.5 oz chunk light oil) | 0.001 | 0.032 |
| COS (12.5 oz chunk light water) | 0.177 | 0.150 |
| STK (12.5 oz chunk light water) | 0.176 | 0.149 |
| STK (6.12 oz solid white water) | 0.015 | 0.044 |
| STK (6.12 oz chunk light water) | 0.120 | 0.103 |
| STK (6.12 oz chunk light oil) | 0.001 | 0.032 |
| BB (6.12 oz solid white water) | 0.012 | 0.035 |
| BB (6.12 oz solid white oil) | 0.000 | 0.007 |
| BB (6.12 oz chunk light water ) | 0.011 | 0.032 |
| BB (6.12 oz chunk light oil) | 0.001 | 0.032 |
| COS(6.12 oz chunk light water) | 0.146 | 0.125 |

TABLE 5 Simulated Probabilities of Market Shares under Four Different Scenarios of Changes in Price and Attributes

5(a) Scenario where price per unit of BB (6.12 oz solid albacore water) is increased by 50 cents

| Choice | Base %Share | Scenario %Share | Scenario - Base %Change Share |
|---|---|---|---|
| COS (12.5 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| COS (12.5 oz chunk light water) | 17.134 | 17.334 | 0.200 |
| STK (12.5 oz chunk light water) | 16.506 | 16.699 | 0.193 |
| STK (6.12 oz solid white water) | 3.600 | 4.133 | 0.534 |
| STK (6.12 oz chunk light water) | 5.344 | 5.407 | 0.063 |
| STK (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz solid white water) | 1.924 | 0.055 | -1.869 |
| BB (6.12 oz solid white oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz chunk light water ) | 1.634 | 1.877 | 0.243 |
| BB (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| COS (6.12 oz chunk light water ) | 7.911 | 8.004 | 0.093 |
| Outside | 45.948 | 46.491 | 0.543 |
| **Total** | 100.000 | 100.000 | 0.000 |

5(b) Scenario where prices per unit of COS (12.5 oz chunk light water) and STK (12.5 oz chunk light water) were increased by 75 cents

| Choice | Base %Share | Scenario %Share | Scenario - Base %Change Share |
|---|---|---|---|
| COS (12.5 oz chunk light oil) | 0.000 | 20.651 | 20.651 |
| COS (12.5 oz chunk light water) | 17.134 | 0.082 | -17.052 |
| STK (12.5 oz chunk light water) | 16.506 | 0.079 | -16.427 |
| STK (6.12 oz solid white water) | 3.600 | 3.975 | 0.375 |
| STK (6.12 oz chunk light water) | 5.344 | 6.438 | 1.094 |
| STK (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz solid white water) | 1.924 | 2.124 | 0.200 |
| BB (6.12 oz solid white oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz chunk light water ) | 1.634 | 1.804 | 0.170 |
| BB (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| COS (6.12 oz chunk light water ) | 7.911 | 9.527 | 1.616 |
| Outside | 45.948 | 55.321 | 9.373 |
| **Total** | 100.000 | 100.000 | 0.000 |

5(c) Scenario where prices per unit of COS (12.5 oz chunk light water) is increased by 25 cents and all the products were made chunk light

| Choice | Base %Share | Scenario %Share | Scenario - Base %Change Share |
|---|---|---|---|
| COS (12.5 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| COS (12.5 oz chunk light water) | 17.134 | 8.405 | -8.729 |
| STK (12.5 oz chunk light water) | 16.506 | 51.008 | 34.502 |
| STK (6.12 oz solid white water) | 3.600 | 5.769 | 2.169 |
| STK (6.12 oz chunk light water) | 5.344 | 2.624 | -2.719 |
| STK (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz solid white water) | 1.924 | 3.075 | 1.151 |
| BB (6.12 oz solid white oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz chunk light water ) | 1.634 | 2.611 | 0.977 |
| BB (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| COS (6.12 oz chunk light water ) | 7.911 | 3.890 | -4.021 |
| Outside | 45.948 | 22.618 | -23.330 |
| **Total** | 100.000 | 100.000 | 0.000 |

5(d) Scenario where prices per unit of STK(6.12 oz chunk light water) and COS (6.12 oz chunk light water) were increased by 50 cents and all the products were made chunk light

| Choice | Base %Share | Scenario %Share | Scenario-Base %Change Share |
|---|---|---|---|
| COS (12.5 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| COS (12.5 oz chunk light water) | 17.134 | 16.583 | -0.551 |
| STK (12.5 oz chunk light water) | 16.506 | 15.982 | -0.524 |
| STK (6.12 oz solid white water) | 3.600 | 11.376 | 7.777 |
| STK (6.12 oz chunk light water) | 5.344 | 0.129 | -5.215 |
| STK (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz solid white water) | 1.924 | 6.057 | 4.133 |
| BB (6.12 oz solid white oil) | 0.000 | 0.000 | 0.000 |
| BB (6.12 oz chunk light water ) | 1.634 | 5.146 | 3.512 |
| BB (6.12 oz chunk light oil) | 0.000 | 0.000 | 0.000 |
| COS (6.12 oz chunk light water ) | 7.911 | 0.192 | -7.719 |
| Outside | 45.948 | 44.536 | -1.412 |
| **Total** | 100.000 | 100.000 | 0.000 |