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Essays on valuing non-market goods in imperfectly competitive markets

Laura Beaudin

ESSAYS ON VALUING NON-MARKET GOODS IN IMPERFECTLY COMPETITIVE MARKETS

BY

LAURA BEAUDIN

B.A./B.S., Economics and Mathematics, Saint Michael's College, 2007
M.A., Economics, University of New Hampshire, 2009

DISSERTATION

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This dissertation has been examined and approved.

Ju-Chin Huang

Dissertation Chair, Dr. Ju-Chin Huang,
Professor of Economics at the University of New Hampshire

B Elmslie

Dr. Bruce Elmslie,
Professor of Economics at the University of New Hampshire

J M Halstead

Dr. John M. Halstead,
Professor of Environmental and Resource Economics at the University of New Hampshire

R D Mohr

Dr. Robert D. Mohr,
Associate Professor of Economics at the University of New Hampshire

Min Qiang Zhao

Dr. Min Qiang Zhao,
Assistant Professor of Economics at Wang Yanan Institute for Studies in Economics, Xiamen University, China

Aug. 7, 2013

Date

DEDICATION

This dissertation is dedicated to my parents and my sister. My parents were my first teachers and my sister was my role model and someone who I always strived to emulate. Their love and support throughout this process has allowed me to pursue my true passion; teaching. I will honor them every day as I teach other eager students and continue my own educational journey through my research.

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ABSTRACT

ESSAYS ON VALUING NON-MARKET GOODS IN IMPERFECTLY COMPETITIVE MARKETS

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Debates on climate change have conceded to most parties acknowledging the existence of negative impacts of changing weather patterns. However, these impacts have not fully been assessed. One way which changing climates can negatively impact an economy is by changing the market structures of its most influential industries; making these markets more imperfectly competitive and taking value away from consumers. This dissertation draws on this fact and suggests accurate ways to both identify and quantify the costs of climate change.

In the first chapter of this dissertation, the ski industry is used as a case study. A unique data set along with the econometric technique of discrete time survival analysis is used to estimate the impact of weather on the survival of ski areas over time. Results suggest that changing weather patterns have been an influential factor in the closure of many ski areas throughout the region. For this reason, the ski industry has become much

less competitive allowing ski area managers to increase the price of their lift tickets over their marginal costs.

The second chapter builds off the first to show that since many of the industries which are vulnerable to climate change are imperfectly competitive in nature, there is a need to more precise theoretical techniques of valuing non-market, climate related goods in these industries in which firms can artificially increase the price. Huang (2013) builds off of Feenstra (1995) and adapts the traditional hedonic valuation method to account for imperfect competition in the market. The theoretical technique is discussed and employed against current approaches to show its feasibility in measuring the true value of goods which are marked up when firms enjoy market power.

Together the two chapters of this dissertation develop a strategy for increased precision in the measurement of the costs of climate change. By first identifying vulnerable industries with the econometric techniques used in chapter one and then estimating the value of the climate related goods in these industries with the model presented in chapter two, researchers could determine important factors which have the ability to influence policy debates on climate change.

INTRODUCTION

In 2003 Brodie Mountain, a ski areas in New Ashford, MA, closed its doors for business after nearly 60 years of operation. Local skiers were forced to go to the larger more expensive ski area of Jiminy Peak in neighboring Hancock, MA. Speculations of the cause of Brodie's unfortunate fate began swirling soon after their final ski season. Among the most common theories were bad winters with record low snowfall totals and loss of skiers to easily accessible Jiminy, which had much more to offer skiers both on and off the mountain.

Brodie's experience was not an isolated incident. According to Hamilton (2007) dozens of ski areas have been closing and the industry has been consolidating over the past 100 years. This claim is supported by authors, Jeremy Davis and Jon Gallup, who created the website, "New England's Lost Ski Areas Project," (www.nelsap.org), which documents all of the known lost ski areas in New England. The authors suggest that over 80 percent of the ski areas which were once operational in New England have closed down over the past century. One of the major theories for this phenomenon, like in the case of Brodie Mountain, is that changing weather patterns are to blame for pushing so many ski areas out of the industry.

This "climate change" theory has currently been studied with research which focuses on the common time period within which many ski areas have closed, average winter temperature has risen, and snowfall has declined. However, more thorough econometric studies are needed to investigate the connection between changing local weather patterns and the overall market structure of this industry. In addition, to truly determine the cost of changing weather, further studies involving valuing climatic goods in these vulnerable markets must be conducted under the correct market structure assumptions.

Understanding how changing weather alters market structures and the value of the products within these changing markets will go a long way to helping environmental economists and policy makers. By understanding the markets structure first and how it has changed due to changing weather will help researchers estimate more precisely how products in these markets have changed in value since the weather began to change. These more precise estimates could then be used to determine the most cost effective ways to help prevent the negative impacts of changing weather.

One of the most useful contributions of this dissertation is its emphasis on evaluating the impact of weather both on and within different types of market structures. Market structure is one of the most influential determinants of economic factors. The structure of the market in which products are produced and sold determines everything from the prices and the number of different varieties to quality and availability of the goods. Market structure also significantly influences the profits or losses to the firms which sell the goods and the benefits or costs to the consumers who purchase the goods. Therefore, when the structure of a market changes, because of exogenous and uncontrollable factors, the consequences can be severe.

The first chapter of this dissertation examines the influence of weather on market structure while the second discusses the importance of the acknowledgement of specific market structures before valuing climatic and other types of goods. In both chapters the ski industry within the U.S. is used as the case study, however, the techniques in this dissertation could easily be adapted to investigate the influence of weather on any vulnerable industry.

In the first chapter, more rigorous econometric techniques than those currently employed in other studies, are used to find that changing weather patterns have significant impacts on the market structure in this industry. Particularly, the industry has become much less competitive as many ski areas are forced to shut down due to less than desirable skiing weather conditions.

The results of the first chapter of this dissertation suggest that climate might significantly be affecting the market structure of many industries throughout the economy. This research suggests that many of the vulnerable industries are most likely imperfectly competitive in nature and changing weather might be altering the market structure enough to allow firms to have pricing power. With the pricing power, firms are able to artificially inflate the price of their goods above their marginal costs. In the case of the ski industry, this hypothesis is supported by the fact that the average ski area lift ticket price has increased more than three times inflation over the past 30 years. To help fully understand the total economic cost of changing weather patterns the second chapter of this dissertation discusses and implements a new theoretical technique for valuing climatic goods in markets in which firms enjoy pricing power.

Climatic goods, such as, the amount of natural snowfall, rainfall, or average temperature are non-market goods which are often consumed in combination with other composite products such as a ski lift ticket. One technique for valuing these and other non-market goods is the hedonic valuation approach in which researchers break down the price of the composite product into its components including the environmental good of interest. However, currently the hedonic techniques for valuing environmental goods are limited by oversimplifying assumptions or are too complex to implement based on the rigorous mathematical techniques and large data requirements.

The theoretical technique developed by Huang (2013), which is discussed in the second chapter of this dissertation, is a much more feasible approach and which can account for the increased price over the marginal cost which occurs when the market structure of the industry is less than perfectly competitive. Once discussed, this theoretical technique is implemented, along with other current techniques which account for imperfect competition, to determine the value of the non-market, climatic good which is purchased along with the composite good. The ski lift ticket is the composite good and the amount of natural snowfall is the climatic good of interest.

Chapter two provides evidence that the market structure in which the composite good is being sold must be considered under the hedonic valuation method. In many hedonic approaches the market structure is assumed to be perfectly competitive. However, if the firms in fact do have pricing power, this assumption will not hold and the traditional price equation in the hedonic method will be estimated incorrectly. The resulting values of the environmental and other goods within the composite good could not be trusted. The theoretical technique and econometric implementation of the model suggested by Huang (2013) gives more precise measures of environmental goods; because, this model can account for the imperfectly competitive nature of the market in which the goods are being sold.

As a whole this dissertation highlights and begins to quantify the effects of changing weather patterns on an extremely vulnerable industry within the U.S. The econometric and theoretical techniques used in this dissertation allow for the contributions to the field of Environmental Economics to include both a way to better identify vulnerable industries and then provide more precise values for the climatic goods which are altered as the local weather patterns change. This precision will be vital to policy debates for determining how much, if any, aid should be given to firms to help combat the changing weather.

ESSAY 1:

WEATHER CONDITIONS AND OUTDOOR RECREATION:

A STUDY OF NEW ENGLAND SKI AREAS

1.1 Introduction

Today climate change is a frequently discussed topic in both the media and academia. Since many industries rely on the stability of their local climate for survival, the climate change issue has become a major economic concern (Stern, 2006; Nordhaus, 2012). One way to assess the overall economic impact of climate change is to accurately evaluate how weather affects individual industries (Tol, 2002; Mendelsohn et al, 2000; Tol, 2012). Industries which may be vulnerable to the damages of climate change are diverse; ranging from agricultural to insurance, healthcare to financial services, and fishing to tourism. In this study, the New England ski industry is used as a case study to examine the potential effects of weather conditions on firm behavior. However, the methodology used in the analysis could easily be adapted and applied to other susceptible industries.

The ski industry is chosen because of its reliance on steady and lengthy winter weather conditions. Changes in weather patterns due to global warming, such as reduced snowfall and an upward trend in winter temperature, can be devastating to the operation of a ski area. The ski industry in the United States has been experiencing structural changes. Studying the New England ski industry, Hamilton (2007) reports that ski areas have been closing down at a rapid rate and the industry has been consolidating over the past 100 years. Wake (2005) shows that in New England the average annual temperature and average winter temperature have been rising over the same time period, and the number of days with snow on the ground has been declining in the period from 1970 to 2000.

Because of the ski industry's dependence on particular weather conditions, the common time period in which winter temperatures have risen, snowfall has decreased, and a large number of ski areas have closed, seems to suggest that climate change might have had a significant role in affecting the fate of individual ski areas and changing the market structure of the ski industry as a whole. However, before jumping to this conclusion, it is necessary to explore all factors that can contribute to the structural changes in this industry.

Previous research has identified several factors that may influence the probability of success of a given ski area. Some studies show that physical characteristics of ski areas affect the demand for skiing, which can subsequently influence the survival of ski resorts. Morey (1984) investigates how individual characteristics and characteristics of a ski area influence young skiers' behavior. He finds that skiing terrain may influence an individual's decision to visit a particular ski area. In a later study, Morey (1985) estimates the demand for the development of a Colorado ski area. He investigates specific characteristics of skiers and ski areas that may affect the demand for skiing, and finds that those ski areas with natural endowment that can offer a good variety of activities are valued higher by consumers. Morey's findings can be used to partially explain why so many ski areas have closed in the past century. Specifically, some mountains were able to offer more to their skiers and were able to pull business away from their less diverse counterparts. Geographic locations are important as well. Fukushima et al. (2002) study ski activities in Japan and find that the farther a ski resort is from the major metropolitan area, the less likely it is to draw a large crowd to its mountain.

Some studies have shown connections between climate and visits to ski areas. Palm (2001) finds that 700,000 fewer skiers visited the ski areas in New Hampshire and Vermont during the years with the least snowfall, compared to those with the most. In a similar study, Hamilton et al (2007) find that the amount of snow in the nearest metropolitan area greatly impacted the number of skiers traveled to local ski areas on a particular day in New England. Fukushima et al. (2002) find significant correlation between number of skiers and the depth of snow in ski areas in Japan. They estimate a 30 percent decrease in ski activities for a 3 °C increase in temperature. These studies suggest that climate change can alter the environment and weather conditions, and cause a decrease in skier demand that can jeopardize the success of ski areas.

With the projection of decreasing snowfall, researchers have also studied the strategies from the supply side to adapt to the changing climate. Scott et al. (2003) construct a simulation model, based on the data for the ski industry in Southern Ontario (Canada), to show the importance and effectiveness of snowmaking to battle climate variability and changes. Later Scott and McBoyle (2007) discuss more generally the adaptation options of climate change for ski resorts. The adaptation options can be technological, such as investing in snowmaking equipment and slope development, or operational, such as creating diversified revenue streams by offering a variety of services beyond ski related activities in all seasons. Some ski areas now provide lodging, shopping, and restaurants, as well as extend operations into all four seasons. Scott and McBoyle (2007) show that lift tickets sales are now accounting for less than half of the ski industry's overall revenue, compared to nearly 100 percent of the revenue from ticket sales when the ski industry first began. The abilities to adapt to climate change can contribute to the success and survival of ski areas.

From the literature, four categories of factors are considered to impact the success of a ski resort: resort characteristics, adaptation abilities, location, and weather conditions. The adaptation abilities refer to the abilities to invest and to adjust business operation in response to changes in the physical and business environment, such as acquiring snowmaking machines and enabling operation beyond the ski season. In terms of location, easy access to metropolitan hubs is beneficial. Weather conditions may influence the success of a ski area through multiple channels. They can affect the revenue, therefore the survival, of a ski area directly by reducing the demand faced by the ski area. They may also influence decisions of ski areas to invest and to develop new business strategies which may increase the chances of survival. To assess the effects of weather conditions, it is important to examine them with other factors simultaneously to avoid misrepresentation.

In this paper, the discrete time survival analysis is employed and a structural model to study the direct and indirect effects of climate variables on the closure of a ski area in New England is presented. A unique data set is compiled containing information of the known ski areas that closed down between 1970 and 2007 and a sample of ski resorts that were still in operation by 2007. To our knowledge, this is the first study to empirically examine both the direct and indirect effects of weather conditions, along with other factors, on the exit decisions of firms in the ski industry.

Our results indicate that reduced snowfall, during the studied time period, has contributed directly to the closing of ski resorts in New England. The results also suggest that there have been indirect effects of the climate variables through their impact on investment decisions that improve the probability of survival and offset part of the negative direct effects. Further, it is shown that larger resorts not only have a higher chance of survival in the industry, but are also more likely to make strategic investment decisions to ward off the negative effects of a changing climate. Consequently the results suggest that weather conditions have contributed significantly to the decrease in competitiveness in the New England ski industry.

In the next section, the history of the New England ski industry is presented and the data collection process is described. In Section 3, the strategy of the empirical analysis is outlined. The empirical model and econometric technique, as well as a summary of data, are presented. In Section 4, estimation issues and results are discussed. Based on the estimation results, a simulation of effects of key factors on the probability of closure of a ski area is also presented. Lastly, some concluding remarks are given in Section 5.

1.2 New England Ski Industry and Data Collection

The New England ski industry began as small privately owned hills with single rope tows in the late 1800s. During this time the consistent snowfall supported the growth of the industry, and hundreds of ski areas opened all over New England by the early 1900s. The ski industry soon became a multibillion dollar industry with significant impact on the area's economy (Wright, 2006).

As skiing grew in popularity and the industry continued to have a positive impact on the local economy, the structure of the industry began to change. Many of the once profitable ski areas began to shut down. It is estimated that nearly 80% of the approximately 650 ski areas in Maine, Vermont, New Hampshire, Massachusetts, Connecticut, and Rhode Island combined have shut down over the past 100 years (Davis and Gallup, 2007). In the 1960s, many ski areas were forced to shut down because of an increase in insurance costs. Many of the mom-and-pop ski areas disappeared because they could not afford the payments (Puliafuco, 2006). After 1970 the ski industry continued to experience the trend of consolidation. During this time, winter weather patterns also had noticeable changes as the temperatures rose and snowfall declined, and scientists began to voice their growing concern of global climate change (Peterson et al. 2008). A sizable ski industry, a wide variety of different climate conditions, and a changing market structure, make New England an ideal area for a case study. This study focuses on the years from 1970 to 2007 and data on both operational and closed ski areas are compiled during this time period.

The data of the individual ski resorts no longer in operation by 2007 were collected from the New England Lost Ski Areas Project website (Davis and Gallup, 2007). This website lists the known closed ski areas of the New England states. The specific information of each closed ski area was collected from visits to the deserted mountain, interviews of former owners and patrons of the area, or ski magazines and guides from the years when the area was operational. All of the documented known closed ski areas in New England since 1970 that have sufficient information for the analysis are included. These total to 47 ski areas. The data of ski areas that still operated at the end of the studied year 2007 were collected from their individual websites. According to the online source (http://www.onthesnow.com), there were 61 ski areas in operation in 2007. The sample consists of 31 operational ski areas, about half of all of the New England ski areas in operation in 2007. In total, 78 ski areas are included in this study, 31 were in operation in 2007 and 47 were closed between 1970 and 2007. The characteristics of both the operational and closed ski areas by 2007 are summarized in Table 1.A1. In terms of the basic characteristics, the sample of operational ski areas mimics the population fairly well.[1] Note that the average size of the closed ski areas is noticeably smaller than those still in operation. The ski areas are scattered throughout the states of Maine, New Hampshire, Vermont, Massachusetts, Connecticut, and Rhode Island. See Figure 1.D1 for a mapping of the studied ski areas in operation from 1970 to 2007. The continuous disappearance of ski areas in the past 4 decades is apparent. None of the closed ski areas in the study ever reopened.

The data collected for each of the ski areas was based on the prevalent factors presented in the literature. The climate factors are the factors of interest in this study. Two weather condition measures are constructed: the annual average snowfall and average winter (November – February) temperature. See Figure 1.D2 for the plots of the average snowfall and winter temperature across the region, over the time of this study. These graphs show that there has been a slight upward trend in winter temperature and downward trend in snowfall across this region during the time of the study. The data of basic characteristics of a ski area, including number of lifts, number of trails, and the vertical drop of the mountain, are collected. Two binary variables are also constructed to indicate a ski area's investment activities to adapt to changes in weather conditions and

[1] To ensure that the results are not driven by the sampling of the operational ski areas, the analysis is repeated a few times by excluding 5 randomly selected operational ski areas in the sample each time. The key findings are robust to the random selection of the operational ski areas. An example of the results from one of the randomly selected subsamples of the data can be found in Appendix 1.B, Tables 1.B5 – 1.B7.

business environment. One variable indicates whether or not a ski area owns snowmaking equipment. The other denotes whether a ski area operates beyond the winter ski season and offers activities in all four seasons. The location measures include the distance to Boston, the major metropolitan area in the region,[2] and state dummy variables to control for state fixed effects.

1.3 Empirical Strategy and Data Summary

Discrete Time Survival Analysis

To describe the status of a ski resort over time during the studied period, the following binary dependent variable Y_{it} is constructed.

$$\begin{aligned} Y_{it} &= 1 \text{ if the ski area } i \text{ is closed in year } t \\ &= 0 \text{ if it remains open in year } t \end{aligned} \qquad (1)$$

Multiple observations of Y_{it} are recorded and stacked for each ski area, from 1970 on. For example, for a ski area that was open in 1970 but was closed in 1996, there are 27 observations for the ski area, one for each year between 1970 and 1996. For this resort, $Y = 0$ for the first 26 observations and $Y = 1$ for the last observation. If a ski area remained open in 2007, then there are 38 observations for this ski area with $Y = 0$ for all observations. Stacking the annual observations of operational status of the ski areas enables us to conduct the discrete time survival analysis on the ski areas (Allison, 1992). No ski areas in the study were closed then reopen, so only the model of single event analysis is employed.

[2] The distance variable to the nearest large urban area including New York City, Boston, Hartford,(CT), Burlington (VT), Manchester (NH), and Portland (ME) is also constructed. The qualitative results based on these alternative location measures were the same.

The discrete time duration model has been widely used in event history analysis in fields such as sociology, psychology, political science, and economics. It differs from the continuous duration model by disaggregating time into discrete time units. In contrast to the analysis of the "exact" time of an event in the continuous duration model (e.g., time of death after receiving cancer treatments), the time disaggregation for discrete time survival analysis could be due to the way events are recorded (e.g., grade of school dropout, regardless of the actual time of the year it occurs) or the naturally discrete timing of an event (e.g., labor retention by annual contracts or the outcomes of presidential election). Although the nature of the data may ultimately determine the empirical modeling strategy, there are some advantages of the discrete time analysis. One advantage is that, unlike continuous hazard models, time varying covariates can be incorporated directly into the discrete time model (Allison, 1992). The other advantage is that under certain assumptions, standard binary choice models such as the logit and probit model can be used to analyze discrete time data (Jenkins, 1995). In the data, the year of the closing of a ski resort was recorded. Further, the key covariates of interest, the climate change variables, are time varying. Therefore, the discrete time survival analysis is appropriate for the investigation of the impact of weather conditions on the survival of ski resorts.[3]

Let P_i be the probability that a ski area i closes, as a (nonlinear) function of a set of explanatory variables X.

$$P_i = \Pr(Y_{it} = 1 \mid X_i) = F(X_i; \beta)\,, \tag{2}$$

[3] Alternatively, the number of years of a ski resort that remains open can be treated as a continuous variable and estimate continuous duration models with time varying covariates. Based on the nature of the data, discrete time analysis is chosen.

where $F(.) \geq 0$, is a cumulative distribution function, and β is a set of parameters.

A random variable κ_i is defined to represent the number of years that the ski area i remains open. Assume that κ_i follows a geometric distribution with a probability mass function as follows.

$$f(\kappa_i) = (1 - P_i)^{\kappa_i} P_i \qquad \kappa_i = 0, 1, 2, \ldots \tag{3}$$

The above probability mass function can be rewritten to incorporate Y_{it}.

$$f(\kappa_i) = \prod_{t=1}^{\kappa_i + 1} (1 - P_i)^{1 - Y_{it}} P_i^{Y_{it}} \tag{4}$$

Based on (4), a likelihood function to describe the overall likelihood of observing κ_i for the n ski areas can be written as follows.

$$L = \prod_{i=1}^{n} f(\kappa_i) = \prod_{i=1}^{n} \prod_{t=1}^{\kappa_i + 1} (1 - P_i)^{1 - Y_{it}} P_i^{Y_{it}} = \prod_{i=1}^{n} \prod_{t=1}^{\kappa_i + 1} (1 - F(X_i; \beta))^{1 - Y_{it}} F(X_i; \beta)^{Y_{it}} \tag{5}$$

The likelihood function in Equation (5) can mimic a standard dichotomous choice model by rewriting κ_i into a series of Y_{it}, $t = 1, 2, \ldots, \kappa_i + 1$. Therefore, it can be conveniently estimated by standard statistical software packages. The common choices of specification for $F(X_i; \beta)$ are the cumulative distribution functions of the logistic and normal distributions.

A distinct feature of the geometric distribution is its memoryless property. For the purpose of the study, let s_i be the number of years the ski area i was open up to 1970 and λ_i be the number of years for the ski area i to remain open after 1970, so that $s_i + \lambda_i = \kappa_i$. Then, the conditional probability distribution of κ_i, conditional on $\kappa_i \geq s_i$, can be derived as follows.

$$f(\kappa_i \mid \kappa_i \geq s_i) = \frac{f(\kappa_i)}{\Pr(\kappa_i \geq s_i)} = \frac{f(\kappa_i)}{1-\Pr(\kappa_i < s_i)} = \frac{(1-P_i)^{\kappa_i} P_i}{1-[P_i + (1-P_i)P_i + \ldots + (1-P_i)^{s_i - 1} P_i]}$$

$$= \frac{(1-P_i)^{\kappa_i} P_i}{1-[1-(1-P_i)^{s_i}]} = (1-P_i)^{\kappa_i - s_i} P_i \tag{6}$$

$$= (1-P_i)^{\lambda_i} P_i = f(\lambda_i)$$

As a result, the conditional probability distribution of additional years that a ski resort will remain open does not depend on how many years the ski area stayed open in the past. Equation (6) holds for any arbitrary s_i. The estimation of (5) is not affected by the data truncation at 1970.[4]

Empirical Model

The probability that ski area *i* closes in year *t* may depend on various factors. The set of explanatory variables *X* in Equation (2) is divided into four subcategories in the empirical model.

$$\Pr(Y_{it} = 1) = F(\boldsymbol{Z}_{it}, \boldsymbol{W}_{it}, \boldsymbol{I}_{it}, \boldsymbol{L}_{it}), \tag{7}$$

where $\boldsymbol{Z}_{it}, \boldsymbol{W}_{it}, \boldsymbol{I}_{it}$, and $\boldsymbol{L}_{it}$ represent respectively four groups of variables: characteristics of a ski area, climate, investment activities, and location. The function, *F*(.), is a cumulative distribution function. As seen in Table 1.A2, the climate variables include snowfall and winter temperature; the main characteristics of a ski area are described by number of trails, number of lifts, and vertical drop of the mountain; two binary variables, whether to own snowmaking facilities and whether to operate in all four seasons, are used to signal the activities a ski area undertakes to adapt to changing physical and business

[4] As a robustness check, the data with alternative starting points at 1973, 1975, and 1977 is also analyzed. The key findings remain the same in all sets of results except that the Size variable (the size of a ski area) loses significance in the main equation of the proposed structural model but remains significant in the subsidiary equations when the starting point is set at 1973 and 1975. This suggests that the direct effect of Size may not always be significant, but the overall effect of Size on the probability of survival of a ski area remains significant. The results of this analysis can be found in Tables 1.B11 – 1.B19 of Appendix 1.B.

environments; the distance to Boston is used to indicate the desirability of the location and the state fixed effects dummy variables are included to control for the potential general differences among the New England states.

As discussed in the literature review, the investment decisions may be motivated by adverse weather conditions. They can also be influenced by other characteristics related to the ski area. Two investment activities variables are constructed for Equation (7): I_{1it} = 1 if the ski area i has snowmaking equipment at time t and I_{1it} = 0 otherwise; I_{2it} = 1 if the ski area i operates four seasons at time t and I_{2it} = 0 otherwise. To explore the effects of climate change on investment decisions, two more equations are specified.

$$\Pr(I_{1it} = 1) = G(\boldsymbol{Z}_{it}, \boldsymbol{W}_{it}, \boldsymbol{M}_{it}) \tag{8}$$

$$\Pr(I_{2it} = 1) = H(\boldsymbol{Z}_{it}, \boldsymbol{W}_{it}, \boldsymbol{L}_{it}, N_{it}) \tag{9}$$

where $\boldsymbol{M}_{it}$ indicates the variables such as good sources of water (e.g., number of lakes nearby) and elevation of the mountain that can influence the decision of installing snow making facilities but do not affect the exit decision of a ski area; N_{it} represents the variables indicating the existing size of tourism related businesses surrounding a ski resort that may affect the decision to operate beyond the ski season. Both the decisions to install snowmaking facilities (I_1=1) and to operate four seasons (I_2=1) can be affected by the characteristics of the ski area and weather conditions. The decision to operate beyond the ski season can be affected by the location as well. The functions, $G(.)$ and $H(.)$, are cumulative distribution functions. Equations (7), (8), and (9) together form a structural model; $\boldsymbol{M}_{it}$ and N_{it} serve as the instruments to help identify equations (8) and (9) in the structural model. Assume normality for the cumulative distribution functions $F(.)$,$G(.)$ and $H(.)$ The structural model is estimated with the simulated maximum likelihood method (Cappellari and Jenkins, 2003). Note that climate variables are anticipated to enter both the main equation (7) and the subsidiary equations (8) and (9) in the structural model. The estimation of the structural model helps us examine the direct effects and indirect effects (through decisions of investment) of climate on the survival of a ski area.

Summary of Data

All the explanatory variables, either time varying or time invariant, are stacked according to the observations of *Y*. Table 1.A2 presents the definition of all variables and the summary statistics. Note that the constructed data for the discrete time survival analysis are essentially unbalanced panel data. To get the sense of variation across ski areas each year, the mean and standard deviation across ski areas is first calculated each year for each variable, then average them over years.[5] For comparison, summary statistics for data from 1970 to 1989 and from 1990 to 2007 are also tabulated. Among the 47 ski areas closed by 2007, the closures appear to be more frequent in the first two decades (1970-1989) than in the remaining years, but they do spread out in the whole studied period (of thirty-eight years). Of the 78 ski areas in the dataset, during the study period the average number of years remained open is about twenty-five years.

The three variables Trails, Vertical, and Lifts collectively determine the size of a ski area. The raw data show that the size of ski areas vary quite significantly from a few trails to over a hundred trails and from no lift to over 20 lifts. Comparing the average size of ski areas in 1990-2007 and in 1970-1989, it has noticeably increased over the years. Note that these size characteristic variables are (naturally) correlated. To address the potential collinearity issue, a size indicator based on the first principle component of

[5] The formulae to compute the summary statistics are given at the bottom of Table A2.

these three characteristic variables is constructed: Size = 2.7*Trails + 0.25*Vertical + 0.05*Lifts. In the empirical analysis, results using either all the three characteristic variables or the combined Size indicator are compared. Comparing the average snowfall variable (Snow) and the winter temperature variable (TempWinter) over the different time periods, the slight decrease in snowfall and increase in winter temperature are detected. To examine the cumulative effects of weather conditions, the 3-year and 5-year rolling averages of the snowfall and winter temperature variables (Av3Snow, Av5Snow, Av3TempWinter, Av5TempWinter) are also constructed. These variables will be used to examine the effects of climate in the empirical analysis. Of all the ski areas every year, on average over eighty percent of them have snowmaking equipment and close to half of them are open all four seasons. The average distance to Boston is 127 miles (approximately 2 hours by car). Note that the average distance from a ski area to Boston has increased in the recent two decades comparing to the previous two decades, indicating that more ski areas closer to Boston have closed down. To estimate the effects of climate on the survival of ski areas, it is imperative to simultaneously consider all the other potential impact factors.

Based on the proposed structural model, the potential direct and indirect effects of the variables on the probability of closure of a ski area are hypothesized and summarized, as shown in Table 1.B1. Note that most of the variables have potentially both direct and indirect influences on the probability that a ski area will close because they enter the structural model through both the main Equation (7) and the subsidiary Equations (8) and/or (9). Primarily it is believed that as the temperature warms and snowfall declines ski areas will be less likely to survive. However, if firms make strategic investment decisions, they may be able to offset (partially) the negative effects of the changing weather. These decisions are most likely also influenced by the local weather and expect to see that as the weather patterns change, ski areas will be more likely to change their production processes. Here is where the indirect effect of the climate factors can been seen. The overall impact of weather conditions will be determined by both the direct and indirect effects. Note that the characteristics of ski areas can also have both direct and indirect effects. First, it is likely that larger ski areas may have higher probabilities of success because of economies of scale. At the same time, they probably have larger revenue bases to make strategic investment decisions to boost a secondary increase in their probability of success. Lastly, all else equal, geographical location may also impact directly and indirectly the potential success of a ski area. For example, being close to Boston, the major central business district in New England, may be advantageous and may influence the decision to operate beyond the ski season. All of these hypotheses are tested, focusing on the impact of the climate variables.

In the empirical analysis, the data is limited due to the unavailability of the historical data of the characteristics and investment activities of ski areas. The features of a ski area are only observed in the last year that it was operational. For ski areas which are still open this is the year 2007. It is unknown exactly when a ski area installed snowmaking machinery or started to operate beyond the ski season. As a result, some variables, including the characteristics of a ski area, availability of snowmaking facilities and operation beyond ski season, can only be constructed based on the data in the last year of operation and are assumed to be time invariant.[6] For example, if a ski area had snowmaking facilities in 2007, it is assumed that the ski area had it for the whole studied

[6] Based on this data limitation our estimation of the effects of these features will be conservative.

period (1970-2007), since the exact year of installation is unknown to us. The presence of measurement errors in these variables is a drawback of the empirical analysis. Note that it is reasonable to think that the survival of a ski area depends on continuing improvements. The measurement errors in these explanatory variables tend to occur in the earlier years and bias toward the same direction - in favor of survival, which is likely to dampen the effects of the variables. For this reason, the estimated effects are likely to be more conservative due to the presence of the measurement errors in some variables.

1.4 Estimation and Results

Simplified One-Equation Model

The empirical analysis begins with the estimation of a simple one-equation model given in Equation (7), assuming that the investment decision variables I_1 (snowmaking equipment) and I_2 (four-season operation) are exogenously determined. The dependent variable is $Y_{it}=1$ if the ski area i is closed in year t and $Y_{it}=0$ otherwise. Different specifications are presented for comparison. In addition to the amount of snowfall and winter temperature of the year, alternatively, the 3-year and 5-year rolling averages of snowfall and winter temperature are employed to examine the potential cumulative effects of weather conditions. The three characteristic variables of a ski area (Trails, Vertical, Lifts) are either included individually or collectively as an index (Size). The estimation results of six alternative specifications of the one-equation model are presented in Table B2.

In the first three specifications, Models O1 – O3, in which the three characteristics of a ski area are included, the effect of number of trails is significant with expected sign indicating that more trails decreases the probability of closure. The number of lifts has the expected sign but it is insignificant. The positive and significant coefficient estimate of the vertical drop of the mountain is somewhat unexpected when it is viewed as an indicator of the size of operation. The vertical drop may also indicate the physical environment of a mountain. A taller mountain may also be rockier and icier that makes it harder for a ski area manager to carve multiple and challenge varying trails at the top of the mountain. This difficulty may limit a ski area's abilities to accommodate skiers of all levels and affects the success of the ski area.

When the characteristic variables are combined as in the Models O4-O6, the Size variable is significant. All else equal, larger ski areas are less likely to close down. The only climate variable that is significant in these estimated models is the amount of snowfall. The significant, negative coefficient estimates of the Snow variable in Models O1 and O4 indicate that the more snow, the less likely is a ski area to close down. The 3-year and 5-year rolling averages of the amount of snow as well as the winter temperature do not have significant effect. In contrast, the availability of snowmaking equipment significantly reduces the likelihood of a ski area going under. However, operating in all seasons does not show significant effect on the success of a ski area in these models. Nor does the location seem to matter. Based on these models, the variables with consistent, significant effects are the size of a ski area, the amount of snowfall, and the presence of snowmaking facilities.

Structural Three-Equation Model

The above one-equation model does not address the issue of potentially endogenous investment activities. In Section 3, a structural three-equation model is proposed. In addition to the main Equation (7) to examine the likelihood of the closure of a ski area, the decisions to invest in snowmaking equipment is explicitly modeled - Equation (8) and to operate in all four seasons - Equation (9) as two subsidiary equations to the main equation. To identify Equation (8), two instrumental variables are included; the number of lakes in the surrounding town (Lakes) and the base elevation of the mountain (Elevation). The Lakes factor should influence positively the probability that a ski area invests in snowmaking since snowmaking requires a large amount of water; Elevation should influence it negatively since mountains at higher elevations should be benefitting from more natural snow. To identify Equation (9), an instrumental variable called Industry is included. This variable measures the percentage of the workforce employed in the tourism related businesses such as arts, entertainment, recreation, food services, or accommodations in the surrounding town of the ski resort. It indicates whether the surrounding town has sufficient activities that attract tourists to help support a four-season resort. Similar to the simplified one-equation model, for comparison and robustness check, six alternative specifications (Models S1-S6) are presented. They differ in the ways that climate and characteristics of ski areas are measured. The estimation results of the structural model are shown in Table B3.

The results of the main equation in the three-equation model are similar to those in the one-equation model. Larger ski areas are more likely to remain open. A good amount of snow and whether a ski area is equipped with snowmaking facilities directly affect the survival of the ski area. Winter temperature does not seem to have a direct effect on the probability of a ski area closing down . The coefficient of I_2 is (expectedly) negative but insignificant, that operating beyond the ski season does not seem to have a significant effect on reducing the probability of closure of a ski area. Similar to the one-equation model, location continues to show no significant direct effect on the survival of a ski area.

Turning to the two subsidiary equations regarding adaptation abilities through investment activities of a ski area in the structural model, I_1 (snowmaking) and I_2 (four season operation), it is seen in the results of the I_1 equation that the installation of snowmaking facilities is significantly influenced by the characteristics of a ski resort. The larger the ski resort, the more likely it is to own snowmaking equipment. It is also seen that climate has significant effects. More natural snow and lower winter temperature make it less likely to have snowmaking equipment. As expected, lower elevation of the mountain and more lakes nearby will increase the probability of owning snowmaking equipment.

As for the I_2 equation, larger ski areas are more likely to open all four seasons. It is less likely to open all seasons when there is more snow to support the winter ski activities. The significant, negative coefficient of the winter temperature variable is unexpected with no good explanation, though. The industry variable is positive and significant indicating that the higher percent of workforce in the tourism related businesses near a ski area, the more likely is the ski area to operate all seasons. The location variables (distance to Boston and state dummy variables) are mostly significant. The positive coefficient of Boston seems counterintuitive that within each state the further away from Boston of a ski area, the more likely it operates in all four seasons. A possible explanation is that with the continuing improvement of infrastructure and road conditions over time, it becomes easier to travel a longer distance to a ski area with better services. All else equal, the New England ski areas farther away from Boston might be more likely to operate beyond the ski season to be the all-season, vacation get-away places.

The 3-year and 5-year rolling averages of the climate variables do not appear to impact directly the survival of a ski area in the main equation. However, they are significant in the subsidiary equations, indicating that cumulative climate changes can influence the investment activities; therefore they influence indirectly the survival of a ski area.

Also estimated are the reduced form models which exclude the potentially endogenous I_1 and I_2, and include the instruments from the I_1 and I_2 equations. The results can be found in Table B4. It is clear that the size of a ski area and the amount of snow play significant roles in the success of a ski area. The instrumental variables are mostly insignificant in the estimated reduced form models. Note that when the characteristic variables are combined into the Size variable in the reduced form model, all the instrumental variables are significant in the subsidiary equations in the three-equation structural model but insignificant in the reduced form model, as expected from reasonably good instruments.

Direct and Indirect Effects of Weather Conditions on Closure of Ski Areas

As seen from the estimation results of the structural model in Table B3, the three variables that are consistently significant in the main equation are Size, Snow, and I_1 (snowmaking). These variables impact the probability of closure of a ski area directly. Note that TempWinter (winter temperature) and I_2 (four season operation) are consistently insignificant in the main equation, indicating no significant direct impact from these variables. Further, both the Size and the climate variables are significant in the subsidiary I_1 equation. Along with the significance of I_1 in the main equation, there exist significant, indirect effects of Size, Snow, and TempWinter on the probability of closure of ski areas through their influences on the decision to invest in snowmaking equipment. Table C1 presents the estimated marginal direct and marginal overall effects of Size, Snow, and TempWinter on the probability of closure based on the estimated structural Model S4 in Table B3. As hypothesized in Section 3, the larger a ski area, the better chance it is to survive (direct effect); and the larger the ski area, the better chance it is to be able to engage in investment activities such as installing snowmaking equipment (indirect effect). The indirect effect of Size reinforces its direct effect. The empirical results confirm the hypothesis. As for the climate variables, decreased amount of snow increases the probability of closure (direct effect), but the decreased amount of snow also increases the probability of installing snowmaking equipment (indirect effect). The indirect effect offsets part of the direct effect resulting in the overall effect of Snow being smaller than the direct effect itself. TempWinter is insignificant in the main equation (no direct effect), but it significantly increases the probability of installing snowmaking equipment (indirect effect), so all else equal, the warmer winter temperature has actually reduced the probability of closure of a ski area.

To better understand the effects of the variables Size, Snow, and TempWinter, a simulation of both the direct and overall effects for some incremental changes of these variables are conducted, again based on the estimated Model S4. The predicted probability of closure at the means of all variables is 0.00886 that for a "prototypical" ski area, the estimated probability of closure each year is approximately 1 in 100.[7] This estimated average probability of closure serves as the base to evaluate the effects of changes in variables. The direct effect of an incremental change is computed as the difference between the average probability and the new, updated probability of closure evaluated at the new value(s) of the changed variable(s). In contrast, the overall effect of an incremental change has to be computed in two steps. First, compute the updated probability of I_1 (snowmaking) due to the incremental change(s) in the variable(s). Then plug in the updated I_1 probability along with the updated value(s) of the changed variable(s) into the main equation of the structural model to compute the new probability of closure, to be compared with the average probability of closure that is evaluated at the mean of all variables. Note that I_2 (four seasons) is insignificant in the main equation so that no indirect effect of I_2 is included in the calculation of the overall effect. The simulation results are presented in Table C2.

Compared to the average, a slightly larger ski area with 5 more trails, 1 more lift, and 50 feet longer vertical drop will have an estimated 0.00089 less chance to close down every year, as the direct effect of being slightly larger. Once the indirect effect of larger ski areas being more likely to install snowmaking equipment is taken into account, the overall effect of the larger Size reduces the probability of closing down by 0.00101. The overall effect is slightly higher than the direct effect since the larger ski areas have significantly higher probabilities to own snowmaking equipment, which reinforces the chances of survival. The effects may seem small. However, given that the estimated

[7] As seen in Table 1.A1, there were in total 61 ski areas still in operation in 2007 and 47 (plus a few) ski areas that closed down during the studied period 1970 – 2007. On average the actual annual rate of closure during the studied period is roughly 1 to 1.3 per 100 ski areas. The estimated probability of closure at means of all variables based on Model S4 is close to the actual average rate of closure.

average probability of closure is 0.00886, the estimated change in probability of 0.00101 translates into 11.4% decrease in the probability of closure.

Examining some incremental changes in climate variables, as the amount of natural snow goes down slightly by 0.01 inch a day (3.65 inches a year), the direct effect shows an increase in the probability of closure by 0.00040, but it is partially offset by the increased probability of installing snowmaking equipment. At the end, the overall effect of the decreased snowfall will increase the probability of closure by 0.00036, a 4.1% increase from the average probability of closure. When the amount of snowfall decreases significantly, 0.1 inch a day (36.5 inches a year), the overall effect will increase the probability of closure by 0.00477, which is equivalent to 53.9% increase from the estimated average probability of closure. Regarding the winter temperature, the direct effect of winter temperature is not significant, but the indirect effect through I_1 is. If the winter temperature rises up by 0.5 °F, the indirect effect through the slight increase in the probability of having snowmaking equipment will lower the probability of closure by 0.00003. If the winter temperature is up 3 °F, the probability of closure will go down by 0.00016. The indirect effects of warmer winter temperature are significant but minimal.

Global warming may simultaneously reduce the amount of snow and increase the winter temperature. The last simulation is to invoke simultaneous changes in Snow and TempWinter. Since TempWinter is insignificant in the main equation, the direct, combined effects of changes in Snow and TempWinter are viewed as the same as the direct effects of the changes in Snow alone. The simultaneous decrease in Snow and increase in TempWinter work together to increase the probability of installing snowmaking facilities that offsets partially the direct effect of Snow on the probability of closure. An averaged 0.03 inch decrease in snowfall a day (10.95 inches a year) accompanied by a 1 °F increase in winter temperature will raise the probability of closure by 0.00115, close to 13% increase from the estimated average probability of closure. If winter temperature rises by 3 °F and snowfall decreases by 0.1 inch a day (36.5 inches a year), the probability of closure goes up by 0.00446, about 50% increase from the average probability of closure. The overall effects of decreased snowfall coupled with increased winter temperature are actually slightly smaller than the overall effects of decreased snowfall alone. This is because according to the estimation results, rising temperature increases the probability of having snowmaking equipment that can lower the probability of closure of a ski area.

1.5 Concluding Remarks

By applying the discrete time survival analysis to the data on both closed and operational ski areas, the results suggest that weather conditions have had a significant impact on the survival of New England ski areas in the past four decades. The effects of climate can be direct, or indirect through its influences on the investment activities of a ski area. In fact, the direct detrimental effects of increasing winter temperatures and decreasing snowfall can be partially offset by the installation of snowmaking facilities, as advocated by Scott et al. (2003) and other researchers. In this study, the direct effects of climate on the closure of ski areas and the effects of climate on investment activities of ski areas including installing snowmaking facilities and operating four seasons are confirmed and quantified. Simulation is conducted to demonstrate the estimated effects of changes in weather conditions on the closure of ski areas. The empirical results also suggest that the changing climate may have tipped the scales in favor of the larger ski resorts that are more likely to invest in snowmaking equipment. The average size of ski areas in New England has become larger and the ski industry has become less competitive in nature, and the results indicate that climate change has played a significant role in altering the market structure. To our knowledge, this is the first study to investigate both direct and indirect effects of climate change, along with other key factors, on the survival of ski areas, and to show through survival analysis the connection between climate change and the change in the market structure of the ski industry.

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APPENDICES

APPENDIX 1.A

SUMMARY STATISTICS OF THE DATA

The data in this study represents a sample of the operational ski areas throughout New England beginning in the year 1970. The following tables present summary statistics of the data. The statistics in each table are presented to ensure that the sample of ski areas used in this study is representative of the true population of ski areas.

Table 1.A1 lists the characteristics of all of the 61 ski areas which were operational during the year 2007. The characteristics of the sampled 31 operational ski areas in the study are then presented. The average number of trails, average number of non-rope tow lifts, and the average vertical drop of the sampled ski areas are close to the averages of the true populations. Table 1.A1 also presents these characteristics of the ski areas which survive throughout the sample. This portion of the table shows that the ski areas which survive longer in the data set possess more trails, lifts, and higher vertical drops.

Table 1.A2 presents all of the summary statistics for the dependent and explanatory variables in this study. These statistics show that the sample is mixed with larger and small resorts which are located evenly throughout the studied region. These statistics are also calculated for the first 20 and second 18 years of the study. Again these statistics show that the average characteristics of the ski areas that survive longer in the sample are the larger ski areas. Also, this portion of the analysis shows that the average winter temperature is higher during the second half of the studied time period, and the average snowfall is lower during the second half of the studied time period.

Tables 1.A3 – 1.A6 present the same summary statistics as Table 1.A2 under different subsets of the full data set. These figures are presented to show that the results in this study are not driven by the individual ski areas in the sample and they are not affected by the starting point of the data. The summary statistics remain robust to any subset of the sample from which they are calculated.

Table 1.A1:
The New England Ski Areas in the Study

Characteristic	Ski Areas in Operation in 2007		Ski Areas Closed Down During the Period[c]		
	Pop[a]	Sample[b]	1970-2007	1970-1989	1990-2007
# of ski areas	61	31	47	31	16
Avg. # of Trails	42.82	43.27	9.09	5.94	15.19
Avg. # of Lifts	8.36	7.31	2.00	1.42	3.13
Avg. Vertical Drop	1183.37	1139.99	486.49	416.26	622.56

Summarized from Sources: [a] http://www.onthesnow.com/
[b] Individual websites of ski areas
[c] http://www.nelsap.org/

Table 1.A2:
Variable Definitions and Summary Statistics
Summarizing the Full Sample of Data and Broken into Subsets by Years

Variable	Description	1970-2007		1970-1989		1990-2007	
		Mean[b]	Std[b]	Mean	Std	Mean	Std
Y_{it}[a]	=1 if the ski area *i* was closed in year *t*	2.3%		2.3%		2.3%	
Year[b]	The year in which the ski area was closed	1994.59	12.270	1980.43	4.39	2003.02	6.01
# of years a ski area remained open in the time period[c]		25.587	12.269	11.429	4.384	14.021	6.013
# of ski areas opened at the beginning of period		78		78		47	
# of ski areas closed at the end of period		47		31		16	
# of stacked observations for discrete time survival analysis		1919		1260		659	
Snow	Annual average of per-day snowfall, at nearest weather station (inches)	0.178	0.075	0.184	0.076	0.171	0.074
Av3Snow	Three year rolling average of per-day snowfall, at nearest weather station (inches)	0.174	0.067	0.182	0.073	0.166	0.062
Av5Snow	Five year rolling average of per-day snowfall, at nearest weather station (inches)	0.173	0.062	0.179	0.067	0.167	0.058
TempWinter	Average winter temperature (Nov.-Feb.), at nearest weather station (°F)	30.359	3.544	29.859	3.367	30.915	3.741
Av3TempWinter	Three year rolling average of winter temperature, at nearest weather station (°F)	29.428	3.590	29.085	3.478	29.772	3.703
Av5TempWinter	Five year rolling average of winter temperature, at nearest weather station (°F)	29.466	3.569	29.141	3.419	29.756	3.703

Trails	Number of trails at the ski area	33.207	31.891	27.386	29.386	39.674	34.565
Vertical	Vertical drop of the mountain (ft)	999.70	707.66	876.21	661.49	1136.91	758.96
Lifts	Number of non-rope tow lifts at the ski area	5.714	4.764	4.834	4.435	6.692	5.130
Size	The 1st principle component of Trails, Vertical and Lifts (=2.7*Trails+0.25*Vertical+0.05*Lifts)	339.87	257.72	293.23	240.27	391.68	277.12
***I_1* (Snowmaking)**	= 1 if the ski area has snowmaking equipment	81.3%		71.9%		91.8%	
***I_2* (FourSeason)**	= 1 if the ski area is open all four seasons	47.0%		39.8%		54.9%	
Boston	Distance from the ski area to Boston (miles)	127.02	49.20	121.85	48.97	132.76	49.45
Elevation	Base elevation of the mountain (ft)	976.13	583.66	941.54	563.18	1014.57	606.40
Lakes	# of lakes in the town in which the ski area is located	1.631	1.965	1.518	1.938	1.758	1.995
Industry	Percentage of the workforce that is employed in the businesses of arts, entertainment, recreation, food services and accommodations in the town in which the mountain is located	13.986	9.496	12.978	8.971	15.106	10.078
D_NH	= 1 if the ski area is located in New Hampshire	33.1%		33.2%		32.9%	
D_VT	= 1 if the ski area is located in Vermont	30.2%		31.0%		29.3%	
D_ME	= 1 if the ski area is located in Maine	8.7%		6.9%		10.6%	
D_MA	= 1 if the ski area is located in Massachusetts	22.8%		23.7%		21.7%	

[a] See Section 3 for the detailed description of the construction of the variable Y_{it} and the compilation of the data set. The summary statistics of Y_{it} is the mean of yearly averages. See below for further explanation. The Y_{it} in the following four charts was calculated in the same way.

[b] The summary statistics in the above and following four charts are computed for the expanded data set. Multiple yearly observations for each ski area are present in the expanded data set for discrete time survival analysis. Note that the purpose of the summary statistics here is to show the average conditions every year that ski areas face. Hence, the Mean in this table is derived by first computing the yearly average for each year, then taking the mean of the yearly averages. Similarly, the standard deviation (Std) is the mean of the yearly standard deviations. The formulae to compute Mean and Std are as follows.

$$Mean = \frac{\sum_{t=1}^{T} \bar{X}_{.t}}{T} = \frac{\sum_{t=1}^{T} \frac{\sum_{i=1}^{n_t} X_{it}}{n_t}}{T} \qquad Std = \frac{\sum_{t=1}^{T} \sqrt{\left(\frac{\sum_{i=1}^{n_t} (X_{it} - \bar{X}_{.t})^2}{n_t - 1} \right)}}{T}$$

[c] The summary statistics for this measure are computed based on the raw data of the 78 ski areas, not the expanded (stacked) data. The same is true for the following four charts.

Table 1.A3:
Variable Definitions and Summary Statistics
Summarizing a Random Sample of the Data and Broken into Subsets by Years

Variable	Description	1970-2007		1970-1989		1990-2007	
		Mean[b]	Std[b]	mean	Std	mean	Std
Y_{it}	=1 if the ski area *i* was closed in year *t*	2.3%		2.2%		2.4%	
Year	The year in which the ski area was closed	1993.444	12.252	1980.241	4.421	2002.349	6.260
# of years a ski area remained open in the time period		24.444	12.251	11.241	4.421	13.349	6.260
# of ski areas opened at the beginning of period		73		73		42	
# of ski areas closed at the end of period		42		31		16	
# of stacked observations for discrete time survival analysis		1729		1142		587	
Snow	Annual average of per-day snowfall, at nearest weather station (inches)	0.185	0.078	0.186	0.078	0.184	0.080
Av3Snow	Three year rolling average of per-day snowfall, at nearest weather station (inches)	0.180	0.068	0.241	0.073	0.176	0.063
Av5Snow	Five year rolling average of per-day snowfall, at nearest weather station (inches)	0.178	0.063	0.182	0.067	0.175	0.063
TempWinter	Average winter temperature (Nov.-Feb.), at nearest weather station (°F)	30.279	3.550	29.857	3.339	30.747	3.785
Av3TempWinter	Three year rolling average of winter temperature, at nearest weather station (°F)	30.327	3.515	29.931	3.410	30.724	3.620

Av5TempWinter	Five year rolling average of winter temperature, at nearest weather station (°F)	30.323	3.482	29.944	3.345	29.756	3.603
Trails	Number of trails at the ski area	29.580	31.454	24.879	28.593	34.803	34.633
Vertical	Vertical drop of the mountain (ft)	912.100	647.458	818.842	623.978	1015.719	730.546
Lifts	Number of non-rope tow lifts at the ski area	5.404	4.837	4.633	4.451	6.259	5.266
Size	The 1st principle component of Trails, Vertical and Lifts (=2.7*Trails+0.25*Vertical+0.05*Lifts)	308.161	248.398	272.115	228.482	348.211	270.526
***I_1* (Snowmaking)**	= 1 if the ski area has snowmaking equipment	79.0%		70.0		89.0%	
***I_2* (FourSeason)**	= 1 if the ski area is open all four seasons	40.7%		35.0		47.0%	
Boston	Distance from the ski area to Boston (miles)	129.696	48.421	121.202	48.332	139.136	48.521
Elevation	Base elevation of the mountain (ft)	965.390	569.472	934.932	551.649	999.233	589.276
Lakes	# of lakes in the town in which the ski area is located	1.465	1.934	1.472	1.914	1.456	1.956
Industry	Percentage of the workforce in the town in which the mountain is located which is employed in either arts, entertainment, recreation, food services or accommodations	14.258	9.378	13.090	8.906	15.556	9.902
D_NH	= 1 if the ski area is located in New Hampshire	30.7%		33.6%		27.5%	
D_VT	= 1 if the ski area is located in Vermont	36.8%		33.8%		40.1%	
D_ME	= 1 if the ski area is located in Maine	6.6%		5.3%		8.0%	
D_MA	= 1 if the ski area is located in Massachusetts	22.8%		23.7%		21.9%	

Table 1.A4:
Variable Definitions and Summary Statistics
Summarizing the Full Data and a Subset of Years from 1973-2007

Variable	**Description**	**1970-2007**		**1973-2007**	
		Mean[b]	Std[b]	mean	Std
Y_{it}	=1 if the ski area i was closed in year t	2.3%		2.5%	
Year	The year in which the ski area was closed	1994.59	12.270	1994.61	12.1172
# of years a ski area remained open in the time period		25.587	12.269	25.6184	12.1172
# of ski areas opened at the beginning of period		78		77	
# of ski areas closed at the end of period		47		47	
# of stacked observations for discrete time survival analysis		1919		1888	
Snow	Annual average of per-day snowfall, at nearest weather station (inches)	0.178	0.075	0.169	0.075
Av3Snow	Three year rolling average of per-day snowfall, at nearest weather station (inches)	0.174	0.067	0.171	0.065
Av5Snow	Five year rolling average of per-day snowfall, at nearest weather station (inches)	0.173	0.062	0.173	0.062
TempWinter	Average winter temperature (Nov.-Feb.), at nearest weather station (°F)	30.359	3.544	30.546	3.627
Av3TempWinter	Three year rolling average of winter temperature, at nearest weather station (°F)	29.428	3.590	30.457	3.581
Av5TempWinter	Five year rolling average of winter temperature, at nearest weather station (°F)	29.466	3.569	30.399	3.568

Trails	Number of trails at the ski area	33.207	31.891	34.064	32.834
Vertical	Vertical drop of the mountain (ft)	999.70	707.66	1018.449	729.957
Lifts	Number of non-rope tow lifts at the ski area	5.714	4.764	5.847	4.916
Size	The 1st principle component of Trails, Vertical and Lifts (=2.7*Trails+0.25*Vertical+0.05*Lifts)	339.87	257.72	346.878	265.923
***I_1* (Snowmaking)**	= 1 if the ski area has snowmaking equipment	81.3%		82.8%	
***I_2* (FourSeason)**	= 1 if the ski area is open all four seasons	47.0%		48.0%	
Boston	Distance from the ski area to Boston (miles)	127.02	49.20	127.466	50.483
Elevation	Base elevation of the mountain (ft)	976.13	583.66	982.836	600.770
Lakes	# of lakes in the town in which the ski area is located	1.631	1.965	1.636	2.015
Industry	Percentage of the workforce in the town in which the mountain is located which is employed in either arts, entertainment, recreation, food services or accommodations	13.986	9.496	14.081	9.771
D_NH	= 1 if the ski area is located in New Hampshire	33.1%		33.2%	
D_VT	= 1 if the ski area is located in Vermont	30.2%		30.0%	
D_ME	= 1 if the ski area is located in Maine	8.7%		8.9%	
D_MA	= 1 if the ski area is located in Massachusetts	22.8%		22.7%	

Table 1.A5:
Variable Definitions and Summary Statistics
Summarizing the Full Data and a Subset of Years from 1975-2007

Variable	Description	1970-2007		1975-2007	
		Mean[b]	Std[b]	mean	Std
Y_{it}	=1 if the ski area *i* was closed in year *t*	2.3%		2.5%	
Year	The year in which the ski area was closed	1994.59	12.270	1995.472	11.703
# of years a ski area remained open in the time period		25.587	12.269	26.472	11.703
# of ski areas opened at the beginning of period		78		72	
# of ski areas closed at the end of period		47		47	
# of stacked observations for discrete time survival analysis		1919		1546	
Snow	Annual average of per-day snowfall, at nearest weather station (inches)	0.178	0.075	0.171	0.077
Av3Snow	Three year rolling average of per-day snowfall, at nearest weather station (inches)	0.174	0.067	0.169	0.065
Av5Snow	Five year rolling average of per-day snowfall, at nearest weather station (inches)	0.173	0.062	0.171	0.061
TempWinter	Average winter temperature (Nov.-Feb.), at nearest weather station (°F)	30.359	3.544	30.488	3.614
Av3TempWinter	Three year rolling average of winter temperature, at nearest weather station (°F)	29.428	3.590	30.466	3.567
Av5TempWinter	Five year rolling average of winter temperature, at nearest weather station (°F)	29.466	3.569	30.425	3.560

Trails	Number of trails at the ski area	33.207	31.891	34.704	33.133
Vertical	Vertical drop of the mountain (ft)	999.70	707.66	1032.45	733.384
Lifts	Number of non-rope tow lifts at the ski area	5.714	4.764	5.947	4.940
Size	The 1st principle component of Trails, Vertical and Lifts (=2.7*Trails+0.25*Vertical+0.05*Lifts)	339.87	257.72	352.111	26.265
I_1 **(Snowmaking)**	= 1 if the ski area has snowmaking equipment	81.3%		83.9%	
I_2 **(FourSeason)**	= 1 if the ski area is open all four seasons	47.0%		48.9%	
Boston	Distance from the ski area to Boston (miles)	127.02	49.20	127.830	50.414
Elevation	Base elevation of the mountain (ft)	976.13	583.66	987.874	602.049
Lakes	# of lakes in the town in which the ski area is located	1.631	1.965	1.641	2.010
Industry	Percentage of the workforce in the town in which the mountain is located which is employed in either arts, entertainment, recreation, food services or accommodations	13.986	9.496	14.166	9.798
D_NH	= 1 if the ski area is located in New Hampshire	33.1%		33.3%	
D_VT	= 1 if the ski area is located in Vermont	30.2%		29.9%	
D_ME	= 1 if the ski area is located in Maine	8.7%		9.0%	
D_MA	= 1 if the ski area is located in Massachusetts	22.8%		22.6%	

Table 1.A6:
Variable Definitions and Summary Statistics
Summarizing the Full Data and a Subset of Years from 1977-2007

Variable	Description	1970-2007		1977-2007	
		Mean[b]	Std[b]	mean	Std
Y_{it}	=1 if the ski area i was closed in year t	2.3%		2.5%	
Year	The year in which the ski area was closed	1994.59	12.270	1996.609	10.874
# of years a ski area remained open in the time period		25.587	12.269	27.609	10.874
# of ski areas opened at the beginning of period		78		69	
# of ski areas closed at the end of period		47		38	
# of stacked observations for discrete time survival analysis		1919		1404	
Snow	Annual average of per-day snowfall, at nearest weather station (inches)	0.178	0.075	0.170	0.077
Av3Snow	Three year rolling average of per-day snowfall, at nearest weather station (inches)	0.174	0.067	0.169	0.065
Av5Snow	Five year rolling average of per-day snowfall, at nearest weather station (inches)	0.173	0.062	0.170	0.061
TempWinter	Average winter temperature (Nov.-Feb.), at nearest weather station (°F)	30.359	3.544	30.457	3.597
Av3TempWinter	Three year rolling average of winter temperature, at nearest weather station (°F)	29.428	3.590	30.426	3.546
Av5TempWinter	Five year rolling average of winter temperature, at nearest weather station (°F)	29.466	3.569	30.418	3.39

Trails	Number of trails at the ski area	33.207	31.891	35.373	33.336
Vertical	Vertical drop of the mountain (ft)	999.70	707.66	1046.689	737.064
Lifts	Number of non-rope tow lifts at the ski area	5.714	4.764	6.049	4.967
Size	The 1st principle component of Trails, Vertical and Lifts (=2.7*Trails+0.25*Vertical+0.05*Lifts)	339.87	257.72	357.482	268.684
***I_1* (Snowmaking)**	= 1 if the ski area has snowmaking equipment	81.3%		85.1%	
***I_2* (FourSeason)**	= 1 if the ski area is open all four seasons	47.0%		49.8%	
Boston	Distance from the ski area to Boston (miles)	127.02	49.20	128.270	50.316
Elevation	Base elevation of the mountain (ft)	976.13	583.66	992.479	603.179
Lakes	# of lakes in the town in which the ski area is located	1.631	1.965	1.651	2.009
Industry	Percentage of the workforce in the town in which the mountain is located which is employed in either arts, entertainment, recreation, food services or accommodations	13.986	9.496	14.251	9.819
D_NH	= 1 if the ski area is located in New Hampshire	33.1%		33.4%	
D_VT	= 1 if the ski area is located in Vermont	30.2%		29.8%	
D_ME	= 1 if the ski area is located in Maine	8.7%		9.1%	
D_MA	= 1 if the ski area is located in Massachusetts	22.8%		22.5%	

APPENDIX 1.B

ESTIMATED EFFECTS OF EXPLANATORY VARIABLES ON THE PROBABILITY OF CLOSURE OF A SKI AREA

To examine the connection between weather and the closure of ski areas throughout New England, the discrete times survival analysis approach is employed to determine which factors significantly affect the probability that a specific ski area might close. Many different models are estimated to ensure that the reported results are robust. The section begins with Table 1.B1 which lists all of the explanatory variables in the model and the predicted direct and indirect effects of each of these factors on the probability of closure of the ski area. Tables 1.B2 – 1.B4 contain the estimation results of the models used to draw the main conclusions of this chapter. Starting with the simple one equation models in Table 1.B2, the results suggest that the size of the resort along with its snowmaking capabilities and the amount of annual snowfall each significantly impact the probability of closure of a ski area in the same was as was predicted in Table 1.B1. More convincingly, Table 1.B3 showing the structural three equation model also suggest that size, snowmaking capabilities, and natural snowfall all contribute to the reduction in possible closure of a ski area. Moreover, Table 1.B3 also shows the indirect and significant effects of both the climatic factors and the size of the resort. Finally, Table 1.B4 presents the reduced form models which present evidence that the instruments used in the structural three equation model are strong and alone do not influence the probability of closure of a resort.

Tables 1.B5 – B7 present the same models estimated under a randomly sampled subset of the full data set. The results in each table are extremely similar to the counterparts in Tables 1.B2 – 1.B4. This analysis suggests that, although the data used for the analysis in this chapter does not contain the full population of all operational and closed ski areas in New England, the results which are presented and used for discuss are not significantly affected by the specific ski areas which are summarized in the data set. The results in Tables 1.B5 – 1.B7 are intended to decrease any suspicion about the representativeness of the ski areas in the data set and also dissuade any concern over the application of the results to any ski area in the region.

Tables 1.B8 – 1.B10 present the estimated results of slightly different models than in Tables 1.B2 – 1.B4. In Tables 1.B8 – 1.B10 the models contain the Distance factor which measures the distance of the ski area to the nearest major metropolitan area instead of the Boston factor which only estimates the distance of the ski area to Boston. These models are presented to ensure that the inclusion of the Boston factor does not significantly alter the estimated results of any of the models. The only significant different between the models which include the distance factor and those which include the Boston factor is that the three year rolling average of the TempWinter factor is significant in both Models S2 and S4. The Boston factor is chosen as the primary factor in the model since this study focuses on New England and not the entire Northeast. In New England studies, Boston is often used as the most influential metropolitan area.

Finally, section presents 9 other tables which estimated the original models over the data starting at different point in time. The assumption that the distribution of data is memoryless is needed to employ the discrete time survival estimation technique. This assumption is often disputed and the results in Tables 1.B11 – 1.B19 are presented to support this assumption. Tables 1.B11 – 1.B13, 1.B14 – 1.B16, and 1.B17 – 1.B19 present the estimated results over the data starting in the year 1973, 1975, and 1977 respectively. The results for each of the estimated models are very similar to the results presented in Tables 1.B2 – 1.B4. The only noteworthy different among the models which are estimated for different time periods is the significance of the *size* factor. For models estimated over data starting in the year 1973 and 1975, the Size factor loses significance in the main equations of the structural models. However, both magnitude and sign of the estimated coefficient of *size* are similar to other models. The Size factor is also still highly significant in the investment factor equations. The overall consistency among the models estimated over different time period helps to validate the assumption of the memorylessness of the distribution of data and also adds to the robustness checks of the main results presented in Tables 1.B2 – 1.B4.

The results from Tables 1.B2 – 1.B4 are used to draw the primary conclusions about the connection between weather and the survival of ski areas in the New England region. These results suggest that the most influential factors in the ski industry are the size of the resort, the investment in snowmaking equipment, and the endowment of natural snow. Each of these three factors contributes to the success of the ski area. In addition, the results suggest the investment in snowmaking can offset some of the negative impacts of decreased natural snowfall and larger ski areas are most likely gaining the upper hand in the industry as they are more likely to be able to invest in more snowmaking capital than smaller less solvent resorts.

Table 1.B1:
The Potential Effects on the Probability of Closure of a Ski Area

Variable	Variable Category	Effect	Anticipated Direction of Effect on Closure
Snow	Climate	Direct	-
		Indirect via I_1 and I_2	+
TempWinter	Climate	Direct	+
		Indirect via I_1 and I_2	-
Trails	Firm Characteristics	Direct	-
		Indirect via I_1 and I_2	-
Vertical	Firm Characteristics	Direct	-
		Indirect via I_1 and I_2	-
Lifts	Firm Characteristics	Direct	-
		Indirect via I_1 and I_2	-
Size	Firm Characteristics (combined)	Direct	-
		Indirect via I_1 and I_2	-
I_1 **(Snowmaking)**	Investment Activities	Direct	-
I_2 **(FourSeason)**	Investment Activities	Direct	-
Boston	Location	Direct	+
		Indirect via I_2	+

Table 1.B2:
The Estimated Simple One-Equation Models
on the Full Data Set

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**
Intercept	-1.5899** (0.7997)	-1.6971* (0.9982)	-0.7852 (1.1492)	-1.8344** (0.8048)	-2.0025* (1.0282)	-1.0808 (1.1983)
Trails	-0.0329** (0.0167)	-0.0342* (0.0180)	-0.0366* (0.0202)			
Vertical	0.0007** (0.0003)	0.0007** (0.0003)	0.0008** (0.0004)			
Lifts	-0.0970 (0.0610)	-0.1009 (0.0656)	-0.1128 (0.0720)			
Size				-0.0014** (0.0007)	-0.0015** (0.0007)	-0.0014** (0.0007)
Snow	-1.8591** (0.8474)			-1.6597** (0.7973)		
TempWinter	0.0126 (0.0190)			0.0169 (0.0191)		
Av3Snow		-1.0651 (1.5103)			-0.9763 (1.5024)	
Av3TempWinter		0.0161 (0.0239)			0.0216 (0.0244)	
Av5Snow			-2.1706 (1.4728)			-2.0480 (1.5116)
Av5TempWinter			-0.0016 (0.0294)			0.0032 (0.0303)
I_1 (Snowmaking)	-0.2723 (0.1674)	-0.2843 (0.1735)	-0.3260* (0.1879)	-0.4501*** (0.1680)	-0.4717*** (0.1744)	-0.5120*** (0.1862)
I_2 (FourSeason)	-0.0732 (0.2688)	-0.0535 (0.2716)	-0.1748 (0.2976)	-0.1464 (0.2461)	-0.1290 (0.2464)	-0.2409 (0.2637)
Boston	-0.0008 (0.0020)	-0.0007 (0.0021)	-0.0015 (0.0022)	-0.0001 (0.0019)	-0.0001 (0.0020)	-0.0008 (0.0021)
D_NH	0.1379 (0.3560)	0.0755 (0.3635)	0.0293 (0.3874)	0.2983 (0.3279)	0.2640 (0.3327)	0.2173 (0.3475)
D_VT	0.2313 (0.4269)	0.1576 (0.4442)	0.1822 (0.4791)	0.3367 (0.3865)	0.2976 (0.3967)	0.3332 (0.4176)
D_ME	0.4798 (0.5953)	0.4717 (0.6048)	0.5808 (0.6785)	0.4323 (0.5222)	0.4112 (0.5285)	0.4606 (0.5574)
D_MA	0.1876 (0.3347)	0.1591 (0.3407)	0.1689 (0.3522)	0.1540 (0.3280)	0.1460 (0.3321)	0.1311 (0.3422)
LSL	-183.7350	-180.1057	-170.6178	-190.3394	-187.1056	-178.3709

Note: ***, **, and * denote statistical significance at the .01, 0.5, and .1 levels, respectively, and LSL (Log Pseudo Likelihood) represents the goodness of fit measure for each model.

Table 1.B3:
The Estimated Structural Three-Equation Models
on the Full Data Set

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
Intercept	-1.5907** (0.7997)	-1.6168 (1.0076)	-0.7086 (1.1481)	-1.8152** (0.7985)	-2.0274* (1.0400)	-1.0785 (1.1998)
Trails	-0.0329** (0.0168)	-0.0346** (0.0173)	-0.0378* (0.0197)			
Vertical	0.0007** (0.0003)	0.0008** (0.0003)	0.0010** (0.0004)			
Lifts	-0.0974 (0.0636)	-0.0697 (0.0609)	-0.0890 (0.0682)			
Size				-0.0015** (0.0007)	-0.0012* (0.0007)	-0.0014* (0.0008)
Snow	-1.8547** (0.8547)			-1.6382** (0.8015)		
TempWinter	0.0125 (0.0191)			0.0147 (0.0190)		
Av3Snow		-1.3570 (1.5635)			-1.1187 (1.5024)	
Av3TempWinter		0.0205 (0.0244)			0.0259 (0.0253)	
Av5Snow			-2.5997 (1.4952)			-2.0269 -1.5203
Av5TempWinter			0.0024 (0.0298)			0.0028 (0.0309)
I_1 (Snowmaking)	-0.2647 (0.2133)	-0.5606** (0.2196)	-0.5566** (0.2473)	-0.3811** (0.1858)	-0.5990*** (0.1980)	-0.4991** (0.2149)
I_2 (FourSeason)	-0.0844 (0.3050)	-0.1467 (0.2914)	-0.2327 (0.3366)	-0.1736 (0.2878)	-0.2376 (0.2650)	-0.2309 (0.3053)
Boston	-0.0007 (0.0020)	-0.0011 (0.0021)	-0.0020 (0.0022)	-0.0001 (0.0020)	0.0001 (0.0020)	-0.0008 (0.0022)
D_NH	0.1387 (0.3556)	0.0240 (0.3609)	-0.0069 (0.3895)	0.3029 (0.3270)	0.2450 (0.3313)	0.2185 (0.3469)
D_VT	0.2271 (0.4291)	0.0927 (0.4491)	0.1512 (0.4858)	0.3299 (0.3908)	0.228 (0.4002)	0.3386 (0.4224)
D_ME	0.4813 (0.5962)	0.4874 (0.5982)	0.6029 (0.6760)	0.4364 (0.5221)	0.4138 (0.5264)	0.4599 (0.5563)
D_MA	0.1885 (0.3347)	0.1001 (0.3380)	0.1258 (0.3534)	0.1603 (0.3274)	0.1196 (0.3302)	0.1329 (0.3411)
Dependent Variable: I_1 (=1 if the ski area has snowmaking equipment)						
Intercept	-3.6024*** (0.4990)	-3.5492*** (0.6837)	-3.2629*** (0.8417)	-3.0077*** (0.5994)	-2.6555*** (0.8493)	-2.2225** (1.0428)

Trails	0.1026*** (0.0170)	0.1202*** (0.0198)	0.1155*** (0.0222)			
Vertical	0.0001 (0.0003)	0.0003 (0.0003)	0.0007** (0.0003)			
Lifts	0.4769*** (0.0499)	0.4592*** (0.0571)	0.4814*** (0.0630)			
Size				0.0087*** (0.0005)	0.0094*** (0.0006)	0.0101*** (0.0007)
Snow	-2.4730*** (0.4321)			-1.8463*** (0.4512)		
TempWinter	0.0884*** (0.0145)			0.0987*** (0.0178)		
Av3Snow		-6.0885*** (0.8654)			-5.1428*** (0.7958)	
Av3TempWinter		0.1013*** (0.0190)			0.1041*** (0.0244)	
Av5Snow			-9.7207*** (1.1449)			-8.1308*** (1.0421)
Av5TempWinter			0.1070*** (0.0230)			0.1063*** (0.0298)
Elevation	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)
Lakes	0.1641*** (0.0217)	0.1540*** (0.0248)	0.1221*** (0.0279)	0.1107*** (0.0210)	0.0989*** (0.0235)	0.0781*** (0.0262)
Dependent Variable: I_2 (=1 if the ski area operates in all four seasons)						
Intercept	-0.1132 (0.6360)	2.4423*** (0.8665)	4.2728*** (0.9943)	-0.3926 (0.6088)	1.5648* (0.8273)	2.9207*** (0.9477)
Trails	0.0146*** (0.0048)	0.0138*** (0.0051)	0.0129** (0.0054)			
Vertical	0.0006*** (0.0002)	0.0006*** (0.0002)	0.0006*** (0.0002)			
Lifts	0.1473*** (0.0223)	0.1609*** (0.0242)	0.1682*** (0.0263)			
Size				0.0052*** (0.0002)	0.0052*** (0.0002)	0.0051*** (0.0003)
Snow	-0.5214 (0.4422)			-0.5152 (0.4243)		
TempWinter	-0.0655*** (0.0172)			-0.0473*** (0.0162)		
Av3Snow		-2.0016** (0.7834)			-1.9037*** (0.7373)	
Av3TempWinter		-0.1326*** (0.0233)			-0.0977*** (0.0219)	
Av5Snow			-3.6360*** (0.9244)			-3.3635*** (0.8760)
Av5TempWinter			-0.1763*** (0.0271)			-0.1275*** (0.0253)

Boston	0.0062*** (0.0009)	0.0046*** (0.0010)	0.0038*** (0.0010)	0.0052*** (0.0008)	0.0040*** (0.0009)	0.0034*** (0.0010)
Industry	0.0155*** (0.0075)	0.0241*** (0.0082)	0.0273*** (0.0088)	0.0192*** (0.0072)	0.0259*** (0.0079)	0.0297*** (0.0085)
D_NH	0.0387 (0.1694)	-0.1310 (0.1746)	-0.3123 (0.1829)	-0.1126 (0.1622)	-0.2029 (0.1689)	-0.3470** (0.1755)
D_VT	-1.9101*** (0.1862)	-2.0242*** (0.1949)	-2.1361*** (0.2045)	-2.0930*** (0.1808)	-2.1485*** (0.1903)	-2.2398*** (0.1983)
D_ME	0.9096*** (0.2242)	0.8845*** (0.2564)	1.0391*** (0.3225)	0.6703*** (0.2233)	0.6904*** (0.2536)	0.8676*** (0.3175)
D_MA	-0.2485 (0.1718)	-0.3866** (0.1773)	-0.5618*** (0.1886)	-0.2049 (0.1605)	-0.2809 (0.1655)	-0.4373** (0.1734)
LSL	-1223.3672	-1087.8638	-970.6360	-1416.9048	-1257.5964	-1118.6192

Table 1.B4:
The Estimated Reduced Form Models
on the Full Data Set

Dependent Variable: Y_{it} **(=1 if the ski area i is closed in year t)**						
Model	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
Intercept	-1.6194* (0.9002)	-1.6661 (1.1370)	-0.7536 (1.3522)	-1.9949** (0.9831)	-2.1342* (1.2943)	-1.1450 (1.6065)
Trails	-0.0338* (0.0178)	-0.0361* (0.0193)	-0.0400* (0.0215)			
Vertical	0.0005 (0.0004)	0.0005 (0.0004)	0.0006 (0.0004)			
Lifts	-0.1293** (0.0659)	-0.1340* (0.0718)	-0.1484* (0.0787)			
Size				-0.0028*** (0.0007)	-0.0030*** (0.0007)	-0.0030*** (0.0008)
Snow	-1.9876** (0.8496)			-1.6014** (0.7924)		
TempWinter	0.0099 (0.0217)			0.0131 (0.0240)		
Av3Snow		-1.3757 (1.4379)			-1.0271 (1.4051)	
Av3TempWinter		0.0120 (0.0279)			0.0169 (0.0321)	
Av5Snow			-2.3372* (1.4228)			-1.6842 (1.5394)
Av5TempWinter			-0.0066 (0.0344)			-0.0053 (0.0406)
Elevation	-0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
Lakes	0.0143 (0.0366)	0.0138 (0.0371)	0.0091 (0.0393)	0.0234 (0.0347)	0.0246 (0.0353)	0.0217 (0.0369)
Industry	0.0206 (0.0128)	0.0242* (0.0130)	0.0244* (0.0146)	0.0199 (0.0140)	0.0221 (0.0143)	0.0195 (0.0158)
Boston	-0.0014 (0.0019)	-0.0016 (0.0021)	-0.0025 (0.0023)	-0.0011 (0.0018)	-0.0011 (0.0019)	-0.0020 (0.0021)
D_NH	0.1410 (0.3619)	0.0811 (0.3759)	0.0421 (0.3990)	0.3237 (0.3306)	0.2915 (0.3412)	0.2267 (0.3568)
D_VT	0.3403 (0.3788)	0.2643 (0.4032)	0.3256 (0.4240)	0.5138 (0.3424)	0.4734 (0.3566)	0.5076 (0.3659)
D_ME	0.4548 (0.6070)	0.4943 (0.6128)	0.6531 (0.6937)	0.3832 (0.5085)	0.3811 (0.5124)	0.3976 (0.5382)
D_MA	0.1046 (0.3523)	0.0661 (0.3578)	0.0759 (0.3716)	0.0054 (0.3390)	-0.0153 (0.3452)	-0.0359 (0.3571)
LSL	-183.2439	-179.3260	-170.5820	-192.5365	-189.2488	-181.7463

Table 1.B5:
The Estimated Simple One-Equation Models
on a Random Subset of the Full Data Set

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**
Intercept	-1.6322** (0.8051)	-1.8906** (0.8064)	-1.7511 (1.0013)	-0.8724 (1.1534)	-2.0562** (1.0211)	-1.1695 (1.1942)
Trails	-0.0302* (0.0176)	-0.0314* (0.0188)	-0.0337 (0.0212)			
Vertical	0.0007** (0.0003)	0.0007** (0.0003)	0.0008** (0.0004)			
Lifts	-0.1108* (0.0617)	-0.1148* (0.0660)	-0.1277* (0.0724)			
Size				-0.0014* (0.0007)	-0.0015** (0.0007)	-0.0014* (0.0007)
Snow	-1.8694** (0.8495)			-1.6183** (0.7952)		
TempWinter	0.0141 (0.0192)			0.0178 (0.0191)		
Av3Snow		-1.0895 (1.5119)			-0.9311 (1.4806)	
Av3TempWinter		0.0181 (0.0240)			0.0224 (0.0243)	
Av5Snow			-2.2183 (1.4614)			-1.9511 (1.4913)
Av5TempWinter			0.0014 (0.0295)			0.0048 (0.0302)
I_1 (Snowmaking)	-0.2529 (0.1694)	-0.2660 (0.1748)	-0.3062* (0.1889)	-0.4465*** (0.1665)	-0.4674*** (0.1728)	-0.5040*** (0.1847)
I_2 (FourSeason)	-0.0787 (0.2656)	-0.058 (0.2677)	-0.1803 (0.2930)	-0.1441 (0.2477)	-0.1268 (0.2474)	-0.2392 (0.2649)
Boston	-0.0007 (0.0020)	-0.0006 (0.0021)	-0.0014 (0.0022)	-0.0001 (0.0019)	-0.0001 (0.0020)	-0.0007 (0.0021)
DNH	0.1606 (0.3542)	0.1036 (0.3618)	0.0667 (0.3850)	0.3001 (0.3270)	0.2660 (0.3316)	0.2196 (0.3456)
DVT	0.2395 (0.4234)	0.1708 (0.4406)	0.2026 (0.4749)	0.3378 (0.3823)	0.2983 (0.3921)	0.334 (0.4111)
DME	0.5196 (0.6098)	0.5349 (0.6128)	0.6385 (0.6952)	0.5732 (0.5599)	0.5861 (0.5593)	0.6057 (0.6099)

DMA	0.1832 (0.3343)	0.1555 (0.3405)	0.1648 (0.3523)	0.1541 (0.3271)	0.1471 (0.3312)	0.1311 (0.3414)
LSL	-182.8227	-189.6749	-178.5282	-169.7386	-185.4853	-177.6985

Table 1.B6:
The Estimated Structural Three-Equation Models
on a Random Subset of the Full Data Set

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
Intercept	-1.6098** (0.8089)	-1.7572* (0.9981)	-0.7318 (1.1829)	-1.8866** (0.8055)	-2.0582** (1.0231)	-1.1601 (1.1830)
Trails	-0.0299 (0.0172)	-0.0326* (0.0188)	-0.0317 (0.0209)			
Vertical	0.0007** (0.0003)	0.0007** (0.0003)	0.0009** (0.0004)			
Lifts	-0.0868 (0.0599)	-0.1111* (0.0674)	-0.1064 (0.0731)			
Size				-0.0014* (0.0008)	-0.0016** (0.0008)	-0.0014* (0.0008)
Snow	-1.9329** (0.8422)			-1.6229** (0.8005)		
TempWinter	0.0175 (0.0192)			0.0178 (0.0193)		
Av3Snow		-1.1082 (1.5265)			-0.9168 (1.4808)	
Av3TempWinter		0.0195 (0.0241)			0.0230 (0.0248)	
Av5Snow			-2.6216* (1.5400)			-1.7179 (1.5261)
Av5TempWinter			0.0017 (0.0302)			0.0003 (0.0300)
I_1 (Snowmaking)	-0.4719** (0.2239)	-0.3144 (0.2389)	-0.4739* (0.2725)	-0.4447** (0.1893)	-0.4740** (0.2113)	-0.3793* (0.2167)
I_2 (FourSeason)	-0.1326 (0.3045)	0.0304 (0.3024)	-0.4213 (0.3261)	-0.1158 (0.2913)	-0.0373 (0.2832)	-0.4424 (0.2967)
Boston	-0.001 (0.0020)	-0.0009 (0.0021)	-0.0014 (0.0022)	-0.0001 (0.0019)	-0.0001 (0.0020)	-0.0001 (0.0021)
DNH	0.1295 (0.3520)	0.0905 (0.3604)	0.0379 (0.3886)	0.3002 (0.3277)	0.2633 (0.3305)	0.2198 (0.3438)
DVT	0.2038 (0.4229)	0.1887 (0.4439)	0.1169 (0.4805)	0.3481 (0.3878)	0.3267 (0.3959)	0.2574 (0.4174)
DME	0.5206 (0.6053)	0.5301 (0.6103)	0.6113 (0.7117)	0.5748 (0.5595)	0.5861 (0.5565)	0.5803 (0.6200)
DMA	0.1524 (0.3324)	0.1461 (0.3399)	0.1227 (0.3565)	0.1534 (0.3282)	0.1431 (0.3304)	0.1395 (0.3407)

Dependent Variable: I_1 (=1 if the ski area has snowmaking equipment)						
Intercept	-3.4201*** (0.5073)	-3.0528*** (0.6869)	-2.8027*** (0.8425)	-2.8377*** (0.6064)	-2.3782*** (0.8457)	-2.0512** (1.0312)
Trails	0.0951*** (0.0156)	0.1060*** (0.0177)	0.1171*** (0.0209)			
Vertical	0.0003 (0.0003)	0.0005* (0.0003)	0.0008*** (0.0003)			
Lifts	0.3744*** (0.0474)	0.3408*** (0.0523)	0.3334*** (0.0579)			
Size				0.0086*** (0.0006)	0.0092*** (0.0007)	0.0101*** (0.0008)
Snow	-2.4880*** (0.4647)			-2.2079*** (0.4891)		
TempWinter	0.0853*** (0.0147)			0.0958*** (0.0179)		
Av3Snow		-6.2081*** (0.8639)			-5.6245*** (0.8002)	
Av3TempWinter		0.0916*** (0.0191)			0.0988*** (0.0242)	
Av5Snow			-9.8142*** (1.1523)			-8.6861*** (1.0394)
Av5TempWinter			0.0984*** (0.0232)			0.1036*** (0.0295)
Elevation	-0.0008*** (0.0001)	-0.0008*** (0.0001)	-0.0008*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)
Lakes	0.1595*** (0.0207)	0.1465*** (0.0234)	0.1214*** (0.0257)	0.1049*** (0.0210)	0.0898*** (0.0236)	0.0726*** (0.0267)
Dependent Variable: I_2 (=1 if the ski area operates in all four seasons)						
Intercept	-0.2954 (0.6767)	2.0824** (0.9478)	4.2691*** (1.0718)	-0.5133 (0.6454)	1.5267* (0.8907)	3.2238** * (1.0175)
Trails	0.0440*** (0.0063)	0.0449*** (0.0066)	0.0448*** (0.0071)			
Vertical	0.0004** (0.0002)	0.0004** (0.0002)	0.0004** (0.0002)			
Lifts	0.0740*** (0.0218)	0.0828*** (0.0237)	0.0964*** (0.0260)			
Size				0.0066*** (0.0003)	0.0067*** (0.0003)	0.0067*** (0.0003)
Snow	-0.3356 (0.5284)			-0.3750 (0.5122)		

TempWinter	-0.0694*** (0.0181)			-0.0540*** (0.0171)		
Av3Snow		-1.6448* (0.9198)			-1.6760* (0.8765)	
Av3TempWinter		-0.1315*** (0.0250)			-0.1060*** (0.0234)	
Av5Snow			-3.5303*** (0.9799)			-3.4215*** (0.9366)
Av5TempWinter			-0.1855*** (0.0290)			-0.1464*** (0.0272)
Industry	-0.0215*** (0.0075)	-0.0197** (0.0082)	-0.0166* (0.0091)	-0.0156** (0.0075)	-0.0132 (0.0083)	-0.0103 (0.0091)
Boston	0.0095*** (0.0009)	0.0083*** (0.0010)	0.0070*** (0.0010)	0.0080*** (0.0008)	0.0070*** (0.0009)	0.0061*** (0.0010)
DNH	0.2520 (0.1760)	0.0467 (0.1860)	-0.0986 (0.1887)	-0.0212 (0.1672)	-0.1957 (0.1743)	-0.2821 (0.1774)
DVT	-1.5760*** (0.1903)	-1.7046*** (0.2021)	-1.7669*** (0.2086)	-1.7948*** (0.1761)	-1.9133*** (0.1853)	-1.9434*** (0.1907)
DME	0.3240 (0.2176)	0.2940 (0.2451)	0.3634 (0.2949)	0.0536 (0.2193)	0.0543 (0.2479)	0.1645 (0.3006)
DMA	0.0149 (0.1795)	-0.1025 (0.1895)	-0.2899 (0.1924)	-0.1039 (0.1655)	-0.2063 (0.1736)	-0.3444* * (0.1756)
LSL	-1186.3660	-1061.4141	-936.0363	-1351.523	-1201.9582	-1058.5379

Table 1.B7:
The Estimated Reduced Form Models
on a Random Subset of the Full Data Set

Dependent Variable: Y_{it} **(=1 if the ski area i is closed in year t)**						
Model	**R1**	**R2**	**R3**	**R$**	**R5**	**R6**
Intercept	-1.6736* (0.9024)	-1.7433 (1.1355)	-0.8830 (1.3499)	-2.0424** (0.9814)	-2.1812 (1.2795)	-1.2484 (1.5697)
Trails	-0.0309* (0.0181)	-0.0330* (0.0195)	-0.0370* (0.0215)			
Vertical	0.0005 (0.0004)	0.0005 (0.0004)	0.0006 (0.0004)			
Lifts	-0.1417** (0.0656)	-0.1471** (0.0714)	-0.1619** (0.0786)			
Size				-0.0027*** (0.0007)	-0.0029*** (0.0008)	-0.0030*** (0.0008)
Snow	-2.0239** (0.8583)			-1.5646** (0.7888)		
TempWinter	0.0120 (0.0217)			0.0138 (0.0238)		
Av3Snow		-1.4322 (1.4489)			-0.9810 (1.3783)	
Av3TempWinter		0.0149 (0.0279)			0.0175 (0.0315)	
Av5Snow			-2.4474 (1.4255)			-1.5830 (1.4991)
Av5TempWinter			-0.0020 (0.0344)			-0.0031 (0.0394)
Elevation	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
Lakes	0.0136 (0.0362)	0.0134 (0.0367)	0.0086 (0.0389)	0.0231 (0.0343)	0.0246 (0.0350)	0.0220 (0.0364)
Boston	-0.0013 (0.0019)	-0.0014 (0.0021)	-0.0023 (0.0024)	-0.0009 (0.0018)	-0.001 (0.0019)	-0.0019 (0.0021)
Industry	0.0205 (0.0128)	0.02440* (0.0130)	0.0250* (0.0146)	0.0200 (0.0141)	0.0223 (0.0144)	0.0200 (0.0160)
DNH	0.1797 (0.3613)	0.1274 (0.3767)	0.1049 (0.4011)	0.3273 (0.3302)	0.2939 (0.3405)	0.2314 (0.3549)
DVT	0.3596 (0.3772)	0.291 (0.4024)	0.3674 (0.4239)	0.5086 (0.3406)	0.4667 (0.3541)	0.5021 (0.3622)
DME	0.5346 (0.6128)	0.6045 (0.6132)	0.788 (0.6929)	0.6125 (0.5428)	0.6689 (0.5449)	0.6952 (0.5902)

DMA	0.1114 (0.3525)	0.0723 (0.3585)	0.0854 (0.3732)	0.0107 (0.3377)	-0.0100 (0.3441)	-0.0319 (0.3564)
LSL	-182.1669	-178.1423	-169.3080	-191.8286	-188.4521	-180.9121

Table 1.B8:
The Estimated Simple One-Equation Model
on the Full Data Set
Substituting Distance to Nearest Major Metropolitan Area for Distance to Boston

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**
Intercept	-1.8507**	-2.6258***	-1.8187	-2.1400***	-3.0162***	-2.2663**
	(0.7960)	(0.9361)	(1.1115)	(0.7898)	(0.9527)	(1.1402)
Trails	-0.0311*	-0.0298*	-0.0332			
	(0.0169)	(0.0179)	(0.0204)			
Vertical	0.0006*	0.0006*	0.0007*			
	(0.0003)	(0.0004)	(0.0004)			
Lifts	-0.1085*	-0.1132*	-0.1275*			
	(0.0616)	(0.0666)	(0.0733)			
Size				-0.0015**	-0.0015**	-0.0015**
				(0.0007)	(0.0007)	(0.0007)
Snow	-1.8534**			-1.6139**		
	(0.8374)			(0.7829)		
TempWinter	0.0179			0.0221		
	(0.0199)			(0.0200)		
Av3Snow		-0.8329			-0.7151	
		(1.3807)			(1.3469)	
Av3TempWinter		0.0393*			0.0462*	
		(0.0235)			(0.0242)	
Av5Snow			-1.8117			-1.6142
			(1.3610)			(1.4030)
Av5TempWinter			0.0236			0.0308
			(0.0290)			(0.0300)
I_1 (Snowmaking)	-0.2435	-0.2653	-0.2974	-0.4364***	-0.4736***	-0.5083***
	(0.1707)	(0.1772)	(0.1895)	(0.1672)	(0.1751)	(0.1855)
I_2 (FourSeason)	-0.0998	-0.0537	-0.1888	-0.1681	-0.1268	-0.2545
	(0.2555)	(0.2602)	(0.2819)	(0.2435)	(0.2466)	(0.2597)
Distance	0.0009	0.0018	0.0011	0.0029	0.0037	0.0034
	(0.0024)	(0.0024)	(0.0026)	(0.0021)	(0.0022)	(0.0023)
DNH	0.1541	0.1279	0.0886	0.2761	0.2706	0.2403
	(0.3568)	(0.3644)	(0.3814)	(0.3328)	(0.3388)	(0.3478)
DVT	0.1969	0.1772	0.1482	0.3069	0.3076	0.3003
	(0.3875)	(0.3978)	(0.4231)	(0.3584)	(0.3675)	(0.3783)
DME	0.4611	0.3678	0.58	0.4248	0.3289	0.4833
	(0.5969)	(0.5460)	(0.6427)	(0.5287)	(0.4721)	(0.5270)

DMA	0.1925 (0.3295)	0.1484 (0.3335)	0.1684 (0.3420)	0.1528 (0.3228)	0.1241 (0.3269)	0.1289 (0.3340)
LSL	-183.0172	-178.4573	-169.9135	-189.7030	-185.0456	-177.5560

Table 1.B9:
The Estimated Structural Three-Equation Models on Full Data Set
Substituting Distance to Nearest Major Metropolitan Area for Distance to Boston

Dependent Variable: Y_{it} **(=1 if the ski area i is closed in year t)**						
Model	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
Intercept	-1.8341** (0.8009)	-2.6343*** (0.9396)	-1.8074 (1.1159)	-2.0733*** (0.7920)	-3.0043*** (0.9577)	-2.2391** (1.1482)
Trails	-0.0302* (0.0166)	-0.0302* (0.0173)	-0.0339* (0.0200)			
Vertical	0.0007** (0.0003)	0.0007* (0.0004)	0.0008** (0.0004)			
Lifts	-0.0860 (0.0608)	-0.0863 (0.0626)	-0.1064 (0.0707)			
Size				-0.0015* (0.0009)	-0.0015* (0.0008)	-0.0018** (0.0009)
Snow	-1.8795** (0.8355)			-1.5879** (0.7811)		
TempWinter	0.0189 (0.0200)			0.0203 (0.0202)		
Av3Snow		-1.1150 (1.4139)			-0.8974 (1.3502)	
Av3TempWinter		0.0446* (0.0238)			0.0499** (0.0249)	
Av5Snow			-2.1901 (1.3768)			-1.6288 (1.4063)
Av5TempWinter			0.0281 (0.0295)			0.0303 (0.0308)
I_1 (Snowmaking)	-0.3775* (0.2124)	-0.5208** (0.2173)	-0.5064** (0.2469)	-0.4229** (0.1943)	-0.6089*** (0.1998)	-0.5065*** (0.2152)
I_2 (FourSeason)	-0.3533 (0.2870)	-0.1389 (0.2800)	-0.284 (0.3187)	-0.4025 (0.2744)	-0.2115 (0.2641)	-0.2740 (0.2939)
Distance	0.0014 (0.0024)	0.0020 (0.0024)	0.0012 (0.0026)	0.0035 (0.0022)	0.0039 (0.0022)	0.0035 (0.0023)
DNH	0.1298 (0.3588)	0.0845 (0.3644)	0.0529 (0.3838)	0.2461 (0.3338)	0.2409 (0.3383)	0.2353 (0.3480)
DVT	0.0970 (0.3937)	0.1003 (0.4027)	0.0804 (0.4300)	0.2068 (0.3643)	0.2407 (0.3717)	0.2898 (0.3819)
DME	0.4981 (0.6038)	0.3664 (0.5395)	0.5877 (0.6422)	0.4368 (0.5377)	0.3229 (0.4670)	0.4974 (0.5281)

DMA	0.1742 (0..3314)	0.1081 (0.3309)	0.1350 (0.3418)	0.1354 (0.3236)	0.0935 (0.3252)	0.1252 (0.3329)
Dependent Variable: I_1 (=1 if the ski area has snowmaking equipment)						
Intercept	-3.5499*** (0.4990)	-3.3330*** (0.6835)	-2.9445*** (0.8299)	-3.0658*** (0.5997)	-2.6848** (0.8463)	-2.2463* (1.0261)
Trails	0.0978*** (0.0159)	0.1161*** (0.0181)	0.1159*** (0.0201)			
Vertical	0.0003 (0.0003)	0.0005 (0.0003)	0.0008** (0.0003)			
Lifts	0.3790*** (0.0482)	0.3381*** (0.0527)	0.3299*** (0.0562)			
Size				0.0106*** (0.0006)	0.0115*** (0.0008)	0.0123*** (0.0009)
Snow	-2.4094*** (0.4213)			-1.8925*** (0.4504)		
TempWinter	0.0882*** (0.0146)			0.0997*** (0.0179)		
Av3Snow		-6.1675*** (0.8417)			-5.2973*** (0.8010)	
Av3TempWinter		0.0982*** (0.0191)			0.1045*** (0.0243)	
Av5Snow			-9.6781*** (1.1205)			-8.3485*** (1.0434)
Av5TempWinter			0.1021*** (0.0230)			0.1067*** (0.0294)
Elevation	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0008*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)
Lakes	0.1672*** (0.0207)	0.1561*** (0.0232)	0.1247*** (0.0254)	0.1151*** (0.0213)	0.1021*** (0.0238)	0.0785** (0.0266)
Dependent Variable: I_2 (=1 if the ski area operates in all four seasons)						
Intercept	0.7064 (0.6240)	3.2284*** (0.8223)	5.0941*** (0.9120)	0.1207 (0.5928)	2.0599** (0.7598)	3.4317*** (0.8315)
Trails	0.0248*** (0.0050)	0.0239*** (0.0053)	0.0244*** (0.0056)			
Vertical	0.0007*** (0.0002)	0.0006** (0.0002)	0.0005** (0.0002)			
Lifts	0.1234*** (0.0210)	0.1379*** (0.0226)	0.1438*** (0.0242)			
Size				0.0075*** (0.0003)	0.0073*** (0.0003)	0.0071*** (0.0003)

Snow	-0.6463 (0.4486)			-0.6060 (0.4312)		
TempWinter	-0.0815*** (0.0173)			-0.0602*** (0.0163)		
Av3Snow		-2.3452** (0.8290)			-2.1805** (0.7873)	
Av3TempWinter		-0.1508*** (0.0227)			-0.1123*** (0.0207)	
Av5Snow			-4.2844*** (0.9540)			-3.9056*** (0.9193)
Av5TempWinter			-0.1969*** (0.0254)			-0.1441*** (0.0229)
Distance	0.0145*** (0.0015)	0.0141*** (0.0015)	0.0147*** (0.0016)	0.0158*** (0.0019)	0.0157*** (0.0020)	0.0163*** (0.0021)
Industry	-0.0037 (0.0078)	0.0041 (0.0085)	0.0069 (0.0092)	-0.0049 (0.0078)	0.0015 (0.0084)	0.0049 (0.0091)
DNH	-0.4701** (0.1752)	-0.5988*** (0.1817)	-0.7645*** (0.1886)	-0.5841*** (0.1719)	-0.6673*** (0.1785)	-0.8088*** (0.1853)
DVT	-2.1676*** (0.1905)	-2.2570*** (0.2010)	-2.3768*** (0.2088)	-2.4108*** (0.1897)	-2.4672*** (0.1999)	-2.5682*** (0.2068)
DME	0.4869* (0.2320)	0.6074* (0.2892)	0.9415* (0.4061)	0.2728 (0.2315)	0.4186 (0.2831)	0.7220 (0.3723)
DMA	-0.4450**	-0.5271**	-0.6843***	-0.3951*	-0.4471**	-0.5986***
LSL	-1227.9187	-1088.0589	-967.3726	-1393.6524	-1232.4623	-1092.2939

Table 1.B10: The Estimated Reduced Form Models on Full Data Set Substituting Distance to Nearest Major Metropolitan Area for Distance to Boston

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)

Model	R1	R2	R3	R4	R5	R6
Intercept	-1.9355**	-2.7031***	-1.9971*	-2.3743***	-3.2980***	-2.6016**
	-0.823	-0.9471	-1.1181	-0.9088	-1.0386	-1.2968
Trails	-0.0309*	-0.0303	-0.0338			
	(0.0173)	(0.0187)	(0.0207)			
Vertical	0.0005	0.0004	0.0005			
	(0.0004)	(0.0004)	(0.0004)			
Lifts	-0.1440**	-0.1510**	-0.1708**			
	(0.0641)	(0.0703)	(0.0774)			
Size				-0.0028***	-0.0029***	-0.0029***
				(0.0007)	(0.0007)	(0.0008)
Snow	-2.0193**			-1.5501**		
	(0.8466)			(0.7782)		
TempWinter	0.0173			0.0201		
	(0.0211)			(0.0238)		
Av3Snow		-1.0981			-0.6393	
		(1.3361)			(1.2513)	
Av3TempWinter		0.0385			0.0450*	
		(0.0242)			(0.0272)	
Av5Snow			-1.9585			-1.0688
			(1.3200)			(1.3793)
Av5TempWinter			0.0247			0.0288
			(0.0295)			(0.0346)
Elevation	-0.0001	-0.0001	-0.0001	0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Lakes	0.0164	0.0172	0.0160	0.0205	0.0214	0.0214
	(0.0360)	(0.0364)	(0.0384)	(0.0347)	(0.0356)	(0.0372)
Industry	0.0189	0.0209	0.0209	0.0169	0.0181	0.0154
	(0.0129)	(0.0131)	(0.0147)	(0.0140)	(0.0145)	(0.0161)
Distance	0.0001	0.0009	0.0004	0.0020	0.0027	0.0024
	(0.0025)	(0.0024)	(0.0026)	(0.0021)	(0.0021)	(0.0022)
DNH	0.1929	0.1773	0.1541	0.3381	0.3449	0.3036
	(0.3581)	(0.3666)	(0.3850)	(0.3281)	(0.3319)	(0.3420)
DVT	0.3108	0.2888	0.3093	0.4939	0.5005	0.5017
	(0.3684)	(0.3836)	(0.3994)	(0.3412)	(0.3476)	(0.3548)

DME	0.4378 (0.5950)	0.3762 (0.5403)	0.6039 (0.6247)	0.3965 (0.5113)	0.2990 (0.4519)	0.4149 (0.4936)
DMA	0.1332 (0.3425)	0.0809 (0.3446)	0.1049 (0.3547)	0.0467 (0.3251)	0.0112 (0.3300)	0.0180 (0.3378)
LSL	-182.5343	-177.9067	-169.9813	-192.3582	-187.9118	-181.5893

Table 1.B11:
The Estimated Simple One-Equation Models
Starting Year: 1973

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**
Intercept	-1.1428 (0.8922)	-1.9932* (1.0361)	-1.4922 (1.1433)	-1.4107 (0.8952)	-2.3776** (1.0838)	-1.8908 (1.2096)
Trails	-0.0338* (0.0187)	-0.0304* (0.0183)	-0.0342* (0.0200)			
Vertical	0.0008** (0.0004)	0.0007** (0.0004)	0.0008** (0.0004)			
Lifts	-0.1168* (0.0681)	-0.1286* (0.0694)	-0.1282* (0.0730)			
Size				-0.0014** (0.0007)	-0.0014** (0.0007)	-0.0014** (0.0007)
Snow	-1.2253 (0.8399)			-1.1364 (0.7882)		
TempWinter	0.0029 (0.0223)			0.0067 (0.0220)		
Av3Snow		-2.2205 (1.4521)			-2.0122 (1.4100)	
Av3TempWinter		0.0303 (0.0255)			0.0371 (0.0266)	
Av5Snow			-1.8431 (1.4283)			-1.5571 (1.4820)
Av5TempWinter			0.0175 (0.0288)			0.0239 (0.0302)
Snowmaking	-0.2489 (0.1775)	-0.2962 (0.1817)	-0.3033 (0.1885)	-0.4529** (0.1764)	-0.5079*** (0.1796)	-0.5121*** (0.1852)
Four	-0.1836 (0.2844)	-0.1425 (0.2835)	-0.1711 (0.2921)	-0.2365 (0.2586)	-0.2041 (0.2584)	-0.2276 (0.2612)
Boston	-0.0013 (0.0021)	-0.0007 (0.0021)	-0.0009 (0.0022)	-0.0007 (0.0020)	-0.0001 (0.0021)	-0.0002 (0.0021)
DNH	0.0003 (0.3680)	0.1812 (0.3755)	0.0846 (0.3821)	0.1781 (0.3370)	0.339 (0.3400)	0.2527 (0.3440)
DVT	0.0988 (0.4379)	0.3097 (0.4542)	0.1954 (0.4679)	0.255 (0.3880)	0.4319 (0.4012)	0.3353 (0.4076)
DME	0.4386 (0.6189)	0.5634 (0.5832)	0.6103 (0.6421)	0.3767 (0.5309)	0.5024 (0.4746)	0.4918 (0.5198)
DMA	0.1417 (0.3472)	0.1743 (0.3467)	0.1548 (0.3521)	0.1315 (0.3400)	0.1351 (0.3361)	0.1274 (0.3431)

LSL	-173.3869	-171.8143	-169.9007	-181.3528	-179.5203	-178.3755

Table 1.B12:
The Estimated Structural Three-Equation Models
Starting Year: 1973

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)

Model	S1	S2	S3	S4	S5	S6
constant	-1.1559 (0.8910)	-1.9270* (1.0347)	-1.4287 (1.1433)	-1.4536 (0.8890)	-2.3427** (1.0721)	-1.8865 (1.2096)
Trails	-0.0339* (0.0185)	-0.0303* (0.0181)	-0.0351* (0.0196)			
Vertical	0.0009** (0.0004)	0.0008** (0.0004)	0.0009** (0.0004)			
Lifts	-0.0968 (0.0702)	-0.1079 (0.0705)	-0.1068 (0.0710)			
Size				-0.0009 (0.0007)	-0.0009 (0.0007)	-0.0014* (0.0008)
Snow	-1.2945 (0.8511)			-1.1709 (0.7878)		
TempWinter	0.0049 (0.0224)			0.0096 (0.0224)		
Av3Snow		-2.4240* (1.4770)			-2.1471 (1.4052)	
Av3TempWinter		0.0314 (0.0257)			0.0386 (0.0270)	
Av5Snow			-2.2248 (1.4572)			-1.5542 (1.4878)
Av5TempWinter			0.0210 (0.0293)			0.0237 (0.0309)
I_1 (Snowmaking)	-0.3756 (0.2436)	-0.4464* (0.2436)	-0.5150** (0.2501)	-0.5350** (0.2089)	-0.5973*** (0.2123)	-0.5093** (0.2156)
I_2 (FourSeason)	-0.3495 (0.3258)	-0.3117 (0.3342)	-0.2358 (0.3312)	-0.4571 (0.2942)	-0.4336 (0.3011)	-0.2448 (0.3050)
Boston	-0.0012 (0.0021)	-0.0007 (0.0022)	-0.0013 (0.0022)	-0.0003 (0.0020)	0.0004 (0.0021)	-0.0002 (0.0021)
DNH	-0.0073 (0.3683)	0.1593 (0.3750)	0.0554 (0.3852)	0.1705 (0.3361)	0.321 (0.3383)	0.2522 (0.3434)
DVT	0.0309 (0.4412)	0.2313 (0.4591)	0.1589 (0.4753)	0.1486 (0.3916)	0.3124 (0.4063)	0.3279 (0.4128)
DME	0.4895 (0.6223)	0.5879 (0.5846)	0.6314 (0.6428)	0.3979 (0.5347)	0.4941 (0.4732)	0.4927 (0.5203)

DMA	0.1268 (0.3477)	0.1481 (0.3466)	0.1242 (0.3528)	0.1165 (0.3400)	0.1154 (0.3350)	0.1272 (0.3422)
Dependent Variable: I_1 (=1 if the ski area has snowmaking equipment)						
Intercept	-3.7106*** (0.5927)	-3.3418*** (0.7409)	-2.9593*** (0.8294)	-3.0131*** (0.6887)	-2.5294** (0.9079)	-2.2532* (1.0291)
Trails	0.0933*** (0.0181)	0.1099*** (0.0195)	0.1163*** (0.0202)			
Vertical	0.0005 (0.0003)	0.0006* (0.0003)	0.0008** (0.0003)			
Lifts	0.3789*** (0.0516)	0.3454*** (0.0545)	0.3323*** (0.0563)			
Size				0.0089*** (0.0006)	0.0095*** (0.0006)	0.0100*** (0.0007)
Snow	-2.9929*** (0.6455)			-2.4853*** (0.5312)		
TempWinter	0.0938*** (0.0171)			0.1015*** (0.0204)		
Av3Snow		-6.8975*** (0.9651)			-6.2300*** (0.8613)	
Av3TempWinter		0.1015*** (0.0207)			0.1053*** (0.0260)	
Av5Snow			-9.6224*** (1.1201)			-8.1300*** (1.0306)
Av5TempWinter			0.1024*** (0.0230)			0.1071*** (0.0295)
Elevation	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0008*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)
Lakes	0.1443*** (0.0225)	0.1347*** (0.0242)	0.1228*** (0.0253)	0.1018*** (0.0232)	0.0859*** (0.0242)	0.0780** (0.0262)
Dependent Variable: I_2 (=1 if the ski area operates in all four seasons)						
Intercept	0.401 (0.6959)	2.9814*** (0.8989)	4.3936*** (0.9809)	0.0607 (0.6726)	1.9952* (0.8258)	2.9948** (0.9158)
Trails	0.0143** (0.0052)	0.0137** (0.0053)	0.0132* (0.0054)			
Vertical	0.0007*** (0.0002)	0.0006*** (0.0002)	0.0006*** (0.0002)			
Lifts	0.1367*** (0.0234)	0.1471*** (0.0244)	0.1556*** (0.0257)			
Size				0.0052*** (0.0002)	0.0052*** (0.0003)	0.0051*** (0.0003)

Snow	-1.2253** (0.5908)			-1.1917** (0.5672)		
TempWinter	-0.0749*** (0.0187)			-0.0561*** (0.0178)		
Av3Snow		-2.7085*** (0.8339)			-2.5717*** (0.7926)	
Av3TempWinter		-0.1429*** (0.0245)			-0.1054*** (0.0219)	
Av5Snow			-3.6249*** (0.9293)			-3.4480*** (0.8784)
Av5TempWinter			-0.1787*** (0.0267)			-0.1290*** (0.0244)
Boston	0.0055*** (0.0010)	0.0043*** (0.0010)	0.0037*** (0.0011)	0.0046*** (0.0009)	0.0037*** (0.0009)	0.0033*** (0.0010)
Industry	0.0183** (0.0082)	0.0235*** (0.0084)	0.0271*** (0.0088)	0.0224*** (0.0079)	0.0262*** (0.0080)	0.0300*** (0.0085)
DNH	-0.0322 (0.1786)	-0.2265 (0.1805)	-0.3551 (0.1826)	-0.1383 (0.1713)	-0.2679 (0.1716)	-0.3527** (0.1742)
DVT	-1.9515*** (0.1950)	-2.0912*** (0.1996)	-2.1700*** (0.2031)	-2.1026*** (0.1905)	-2.1849*** (0.1925)	-2.2354*** (0.1965)
DME	1.0669*** (0.2683)	1.0779*** (0.3048)	1.2195** (0.3803)	0.8468** (0.2696)	0.9063** (0.2939)	1.0572** (0.3486)
DMA	-0.3371 (0.1827)	-0.4522* (0.1834)	-0.5558** (0.1879)	-0.2774 (0.1704)	-0.3583* (0.1703)	-0.4438* (0.1733)
LSL	-1092.9766	-1055.9429	-989.4658	-1235.3689	-1192.8971	-1118.2980

Table 1.B13:
The Estimated Reduced Form Models
Starting Year: 1973

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)

Model	R1	R2	R3	R4	R5	R6
Intercept	-1.1727 (0.9891)	-2.0577* (1.1305)	-1.5199 (1.2838)	-1.5162 (1.0755)	-2.5627** (1.2590)	-2.0439 (1.4865)
Trails	-0.0357* (0.0196)	-0.0319 (0.0198)	-0.0368 (0.0215)			
Vertical	0.0006 (0.0004)	0.0005 (0.0004)	0.0006 (0.0004)			
Lifts	-0.1446** (0.0719)	-0.1649** (0.0755)	-0.1640** (0.0799)			
Size				-0.0027*** (0.0007)	-0.0028*** (0.0007)	-0.0029*** (0.0008)
Snow	-1.2747 (0.8688)			-1.0425 (0.7872)		
TempWinter	0.0006 (0.0247)			0.0015 (0.0269)		
Av3Snow		-2.3809 (1.4858)			-1.7598 (1.3957)	
Av3TempWinter		0.0284 (0.0277)			0.0327 (0.0309)	
Av5Snow			-2.0663 (1.3888)			-1.1579 (1.4822)
Av5TempWinter			0.0147 (0.0322)			0.0178 (0.0370)
Elevation	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
Lakes	0.0095 (0.0379)	0.0138 (0.0387)	0.0116 (0.0392)	0.0216 (0.0362)	0.0237 (0.0371)	0.0241 (0.0373)
Industry	0.0184 (0.0138)	0.0207 (0.0138)	0.0236 (0.0146)	0.0164 (0.0152)	0.0183 (0.0154)	0.0186 (0.0159)
Boston	-0.002 (0.0021)	-0.0013 (0.0022)	-0.0017 (0.0023)	-0.0017 (0.0019)	-0.001 (0.0020)	-0.0014 (0.0021)
DNH	0.0163 (0.3756)	0.2238 (0.3888)	0.1261 (0.3953)	0.2164 (0.3403)	0.3795 (0.3413)	0.2793 (0.3500)
DVT	0.235 (0.3894)	0.4695 (0.4061)	0.363 (0.4160)	0.4604 (0.3466)	0.6339 (0.3485)	0.5241 (0.3564)
DME	0.4577 (0.6254)	0.5983 (0.5988)	0.6957 (0.6565)	0.3284 (0.5105)	0.4434 (0.4538)	0.4246 (0.4930)

DMA	0.0672 (0.3610)	0.0968 (0.3677)	0.0726 (0.3724)	-0.0152 (0.3492)	-0.0221 (0.3506)	-0.0327 (0.3603)
LSL	-173.4138	-171.7673	-169.7282	-184.3427	-182.9276	-181.7918

Table 1.B14:
The Simple One-Equation Models
Starting Year: 1975

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**
Intercept	-1.6080**	-1.7240*	-0.8349	-1.8338**	-2.0017*	-1.0801
	(0.8012)	(0.9979)	(1.1475)	(0.8051)	(1.0286)	(1.1992)
Trails	-0.0317*	-0.0329*	-0.0351			
	(0.0167)	(0.0179)	(0.0201)			
Vertical	0.0007**	0.0007**	0.0008**			
	(0.0003)	(0.0003)	(0.0004)			
Lifts	-0.1099*	-0.1139*	-0.1272*			
	(0.0616)	(0.0659)	(0.0722)			
Size				-0.0015***	-0.0015***	-0.0014**
				(0.0007)	(0.0007)	(0.0007)
Snow	-1.8862***			-1.6596***		
	(0.8503)			(0.7973)		
TempWinter	0.0136			0.0168		
	(0.0191)			(0.0191)		
Av3Snow		-1.1040			-0.9773	
		(1.5188)			(1.5020)	
Av3TempWinter		0.0174			0.0216	
		(0.0240)			(0.0244)	
Av5Snow			-2.2507			-2.0474
			(1.4661)			(1.5118)
Av5TempWinter			0.0005			0.0032
			(0.0294)			(0.0303)
I_1 (Snowmaking)	-0.2512	-0.2643	-0.3061	-0.4489***	-0.4704***	-0.5106***
	(0.1698)	(0.1752)	(0.1892)	(0.1679)	(0.1743)	(0.1860)
I_2 (FourSeason)	-0.0816	-0.0616	-0.1845	-0.1450	-0.1274	-0.2391
	(0.2659)	(0.2686)	(0.2941)	(0.2461)	(0.2464)	(0.2637)
Boston	-0.0007	-0.0007	-0.0015	-0.0001	-0.0001	-0.0008
	(0.0020)	(0.0021)	(0.0022)	(0.0019)	(0.0020)	(0.0021)
DNH	0.1587	0.1004	0.0641	0.2994	0.2653	0.2186
	(0.3550)	(0.3627)	(0.3864)	(0.3280)	(0.3327)	(0.3475)
DVT	0.2381	0.1681	0.2001	0.3385	0.2997	0.3351
	(0.4260)	(0.4433)	(0.4779)	(0.3868)	(0.3971)	(0.4180)
DME	0.4716	0.4681	0.5849	0.4348	0.4141	0.4641
	(0.5935)	(0.6012)	(0.6735)	(0.5224)	(0.5287)	(0.5575)

DMA	0.1845 (0.3354)	0.1557 (0.3416)	0.1667 (0.3535)	0.154 (0.3280)	0.1459 (0.3321)	0.131 (0.3422)
LSL	-182.969	-190.293	-179.288	-169.724	-187.052	-178.320

Table 1.B15:
The Structural Three-Equation Models
Starting Year: 1975

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
Intercept	-1.3440 (0.8998)	-1.1264 (1.1158)	-0.7313 (1.2234)	-1.5177* (0.8830)	-1.3892 (1.1257)	-1.0248 (1.2339)
Trails	-0.0409** (0.0207)	-0.0386* (0.0203)	-0.0403* (0.0210)			
Vertical	0.0011*** (0.0004)	0.0010*** (0.0004)	0.0010** (0.0004)			
Lifts	-0.0847 (0.0649)	-0.0843 (0.0631)	-0.0900 (0.0655)			
Size				-0.0011 (0.0007)	-0.0010 (0.0007)	-0.0012 (0.0007)
Snow	-2.0346*** (0.9953)			-1.8079*** (0.9104)		
TempWinter	0.0168 (0.0230)			0.0152 (0.0226)		
Av3Snow		-3.0518** (1.6084)			-2.8743* (1.5513)	
Av3TempWinter		0.0165 (0.0285)			0.0174 (0.0286)	
Av5Snow			-3.2691** (1.5388)			-2.8730* (1.5459)
Av5TempWinter			0.0052 (0.0314)			0.0064 (0.0315)
I_1 (Snowmaking)	-0.4841** (0.2464)	-0.5797** (0.2369)	-0.5074** (0.2400)	-0.4998** (0.2267)	-0.5836*** (0.2219)	-0.5280** (0.2250)
I_2 (FourSeason)	-0.3439 (0.3294)	-0.3407 (0.3318)	-0.3009 (0.3365)	-0.3806 (0.2950)	-0.3608 (0.2993)	-0.3307 (0.2995)
Boston	-0.0016 (0.0023)	-0.0021 (0.0024)	-0.0023 (0.0024)	-0.0007 (0.0022)	-0.0011 (0.0023)	-0.0013 (0.0023)
DNH	0.0339 (0.3859)	0.0958 (0.3954)	0.0989 (0.4013)	0.2182 (0.3443)	0.2872 (0.3524)	0.2734 (0.3543)
DVT	0.0937 (0.4767)	0.2144 (0.4917)	0.2387 (0.5074)	0.2542 (0.4117)	0.3825 (0.4290)	0.3861 (0.4420)
DME	0.7524 (0.6885)	0.7866 (0.6859)	0.8022 (0.7180)	0.4944 (0.5521)	0.5665 (0.5649)	0.553 (0.5790)
DMA	0.095 (0.3670)	0.0974 (0.3687)	0.1113 (0.3722)	0.0775 (0.3515)	0.0717 (0.3497)	0.0758 (0.3517)

Dependent Variable: I_1 (=1 if the ski area has snowmaking equipment)						
Intercept	-3.9480*** (0.6469)	-3.7544*** (0.8321)	-3.0772*** (0.9188)	-3.2580*** (0.7511)	-3.0128** (1.0092)	-2.2450* (1.1259)
Trails	0.0899*** (0.0203)	0.1062*** (0.0215)	0.1120*** (0.0225)			
Vertical	0.0007** (0.0003)	0.0008** (0.0003)	0.0009*** (0.0003)			
Lifts	0.3674*** (0.0558)	0.3472*** (0.0579)	0.3423*** (0.0588)			
Size				0.0092*** (0.0007)	0.0098*** (0.0007)	0.0103*** (0.0007)
Snow	-3.2141*** (0.6698)			-2.7099*** (0.5547)		
TempWinter	0.1034*** (0.0191)			0.1123*** (0.0224)		
Av3Snow		-7.0021*** (1.0403)			-6.0044*** (0.9173)	
Av3TempWinter		0.1138*** (0.0236)			0.1201*** (0.0293)	
Av5Snow			-10.0757*** (1.2181)			-8.9423*** (1.1332)
Av5TempWinter			0.1076*** (0.0255)			0.1112*** (0.0322)
Elevation	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0008*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)	-0.0010*** (0.0001)
Lakes	0.1382*** (0.0244)	0.1208*** (0.0255)	0.1096*** (0.0264)	0.0997*** (0.0253)	0.0793*** (0.0262)	0.0657** (0.0274)
Dependent Variable: I_2 (=1 if the ski area operates in all four seasons)						
Intercept	0.3753 (0.7134)	2.9491*** (0.9387)	4.6075*** (1.0521)	0.0600 (0.6858)	1.9883** (0.8867)	3.1053*** (0.9907)
Trails	0.0125** (0.0054)	0.0126** (0.0055)	0.0127** (0.0056)			
Vertical	0.0007*** (0.0002)	0.0006*** (0.0002)	0.0006*** (0.0002)			
Lifts	0.1431*** (0.0252)	0.1527*** (0.0262)	0.1591*** (0.0267)			
Size				0.0051*** (0.0003)	0.0051*** (0.0003)	0.0051*** (0.0003)
Snow	-1.2517** (0.6205)			-1.2908** (0.5935)		

TempWinter	-0.0724*** (0.0192)			-0.0537** (0.0182)		
Av3Snow		-2.7344*** (0.8779)			-2.6497*** (0.8433)	
Av3TempWinter		-0.1403*** (0.0255)			-0.1030*** (0.0236)	
Av5Snow			-3.8360*** (1.0206)			-3.6017*** (0.9699)
Av5TempWinter			-0.1837*** (0.0286)			-0.1311*** (0.0263)
Industry	0.0215** (0.0090)	0.0266*** (0.0091)	0.0296*** (0.0093)	0.0264*** (0.0086)	0.0301*** (0.0088)	0.0321*** (0.0089)
Boston	0.0050*** (0.0010)	0.0039*** (0.0011)	0.0033*** (0.0011)	0.0042*** (0.0009)	0.0034*** (0.0010)	0.0030*** (0.0010)
DNH	-0.0511 (0.1845)	-0.2506 (0.1871)	-0.3581* (0.1878)	-0.1472 (0.1774)	-0.2881* (0.1793)	-0.3520** (0.1794)
DVT	-1.9280*** (0.2005)	-2.0803*** (0.2062)	-2.1566*** (0.2087)	-2.0953*** (0.1971)	-2.1955*** (0.2017)	-2.2325*** (0.2031)
DME	1.4003*** (0.3718)	1.2423*** (0.3778)	1.1530*** (0.3826)	1.1842*** (0.3739)	1.0660*** (0.3806)	1.0240*** (0.3820)
DMA	-0.3834** (0.1908)	-0.4967*** (0.1928)	-0.5706*** (0.1934)	-0.3163* (0.1776)	-0.4016** (0.1788)	-0.4551** (0.1783)
LSL	-983.9779	-955.0393	-935.2731	-1102.2808	-1073.9638	-1052.6689

Table 1.B16:
The Reduced Form Models
Starting Year: 1975

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
Intercept	-1.6483* (0.8967)	-1.7130 (1.1299)	-0.8367 (1.3458)	-1.9920** (0.9832)	-2.1294 (1.2944)	-1.1402 (1.6070)
Trails	-0.0323* (0.0177)	-0.0345* (0.0192)	-0.0382* (0.0213)			
Vertical	0.0005 (0.0004)	0.0005 (0.0004)	0.0006 (0.0004)			
Lifts	-0.1405** (0.0656)	-0.1459** (0.0715)	-0.1616** (0.0787)			
Size				-0.0028*** (0.0007)	-0.0030*** (0.0007)	-0.0030*** (0.0008)
Snow	-2.0400** (0.8576)			-1.6022** (0.7924)		
TempWinter	0.0115 (0.0217)			0.0131 (0.0240)		
Av3Snow		-1.4519 (1.4570)			-1.0320 (1.4040)	
Av3TempWinter		0.0142 (0.0278)			0.0168 (0.0321)	
Av5Snow			-2.4908 (1.4339)			-1.6888 (1.5388)
Av5TempWinter			-0.0031 (0.0344)			-0.0054 (0.0406)
Elevation	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)
Lakes	0.0131 (0.0363)	0.0127 (0.0368)	0.0079 (0.0390)	0.0232 (0.0347)	0.0244 (0.0353)	0.0215 (0.0369)
Boston	-0.0014 (0.0020)	-0.0015 (0.0021)	-0.0024 (0.0024)	-0.0011 (0.0018)	-0.0011 (0.0019)	-0.0021 (0.0021)
Industry	0.0206 (0.0128)	0.0245* (0.0129)	0.0249 (0.0146)	0.0200 (0.0140)	0.0223 (0.0143)	0.0197 (0.0158)
DNH	0.1768 (0.3622)	0.1243 (0.3777)	0.102 (0.4027)	0.3241 (0.3306)	0.2921 (0.3412)	0.2272 (0.3568)
DVT	0.3608 (0.3790)	0.2923 (0.4046)	0.3692 (0.4269)	0.515 (0.3424)	0.475 (0.3566)	0.5091 (0.3659)
DME	0.4666 (0.6047)	0.5107 (0.6101)	0.6871 (0.6897)	0.3864 (0.5089)	0.385 (0.5127)	0.4022 (0.5385)

DMA	0.1127 (0.3538)	0.0736 (0.3600)	0.0883 (0.3746)	0.0052 (0.3390)	-0.0158 (0.3453)	-0.0364 (0.3572)
LSL	-182.299	-178.298	-169.572	-192.447	-189.146	-181.641

Table 1.B17:
The Estimated Simple One-Equation Models
Starting Year: 1977

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**O1**	**O2**	**O3**	**O4**	**O5**	**O6**
Intercept	-1.2139 (0.9784)	-1.127 (1.2371)	-0.607 (1.3956)	-1.2834 (0.9812)	-1.1612 (1.2905)	-0.6827 (1.4757)
Trails	-0.0351 (0.0191)	-0.0327 (0.0189)	-0.0341 (0.0191)			
Vertical	0.0010* (0.0004)	0.0010* (0.0004)	0.0010* (0.0004)			
Lifts	-0.1045 (0.0643)	-0.1121 (0.0650)	-0.106 (0.0648)			
Size				-0.0008 (0.0007)	-0.0008 (0.0007)	-0.0007 (0.0007)
Snow	-2.0804 (1.1165)			-2.0226 (1.0426)		
TempWinter	0.0164 (0.0255)			0.015 (0.0250)		
Snowmaking	-0.4341* (0.2015)	-0.4808* (0.2056)	-0.4940* (0.2075)	-0.6112** (0.2112)	-0.6592** (0.2158)	-0.6649** (0.2175)
Four	-0.1671 (0.3056)	-0.141 (0.3099)	-0.1539 (0.3128)	-0.1986 (0.2707)	-0.1789 (0.2759)	-0.1888 (0.2771)
Boston	-0.0024 (0.0023)	-0.0029 (0.0024)	-0.0032 (0.0024)	-0.0021 (0.0021)	-0.0027 (0.0023)	-0.0029 (0.0023)
DNH	-0.0449 (0.3869)	0.0706 (0.3961)	0.0348 (0.4020)	0.1285 (0.3554)	0.2222 (0.3636)	0.1831 (0.3683)
DVT	0.0734 (0.4831)	0.272 (0.5011)	0.2314 (0.5140)	0.2451 (0.4222)	0.4262 (0.4403)	0.3818 (0.4555)
DME	. .	. .	. .	. .	. .	. .
DMA	0.0651 (0.3725)	0.0849 (0.3717)	0.0779 (0.3755)	0.0342 (0.3623)	0.0242 (0.3594)	0.015 (0.3629)
Av3Snow		-3.3043 (1.8267)			-3.368 (1.8016)	
Av3TempWinter		0.0197 (0.0323)			0.0182 (0.0329)	
Av5Snow			-3.5313* (1.6961)			-3.5313* (1.7788)
Av5TempWinter			0.0061 (0.0366)			0.0058 (0.0378)

LSL	-143.8191	-14.9183	-143.9464	-151.2016	-150.0964	-151.2380

Table 1.B18:
The Estimated Structural Three-Equation Models
Starting Year: 1977

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**
Intercept	-1.2802 (0.9674)	-1.2449 (1.2242)	-0.7537 (1.3735)	-1.2858 (0.9657)	-1.1985 (1.2527)	-0.7714 (1.4189)
Trails	-0.0368 (0.0190)	-0.0339 (0.0189)	-0.0354 (0.0192)			
Vertical	0.0009* (0.0004)	0.0009* (0.0004)	0.0009* (0.0004)			
Lifts	-0.1047 (0.0632)	-0.1187 (0.0644)	-0.1132 (0.0632)			
Size				-0.0015** (0.0007)	-0.0016** (0.0007)	-0.0015** (0.0007)
Snow	-2.0307 (1.0996)			-1.9103 (1.0389)		
TempWinter	0.0206 (0.0254)			0.0124 (0.0251)		
Av3Snow		-3.2182 (1.8126)			-3.0275 (1.7857)	
Av3TempWinter		0.0238 (0.0319)			0.0137 (0.0324)	
Av5Snow			-3.4227* (1.6987)			-3.0945 (1.7800)
Av5TempWinter			0.0106 (0.0358)			0.0021 (0.0364)
I_1 (Snowmaking)	-0.4995 (0.2587)	-0.4739 (0.2684)	-0.4825 (0.2551)	-0.4665 (0.2469)	-0.4476 (0.2584)	-0.4640 (0.2453)
I_2 (FourSeason)	0.1783 (0.3332)	0.2301 (0.3432)	0.2171 (0.3356)	0.1667 (0.3015)	0.2312 (0.3104)	0.2042 (0.3004)
Boston	-0.003 (0.0023)	-0.0034 (0.0024)	-0.0037 (0.0024)	-0.0025 (0.0021)	-0.003 (0.0022)	-0.0032 (0.0023)
DNH	-0.0618 (0.3833)	0.0746 (0.3928)	0.0478 (0.4016)	0.1456 (0.3508)	0.261 (0.3593)	0.2298 (0.3643)
DVT	0.1868 (0.4839)	0.4064 (0.5047)	0.372 (0.5196)	0.4077 (0.4198)	0.6188 (0.4403)	0.5661 (0.4528)
DME	-2.9587*** (0.4499)	-3.1596*** (0.4780)	-3.1274*** (0.5041)	-3.2773*** (0.3245)	-2.9206*** (0.3433)	- 3.1637*** (0.3604)

DMA	0.0578 (0.3688)	0.0925 (0.3690)	0.0936 (0.3736)	0.0469 (0.3583)	0.0617 (0.3570)	0.0611 (0.3596)
Dependent Variable: I_1 (=1 if the ski area has snowmaking equipment)						
Intercept	-4.2062*** (0.7208)	-4.4050*** (0.9724)	-3.8238*** (1.1064)	-3.7265*** (0.8263)	-3.8707*** (1.1736)	-3.2876* (1.3556)
Trails	0.0841*** (0.0232)	0.1024*** (0.0248)	0.1135*** (0.0256)			
Vertical	0.0009* (0.0004)	0.0010** (0.0004)	0.0011** (0.0004)			
Lifts	0.3550*** (0.0607)	0.3243*** (0.0631)	0.3184*** (0.0642)			
Size				0.0095*** (0.0008)	0.0102*** (0.0008)	0.0107*** (0.0008)
Snow	-2.8435*** (0.6898)			-2.2942*** (0.5729)		
TempWinter	0.1115*** (0.0216)			0.1271*** (0.0249)		
Av3Snow		-6.7209*** (1.1168)			-5.7663*** (0.9918)	
Av3TempWinter		0.1357*** (0.0284)			0.1482*** (0.0345)	
Av5Snow			-9.8890*** (1.3353)			-8.4749*** (1.2187)
Av5TempWinter			0.1311*** (0.0317)			0.1430*** (0.0396)
Elevation	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0009*** (0.0001)	-0.0011*** (0.0001)	-0.0011*** (0.0001)	-0.0010*** (0.0001)
Lakes	0.1331*** (0.0264)	0.1080*** (0.0282)	0.0957** (0.0295)	0.1010*** (0.0282)	0.0736* (0.0295)	0.0576 (0.0315)
Dependent Variable: I_2 (=1 if the ski area operates in all four seasons)						
Intercept	0.2024 (0.7331)	2.7652** (0.9491)	4.7363*** (1.0858)	-0.0835 (0.7120)	1.9515* (0.9210)	3.3706** (1.0483)
Trails	0.0116* (0.0057)	0.0116* (0.0058)	0.0119* (0.0059)			
Vertical	0.0007*** (0.0002)	0.0007*** (0.0002)	0.0006** (0.0002)			
Lifts	0.1422*** (0.0265)	0.1509*** (0.0273)	0.1581*** (0.0280)			
Size				0.0050*** (0.0003)	0.0049*** (0.0003)	0.0049*** (0.0003)

Snow	-1.4419* (0.6488)			-1.4687* (0.6313)		
TempWinter	-0.0670*** (0.0197)			-0.0494** (0.0188)		
Av3Snow		-3.3165*** (0.9279)			-3.2970*** (0.9024)	
Av3TempWinter		-0.1330*** (0.0259)			-0.0997*** (0.0246)	
Av5Snow			-4.5721*** (1.0925)			-4.3733*** (1.0518)
Av5TempWinter			-0.1844*** (0.0295)			-0.1357*** (0.0279)
Boston	0.0048*** (0.0011)	0.0037*** (0.0011)	0.0030** (0.0011)	0.0041*** (0.0010)	0.0032** (0.0010)	0.0027* (0.0010)
Industry	0.0276** (0.0097)	0.0339*** (0.0099)	0.0379*** (0.0101)	0.0337*** (0.0093)	0.0389*** (0.0095)	0.0415*** (0.0097)
DNH	-0.0132 (0.1922)	-0.1985 (0.1924)	-0.344 (0.1927)	-0.0947 (0.1856)	-0.2299 (0.1859)	-0.3302 (0.1866)
DVT	-1.8782*** (0.2066)	-2.0082*** (0.2113)	-2.1153*** (0.2140)	-2.0569*** (0.2052)	-2.1401*** (0.2085)	-2.2087*** (0.2107)
DME	4.1306*** (0.1889)	4.3539*** (0.1951)	4.2400*** (0.2013)	4.2401*** (0.1844)	3.9120*** (0.1904)	4.1118*** (0.1951)
DMA	-0.4188* (0.2012)	-0.5590** (0.2022)	-0.6579** (0.2032)	-0.3421 (0.1885)	-0.4615* (0.1894)	-0.5334** (0.1899)
LSL	-875.8015	-845.7513	-828.6231	-969.1502	-937.5721	-922.6628

Table 1.B19:
Estimated Reduced Form Models
Starting Year: 1977

Dependent Variable: Y_{it} (=1 if the ski area i is closed in year t)						
Model	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
Intercept	-1.1410 (1.0813)	-0.9281 (1.4443)	-0.3522 (1.6821)	-1.2285 (1.1651)	-0.9386 (1.6600)	-0.4611 (1.9762)
Trails	-0.0473* (0.0231)	-0.0471* (0.0236)	-0.0494* (0.0238)			
Vertical	0.0008 (0.0004)	0.0008 (0.0005)	0.0008 (0.0005)			
Lifts	-0.1234 (0.0728)	-0.1307 (0.0747)	-0.1234 (0.0744)			
Size				-0.0026** (0.0008)	-0.0028*** (0.0008)	-0.0027*** (0.0008)
Snow	-2.0506* (1.1238)			-1.8141** (0.9961)		
TempWinter	0.0085 (0.0283)			0.0029 (0.0302)		
Av3Snow		-3.3806* (1.7957)			-3.1460* (1.7109)	
Av3TempWinter		0.0075 (0.0379)			0.0006 (0.0430)	
Av5Snow			-3.5294** (1.6447)			-3.0036 (1.8040)
Av5TempWinter			-0.0082 (0.0443)			-0.0131 (0.0508)
Elevation	0.0001 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)	0.0002 (0.0002)
Lakes	-0.0244 (0.0457)	-0.0279 (0.0459)	-0.0302 (0.0448)	-0.0045 (0.0426)	-0.0078 (0.0428)	-0.0085 (0.0421)
Industry	0.0256 (0.0174)	0.0301 (0.0172)	0.0312 (0.0171)	0.0188 (0.0177)	0.0220 (0.0176)	0.0216 (0.0173)
Boston	-0.0036 (0.0022)	-0.0045 (0.0025)	-0.0048 (0.0025)	-0.0036 (0.0019)	-0.0044* (0.0020)	-0.0046* (0.0022)
DNH	-0.0155 (0.3941)	0.0977 (0.4192)	0.0446 (0.4257)	0.1582 (0.3508)	0.2188 (0.3651)	0.1544 (0.3741)
DVT	0.2069 (0.4244)	0.4023 (0.4516)	0.3468 (0.4591)	0.4182 (0.3685)	0.5569 (0.3794)	0.4798 (0.3907)
DME	. .	. .	. .	. .	. .	. .

DMA	0.0047 (0.3905)	0.0194 (0.4009)	0.0095 (0.4038)	-0.1182 (0.3668)	-0.1508 (0.3689)	-0.1571 (0.3745)
LSL	-144.6537	-143.6035	-144.5892	-155.1205	-154.0551	-155.1977

APPENDIX 1.C

ESTIMATED MARGINAL AND SIMULATED EFFECTS OF SIZE AND CLIMATE VARIABLES

The models presented in Appendix 1.B examine the connection between weather and ski area survival. To examine the impact of climate change on the ski industry further analysis was needed. In the next two tables, calculations of changes in probability of closure of a ski area were estimated under specific changes in the climatic and size factors. This analysis relates the study to the climate change issue as projected changes in the climatic factors are used to examine the fate of existing operational ski areas.

Table 1.C1 presents the marginal effects of the significant factors within the main and endogenous equations of the structural three equation model. The model used for this calculation was model S4 in Table 1.B2. Both the direct and overall marginal effects are calculated. Note that an incremental increase in the size of the resort results in a decrease in the probability of closure. Also note that the overall effect of a marginal increase in the size of the ski area has a larger impact than the direct effect alone. An increase in snowfall also results in a direct decrease of the probability of closure. There is no significant direct effect of an increase in temperature on the probability of closure. Finally, note that the overall effect of an increase in snowfall has a smaller absolute affect than the direct effect and that an increase in winter temperature decreases the probability of closure. These results are due to the fact that increased snowfall decreases the probability of owning snowmaking equipment, and increased temperature increases the probability of owning snowmaking equipment.

Table 1.C2 presents the direct and overall effects of larger changes in the climatic and size factors on the probability of closure of the ski area. The results in this table are similar to those in Table 1.C1.

Table 1.C1:
The Estimated Marginal Effects of Size and Climate Variables on the Probability of Closure of a Ski Area

Variable	Direct Effect	Overall Effect
Size	-0.000036	-0.000042
Snow (inch/day)	-0.039255	-0.037975
TempWinter (°F)	No significant direct effect	-0.000068

Note: The effects are computed based on the estimates of the structural model S4 in Table 1.B3.

Table 1.C2:
The Simulated Effects of Some Incremental Changes in Size and Climate Variables on the Probability of Closure of a Ski Area

Variable	Changes	Direct Effect on P(Y=1)	Overall Effect on P(Y=1)
Size	5.4 (2 trails, 0 lift, 0 ft)	-0.00019 [2.2%↓]	-0.00022 [2.5%↓]
	26.05 (5 trails, 1 lift, 50 ft)	-0.00089 [10.1%↓]	-0.00101 [11.4%↓]
	52.1 (10 trails, 2 lift, 100 ft)	-0.00171 [-19.3%↓]	-0.00188 [21.2%↓]
Snow	↓ 0.01 inch/day	0.00040 [4.5%↑]	0.00036 [4.1%↑]
	↓ 0.03 inch/day	0.00125 [14.1%↑]	0.00121 [13.6%↑]
	↓ 0.1 inch/day	0.00477 [53.9%↑]	0.00462 [52.1%↑]
TempWinter	↑ 0.5 °F	No significant direct effect	-0.00003 [0.4%↓]
	↑ 1 °F	No significant direct effect	-0.00006 [0.7%↓]
	↑ 3 °F	No significant direct effect	-0.00016 [-1.8%↓]
Snow & TempWinter	↓ 0.01 inch/day & ↑ 0.5 °F	0.00040 [4.5%↑]	0.00035 [4.0%↑]
	↓ 0.03 inch/day & ↑ 1 °F	0.00125 [14.1%↑]	0.00115 [12.9%↑]
	↓ 0.1 inch/day & ↑ 3 °F	0.00477 [53.9%↑]	0.00446 [50.4%↑]

Note: The effects, the changes in probability of closure, are computed based on the estimates of the structural model S4 in Table 1.B3. The estimated average probability of closure is 0.00886 that serves as the base probability for comparison. The effects are converted into percentage changes in the probability of closure, given in the square brackets.

APPENDIX 1.D

FIGURES

The tables in Appendix 1.A present calculations of the data to show that the data is representative of the true population. In this section, two figures are presented to reinforce the representativeness of the data and to show that the trends within the overall ski industry, which are discussed in the current literature, also occur in the data used for this study.

Figure D1 shows a mapping of the ski areas in the data set over time. Note that the ski areas are spread evenly throughout the region. Of the 78 ski areas in the data set which are in operation in 1970 only 31 survive by 2007.

Figure D2 shows the climatic averages within the data set over time. Each data point in the graphs represents the average winter temperature and snowfall at the ski areas in the data set. Note that the average winter temperature is rising slightly over time, while the average snowfall is decreasing slightly over time.

Figure 1.D1:
Mapping of Ski Areas in New England over Four Decades

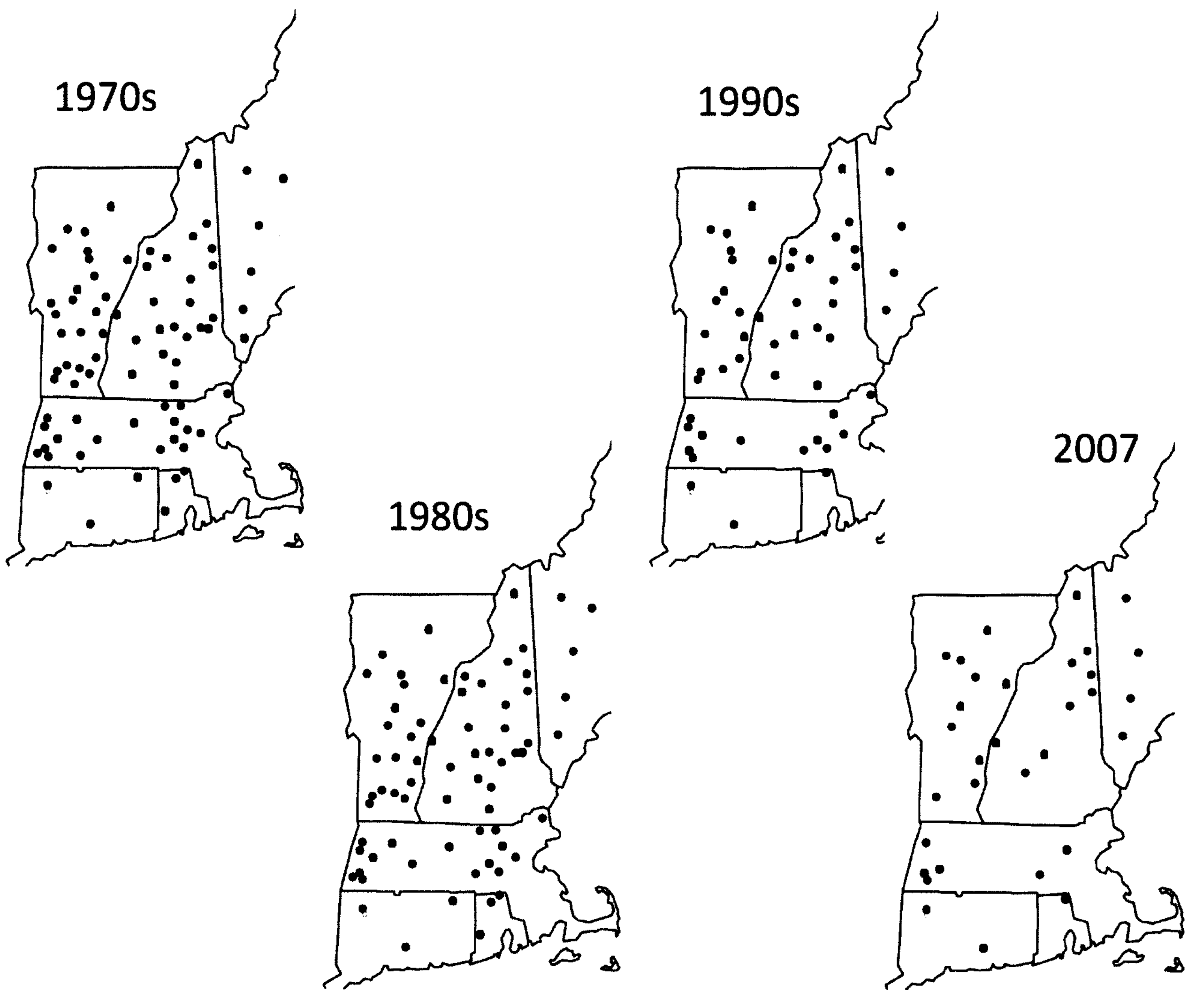
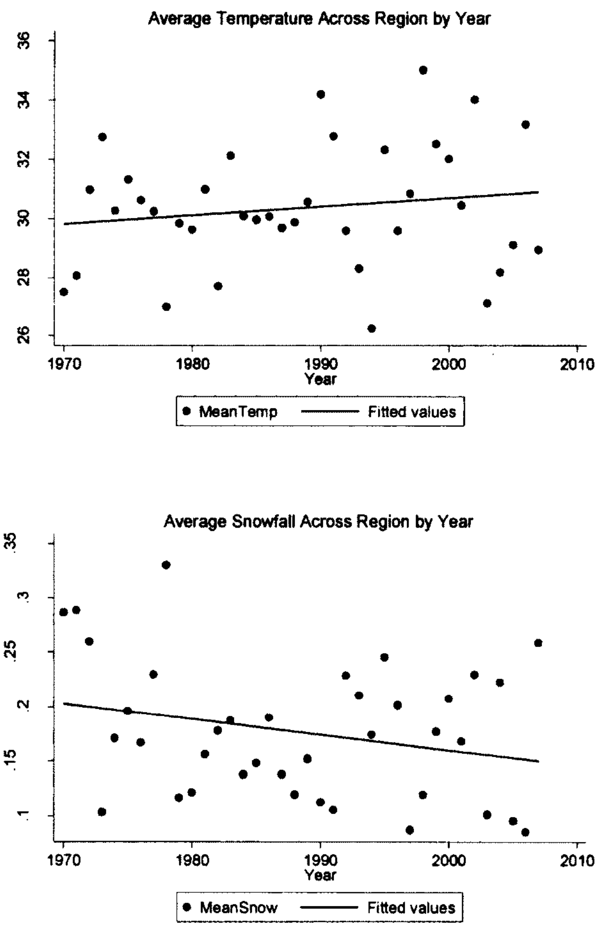


Figure 1.D2:
Average Winter Temperature and Snowfall in New England, 1970 – 2007



ESSAY 2:

ADAPTATION OF THE HEDONIC VALUATION METHOD: TO INVESTIGATE THE VALUE OF NON-MARKET CLIMATE RELATED GOODS IN IMPERFECTLY COMPETITIE MARKETS

2.1 Introduction

The two stage hedonic pricing method makes use of the idea that the price of a differentiated good reflects the value that consumers have for its underlying characteristics or attributes. This method has often been employed to estimate the value of goods or the characteristics of goods which are not sold in traditional markets. Some of the most common applications use the differentiation among the prices of homes, in the same housing market, to determine the value of environmental amenities, such as, air quality or water quality (Nelson (1978); Li and Brown (1980); Smith and Huang (1995); Michael et al (1996); Chattopadhyay (1999); Taylor and Smith (2000); and Nelson (2007)). The resulting consumer welfare calculations give this methodology the potential to influence environmental policy.

In the wake of global climate change, the hedonic pricing method could prove to be extremely useful in estimating individual benefits and losses from changing weather patterns in various industries. Industries vulnerable to climate change are diverse including the recreational, agricultural, tourism, healthcare, and fishing industries. The combinations of these and other vulnerable industries affect nearly, if not all, of the citizens of global economies.

The economic characteristics of these industries are similar. Each can be characterized as imperfectly competitive, selling differentiated goods with environmental, non-market attributes that change as the local climate changes. The firms in these markets often enjoy a portion of market power and are able to price their product above the marginal cost of producing the goods. Determining the value of these non-market goods and using them to calculate the changes in consumer welfare would give better measures of the total welfare loss which accrues in the economy as these environmental attributes change. However, the methods for valuing non-market goods in imperfectly competitive markets are cumbersome and warrant a large amount of data to tease out the true value of the characteristics from the marked up value imposed by the firms.

2.2 Purpose and Objectives

This paper explores the current extensions to the hedonic method which account for the influence of market power on the price of differentiated goods. And, more feasible methodologies for valuing non-market goods in markets characterized by firms with pricing power are introduced and discussed. By highlighting the importance of both the market structure as well as the underlying functional forms within the theoretical framework of the hedonic model, both Feenstra (1995) and Huang (2013) have advanced the applicability and reliability of the hedonic method. The empirical implementation of both Feenstra's (1995) and Huang's (2013) as well as other authors' methodologies are discussed. In particular, the methodology developed by Huang (2013) accounts for marked up prices and allows for direct estimation of the price-cost markup in the hedonic model. This paper uses Huang's (2013) approach and also derives another hedonic price function under a different set of underlying functional forms. By increasing the number of possible hedonic price functions, we are able to estimation hedonic price functions which are consistent with the theoretical foundations.

The purpose of this paper is to review the current hedonic methods and to show the increased estimation feasibility of the marginal values of the characteristics of the differentiated product under the newest methodological approaches. The empirical implementation of these theoretical models require less data than the current approaches, and one can easily estimate both the markup on the price, as well as, the marginal values of the attributes with one model.

Taking the methodology a bit further, a case study related to climate change is used to empirically estimate many different hedonic price models under a variety of alternative estimation techniques. The techniques include both parametric and semi-parametric variations. The flexibility of these different estimation approaches, along with the rigor of the newly proposed models, increases the applicability of the hedonic method by decreasing the limitations and over simplifications found in previous approaches.

2.3 History of the Hedonic Approach

Triplet (1986), argues that the relationship between product attributes and their prices was articulated and studied long before the conceptual framework of the hedonic method was formulated. Some researchers believe that Court (1914) was the first to make any meaningful contributions to the theory but others argue that authors such as Haas studied hedonic prices 15 years before Court published his study. However, the current methodology is credited mainly to the work of Lancaster (1966) and Rosen (1974).

Lancaster's (1966) and Rosen's (1974) hedonic models explain the theory driving the various prices of differentiated goods in single markets. Both rest on the unique feature in the utility theory which characterizes and distinguishes all hedonic price theoretical arguments; that utility is gained from the characteristics or the attributes of the good instead of the total good. The general utility function is shown in Equation (1) below.

$$U = U(z_1, \dots, z_n) \tag{1}$$

The vector of z's represent the characteristics of the differentiated product, each of which contribute individually to the consumer's utility.

The theoretical arguments of Lancaster (1966) and Rosen (1974) deviate from one another in the form of the price function, as well as, in the types of goods which are defined in the utility function. Lancaster's (1966) model assumes that consumers buy goods which are members of a larger group. These goods are assumed to be consumed in combinations which are determined by the consumers' preferences and budget constraints. This approach is well suited for studying consumer goods, such as clothing and food.

Rosen's (1974) model describes a spectrum of goods which vary in their attributes. These goods are assumed to be consumed discretely. Rosen's (1974) model also allows for non-linear relationships between the level of attributes and the price of the good. This assumption has proved to be more realistic than Lancaster's (1966) linearity assumption (Ekeland et al (2002); Ekeland, Heckman, and Nesheim (2004); Bayer et al (2004); and Bajari and Benkard (2005)). Rosen's (1974) approach is better suited for studying durable goods such as cars and homes. This is the model which is considered and critiqued in this analysis due to the fact that it has a greater potential for being used to examine the value of environmental goods which are purchased as attributes of the durable goods.

Rosen (1974) developed a two stage methodology. In the first stage, the researcher is able to uncover the marginal values or implicit prices of the attributes of interest by regressing the price of the good on its characteristics. This stage does not reveal the inverse demand functions for the attributes. Using more data on the individual consumers and sales, the researcher is able to impute the second stage of the methodology to uncover the inverse demand curves or the marginal willingness to pay functions. In this stage, the researcher uses the implicit prices of the characteristics, which they estimated in the first stage.

The critique and suggestion for increased realistic and reliable results relates only to Rosen's (1974) first stage. Therefore, in this paper, only the assumptions, conclusions, and critiques of this first stage are considered and the newest contributions to the methodology are discussed. The second stage can then be employed using the more accurate estimates from the first stage methodology to uncover reliable measures of the marginal willingness to pay functions for the individual characteristics.

2.4 Rosen's Methodology

Rosen's theoretical model, like all other hedonic methods, rests on the hypothesis that the value of differentiated goods is determined by their underlying characteristics which influence consumers' utility. And, that a price, $P(\boldsymbol{z})$, called the hedonic price function, is well-defined for every possible bundle of characteristics which the differentiated good can possess. Under Rosen's analysis, it is this price which guides both consumer and producer behavior.

Rosen begins by assuming that no one consumer or producer has the ability to alter the hedonic price function and therefore each treat, $P(\boldsymbol{z})$ as exogenous. In this analysis, $P(\boldsymbol{z})$ is fully determined by a few market clearing conditions. First, the amount of the differentiated good offered by producers at every possible bundle of characteristics must be equal to the amount of that goods with those characteristics which is demanded by consumers. Second, both the decisions of the consumers and those of the producers are results of their own utility and profit maximizing behavior. Finally, all possible optimal outcomes are feasible and Pareto efficient.

Under these market clearing conditions along with two more assumptions, the product markets implicitly reveal the hedonic price function, $P(\boldsymbol{z})$ which is the minimum price of any bundle of characteristics and which is also increasing in $\boldsymbol{z}$. The other two assumptions are, first, that all consumers perceive the characteristics of the differentiated products identically, and second, that there are enough differentiated products and characteristics such that the consumers and producers choices of the bundles of the characteristics are continuous.

Then using both consumer and producer maximizing behavior under these conditions, Rosen derives a hedonic price function which can be estimated and which reveals the value which consumers place on the underlying characteristics of the good.

Rosen's theoretical arguments begin with the conventional consumer's maximization problem. Altering Equation (1) slightly, the consumer's utility function is defined in Equation (2).

$$U = U(x, z_1, \dots, z_n) \tag{2}$$

Here x is the numeraire good and the vector of z's still represent the level of each of the characteristics of the differentiated product. The utility function is assumed to be strictly concave.

Allowing y to represent the income of the consumer, the budget constraint can be written in terms of the numeraire good, and is shown below in Equation (3).

$$x = y - P(\mathbf{z}), \tag{3}$$

Combining Equations (2) and (3), the consumers maximization problem becomes the following, in which the one choice variables are the characteristics of the goods.

$$Max \quad U\left(\left(y - P(\mathbf{z})\right), z_1, \dots, z_n\right) \tag{4}$$

The general first order conditions for the i^{th} characteristics is shown in Equation (5).

$$\partial P(\mathbf{z}) / \partial z_i = \frac{\partial U / \partial z_i}{\partial U / \partial x} \tag{5}$$

The first derivative of the hedonic price function with respect to the i^{th} characteristic, represents the implicit marginal value of the i^{th} characteristics, since this is equal to the marginal rate of substitution between the i^{th} characteristics and money.

This point is made more explicit by examining the consumer's bid function.

$$\theta(z_1, \dots z_n; u, y) \tag{6}$$

Here, $u = U\left((y - \theta), z_1, \dots, z_n\right)$, is the utility index, and therefore, Equation (6) is the expenditure the consumer is willing to give up for different bundles of $\mathbf{z}$, at a given u and y.

Because the hedonic price function, $P(\mathbf{z})$, is the minimum price of all bundles, utility is maximized when the following equality holds.

$$\theta(\mathbf{z}^*; u^*, y) = P(\mathbf{z}^*) \tag{7}$$

Again, $\partial\theta/_{\partial z_i} = \partial P(\boldsymbol{z}^*)/_{\partial z_i}$ showing again that the first derivative of the hedonic price function, at the optimal level of characteristics, gives the implicit marginal value of the i^{th} characteristic at a given level of utility and income since it is equal to the marginal rate of substitution between the i^{th} characteristic and money.

Producers maximize profits. Their profit function can be represented by,

$$\pi = M \cdot P(\boldsymbol{z}) - C(M, \boldsymbol{z}; \boldsymbol{\beta}), \tag{8}$$

where M is the number of units of the product that the firm produces and $C(M, \boldsymbol{z}; \boldsymbol{\beta})$ is the cost of producing the product which depends on the number of units, M, the level of characteristics, $\boldsymbol{z}$, and $\boldsymbol{\beta}$; a vector of technologies specific to each firm in the market. Firms choose both the number of products produced and the level of characteristics. From this optimization problem, the first order conditions, ensure that the marginal revenue from increasing a characteristic is equal to the per unit marginal cost.

$$\partial P(\boldsymbol{z})/_{\partial z_i} = \frac{\partial C(M,\boldsymbol{z};\boldsymbol{\beta})/_{\partial z_i}}{M} \quad . \tag{9}$$

And the level of output chosen by the firm will equate the price and the marginal cost of the output.

$$P(\boldsymbol{z}) = \partial C(M, \boldsymbol{z}; \boldsymbol{\beta})/_{\partial M} \tag{10}$$

Like the consumer's behavior, the firms actions can be thought of as offer curves and represented as,

$$\emptyset(\boldsymbol{z}, \bar{\pi}; \boldsymbol{\beta}), \tag{11}$$

which gives the unit price that a producer is willing to accept for their product with characteristic levels represented by $\mathbf{z}$, in which case they will make profits $\bar{\pi}$, given their technology, $\boldsymbol{\beta}$.

Equation (11) comes from eliminating M from the following equation to get (13).

$$\pi = M\emptyset - C(M, z_1, \dots, z_n) \tag{12}$$

$$\partial C(M,\mathbf{z})/_{\partial M} = \emptyset \tag{13}$$

From Equations (12) and (13), we have $\partial\emptyset/_{\partial z_i} = \dfrac{\partial C(M,\mathbf{z};\boldsymbol{\beta})/_{\partial z_i}}{M}$ and $\partial\emptyset/_{\partial\pi} = \frac{1}{M}$ and

therefore, $\partial\emptyset/_{\partial z_i} = \partial P(\mathbf{z})/_{\partial z_i}$ at the optimal choice of characteristics.

Again, $P(\mathbf{z})$ is the minimum price of the bundle $\mathbf{z}$ which means it is the maximum price which the firm can get for that product with characteristics $\mathbf{z}$, then the firm maximizes profit when the offer price subject is maximized and the constraint $P(\mathbf{z}) = \emptyset$ is met.

Producer's profits are maximized when $\emptyset(\mathbf{z}^*; \bar{\pi}^*, \boldsymbol{\beta}) = P(\mathbf{z}^*)$ and $\partial\emptyset/_{\partial z_i} = \partial P(\mathbf{z}^*)/_{\partial z_i}$. Therefore, the producers' equilibrium choices of characteristics, are those points at which the profit-characteristics offer curves are tangent to the characteristics-implicit price curve or the hedonic price function.

As firms and consumers start to interact, the prices of the differentiated products at each level of characteristics are determined in the market. See Figure 1 in Appendix

2.D.[1] All of the tangencies between all of the bid functions and offer curves at every possible combination of $\boldsymbol{z}$ define the hedonic price function represented by $P(\boldsymbol{z})$. This result indicates that the hedonic price function is made up of equilibrium points at which the bid functions of the consumers are tangent to the offer curves of the producers. Therefore, the partial derivatives of the hedonic price function for each characteristic represent both the marginal value and the marginal cost of that characteristic at a specific point.

To empirically implement Rosen's (1974) theoretical approach the researcher regresses the price of the differentiated product on the levels of its characteristics to uncover the marginal values using ordinary least squares (OLS) regression. In the simple case, in which the hedonic price function is estimated as a linear equation, the coefficients are simply the partial derivatives of the hedonic price function and thus will be exactly equal to the marginal values of these characteristics. In the case of other functional forms for the hedonic price function, only elementary calculations are needed to transform the coefficients into exact marginal values. The semi-log hedonic price specification is shown below.

$$ln\big(P(z)\big) = \beta_0 + \sum \beta_i z_i \tag{14}$$

$$\partial P(\boldsymbol{z})\big/_{\partial z_i} = P\beta_i \tag{15}$$

Here, β_i represent the estimated coefficients of each characteristic which enter into the model independently. Equation (15) shows that to obtain the marginal value estimates of

[1] This figure is a simplification of the hedonic price function since it is only shown in two dimensions. The first characteristic, z_1, is represented on the x-axis. However, it should be noted that this hedonic price function is actually a surface in l-dimensional space where l is the number of the characteristics of the differentiated good.

each characteristic when the hedonic price function is estimated using the semi-log form, the coefficients simply need to be multiplied by the observed price of the good.

2.5 Limitations of Rosen's Theoretical Arguments

To ensure the existence of the well-defined hedonic price function it was necessary for Rosen (1974) to make some assumptions in his theoretical arguments. First, Rosen (1974) argues that there must be a continuum of possible characteristic combinations for the differentiated product. With this assumption imposed, the choices of both the consumers and producers will be continuous. The second assumption is that there are enough buyers and sellers in the market so that no one consumer or one producer can affect the equilibrium price of the good. Therefore, both treat the prices as exogenous to their decisions making. Buyers and sellers base their decisions on maximizing behavior and equilibrium prices are determined so that the amount of the product produced at every price is equal to the amount of that product demanded by the consumers at that price. Finally, he assumes that all characteristics of the product are observed and equally perceived by each consumer and producer in the market.

By imposing these assumptions in combination, Rosen (1974) assumes that the goods which are being valued under his method are sold in purely competitive markets in which firms have no pricing power. However, when Rosen's (1974) methodology is applied to other markets in which firms do have the power to price products above marginal costs, the theoretical foundation becomes flawed and the resulting empirical estimations are biased. Rosen (1974) noted that this would occur in his original work saying that his methodology applied to the special case of perfect competition knowing that this was a common assumption when studying market behavior and product values.

However, since Rosen's work, many authors have tried to expand his theoretical foundation to allow for goods to be sold in markets where firms have some pricing power. In markets which are not purely competitive, the market power will vary among the specific firms. Each firm in the market will be able to increase the price of their product over its marginal value based on their individual market power. In doing so, the firms are misrepresenting the true value that consumers place on the product.

There are two ways in which the significant market power of the firms would influence the price of the differentiated good and bias the results of the estimated hedonic price equation proposed by Rosen (1974). The markup could simply be an incremental increase of the price. To capture this type of market power influence, Rosen's model does not need any theoretical alterations; however, the resulting estimated empirical model needs some slight adjustment.

Authors such as Li and Brown (1980) were some of the earliest authors to adapt Rosen's (1974) empirical model and include location and environmental attributes to capture some of the pricing power and artificial increase in price in specific markets. Li and Brown (1980) use the prices and characteristics of 781 homes in 15 suburbs of Boston, MA to estimate three separate hedonic price functions which highlight their critique of Rosen's initial method. The first estimated model omits location variables. The second model includes the location variables. And, the third is a variation on the functional form of the second and includes a simple interaction term. Each of the three models is estimated using OLS. In the second and third models the location variables are estimated as significant factors in the price function. Both the significance level and sign of other variables change from the first model to the second and third while variable's sign and significance do not change from the second to the third, indicating the importance of the location variables for consistent and unbiased estimation.

Although these authors do not contribute to the theoretical foundation, one might argue that their inclusion of location variables was an acknowledgement of the market power resulting from the differentiation of the houses in the same housing market. Market power often arises because of non-controllable physical variations within the market. Firms can begin to charge different prices not simply based on the attributes and quality of their product but because of some sort of physical or monetary barrier. The inclusion of location, environmental, and other physical and regional characteristics has now become standard in the modeling of hedonic prices throughout the literature.

In other cases, the markup could be an incremental increase, as well as, an additional increase based on the individual characteristics of the good. Simply adding explanatory variables to the estimated hedonic price function would no longer capture the entire influential markup in the price and delete the biased results among the coefficients of all other attributes. The entire theoretical foundation of the model would need to be altered to capture this type of price increase. In the next section, the critiques of Rosen's (1974) model are discussed to show how many authors have expanded Rosen's (1974) work to allow for settings where firms enjoy market power. Some authors such as Feenstra (1995) and Huang (2013) have been able to incorporate oligopolistic behavior directly into the hedonic pricing model while others such as Bajari and Benkard (2005) and Ekeland et al (2004) have adopted a set of less restrictive assumptions to allow for less competitive market settings. These theoretical arguments of the possible impact of market power on the price of the good are highlighted and the empirical implications of resulting estimates of the marginal values are examined.

2.6 Hedonic Method under Imperfect Competition

Theoretical critiques of Rosen's (1974) analysis came at a time when environmental awareness and debate grew stronger and researchers began to grasp the value of the hedonic method. The applications to which the hedonic method can be applied are often geared toward influencing environmental or other policy regulations. Based on the estimated marginal value of the environmental good of interest, policy makers can be informed about how much to spend on a specific agenda. To ensure that policy is influenced through more reliable results many authors have attempted to alter the theoretical arguments and empirical approaches to capture the market power of the firms and its influence on the overall price of the good.

Feenstra (1995) highlights the effect of market power by altering the firm's maximization problem in Rosen's (1974) approach to allow for firms to influence the price. The new maximization problem can be written in the following way.[2]

$$Max \quad \pi_j = \left(P_j - C_j(\mathbf{z}_j)\right) M_j \tag{16}$$

Here, Feenstra (1995) considers a market with J firms so that $j = 1 \ldots J$ represents the j^{th} firm. Both P_j and $\mathbf{z}_j$ are considered choice variables for the firm, where $\mathbf{z}_j$ is the product produced by the j^{th} firm and P_j is its corresponding price. Finally, M_j is the amount of $\mathbf{z}_j$ products demanded by consumers. To solve the maximization problem the functional

[2] For the remainder of the paper we use notation which is consistent with Rosen's initial model however, this notation may differ from that used in the papers which are discussed in this and the following sections.

forms of both P_j and M_j must be considered. Feenstra (1995) does not place a great deal of structure on the price function except to express it as a function of the quality adjusted price, denoted $q_j = \varphi_j(P_j, \mathbf{z}_j)$ and characteristics $\mathbf{z}_j$ so that the price can be written in the following way.

$$P_j = \rho_j(q_j, \mathbf{z}_j) \tag{17}$$

The quality adjusted price allows for the price of two varieties of the same differentiated good to be compared by accounting for the differences in the underlying attributes. Changes in the quality adjusted price reflect only the changes in the pure price which does not depend on the changes in the characteristics. The hedonic price in (17) is simply the inverse of the quality adjusted price.

The functional form of M comes from the indirect utility function of the representative consumer given as V.[3] By Roy's Identity,

$$M_j = -\left(\frac{\partial V/\partial P_j}{\partial V/\partial Y}\right) = -\left(\partial\varphi_j/\partial P_j\right)\left(\frac{\partial V/\partial\varphi_j}{\partial V/\partial Y}\right) = -\left(\partial\rho_j/\partial q_j\right)^{-1}\left(\frac{\partial V/\partial\varphi_j}{\partial V/\partial Y}\right). \tag{18}$$

In the above equation, Y represents total income of the consumers. And, the last equality holds since ρ_j and φ_j are inverses.

Equation (18) can be simplified by considering the following. Let $\{P_j^*, \mathbf{z}_j^*\}$ be the Nash equilibrium at which the firms' profits are maximized by the choice of both characteristics and prices. Then,

[3] Feenstra (1995) discusses the functional form of the utility function in great detail and also discusses whether the demand for each product variety can be consistent with the utility maximization of a representative consumer. If so then the demands can be computed by using Roy's Identity on the aggregate indirect utility function V. Feenstra (1995) argues that there is a broad class of such utility functions which allow for the maximization of the social utility function to be consistent with the maximization of the individual consumers. We leave this discussion to Feenstra and consider V to be in this broad class of utility functions.

$$q_j^* = \varphi_j(P_j^*, \mathbf{z}_j^*) \tag{19}$$

is the equilibrium quality adjusted price. If other choices $\{P_j', \mathbf{z}_j'\}$ are considered as possible equilibria, then they must also satisfy $P_j^* = \rho_j(q_j^*, \mathbf{z}_j^*)$. Feenstra (1995) argues that each of these possibilities, holds the quality adjusted price constant at q^*. Additionally, all of the arguments of the indirect utility function V will remain unaffected due to the characteristics of the function described in Feenstra (1995). Therefore, $\frac{\partial V / \partial \varphi_j}{\partial V / \partial Y}$ will be constant for all possibilities of $\{P_j', \mathbf{z}_j'\}$ satisfying, $P_j^* = \rho_j(q_j^*, \mathbf{z}_j^*)$. This assures that demand M_j is only changed if $\left(\partial \rho_j / \partial q_j \right)^{-1}$ changes and Equation (18) is reduced to $M_j = \left(\partial \rho_j / \partial q_j \right)^{-1}$.

The maximization problem in Equation (16) can now be simplified to the following.

$$Max \quad [\rho_j(q_j^*, \mathbf{z}_j) - C_j(\mathbf{z}_j)] \left(\partial \rho_j(q_j^*, \mathbf{z}_j) / \partial q_j \right)^{-1} \tag{20}$$

In this objective function, the only choice variables are the characteristics of the differentiated goods.

The general first order conditions resulting from this maximization problem take the following form.

$$\partial C_j(\mathbf{z}_j) / \partial z_{ji} = \partial \rho_j(q_j^*, \mathbf{z}_j) / \partial z_{ji} \left[1 - \left(\frac{P_j^* - C_j(z_j)}{P_j^*} \right) \left(\frac{1}{\sigma_{ji}} \right) \right] \tag{21}$$

Here, since $P_j^* = \rho_j(q_j^*, \mathbf{z}_j)$, the expression $\partial\rho_j(q_j^*, \mathbf{z}_j)/\partial z_{ji}$ represents the marginal value of the i^{th} characteristic. This is because this measures the increase in the price that consumers would be willing to spend for an additional increase in characteristic i, while keeping both the quality adjusted price and the utility level constant.

Feenstra's (1995) first order condition differs from Rosen's (1974) in that the marginal cost of the characteristic is no longer simply equal to its marginal value. Instead, the marginal cost is equal to the marginal value and also depends on the price-cost markup in the industry as well as the elasticity of substitution between the quality adjusted price and the characteristic, which is denoted as σ_{ji}. Therefore, Rosen's (1974) first order conditions are no longer applicable in situations in which firms have some form of market power.

To show the extent to which Rosen's (1974) theoretical foundation must be altered to study goods in imperfectly competitive markets, Feenstra (1995) derives the hedonic price function which results in imperfectly competitive markets. The resulting hedonic price function are not only affected by the market structure of the industry but also the functional forms of both the cost structures of the firms and the utility functions of the consumers. Feenstra (1995) argues that each of these components of the theoretical model must be empirically tested and addressed to ensure that a theoretically consistent hedonic price function is derived and estimated.

Feenstra (1995) starts with the firm's marginal cost equation. To show the significance of the underlying functional forms within the theoretical foundation on the resulting hedonic price function, Feenstra (1995) considers both the semi-log and linear marginal cost structures of the firms. To begin, allow the marginal costs to take the semi-log form as shown below where $c_j(\boldsymbol{z}_j)$ represents the marginal cost.

$$lnc_j(\boldsymbol{z}_j) = \alpha_j + \sum_{i=1}^{K} \beta_{ji} z_{ji} + v_j \tag{22}$$

Here α_j is the constant, while β_{ji} is the coefficient of each characteristic in the marginal cost function. The random term v_j captures all other factors which could influence the marginal cost. To get an expression which involves the price of the good, add $ln(P_j)$ to both sides of (22) and subtract $ln\left(c_j(\boldsymbol{z}_j)\right)$ to both sides of the (22) to obtain the following.

$$ln(P_j) = \alpha_j + \sum_{i=1}^{N} \beta_{ji} z_{ji} + ln(P_j) - ln\left(c_j(\boldsymbol{z}_j)\right) + v_j \tag{23}$$

Now let, $ln(P_j) - ln\left(c_j(\boldsymbol{z}_j)\right) = \frac{P_j}{c_j(\boldsymbol{z}_j)} - 1$, by the Taylor series expansion and substitute the first order condition into (23) to get the following.

$$ln(P_j) \approx \alpha_j + \sum_{i=1}^{K} \left(\frac{P_j}{c_j(\boldsymbol{z}_j)}\right) \gamma_{ji} z_{ji} + \left(\frac{P_j}{c_j(\boldsymbol{z}_j)} - 1\right)\left[1 - \sum_{i=1}^{K} \frac{\gamma_{ji} z_{ji}}{\sigma_{ji}}\right] + v_j \tag{24}$$

Here, $\gamma_{ji} = {\partial ln\rho_j}/{\partial z_{ji}}$ so that $P_j \gamma_{ji}$ now equals the marginal value of the characteristics.

Now if the quality adjusted prices take the following form,

$$\varphi_j(P_j, \boldsymbol{z}_j) = \omega_j \left[\frac{P_j - g_j(\boldsymbol{z}_j)}{h_j(\boldsymbol{z}_j)}\right] \tag{25}$$

where, $\omega_j > 0,\ \omega_j' > 0,\ h_j > 0,\ {\partial g_j}/{\partial z_{ji}} \geq 0$, and ${\partial h_j}/{\partial z_{ji}} \geq 0$, then the indirect utility function takes the specific functional from discussed in Feenstra (1995). This causes the third term in (24) to vanish leaving the hedonic price function to take the following form.

$$ln(P_j) \approx \alpha_j + \sum_{i=1}^{K} \left(\frac{P_j}{c_j(z_j)}\right) \gamma_{ji} z_{ji} + v_j \tag{26}$$

This hedonic price equation differs from Rosen's proposed hedonic price equation since the coefficients on the characteristics now consist of two components. The first is the price-cost ratio, the second is the marginal value of the characteristics expressed as an elasticity; $\gamma_{ji} = \frac{1}{\rho_j} \partial\rho_j \big/ \partial z_{ji}$. This result highlights the problem which arises when researcher estimate a hedonic price function in an industry in which the firms have pricing power and the marginal cost functions of the firms take the usual semi-log form. The estimated coefficients no longer represent the marginal value of the characteristic alone and it is very difficult to separate out the price-cost ratio. In industries in which firms have pricing power this ratio will be greater than 1 causing the inflation of the estimated coefficients in the model. This results in marginal value estimates which are larger than the actual value which consumers place on the attributes of the goods.

However, Feenstra also shows that under the linear marginal cost structure and the same quality adjusted price and utility function as above, the resulting hedonic price function take the following form.

$$P_j = \alpha_j + \sum_{i=1}^{K} \delta_{ji} z_{ji} + v_j \tag{27}$$

Here, $\delta_{ji} = \partial\rho_j \big/ \partial z_{ji}$, and the researcher can feel confident that the estimated coefficients on the characteristics will give unbiased estimates of their marginal values.

The main contribution of Feenstra's (1995) paper is to argue that hedonic models must first be specified correctly, and that the coefficients in the price equation under any specification other than the linear specification will no longer solely represent the marginal value of the characteristics when firms enjoy pricing power. The main problem is that the price-cost markup is unknown to the researcher and some authors have attempted to tease out this value using cumbersome econometric techniques.

Taylor and Smith (2000) follow up Feenstra's (1995) theoretical analysis with the first empirical estimation using his model and approach. To uncover the price-cost markup, when firms have market power, the authors use a residual demand approach. Once the market share has been estimated the authors are able to then evaluate the underlying marginal values of the product characteristics embedded in the estimated coefficients in the hedonic price equation. These authors apply Feenstra's (1995) model to beach rental properties on the Outer Banks of North Carolina. They obtain rental prices and property characteristic data for 4 management firms owning approximately 100 to 400 properties each. Their data was collected for the years from 1987 to 1992 using pricing brochures and data consisting of weekly occupancy rates were obtained directly from the property management firms in the study.

The authors argue that number of bedrooms, dishwasher capabilities, and carpeting all differentiate the rental properties, but since these characteristics can easily be duplicated to competing properties they should not lead to market power. However, there is one characteristic which they view as an amenity which cannot be duplicated. This feature is the rental's proximity to the ocean. This variable measures the ease with which renters would have access to the nearest beach. These authors argue that it is a type of market power. Therefore, they argue using Equation (26) above, that the coefficients in the hedonic price equation will incorrectly represent the marginal values of the rental characteristics.

To uncover the unbiased marginal values, the authors conduct a three step analysis. First, they estimate the hedonic price equation for each firm. Next, they estimate the residual demand model to tease out the amount of market power held by each firm in their analysis. Finally, the coefficients in the hedonic price equation are divided by estimated price-cost markups from the residual demand equations to get the marginal values of each characteristic.

Oktem and Huang (2011) take a similar approach to Taylor and Smith (2000) by examining how market power can affect how much of a tax burden firms are able to shift to their consumers. These authors use a case study of the vacation rental market in the New Hampshire Lakes Region. The authors examine 6 management firms. These firms range in size to owing slightly less than 40 to approximately 100 rental units.

By gathering information on the vacation rentals' prices, property attributes, and tax information, the authors were able to estimate a hedonic price function. Much like Taylor and Smith (2000) the authors then use a residual demand model approach to tease out the market power of each firm. In the end, they are able to show that the firms with the most market power were the ones which were most able to pass off their tax burden to the consumers. In doing so, they show that the artificially high price of these firms' products are not due to higher valuation from the consumers but the market power that the firms possess.

The functional forms of the hedonic price function and the other underlying functions in the theoretical models have been a topic of debate since the inception of the methodology dating back to Lancaster (1966) and Rosen (1974). Authors such as Bajari and Benkard (2005) wanted to redefine the underlying theory to broaden the applicability of the methodology and reliability of the resulting marginal value estimates. They do so by both altering the limiting assumptions made in Rosen's (1974) initial analysis, and by decreasing the reliance on the functional form of all functions in the theoretical model.

Their basic utility function varies slightly from Rosen's (1974),

$$U = (x, \mathbf{z}, \xi) \tag{28}$$

The new component, ξ represents an unobserved characteristic.

In an attempt to reduce the bias in the resulting implementation of their methodology, these authors place assumptions on the utility theory rather than the market structure to ensure the existence of the hedonic price function. The three assumptions which must hold for each consumer to ensure that a well-defined hedonic price function will exist are the following.

(1) The utility function is continuously differentiable and strictly increasing in x, and $\partial U / \partial x > 0$ with $x \in (0, y]$.

(2) The utility function is Lipschitz continuous in $\mathbf{z}$ and ξ.

(3) The utility function is increasing in ξ.

Through a vigorous proof which can be found in the Appendix of Bajari and Benkard (2005), the authors show that if the above three assumptions hold, then the following three conclusions will hold.

(1) If $x_j = x_{j'}$ and $\xi_j = \xi_{j'}$ then $P_{jt} = P_{j't}$

(2) If $x_j = x_{j'}$ and $\xi_j > \xi_{j'}$ then $P_{jt} > P_{j't}$

(3) $|P_{jt} - P_{j't}| \leq M(|x_j - x_{j'}| + |\xi_j - \xi_{j'}|)$ for some $M < \infty$.

These results show that a well-defined hedonic price function still exists without Rosen's (1974) limiting assumptions. Bajari and Benkard (2005) do not explicitly discuss the market structure or the price-cost markup of the firm. However, the expansion of the their theoretical arguments can allow the theory to be applied to market structures other than perfectly competitive, since the assumptions are only placed on the utility function.[4]

Using the suggestions of these authors, Bajari et al (2011) study the purchase of homes in California's Bay Area for the years 1990 to 2006. The purpose of this study is to estimate homebuyer's marginal willingness to pay for reductions in air pollutants. The main issue that the authors encounter in their analysis is that many of the characteristics of houses that consumers consider to be valuable are not observed by the researcher and therefore this market could not be considered perfectly competitive. To account for the unobservables the authors include lagged prices of the homes as future indicators of home prices and estimate the model and show that their approach could be extended to nonparametric estimation techniques (Rosenblatt, 1956; Parzen, 1962).

The conclusions of Bajari et al (2011) not only indicate the usefulness of more flexible estimation techniques but advance the theory of hedonic estimation by examining

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[4] Ekeland et al. (2004) argue that imposing a simplifying functional form on the hedonic price function limits its applicability, biases results, and depletes the available information embedded in the function. Using a theoretical argument rooted in wages and the labor market, these authors show that Rosen (1974) failed to acknowledge of the economic information embedded in the hedonic price function. Through utility and profit maximization of the two sides of the market, Ekeland et al (2004) derive a second order partial differential equation which describes the hedonic price function. Each point that satisfies the second order differential equation is a point where supply is equal to demand. Therefore, these must also be the points on the hedonic price function. This equation shows that at every point on the hedonic price function, the curvature is a weighted average of the average curvature of the consumer's utility function and the average curvature of the firm's profit function. Curvature is an important source of economic information which defines how the consumers and producers respond to changes in the prices and the level of attributes. Imposing arbitrary functional forms on the hedonic price function would ultimately deplete this information causing the estimated model to be bias due to the fact that relevant economic information was lost. Therefore, again these authors argue for the semi-parametric or nonparametric estimation of the hedonic price function.

Ekeland et al (2004) do not address market structure directly, however, their estimation technique allows for the model to be more flexible and capture more of the economic information embedded in the data. This paper is cited here to show that the semi-parametric and nonparametric techniques of estimating the hedonic price function have been widely adopted to decrease the biased results which result when too much structure is imposed on the model.

the relationship between home prices over time as they are able to also account for time-varying correlation in their model. These papers highlight the usefulness of examining the preference structure of the consumer's utility function to determine the marginal values of the characteristics of interest. For the purposes of this paper, their use of more flexible estimation techniques is highlighted. Although nonparametric estimation deletes the bias of choosing the functional form, it comes with tradeoffs. Mainly, the researchers need to increase, almost exponentially, the number of observations used with each increase in explanatory variables added to the price function, to ensure accuracy in their estimation. Often this level of data is not available.

Both Feenstra (1995) and Bajari and Benkard (2005) take the theoretical arguments of Rosen (1974) and adapt them to result in more reliable and realistic measures of the marginal values. Their suggestions along with Ekeland et al (2004) have given researchers more power to produce dependable results which could be used by policy makers. However, their methodologies are still limited. Feenstra's (1995) analysis depends on functional form choice and Bajari and Benkard (2005) had less restrictive but still often unrealistic assumptions. Finally, the residual demand and nonparametric approaches requires a large amount of data which is not always attainable.

Some authors have seen semi-parametric approaches as a compromise to the restrictions of the large data requirement needed for nonparametric estimation. In this approach, the data is still very influential in determining the estimated coefficients of the model. The functional form of the estimated model must still be specified; however the underlying distribution of the data, which is used to calculate the characteristics coefficients in the model, is determined by the specific data point in the dataset. One of the most common semi-parametric estimation approaches is the Generalized Method of Moments (GMM). This approach is discussed in depth later in this paper. Another preferred approach which reduces the bias from imposed functional form is the bootstrapping method in which the underlying distributions of the data are determined by repeated random sampling from the same dataset. (Powell, 2008)

In the next section, a methodology introduced by Huang (2013), which is heavily influenced by Feenstra's (1995) analysis, is discussed. Then, it is shown that this approach is more feasible than the approaches which followed Feenstra's (1995) initial paper. Finally, this study is the first to estimate a model using Huang's (2013) theoretical approach and extend this empirical study by combining the suggestions of Huang (2013) along with the semi-parametric techniques of Bajari and Benkard (2005) and Ekeland et al (2004). This new combined approach could prove to be very useful in estimating important values based on the market power in the industry but without imposing functional form restrictions which would also bias the results.

2.7 Extension to Feenstra's Model

Drawing from the Oktem and Huang (2011) results, Huang (2013) develops a methodology to incorporate imperfect competition and market power into the underlying theory of the hedonic approach. The current methodologies for accounting for imperfect competition in the hedonic pricing method are cumbersome and require a large amount of data. This methodology is much more feasibly implemented. This analysis, follows Feenstra (1995) closely and shows how the price-cost markup in the market and therefore, in the hedonic price equation, can be estimated using a theoretical approach which considers the additional costs which are paid by every firm in imperfectly competitive markets.

Imperfectly competitive markets are often characterized by the additional costs that firms must pay. As shown in Oktem and Huang (2011), the firms with the most market power are able to pass this additional cost off to consumers by increasing the price their product over the marginal cost. Incorporating this into the hedonic theoretical framework, Huang (2013) assumes that each firm in the market is subject to a tax, T_j. This tax is paid on every unit of sale that the firm makes.

The representative firm's profit maximization problem can be written in the following way.

$$Max\left[(1 - T_j)P_j - C_j(\mathbf{z}_j)\right]M_j \tag{29}$$

Following Feenstra, this objective function can be written in the following way.

$$Max\ \left[(1 - T_j)\rho_j(q_j^*, \mathbf{z}_j) - C_j(\mathbf{z}_j)\right]\left(\frac{\partial \rho_j(q_j^*, \mathbf{z}_j)}{\partial q_j}\right)^{-1} \tag{30}$$

The first order conditions which follow from this maximization problem take the following form.

$$\partial C_j(\mathbf{z}_j)\Big/\partial z_{ji} = (1 - T_j)\left(\partial \rho_j(q_j^*, \mathbf{z}_j)\Big/\partial z_{ji}\right)\left[1 - \left(\frac{(1-T_j)P_j - C_j(\mathbf{z}_j)}{(1-T_j)P_j}\right)\left(\frac{1}{\sigma_{ji}}\right)\right] \tag{31}$$

This result is very similar to Feenstra's except that the tax is still present in the first order condition. The tax decreases the amount of the price that the producer actually gets to keep from the sale.

From here, Huang (2013) follows the same steps as Feenstra to derive the hedonic price function from the marginal cost function and the quality adjusted price and utility function. The functional forms used in Huang's (2013) analysis are exactly equal to those used in Feenstra's derivation. Under the semi-log marginal cost structure, the hedonic price function which is derived takes the following form.

$$ln(P_j) = \alpha + \sum_{i=1}^{K} \frac{P_j}{c_j} \gamma_{ji} z_{ji} - \sum_{i=1}^{K} \frac{P_j}{c} \gamma_{ji} z_{ji} T_j + \frac{P_j}{c_j} T_j + v_j \tag{32}$$

Equation (32) differs from Feenstra's derived hedonic price equation under the semi-log marginal cost structure due to the fact that in Huang's (2013) analysis, firms are subject to a tax. For this reason, this hedonic price function includes two more terms, the third term on the right hand side of the equation includes the interactions of the tax and all of the characteristics of the good, and the fourth term includes the tax alone. This shows that if the firms are subject to a tax, Feenstra's hedonic price function is misspecified.

Beyond, the more rigorous theoretical derivation of the hedonic price function, Huang's (2013) analysis has an important empirical result. The price cost ratio which was embedded in the coefficients in Feenstra's model and now in Huang's is also the coefficient on the tax variable. Therefore, if the researcher estimates a model in which the price of the good is regressed on its characteristics, the tax, and the interaction of the tax and characteristic and the coefficient of each characteristic can be divided by the coefficient of the tax variable to uncover its unbiased marginal value.

Like Feenstra's (1995) analysis, this result is the product of functional form specification. To highlight this point further, this paper takes Huang's analysis a step further to show what the correct specification of the hedonic price equation would be under the linear marginal cost structure but when firms are still subject to a tax.

The cost structure for the specific firm would take the following form, which is exactly the same in Feenstra's analysis except for the tax's influence on the price.

$$\left(1 - T_j\right)P_j = \alpha + \sum_{i=1}^{K} \beta_i \boldsymbol{z}_{ji} + \left(1 - T_j\right)P_j - C_j\left(\boldsymbol{z}_j\right) + v_j \tag{33}$$

Plugging the first order condition in to the cost function and simplifying this becomes the following.

$$(1-T_j)P_j = \alpha + \sum_{i=1}^{K}\left((1-T_j)\delta_{ji}\left[1-\left(\frac{(1-T_j)P_j - C_j(\mathbf{z}_j)}{(1-T_j)P_j}\right)\left(\frac{1}{\sigma_{ji}}\right)\right]z_{ji}\right) + (1-T_j)P_j - C_j(\mathbf{z}_j) + v_j \tag{34}$$

Simplifying this equation and making use of Feenstra's Proposition 8, this hedonic price function gets simplified to the following function.

$$(1-T_j)P_j = \alpha + \sum_{i=1}^{K}(1-T_j)\delta_{ji}z_{ji} + v_j \tag{35}$$

Again, we see a similar result to Feenstra with a slight difference in specification due to the tax factor. Overall, however, the major result is the same. When the marginal cost functions are linear, the hedonic price function is also linear. Here, the coefficients are not just the marginal value of the characteristics, instead they are the marginal values times 1 minus the tax factor. Therefore, to uncover the marginal value of each characteristic the coefficient would simply need to be divided by 1 minus the tax.

The main contribution of Huang's (2013) work is that under this most general and often very realistic specification of the model, the marginal values of the characteristics and the price-cost markup can be recovered in one simple model. This paper extends Huang's (2013) work by deriving the hedonic price function under other common cost and utility functions. By extending the work in this way, the analysis in this paper helps to advance the applicability of the hedonic method by allowing different hedonic price equations to be estimated based on the aspects of the specific market being studied. These models are each estimated under two different estimation techniques to show how more flexible techniques can be used to examine these models are provide more reliable estimates of the marginal values of interest.

In the following sections, the price of ski lift tickets is examined using the previously discussed hedonic methodologies and empirical implementations. This study concludes with a model which combines the traditional and newest theoretical models and the semi-parametric estimation technique. This case study shows that estimates of the marginal values of the climate related characteristics of the ski areas will vary widely based on the assumptions embedded in the theoretical models. Therefore, the empirical models estimated in this study are carefully tested to see which model most accurately represents the conditions in the market and which will give the more reliable estimates of the marginal values. Due to the fact that the ski industry has been relying more on artificial snow as the climate changes, this empirical exercise has implications for the sustainability of the overall ski industry as natural snowfall continues to decrease throughout the country.

2.8 The US Ski Industry Data

The ski industry lends itself well as a case due to the fact that there are a large number of ski areas across the United States all selling their lift tickets at different prices. Each lift ticket sold provides the skier with a unique ski experience based on the specific amenities of the particular mountain. Therefore, the lift ticket is treated as a differentiated good and it is argued that the price of the lift ticket should reflect the values that consumers place on each aspect of the mountain. Since this study relates to the issue of climate change, the mountain characteristic of most interest is the average yearly natural snowfall.

Based on the available data, 344 ski areas are included in the data set, which were operational during the 2011-2012 ski season. These ski areas represent nearly 80 percent of all operational ski areas during the time of the study. The ski areas in the data cover the scope of the United States ranging from the West Coast to the Northeast, down to the Southeast across to the Mid-Atlantic, and through the Midwest and the Rocky Mountains.[5] The data include all types of ski areas from small rope tow only areas to mountains with over 100 trails and nearly 5000 foot vertical drops. This diversification in the data set gives the analysis a large amount of power.

To ensure that the data used in this analysis is representative of all ski areas throughout the United States the averages of a few of the key characteristics of all of the ski areas in the U.S. are compared to the averages of the ski areas used in this analysis. These statistics can be found in Tables 2.A1 and 2.A2. Note that the ski areas used in this analysis closely represent the true population of all operational ski areas. Also note that the number of ski areas per region in the data set is consistent with the true distribution of ski areas throughout the country.

The ski industry in the U.S. is also an interesting case study because it has been argued to be an imperfectly competitive market since each ski area sells a lift ticket which is slightly different from all other lift tickets and many argue that firms have some power to price their lift ticket above its marginal value, based on their individual market power. This discuss of market power in the industry has been fueled by two main sources. First, is the fact that ski areas throughout the U.S. have been shutting down

[5] This study treats the whole US ski industry as one market. The extent of the market is often a topic of discussion in hedonic studies due to the fact that the underlying assumptions in the model suggest that certain values are held constant over the whole market. Sources such as www.nsaa.org suggest that many ski areas draw a large percentage of their skiers from out of state. This data supports the assumption that the US ski industry can be treated as one market.

causing the overall number of firms to decrease (NewEnglandLostSkiAreasProject.org). As the number of firms decrease, competition also decreases. Also, this assumption is supported by the evidence that lift ticket prices in the US have increased about 2.5 times more than inflation over the past 30 years (www.NewEnglandSkiHistory.com). However, this figure does not include the costs of the ski areas. With the ever increasing technological push to stay one step ahead of competitors and the increased reliability on artificial snow and other weather supplementing activities the cost of running a ski areas has increased as well. The fact is, that the existence and the possible influence of any market power in the industry have not been examined empirically in the literature. This empirical exercise will not indicate the level of market power of the firms in the industry; however, more importantly, it will show that researchers can still estimate unbiased marginal value estimates through empirical tests of rigorous theoretical models instead of ignoring influential market structure and other important cost related factors in the market.

This case study treats the lift ticket as the differentiated good. Since some ski areas charge different prices during different times of the day or season, a lift ticket price for the dependent variable which was consistent across all areas was needed. Since each area in the data set was open on the weekend and sold an 8 hour pass each weekend day, the full-day weekend lift ticket price was chosen for the dependent variable and is called Price.[6] Each ski area lists the price of a full-day weekend lift ticket on its website and this is where each dependent variable was collected from.

[6] Other options for the dependent variable would be half-day passes or weekday passes as well as peak period passes, however, not all ski areas have these different prices.

The explanatory variables in the data set are the attributes of the mountain that influence the price of the lift ticket. Table 2.A3 lists the summary statistics of all of these variables, while Table 2.B1 gives the hypothesized sign of their influence on the price of a lift ticket. Among the explanatory variables are factors which describe the terrain and technology of the mountain. These include the number of trails; Trails, the difficulty of the trails; Beginner, Moderate, and Advanced, the vertical drop of the mountain; Vertical, the skiable area; Area, and the number of ski lifts; Lifts. It is assumed that skiers will pay more for diverse and challenging mountains which have also invested in newer technologies to ensure that skiers get the most out of their day.

Location variables are also included. These variables act as the first step in controlling for differences across the market in terms of market power. Distance measures the distance to the nearest metropolitan area. Metropolitan areas have the largest populations and also have airports and other travel facilities that help people get to the areas much easier. It is hypothesized that ski areas closer to metropolitan areas should be able to charge higher prices. Also, region dummy variable are included in the data. Including these variables in the estimations helps to ensure that fixed effects, or patterns in the data which could result from unobserved differences across the regions, are accounted for. These might include private interference such as local budgets for ski resort expenditures on environmentally beneficial projects. They could also include naturally occurring attributes such as scenic pleasure which could effects the demand differently in each region.

The data set also includes two climate related variables. The variable of interest is the annual snowfall in the region; Snowfall, and it is hypothesized that ski areas with more natural snow will be able to charge more for their lift ticket. Information on the snowmaking capabilities of the ski area is also included. The Snowmaking variable measures the percentage of the total skiable area that can be covered with artificial snow. Snowmaking supplements natural snow with artificial snow. It has been widely hypothesized, among the industry experts, that skiers prefer natural snow over artificial snow, however, it is unknown if any academic studies have investigated this claim.

Finally, two tax variables are included in the analysis. The two taxes in the data set are the state sales tax and the excise tax. Of course, ski areas will pay other taxes; however, only the taxes which will directly influence the price of the lift ticket are included. Taxes such as property taxes are considered sunk costs for the firms and are not included in the data set.

2.9 Econometric Issues and Data Construction

The nature of the data and the underlying theoretical model present a few econometric issues which must be resolved before the influence of the explanatory variables on the price of the ski lift tickets can be empirically examined. First, as with most hedonic applications, many of the variables suffer from multicollinearity. Some authors feel that this is a necessary limitation of the nature of the data and simply include all explanatory variables in their model. However, the issue of multicollinearity can be addressed easily if the variable of interest is not one of the collinear covariates. In this study, Snowfall is not correlated with any of the other independent variables and principle components analysis is used to remedy the issue of multicollinearity among a specific group of explanatory variables.

The variables which describe the characteristics of the mountain are all highly correlated. Mountains which are taller generally have more trails and need more lifts to get people to the trails. Also, as the number of trails increases the skiable acreage will also increase. Therefore, principle components analysis is used to combine the characteristic variables into one overall variable which ultimately describes the size of the mountain. In addition, many of these variable are much larger than the dependent variable. Therefore, they are also scaled to aid in reporting the coefficients for the overall Size variable. The equation for this Size variable is given below.

$$Size = 2.1 * Trails/100 + .75 * Vertical/1000 + .50 * Lifts + 1.79 * Area/1000 \quad (36)$$

A different econometric concern relates to the factors describing the difficulty of the mountains. There is no uniform documentation which governs ski areas on how to describe the difficulty of the trails at their mountain. One mountain might categorize a trail as beginner while another mountain would categorize the same trail as intermediate at their ski area. The reason for this is because the difficulty of the trails is often measured in relation to the other trails at the same mountain but not across mountains. Therefore, to try and eradicate some of the inconsistency across ski areas only the percentage of advanced ski trails is included. Advanced is chosen because these are often the trails which have the least amount of discretionary consideration among the ski areas. It is easier to distinguish a difficult trail from an intermediate or easy trail than it is to distinguish between an intermediate and easy trail.

Also, the tax variables are combined into one overall tax variable. In this case, since the tax is levied on the individual lift tickets, the sales tax and the excise tax are added together to get the overall tax used in the analysis. The new tax variable is shown below.

$$Tax = SalesTax + TourismExciseTax \tag{37}$$

Another issue which must be addressed before estimation is the endogeneity of one of the explanatory variables. The amount of the area which can be covered by snowmaking is a conscience decision of investment made by the owner of the ski area to supplement the inadequate amount of natural snowfall. The snowmaking capability of the resort is directly influenced by the amount of snowfall that the resort naturally receives and other uncontrollable factors. Therefore, the issue of endogeneity is addressed by first determining the components which influence the amount of snowmaking that each resort has.

An instrumental variable approach is used to identify the Snowmaking equation which is shown below.

$$\widehat{Snowmaking} = \gamma_0 + \gamma_1 Snowfall + \gamma_2 Elevation + \gamma_3 Size + \gamma_4 Area \tag{38}$$

Elevation, which is the base elevation measured in feet at the ski area, is used as the instrument for this analysis. Snowmaking will likely, also be influenced by the natural snowfall as was mentioned above, as well as, the size of the resort. In addition, since the variable is measured as a percentage of overall area, the Area variable is included separately in this snowmaking equation.[7]

Finally, the functional form of the hedonic price models which will be estimated must be considered. As noted by the previous authors, (Feenstra, (1995); Huang, (2013), Bajari and Benkard, (2005); and Ekeland et al, (2004)) the functional form of the hedonic price model will greatly influence the meaning of the coefficients in the model.

[7] Estimation results of models in which the Snowmaking variable is treated as an exogenous variable are also presented in the Appendix in Tables 2.B6 and 2.B7. Note that the results are similar to the other estimated models. However, there is no significant evidence of market power in these models.

The functional form of the model is tested using the Box Cox regression method. This test, along with others such as the Link Test, indicates that the linear functional form most closely represents the conditions in the market. However, the semi-log models are also estimated for comparison and to point out the variance which can occur with the marginal value estimates under misspecified hedonic price models.

2.10 Hedonic Price Models

With the resolution of these few econometric issues the hedonic price models can be presented. Three different models are run, each of which represents a phase in the evolution of the hedonic method. The first model is the base model. This model only includes the characteristics of the ski area as explanatory variables.

Model 1:

$$Price = \beta_0 + \beta_1 Size_i + \beta_2 Advanced_i + \beta_3 Snowfall_i + \beta_4 \widehat{Snowmaking_i}$$

$$\widehat{Snowmaking_i} = \gamma_0 + \gamma_1 Elevation_i + \gamma_2 Snowfall_i + \gamma_3 Area_i + \gamma_4 Size_i \qquad (39)$$

In each model, the Snowmaking equation is estimated first using the instrumental variable, Elevation, and the predicted values of the Snowmaking variable are then used as the explanatory variables in the main hedonic price equation.

The second model represents the most elementary method for accounting for market power. This model includes both the characteristics of the mountain and the location variables, and is again estimated using two stage least squares.

Model 2:

$$Price = \beta_0 + \beta_1 Size_i + \beta_2 Advanced_i + \beta_3 Snowfall_i + \beta_4 \widehat{Snowmaking_i}$$
$$+\beta_5 Distance_i + \beta_6 NE_i + \beta_7 MA_i + \beta_8 SE_i + \beta_9 MW_i + \beta_{10} RM_i \tag{40}$$
$$\widehat{Snowmaking_i} = \gamma_0 + \gamma_1 Elevation_i + \gamma_2 Snowfall_i + \gamma_3 Area_i + \gamma_4 Size_i$$

Each of the first two models is also altered slightly to include the Tax variable. These models are called, Model 1A and Model 2A. They are shown below.

Model 1A:

$$Price = \beta_0 + \beta_1 Size_i + \beta_2 Advanced_i + \beta_3 Snowfall_i + \beta_4 \widehat{Snowmaking_i} + \beta_5 Tax_i$$
$$\widehat{Snowmaking_i} = \gamma_0 + \gamma_1 Elevation_i + \gamma_2 Snowfall_i + \gamma_3 Area_i + \gamma_4 Size_i Area \tag{41}$$

Model 2A:

$$Price = \beta_0 + \beta_1 Size_i + \beta_2 Advanced_i + \beta_3 Snowfall_i + \beta_4 \widehat{Snowmaking_i} +$$
$$\beta_5 Distance_i + \beta_6 NE_i + \beta_7 MA_i + \beta_8 SE_i + \beta_9 MW_i + \beta_{10} RM_i + \beta_{11} Tax_i \tag{42}$$
$$\widehat{Snowmaking_i} = \gamma_0 + \gamma_1 Elevation_i + \gamma_2 Snowfall_i + \gamma_3 Area_i + \gamma_4 Size_i$$

The last two models are the result of the methodology described in Huang (2013) and the extension to Huang's (2013) work described in this paper. The model includes all characteristic and location variables multiplied by the $(1 - Tax)$ variable. The dependent variable is also altered slightly by multiplying each price by $(1 - Tax)$.

Model 3:

$$
\begin{aligned}
(1-Tax_i)Price_i &= \beta_0 + \beta_1(1-Tax_i)*Size_i + \beta_2(1-Tax_i)*Advanced_i \\
&+\beta_3(1-Tax_i)*Snowfall_i + \beta_4(1-Tax_i)*\widehat{Snowmaking}_i \\
&+\beta_5(1-Tax_i)*Distance_i + \beta_6(1-Tax_i)*NE_i + \beta_7(1-Tax_i)*MA_i \\
&+\beta_8(1-Tax_i)*SE_i + \beta_9(1-Tax_i)*MW_i + \beta_{10}(1-Tax_i)*RM_i \\
\widehat{Snowmaking}_i &= \gamma_0 + \gamma_1 Elevation_i + \gamma_2 Snowfall_i + \gamma_3 Area_i + \gamma_4 Size_i
\end{aligned}
\tag{43}
$$

Model 3 is the appropriate model to estimate if the marginal cost structure faced by each firm is linear and the utility function is consistent with the utility function described in Feenstra (1995)

Model 3A is the model which was derived by Huang (2013) under the assumptions that the firms face a semi-log marginal cost structure. In this case the hedonic price function also takes the semi-log form.

Model 3A:

$$
\begin{aligned}
\ln(Price_i) &= \beta_0 + \beta_1 Tax + \beta_2(1-Tax_i)*Size_i + \beta_3(1-Tax_i)*Advanced_i \\
&+\beta_4(1-Tax_i)*Snowfall_i + \beta_5(1-Tax_i)*\widehat{Snowmaking}_i \\
&+\beta_6(1-Tax_i)*Distance_i + \beta_7(1-Tax_i)*NE_i + \beta_8(1-Tax_i)*MA_i \\
&+\beta_9(1-Tax_i)*SE_i + \beta_{10}(1-Tax_i)*MW_i + \beta_{11}(1-Tax_i)*RM_i \\
\widehat{Snowmaking}_i &= \gamma_0 + \gamma_1 Elevation_i + \gamma_2 Snowfall_i + \gamma_3 Area_i + \gamma_4 Size_i
\end{aligned}
\tag{44}
$$

Note that Model 3A differs from Model 3 in the overall functional form as well as the fact that the right hand side of the model includes the Tax variable as a separate explanatory variable. This model allows the potential price-cost markup to be estimated directly in the hedonic price equation as an incremental increase as well as an increase through each of the characteristics of the product.

Each of the models 1, 1A, 2, and 2A is estimated as both a linear and semi-log model of the weekend lift ticket price using 2SLS, the semi-parametric approach of GMM. Models 3 and 3A are also estimated using 2SLS, and GMM. Each of the three estimation techniques is described in detail in the next section.

2.11 Estimation Techniques

It has been shown that both the functional form of the hedonic model as well as the estimation technique used to estimate the model can significantly influence the outcome of the estimated marginal values of the product characteristics. To highlight this point, this study uses three different estimation techniques to estimate the five proposed hedonic models. The first is the traditional OLS technique.

The OLS method begins with the assumption that the dependent variable relates to the independent variables in the following way.

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta}_{OLS} + \boldsymbol{\varepsilon} \tag{45}$$

Here, $\boldsymbol{y}$ is the vector of dependent variables. $\boldsymbol{X}$, an $(n \times k)$ matrix of explanatory variables, where n is the number of observations and k is the number of explanatory variables, and $\boldsymbol{\varepsilon}$ is the error term.

In Equation (45), $\boldsymbol{\beta}_{OLS}$ is unknown and must be estimated. Under this procedure this vector of coefficients are estimated by minimizing the squared distance between the predicted values of the estimated model and the true values in the data set of each observation. The minimization problem is shown below where S is the sum of these squared errors.

$$S = min \sum_{i=1}^{n} (\boldsymbol{y} - \boldsymbol{X}\widehat{\boldsymbol{\beta}}_{OLS}) \tag{46}$$

$\widehat{\boldsymbol{\beta}}_{OLS}$ is chosen to minimize S. In general the OLS estimator is calculated using the formula in Equation (47).

$$\widehat{\boldsymbol{\beta}}_{OLS} = (\boldsymbol{X}'\boldsymbol{X})'\boldsymbol{X}'\boldsymbol{y} \tag{47}$$

Here $\boldsymbol{X}'$is the inverse matrix of $\boldsymbol{X}$.

Since the Snowmaking variable is endogenous, this study uses a slight variation of the traditional OLS estimation technique called two stage least squares. The two stage least squares estimation is used to determine the coefficients in the following model which contains multiple equations.

$$\boldsymbol{y} = \boldsymbol{X}_{-j}\boldsymbol{\beta}_{-j} + \boldsymbol{x}_j\boldsymbol{\beta}_j + \varepsilon \tag{48}$$

$$\boldsymbol{x}_j = \boldsymbol{Z}\boldsymbol{\gamma} + \boldsymbol{\mu} \tag{49}$$

Here, Equation (45) has been expanded slightly to show the endgoneous variable. In (48) $\boldsymbol{X}_{-j}$ is an $(n \times k - 1)$ matrix of all of the exogenous explanatory variables and $\boldsymbol{x}_j$ represents the vector of the endogenous variable. Together, $\boldsymbol{\beta}_{-j} + \boldsymbol{\beta}_j = \boldsymbol{\beta}_{2SLS}$.

The endogenous variable can be represented by the stochastic relationship shown in (49). Here, the $\boldsymbol{Z}$ matrix contains all of the exogenous explanatory variables that influence $\boldsymbol{x}_j$. Again, this relationship will have some unexplainable components which are captured in $\boldsymbol{\mu}$, the error term. The explanatory variables which are present in $\boldsymbol{Z}$ may also be present in $\boldsymbol{X}$. However, for this method to work, there must be at least one explanatory variable in $\boldsymbol{Z}$ which is not in $\boldsymbol{X}$. These are the instrumental variables which are correlated with the endogenous explanatory variable $\boldsymbol{x}_i$ but not with the dependent variable $\boldsymbol{y}$. Let the set of all instrumental variables be represented by the matrix $\boldsymbol{V}$, where $\boldsymbol{V}$ is an $(n \times L)$ matrix, where L is the number of instrumental variables.

Under 2SLS, OLS regression is carried out twice. The first time is for the endogenous variable's equation. Then, using $\widehat{\boldsymbol{x}}_j$ in Equation (45), OLS can be conducted again to get the estimated coefficients in (45).

The general formula for the $\widehat{\boldsymbol{\beta}}_{2SLS}$ is shown below.

$$\widehat{\boldsymbol{\beta}}_{2SLS} = \left[\boldsymbol{X}'\boldsymbol{V}(\boldsymbol{V}'\boldsymbol{V})^{-1}\boldsymbol{V}'\boldsymbol{X}\right]^{-1}\boldsymbol{X}'\boldsymbol{V}(\boldsymbol{V}'\boldsymbol{V})^{-1}\boldsymbol{V}'\boldsymbol{y} \tag{50}$$

If the 2SLS approach is carried out manually, the standard errors of the estimated coefficients will be biased. The correct form of the standard errors is the square root of the variance given below.

$$Variance(\widehat{\boldsymbol{\beta}}_{2SLS}) = n[\boldsymbol{X}'\boldsymbol{V}(\boldsymbol{V}'\boldsymbol{V})^{-1}\boldsymbol{V}'\boldsymbol{X}]^{-1}\left[\boldsymbol{X}'\boldsymbol{V}(\boldsymbol{V}'\boldsymbol{V})^{-1}\widehat{\boldsymbol{S}}(\boldsymbol{V}'\boldsymbol{V})^{-1}\boldsymbol{V}'\boldsymbol{X}\right][\boldsymbol{X}'\boldsymbol{V}(\boldsymbol{V}'\boldsymbol{V})^{-1}\boldsymbol{V}'\boldsymbol{X}]^{-1} \tag{51}$$

When this procedure is carried out with computer software, the computer will correct the standard errors and report the square root of Equation (51) for each coefficient.

In order for the 2SLS estimator to be consistent and unbiased, many assumptions must hold. One of which is most concerning in this analysis is the assumption of homoscedasticity of the variance of the error terms. Since the data used in this study includes information on both large and small ski areas, it would be naïve to assume that the distribution of the error terms followed allowed for constant variance. The data is more likely clustered into groups. To try and remedy this characteristic of the data, robust standard errors are calculated. However, this approach is still limited by the strict assumptions on the nature of the data.

For this reason, both the semi-parametric and nonparametric approaches add flexibility to the estimation procedure and increase the likelihood of estimating consistent coefficients which represent the marginal values of the product attributes. The GMM procedure is similar to the 2SLS procedure; however, the two equations in the model are estimated simultaneously using the moment conditions of the system of equations. The assumed relationship takes the same form as in Equations (52) and (53).

$$\boldsymbol{y} = \boldsymbol{X}_{-j}\boldsymbol{\beta}_{-j} + \boldsymbol{x}_j\boldsymbol{\beta}_j + \varepsilon \tag{52}$$

$$\boldsymbol{x}_j = \boldsymbol{Z\gamma} + \boldsymbol{\mu} \tag{53}$$

Now, let $\boldsymbol{\beta}_{-j} + \boldsymbol{\beta}_j = \boldsymbol{\beta}_{GMM}$.

The GMM procedure to estimate the coefficients in the main model begins with an assumption about the first moment of the distribution of the dependent variable. It uses the fact that the instrumental variables in Equation (53) are exogenous and uncorrelated with the dependent variable and the error terms in Equation (52). Recall that $\boldsymbol{V}$ is an $(n \times L)$ matrix of L instrumental variables. Then it is given that the following holds.

$$E[\boldsymbol{v}_i'\varepsilon_i] = 0 \tag{54}$$

Equation (37) states that the expected value of the product of the instrumental variables, $\boldsymbol{v}_i$, and the error term at any observation, i, is equal to zero. This gives an entire set of L moments which are shown below.

$$g_i(\widehat{\boldsymbol{\beta}}_{GMM}) = \boldsymbol{v}_i'\hat{\varepsilon}_i = \boldsymbol{v}_i'(y_i - \boldsymbol{x}_i\widehat{\boldsymbol{\beta}}_{GMM}) \tag{55}$$

Here, g_i, is a vector valued function. Combining Equation (55) with Equation (54), the following holds.

$$m(\boldsymbol{\beta}_{GMM}) = E[g_i(\boldsymbol{\beta}_{GMM})] = 0 \tag{56}$$

To estimate $\boldsymbol{\beta}_{GMM}$ an iterative procedure is performed. First, the theoretical expected value in Equation (56) is replaced with the empirical sample average and is shown below.

$$\widehat{m}(\widehat{\boldsymbol{\beta}}_{GMM}) = \widehat{E}[g_i(\widehat{\boldsymbol{\beta}}_{GMM})] = \frac{1}{n}\sum_{i=1}^{n} g_i(\widehat{\boldsymbol{\beta}}_{GMM}) = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{v}_i'(y_i - \boldsymbol{x}_i\widehat{\boldsymbol{\beta}}_{GMM}) = \frac{1}{n}\boldsymbol{V}'\hat{\varepsilon} \tag{43}$$

By the law of large numbers, Equation (56) will approximately equal the true value of $m(\boldsymbol{\beta}_{GMM})$ when n is sufficiently large. Under the GMM procedure, $\widehat{\boldsymbol{\beta}}_{GMM}$ is chosen to make $\widehat{m}(\widehat{\boldsymbol{\beta}}_{GMM})$ as close to zero as possible. This is the equivalent of minimizing the norm of $\widehat{m}(\boldsymbol{\beta}_{GMM})$; $\|m\|$. The parameter $\widehat{\boldsymbol{\beta}}_{GMM}$ will depend on the specific norm equation chosen for the estimation. Under the GMM procedure an entire family of norm functions is possible. These are given below.

$$\|\widehat{m}(\boldsymbol{\beta}_{GMM})\|_W^2 = \widehat{m}(\boldsymbol{\beta}_{GMM})'\boldsymbol{W}\widehat{m}(\boldsymbol{\beta}_{GMM}) \tag{57}$$

Here $\boldsymbol{W}$ is a weight matrix. And Equation (57) is minimized to find $\widehat{\boldsymbol{\beta}}_{GMM}$. Rewriting Equation (57) becomes,

$$\widehat{\boldsymbol{\beta}}_{GMM} = min\left(\frac{1}{n}\sum_{i=1}^{n} g_i(\boldsymbol{\beta}_{GMM})\right)'\widehat{\boldsymbol{W}}\left(\frac{1}{n}\sum_{i=1}^{n} g_i(\boldsymbol{\beta}_{GMM})\right) \tag{58}$$

The weight matrix, $\widehat{\boldsymbol{W}}$ is computed based on the data which is to be analysis under the GMM procedure. Here is where the GMM estimation has its flexibility. By definition the weight matrix can takes the form

$$\widehat{\boldsymbol{W}} = \left(\frac{1}{n}\sum_{i=1}^{n} g_i(\widehat{\boldsymbol{\beta}}_{GMM})g_i(\widehat{\boldsymbol{\beta}}_{GMM})'\right)^{-1} \tag{59}$$

There are three common procedures to compute $\widehat{\boldsymbol{\beta}}_{GMM}$. The first is the two step procedure. Under this procedure, the weight matrix is initially assumed to be the identity matrix. Then the objective function in Equation (58) can be minimized. The resulting estimate is denoted $\widehat{\boldsymbol{\beta}}_{GMM_{(1)}}$. This value is then substituted into the generic weight matrix in Equation (59). Equation (59) becomes the following.

$$\widehat{\boldsymbol{W}} = \left(\frac{1}{n}\sum_{i=1}^{n} g_i\left(\widehat{\boldsymbol{\beta}}_{GMM_{(1)}}\right) g_i\left(\widehat{\boldsymbol{\beta}}_{GMM_{(1)}}\right)'\right)^{-1} \tag{60}$$

And Equation (58) is again minimized with Equation (60) as the weight matrix. This time the resulting $\widehat{\boldsymbol{\beta}}_{GMM}$ is used as the GMM estimator.

Alternatively, this procedure can continue under the iterated GMM procedure and the weight matrix can be updated many times before the GMM estimator is chosen. Finally, $\widehat{\boldsymbol{\beta}}_{GMM}$ can be estimated simultaneously with the weight matrix and the equation below is minimized.

$$\widehat{\boldsymbol{\beta}}_{GMM} = min\left(\frac{1}{n}\sum_{i=1}^{n} g_i(\boldsymbol{\beta}_{GMM})\right)'\left(\frac{1}{n}\sum_{i=1}^{n} g_i(\widehat{\boldsymbol{\beta}}_{GMM}) g_i(\widehat{\boldsymbol{\beta}}_{GMM})'\right)^{-1}\left(\frac{1}{n}\sum_{t=1}^{n} g_i(\boldsymbol{\beta}_{GMM})\right) \tag{61}$$

In general the $\widehat{\boldsymbol{\beta}}_{GMM}$ estimator can be derived with the following formula.

$$\widehat{\boldsymbol{\beta}}_{GMM} = (\boldsymbol{X}'\boldsymbol{V}\boldsymbol{W}\boldsymbol{V}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{V}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{y} \tag{62}$$

The GMM estimator will be consistent and efficient. The flexibility of the GMM procedure increases the reliability of the resulting marginal value estimates. The underlying distribution of the data is not arbitrarily assumed to be normal or any other distribution. By allowing the data to influence this function and the weight matrix, the procedure captures more of the economic information embedded in the prices of the products.[8]

[8] This paper has made reference to the nonparametric estimation technique. The empirical exercise used to examine the difference which occur under different functional form assumptions and estimation procedures does not examine the nonparametric approach because this approach involves examining the preference structure of the consumer's as well as the cost structures of the firms. The data used for the empirical exercise was not rich enough to examine the preference structure of the consumer as well. We feel that without the nonparametric estimation, the empirical exercise still gives an important indication of the influence of both market structure and functional form specification of the hedonic price function and should be viewed as an exercise to highlight the importance of correct specification before an policy recommendations should be made from hedonic price studies.

2.12 Results

The estimation results of the linear hedonic models can be found in Tables 2.B2 and 2.B4 of the Appendix. Table 2.B2 shows the results of the 2SLS estimation and Table 2.B4 shows the results of the GMM estimation. The results of the semi-log models can be found in Tables 2.B3 and 2.B5 with the 2SLS and GMM estimation results reported respectively.

Note first, that the Snowmaking equations in each of the estimated models are always very highly significant in all explanatory variables and the magnitude of the explanatory variables is highly consistent throughout each model. For the semi-parametric they are exactly the same estimated results in each of the models. This is because the 2SLS estimation of the model is used first and then the predicted values are used in the semi-parametric estimation.[9]

The key factors to note in each of the estimated Snowmaking equations are the sign and significance of the Snowfall variable. All results suggest that as natural snow decreases, the need for more artificial snow increases and ski areas increase the overall coverage capabilities of their snowmaking machinery.[10] These results indicate that Snowfall among other factors is a leading indicator of whether a ski area will invest in snowmaking. Some ski areas which have the most snowfall still do not invest in snowmaking and are able to give skiers the unique experience of skiing on purely natural snow. However, most ski areas in this representative data set do not have this luxury as

[9] In each case the standard errors are adjusted accordingly.

[10] Note that the data only contained percentage of total acreage capable of being covered by artificial snow. We do not have data on how much artificial snow was created in inches. This richer data would help to better assess the substitutability between artificial and natural snowfall. However, this data is unavailable.

the ever decreasing amount of snowfall has lead most ski areas to invest in at least a percentage of artificial snow coverage.

Another important significant factor in the Snowmaking equation is the Size variable. Larger resorts have a larger percentage of snowmaking coverage. This is most likely due to the fact that larger resorts most often have larger revenue bases with which to invest in the capital needed to offset poor natural snow conditions.

Now consider the main hedonic price models. Note that similar to Li and Brown (1980), as the location variables are added, the significance and magnitude of many of the explanatory variables in the main equation are altered. In each model there exist significant effects of the location of the ski area, suggesting that Models 1 and 1A were not specified correctly. Models 1 and 1A are only included to show the importance of a correctly specified hedonic price model and are not used to draw any conclusions about the industry as a whole. The previous theoretical arguments would also suggest that Models 2 and 2A were also misspecified due to the fact that the tax variable is not incorporated into the model correctly.

Both Models 3 and 3A did not fail any of the specification tests which were performed in the econometric analysis. However when compared directly, Model 3 was significantly preferred to Model 3A. Also, since GMM is a slightly more flexible estimation technique, the results of Model 3 estimated using GMM are highlighted and used to draw most conclusions about the industry as a whole.

The results of this model suggest that the size, snow conditions, and location all have a significant role in determining the price of the lift ticket of the resort. Larger resorts are able to charge a higher price most likely give the skier more choices during their day at the ski mountain. Also, ski areas with more natural snow and which invest in snowmaking can charge a higher price. Skiers will pay more for more consistent, reliable, and safer ski conditions which occur when the ski area has a large natural snow base or can supplement the snowfall with artificial coverage. Each of these results is consistent with the findings of previous research and the arguments of the industry officials as a whole (www.nsaa.org).

Studies such as this one are important for determining the well-being of an industry which is vulnerable to climate change. Both the Size and Snowmaking variables are consistently significant, throughout all models and estimation techniques, and are highly significant under the most reliable model. This exercise can be used to suggest where and how the industry might be able to ensure survival of its resorts, even as the natural snowfall continues to decline. For example ski areas which are able to expand their offerings and become larger or those which can increase their snowmaking capability might be able to charge higher prices and remain solvent in the uncertain industry. However, ski areas can only continue to grow and increase their capital for so long.

Taking this analysis a step further, this empirical exercise is used to calculate the marginal values of the key climatic variables of interest as well as run some simulations on Model 3 to show what happens to the price as changes in the natural snowfall occur. This analysis could better assess the current and future states of the industry.

2.13 Marginal Effects and Simulation of Climate Variables

Once each of the models has been estimated, these models are then used to calculate the marginal value that consumers place on the climate variable of interest; Snowfall. These and the Snowmaking marginal values are presented at the bottom of each table for each model. The direct marginal value of the Snowfall and Snowmaking are calculated using the main hedonic price model. The overall marginal value of Snowfall is also estimated. Since Snowfall is significant in both the main hedonic price equation and the Snowmaking equation, both of these equations are used to find the overall marginal value of this factor.

Since each of these models is estimated under specific assumptions and varying functional forms, each set of marginal values is calculated differently in each table. The formulas used for each marginal value can be found in Appendix 2.C and the calculated values can be found at the bottom of the tables for each estimated model.

Note that the predicted direct and overall marginal values of the Snowfall factor as well as the direct marginal value of the Snowmaking factor are very different among all the estimated models. The difference among the estimated values is another indication of the mis-specification of Models 1, 1A, 2, and 2A. These differences also occur because of the different functional forms and estimations techniques which are used. However, the differences across functional forms of the models which include the same right hand side variables are smaller than the differences across the three different models. This conclusion supports the claims of Feenstra (1995), Bajari and Benkard (2005), and Ekeland et al (2004) among others who argue that functional form is significant in determining the value of nonmarket goods, especially when market power is present. These results are some of the only empirical results to point toward the diversity which comes from estimating the same theoretical model using different functional forms and estimation techniques.

Of all the estimated models, the estimation of Model 3 is most reliable. Both the 2SLS and GMM estimations are qualitatively similar. When Model 3 is estimated using GMM, the direct marginal value of Snowfall is positive and the overall is negative. Also the estimated marginal value of Snowmaking is positive. The switch in the sign between the direct and overall marginal value of the Snowfall factor is interesting. This result indicates that when ski areas do not have snowmaking capabilities, additional natural snowfall is very important to the consumer. This result also indicates that consumers will prefer some snow, whether it is artificial or natural, over no snow. Consumers appreciate the reliability of artificial snow, which is shown by the positive marginal value calculation of the Snowmaking factor. However, since Snowfall significantly decreases the amount of snowmaking capability that a ski area will invest in, and consumers gain benefit from snowmaking, its overall impact becomes negative. It is expected that the overall marginal value of the Snowfall factor should be slightly smaller than the direct marginal value because natural snow can be supplemented with artificial snow. However, in this study, the impact of Snowfall on Snowmaking completely counteracts the direct benefits of natural snow to consumers.[11]

This empirical exercise shows that the calculated marginal values of these factors vary between the linear and semi-log functional form of the hedonic price equation, under

[11] One reason why this result is occurring is most likely because the two factors Snowfall and Snowmaking are not measured in the same way. Snowfall is measured in inches and Snowmaking is measured in percentage of acres. To really understand the overall impact of Snowfall these two factors would both need to be measured in inches, however, this data is not available. Therefore, the overall marginal value calculation of Snowfall should be reviewed with caution.

different model specifications, and under the two different estimation techniques. Model 3 can compensate for any market power in the industry by including a theoretically consistent form of the tax factor in the hedonic price model. This exercise has shown the rigor with which these hedonic price models must be both theoretically derived and empirically tested to ensure that reliable marginal value estimates can be recovered from this first stage of the hedonic estimation.

Finally, Table 2.B8 presents a simulation using Model 3 estimated under GMM to show how the price of the lift ticket changes with some incremental changes in the snowfall. Both the direct effects of the change in snowfall on the price, as well as, the indirect effects are presented in this table. The overall effects combine the direct and indirect effects. The formulas for these calculations can be found in Appendix 2.C.

The incremental changes in snowfall used to run the simulations are based on the country-wide average decrease in annual snowfall coverage over the past 10, 20 and 30 years respectively (Wake, 2005; NRC 2011). Note that the direct effect of a decrease in snowfall results in a decrease of the price. This is most likely due to the fact that less snowfall decreases the quality of the ski area and decreases the overall value of the lift ticket. However, the overall affect is an increase in price. As the snowfall declines the ski areas make more artificial snow. The price increase is likely due to the fact that the ski areas supplement the poor natural snow conditions with artificial snow and this increased investment raises their costs. As their costs rise the ski areas are likely to raise the price of the lift ticket.

Current analysis would suggest that ski areas which increase their prices at the same time that they increase their artificial snow cover can continue to be successful.

However, the real cost falls on consumers. Therefore, this result highlights an increased cost of climate change which accrues to consumers as the price of the lift tickets throughout the country increase as the snowfall decreases. Future analysis could investigate this industry-wide trend to see how much ski areas are able to pass off the cost of increased capital to their consumers and where the choke price for different groups of consumers might be. This analysis would help to predict the future well-being of the industry if prices are projected to continue to rise.

2.14 Concluding Remarks

The results of this study have both theoretical and practical implications. Feenstra (1995) shows that the traditional hedonic price model suffers from omitted variable bias when the assumption of perfect competition is imposed and when the relationship between the price of the goods and its characteristics is nonlinear. Some authors have attempted to remedy this issue by using nonparametric estimation techniques or with the rigorous econometric approach of residual demand modeling. However, these methods need a lot of data points.

Huang's (2013) theoretical argument results in a model which is much more feasibly implemented. However, the functional form of the cost function of the firms is still highly influential and will alter the functional form of the hedonic price function and the underlying meaning of the coefficients in the estimated model. This paper takes Huang's (2013) theoretical a step further and derives the hedonic price function under the linear cost structure.

This paper is the first to empirically estimate the model presented in Huang (2013) and its extension in this paper and show that if the functional form of the hedonic price equation is estimated correctly, the unbiased marginal values of the explanatory parameters are easily uncovered. By estimating many models of different functional forms, under different estimation techniques, this paper also shows the real differences which occur in marginal value estimates when the functional form is mis-specified or when market power is unaccounted for. Under these studies the estimates of the marginal values cannot be trusted.

The results of this study also have practical implications. The case study of the US ski industry has relevance to the economic issue of global climate change. This industry has been argued to be suffering from climate change and many industry officials have wondered how the ever growing reliance on artificial snow has impacted the welfare of skiers and ski areas. This study indicates that consumers prefer some snow to no snow and will pay more for resorts which have more snowmaking capability. However, as the ski areas continue to increase their reliance on artificial snow; this study suggests that the price of the lift ticket will continue to rise. More analysis would be helpful to examine if the increased costs of the price ticket due to increased investment of the resorts will eventually mean or maybe has already meant the loss of some consumers in the industry due to prices being unattainable. Understanding this impact of climate change on the industry would help to predict the future well-being of the industry.

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APPENDICES

APPENDIX 2.A

SUMMARY STATISTICS OF THE DATA

The data used to evaluate the major differences between the existing approaches, to accounting for imperfect competition in the hedonic method, consists of 344 ski areas throughout the United States. These 344 ski areas represent over 75 percent of the operational ski areas during the 2011-2012 ski season. The other ski areas which were operational during the season were omitted from the data set because all relevant information needed for the study was not available.

To ensure that the data used for the analysis in this study was representative of the true population of all operational ski areas a comparison of a few key characteristics of all ski areas were compared to the same characteristics of the ski areas in the sample. These statistics are shown in Table 2.A1 and 2.A2. Table 2.A1 presents the average number of trails and vertical drop for all the ski areas by region. Table 2.A2 presents these averages for the ski areas in the data set. Even though many ski areas needed to be dropped from the data set because of missing values, the set averages are still very close to the true statistics.

Table 2.A3 presents the definitions and the summary statistics of all of the variables used in the analysis. Note that the dependent variable in the analysis is the price of a full-day weekend lift ticket. This price varies substantially throughout the data ranging from below 5 dollars to over 100 dollars with an average price of approximately 50 dollars. The other explanatory variables also vary widely throughout the data including the variable of most interest which is the annual snowfall. The annual snowfall

measures at the resorts in the data set range from 10 to nearly 800 inches annually. The ranges of the dependent and all of the explanatory variables, as well as, the variability in the location of the ski areas also helps to ensure that the data used is representative of the true population of all ski areas.

Table 2.A1:
Characteristic Averages of All Operational Ski Areas

Characteristic	Northeast	Mid-Atlantic	Southeast	Mid-West	Rocky Mountains	West
Number of Ski Areas	75	51	17	116	98	70
Average Number of Trails	32	29.8	11.6	22.5	84.6	42.9
Average Vertical Drop	1126	917	598	352	2111.7	1662

Source: www.wikipedia.com; www.liftopia.com

Table 2.A2:
Characteristic Averages of Ski Areas in Data Set

Characteristic	Sample Northeast	Sample Mid-Atlantic	Sample Southeast	Sample Mid-West	Sample Rocky Mountains	Sample West
Number of Ski Areas	63	45	16	84	78	58
Average Number of Trails	44.5	29.9	19.1	22.4	65.9	47.2
Average Vertical Drop	1261	865.7	754.4	367.5	2020.5	1575.7

Table 2.A3:
Summary Statistics of All Variables

Variable	Definition	Mean	Standard Error	Min	Max
Lift Ticket Price	The price of the full-day weekend lift ticket.	50.044	18.983	4	105
Trails	The number of skiable trails at the mount.	41.345	36.025	1	193
Vertical	The vertical drop of the mountain measured in feet.	1192.840	952.264	40	4425
Lifts	The number of operational non-rope-tow lifts at the mountain.	5.895	4.759	0	33
Area	The skiable area of the mountain measured in acres.	596.488	944.496	8	7000
Beginner	The percentage of trails designated as beginner level difficulty.	26.717	10.938	0	80
Moderate	The percentage of trails designated as moderate level difficulty.	41.102	11.717	0	100
Advanced	The percentage of trails designated as advanced level difficulty.	32.131	13.502	8	100
Snowfall	The average annual snowfall measured in inches.	182.322	139.776	10	782
Snowmaking	The percentage of the skiable area that can be covered with artificial snow using snowmaking equipment.	61.596	41.903	0	100
Distance	The distance to nearest major metropolitan area.	128.362	93.944	0	507.30
NE	Dummy variable equal to 1 if the ski area is located in New England.	0.175	0.380	0	1
MA	Dummy variable equal to 1 if the ski area is in the Mid-Atlantic.	0.125	0.330	0	1
SE	Dummy variable equal to 1 if the ski area is in the South East.	0.044	0.206	0	1
MW	Dummy variable equal to 1 if the ski area is in the Mid-West.	0.236	0.425	0	1
RM	Dummy variable equal to 1 if the ski area is in the Rocky Mountains.	0.225	0.418	0	1
SalesTax	The state sales tax placed on the sale of every lift ticket.	0.047	0.023	0	0.075
TourismTax	The state tourism tax placed on the sale of every lift ticket.	0.047	0.025	0	0.120
Elevation	The base elevation of the ski area measured in feet.	3298.598	3123.663	0	10780

APPENDIX 2.B

ESTIMATED EFFECTS OF EXPLANATORY VARIABLES ON THE PRICE OF THE LIFT TICKET

The connection between the characteristics, amenities, and locations of the individual ski areas to their lift ticket prices were examined with many different models under two different estimation strategies. Table 2.B1 provides the hypothesized direction of influence for each explanatory variable on the price of the lift ticket. Although the price of the full-day weekend lift ticket is presented as the dependent variable is Table 2.A1, the log of the price of the full-day weekend lift ticket is also used as the dependent variable in some models. The hypothesized signs for these models are the same.

Table 2.B2 presents the results of the 2SLS estimation of the five models explained in section 2. Note that the dependent variable for each of the main equations in these models is the price of the full-day weekend lift ticket except for Model 3 in which the dependent variable is the price of the full-day weekend lift ticket times one minus the tax. Table 2.B3 presents the same estimation strategy of the five models with the log of the full-day weekend lift ticket as the dependent variable. Both tables present similar results. Regardless of the functional form in both sets of the results the Size, Snowfall, and Snowmaking variables are significant indicators of the price of the lift ticket in Models 2, 2A, and 3. These models are those which account for some form of pricing power in the market. The Snowmaking equation is also highly significant in each model. The instrument of Elevation is significant and has the correct negative sign. Also, Snowfall and Size are significant in these estimated equations. This shows that both of these factors have indirect influences on the price of the lift ticket through their effect on the amount of capital used in the form of snowmaking machinery at the mountain. For

the rest of the estimated results the Snowmaking equation remains extremely consistent and significant.

The results of Tables 2.B2 and 2.B3 also show that the tax variable is only significant in Model 3A, and many of the tax interactions terms are also significant in Models 3 and 3A. Model 3A is the only model which can capture both the incremental increase on the price which occurs due to market power along with the increase which occurs through the influence on the individual characteristics of the good. However, Model 3A was tested and shown to be the wrong functional form for this particular industry. Model 3 more closely represents the actual market. Therefore, there is most likely some market power influence in this market, however, it is not influencing the price as much as Model 3A would suggest.

Tables 2.B4 and 2.B5 present the estimation results of the same five models using the GMM semi-parametric estimation procedure. In Table 2.B4 the linear models are presented and in Table 2.B5 presents the results of the semi-log models. These results are similar to those presented in Tables 2.B2 and 2.B3. The main difference is that the tax variable is significant in Model 1A under both functional forms. However, once the location is controlled for the significance on the tax variable in Model 2A disappears. Model 1A is most likely picking up the market power which arises from location differences and attributing this falsely to the tax. Again Model 3A consistently suggests that there are both forms of price inflation over marginal cost in the industry. However, again, due to econometric tests, this model is not correctly specified, and Model 3 would suggest that along the market power is most likely present, it does not have as large of an influence on the price as one might initially believe. Overall the models in Tables 2.B4 and 2.B5 are considered most reliable because they combine the flexibility of the estimation technique with the rigor of a more theoretically sound model.

Finally, Tables 2.B6 and 2.B7 show the results of models which are estimated under the assumption that the Snowmaking variable is exogenous. These are included to show the consistency of most of the variables even under different assumptions. However, there is no significant indication of market power in these models. This is most likely again due to the fact that these models are not correctly specified.

The marginal values of the key variables of interest are presented at the bottom of each of the tables 2.B2-2.B5. Since Snowfall is significant in determining both the amount of Snowmaking at the mountain and the price of the lift ticket the direct and overall marginal values for this variables are presented. Note that there is a large range between the values for each of the model and under each of the estimation strategies. These results suggest that the estimation strategy, the functional form, and the estimated model all significantly influence the calculated marginal values.

Finally, Table 2.B8 shows the simulated results of the changes in price which are estimated to occur with incremental decreases in the snowfall factor. These incremental changes are based on the country-wide average decrease in annual snowfall coverage over the past 10, 20 and 30 years respectively. Note that the direct effect of a decrease in snowfall results in a decrease of the price most likely since conditions are worsened by less snowfall. However, the overall affect is an increase in price since ski areas invest in snowmaking equipment and to cover their increased costs they will most likely raise the price. Therefore, this result highlights an increased cost of climate change which accrues to consumers as the price of the lift tickets throughout the country increase as the snowfall decreases.

Table 2.B1:
Definitions and Hypothesized Direction of Influence of Explanatory Variables

Variable	Definition	Hypothesized Sign
Trails	The number of skiable trails at the mount.	+
Vertical	The vertical drop of the mountain measured in feet.	+
Lifts	The number of operational non-rope-tow lifts at the mountain.	+
Area	The skiable area of the mountain measured in acres.	+
Beginner	The percentage of trails designated as beginner level difficulty.	-
Moderate	The percentage of trails designated as moderate level difficulty.	+
Advanced	The percentage of trails designated as advanced level difficulty.	+
Snowfall	The average annual snowfall measured in inches.	+
Snowmaking	The percentage of the skiable area that can be covered with artificial snow using snowmaking equipment.	+
Distance	The distance to nearest major metropolitan area.	-
NE	Dummy variable equal to 1 if the ski area is located in New England.	N/A
MA	Dummy variable equal to 1 if the ski area is in the Mid-Atlantic.	N/A
SE	Dummy variable equal to 1 if the ski area is in the South East.	N/A
MW	Dummy variable equal to 1 if the ski area is in the Mid-West.	N/A
RM	Dummy variable equal to 1 if the ski area is in the Rocky Mountains.	N/A
SalesTax	The state sales tax placed on the sale of every lift ticket.	+
TourismTax	The state tourism tax placed on the sale of every lift ticket.	+

Table 2.B2:
Linear Models Estimated with 2SLS

Model	Model 1	Model 1A	Model 2	Model 2A	Model 3[12]
Dependent Variable: Price of Full-Day Weekend Lift Ticket					
Intercept	31.3007*** (3.2878)	30.1897*** (3.2585)	5.9007 (4.9175)	4.2345 (4.7590)	26.6349*** (1.8119)
Size	0.1839*** (0.0073)	0.1843*** (0.0074)	0.1555*** (0.0095)	0.1551*** (0.0096)	
Advanced	-0.0321 (0.0361)	-0.0271 (0.0362)	-0.0069 (0.0357)	-0.0033 (0.0360)	
Snowfall	0.0058 (0.0076)	0.0051 (0.0079)	0.0568*** (0.0089)	0.0582*** (0.0089)	
Snowmaking	0.0499 (0.0304)	0.0422 (0.0335)	0.5352*** (0.1092)	0.5516*** (0.1073)	
Distance			0.0121* (0.0074)	0.0128* (0.0073)	
NE			-18.0404*** (5.6613)	-19.2078*** (5.4616)	
MA			-17.7370** (7.3978)	-18.8766** (7.1849)	
SE			-13.9596* (7.8319)	-15.0389** (7.6245)	
MW			-29.5713*** (7.0272)	-30.6927*** (6.8201)	
RM			-3.2420** (1.4690)	-3.3635** (1.4979)	
Tax		15.9380 (15.5161)		9.8031 (15.3566)	
(1-Tax)Size					0.1799*** (0.0066)
(1-Tax)Advanced					-0.0064 (0.0327)
(1-Tax)Snowfall					0.0135*** (0.0050)
(1-Tax)Snowmaking					0.1064*** (0.0171)
(1-Tax)Distance					0.0017 (0.0048)
(1-Tax)NE					-2.5050 (1.8596)
(1-Tax)MA					1.4114 (2.1299)
(1-Tax)SE					4.1357 (2.6409)
(1-Tax)MW					-11.1632*** (2.0098)
(1-Tax)RM					-5.4737*** (1.3624)
Chi Squared	1015.94	1006.30	1201.77	1195.02	1553.70

[12] The dependent variable is Model 3 is $(1 - Tax)(Price\ of\ Weekend\ Lift\ Ticket)$.

Dependent Variable: Snowmaking					
Intercept	95.7457*** (1.9994)	95.8087*** (1.9974)	95.9233*** (2.0451)	95.9625*** (2.0449)	95.3086*** (2.0469)
Snowfall	-0.1265*** (0.0113)	-0.1264*** (0.0113)	-0.1380*** (0.0116)	-0.1386*** (0.0116)	-0.1261*** (0.0117)
Elevation	-0.0053*** (0.0004)	-0.0054*** (0.0004)	-0.0048*** (0.0004)	-0.0048*** (0.0004)	-0.0054*** (0.0005)
Size	0.1465*** (0.0201)	0.1459*** (0.0201)	0.1385*** (0.0204)	0.1377*** (0.0204)	0.1551*** (0.0205)
Area	-0.0100*** (0.0018)	-0.0099*** (0.0018)	-0.0088*** (0.0019)	-0.0087*** (0.0019)	-0.0110*** (0.0019)
Chi Squared	899.27	899.74	822.96	821.62	860.64
Marginal Values					
Direct Snowfall	0.0058	0.0051	0.0568	0.0582	0.0135
Overall Snowfall	0.0005	0.0002	-0.0171	-0.0183	0.0001
Direct Snowmaking	0.0499	0.0422	0.5352	0.5516	0.1065

Table 2.B3:
Semi-Log Models Estimated with 2SLS

Model	Model 1	Model 1A	Model 2	Model 2A	Model 3A
Dependent Variable: Log Price of Weekend Full-Day Lift Ticket					
Intercept	3.4238*** (.1096)	3.3973*** (.0769)	2.7899*** (.1178)	2.7449*** (.1140)	3.2788*** (0.05750
Size	0.0033*** (0.0002)	0.0033*** (0.0002)	0.0027*** (0.0002)	0.0027*** (0.0002)	
Advanced	0.0003 (0.0012)	0.0004 (0.0008)	0.0009 (0.0009)	0.0010 (0.0009)	
Snowfall	0.0002 (0.0002)	0.0002 (0.0002)	0.0015*** (0.0002)	0.0016*** (0.0002)	
Snowmaking	0.0014 (0.0010)	0.0012 (0.0008)	0.0135*** (0.0026)	0.0139*** (0.0026)	
Distance			0.0002 (0.0002)	0.0003 (0.0002)	
NE			-0.4598*** (0.1356)	-0.4912*** (0.1309)	
MA			-0.4472** (0.1772)	-0.4775*** (0.1722)	
SE			-0.3465* (0.1876)	-0.3754** (0.1827)	
MW			-0.7083*** (0.1683)	-0.7384*** (0.1635)	
RM			-0.0647* (0.0351)	-0.0681* (0.0359)	
Tax		0.3792 (0.3626)		0.2684 (0.3675)	0.9404*** (0.3333)
(1-Tax)Size					0.0035*** (0.0002)
(1-Tax)Advanced					0.0008*** (0.0009)
(1-Tax)Snowfall					0.0005*** (0.0001)
(1-Tax)Snowmaking					0.0033*** (0.0004)
(1-Tax)Distance					-0.0001 (0.0001)
(1-Tax)NE					-0.0706 (0.0515)
(1-Tax)MA					0.0302 (0.0567)
(1-Tax)SE					0.1105 (0.0697)
(1-Tax)MW					-0.2801*** (0.0536)
(1-Tax)RM					-0.1279*** (0.0360)
Chi Squared	637.56	630.58	839.38	838.84	1011.83
Dependent Variable: Snowmaking					
Intercept	95.8300***	95.8979***	95.9316***	95.9748***	95.3255***

	(2.8226)	(1.9935)	(2.0450)	(2.0448)	(2.0468)
Snowfall	-0.1265*** (0.0159)	-0.1265*** (0.0113)	-0.1382*** (0.0116)	-0.1388*** (0.0116)	-0.1262*** (0.0117)
Elevation	-0.0054*** (0.0006)	-0.0054*** (0.0004)	-0.0048*** (0.0004)	-0.0048*** (0.0004)	-0.0054*** (0.0005)
Size	0.1455*** (0.0287)	0.1449*** (0.0200)	0.1383*** (0.0204)	0.1374*** (0.0204)	0.1548*** (0.0205)
Area	-0.0098*** (0.0025)	-0.0097*** (0.0018)	-0.0088*** (0.0018)	-0.0087*** (0.0019)	-0.0110*** (0.0018)
Chi Squared	899.41	899.98	822.61	821.10	860.58
Marginal Values					
Direct Snowfall	0.1653	0.1645	0.0749	0.0803	0.0266
Overall Snowfall	0.1562	0.1581	-0.0181	-0.0168	0.0044
Direct Snowmaking	0.0697	0.0609	0.6726	0.6959	0.1756

Table 2.B4:
Linear Models Estimated with GMM

Model	Model 1	Model 1A	Model 2	Model 2A	Model 3[13]
Dependent Variable: Full Day Weekend Lift Ticket					
Intercept	32.8795*** (3.1649)	30.8025*** (3.1674)	13.9197** (6.8013)	13.5894** (6.6331)	11.7086** (5.9819)
Size	0.1862*** (0.0090)	0.1878*** (0.0088)	0.1583*** (0.0129)	0.1581*** (0.0129)	
Advanced	-0.0555* (0.0329)	-0.0470 (0.0337)	0.0114 (0.0476)	0.0119 (0.0488)	
Snowfall	0.0049 (0.0077)	0.0027 (0.0079)	0.0372*** (0.0121)	0.0374*** (0.0121)	
Snowmaking	0.0372 (0.0298)	0.0167 (0.0336)	0.4621*** (0.1446)	0.4642*** (0.1423)	
Distance			0.0148 (0.0102)	0.0149 (0.0102)	
NE			-18.0790** (7.3346)	-18.3149*** (7.0951)	
MA			-19.7936** (9.6501)	-20.0052** (9.4111)	
SE			-17.9188* (10.1045)	-18.1314* (9.8458)	
MW			-31.1035*** (9.1378)	-31.3243*** (8.8796)	
RM			-4.3763** (2.0179)	-4.4102** (2.0745)	
Tax		35.2679** (14.7584)		3.0530 (15.3511)	
(1-Tax)Size					0.1566*** (0.0130)
(1-Tax)Advanced					0.0181 (0.0448)
(1-Tax)Snowfall					0.0392*** (0.0121)
(1-Tax)Snowmaking					0.4790*** (0.1382)
(1-Tax)Distance					0.0169* (0.0100)
(1-Tax)NE					-19.2628*** (6.7370)
(1-Tax)MA					-21.2133** (9.0061)
(1-Tax)SE					-19.1000** (9.4752)
(1-Tax)MW					-32.4138*** (8.5303)
(1-Tax)RM					-4.4676** (2.0844)
Wald Chi Squared	777.37	846.52	960.75	962.56	954.68

[13] The dependent variable in Model 3 is $(1 - Tax)(Price\ of\ Weekend\ Lift\ Ticket)$.

Dependent Variable: Snowmaking					
Intercept	95.2332*** (2.0394)	95.2332*** (2.0394)	95.2332*** (2.0394)	95.2332*** (2.0394)	95.2332*** (2.0394)
Snowfall	-0.1243*** (0.0115)	-0.1243*** (0.0115)	-0.1243*** (0.0115)	-0.1243*** (0.0115)	-0.1243*** (0.0115)
Elevation	-0.0053*** (0.0005)	-0.0053*** (0.0005)	-0.0053*** (0.0005)	-0.0053*** (0.0005)	-0.0053*** (0.0005)
Size	0.1425*** (0.0203)	0.1425*** (0.0203)	0.1425*** (0.0203)	0.1425*** (0.0203)	0.1425*** (0.0203)
Area	-0.0104*** (0.0019)	-0.0104*** (0.0019)	-0.0104*** (0.0019)	-0.0104*** (0.0019)	-0.0104*** (0.0019)
F Statistic	256.74	256.74	256.74	256.74	256.74
Marginal Values					
Direct Snowfall	0.0049	0.0027	0.0372	0.0374	0.0392
Overall Snowfall	0.0003	0.0006	-0.0202	-0.0203	-0.0204
Direct Snowmaking	0.0372	0.0167	0.4621	0.4642	0.4791

Table 2.B5:
Semi-Log Models Estimated with GMM

Model	Model 1	Model 1A	Model 2	Model 2A	Model 3A
Dependent Variable: Log of Full Day Weekend Lift Ticket					
Intercept	3.4361*** (.0762)	3.3865*** (.0750)	3.0807*** (.1443)	3.0453*** (.1397)	3.0186*** (0.1440)
Size	0.0034*** (0.0002)	0.0034*** (0.0002)	0.0028*** (0.0003)	0.0028*** (0.0003)	
Advanced	-0.0002 (0.0008)	-0.0001 (0.0008)	0.0013 (0.0011)	0.0014 (0.0011)	
Snowfall	0.0003 (0.0002)	0.0002 (0.0002)	0.0009*** (0.0003)	0.0009*** (0.0003)	
Snowmaking	0.0014** (0.0007)	0.0010 (0.0008)	0.0097*** (0.0029)	0.0099*** (0.0028)	
Distance			0.0002 (0.0002)	0.0002 (0.0002)	
NE			-0.3705*** (0.1440)	-0.3986*** (0.1438)	
MA			-0.3739** (0.1886)	-0.3999** (0.1879)	
SE			-0.3132 (0.1974)	-0.3389* (0.1962)	
MW			-0.6310*** (0.1784)	-0.6569*** (0.1772)	
RM			-0.1058** (0.0459)	-0.1107** (0.0491)	
Tax		0.7789** (0.3394)		0.3227 (0.3842)	1.0129*** (0.3681)
(1-Tax)Size					0.0031*** (0.0002)
(1-Tax)Advanced					0.0011 (0.0012)
(1-Tax)Snowfall					0.0010*** (0.0003)
(1-Tax)Snowmaking					0.0105*** (0.0029)
(1-Tax)Distance					0.0002 (0.0002)
(1-Tax)NE					-0.4154*** (0.1464)
(1-Tax)MA					-0.4211** (0.1918)
(1-Tax)SE					-0.3524* (0.2001)
(1-Tax)RM					-0.7082*** (0.1802)
(1-Tax)MW					0.1358*** (0.0516)
Wald Chi Squared	554.64	605.18	811.09	809.64	838.68
Dependent Variable: Snowmaking					
Intercept	95.2332*** (2.0394)	95.2332*** (2.0394)	95.2332*** (2.0394)	95.2332*** (2.0394)	95.2332*** (2.0394)

Snowfall	-0.1243*** (0.0115)	-0.1243*** (0.0115)	-0.1243*** (0.0115)	-0.1243*** (0.0115)	-0.1243*** (0.0115)
Elevation	-0.0053*** (0.0005)	-0.0053*** (0.0005)	-0.0053*** (0.0005)	-0.0053*** (0.0005)	-0.0053*** (0.0005)
Size	0.1425*** (0.0203)	0.1425*** (0.0203)	0.1425*** (0.0203)	0.1425*** (0.0203)	0.1425*** (0.0203)
Area	-0.0104*** (0.0019)	-0.0104*** (0.0019)	-0.0104*** (0.0019)	-0.0104*** (0.0019)	-0.0104*** (0.0019)
F Statistic	256.74	256.74	256.74	256.74	256.74
Marginal Values					
Direct Snowfall	0.0142	0.0091	0.0454	0.0454	0.0494
Overall Snowfall	0.0052	0.0039	-0.0156	-0.0168	-0.0151
Direct Snowmaking	0.0697	0.0505	0.4849	0.4967	0.5188

Table 2.B6:
Linear Models Estimated using OLS
Under the Assumption that Snowmaking is an Exogenous Variable

	Model 1	Model 1A	Model 2	Model 2A	Model 3[14]
Dependent Variable: Price of Weekend Lift Ticket					
Intercept	23.1057*** (1.8995)	22.2886*** (2.3325)	27.1494*** (2.0281)	25.7758*** (2.3089)	24.6721*** (1.8485)
Size	0.1812*** (0.0070)	0.1813*** (0.0070)	0.1793*** (0.0067)	0.1802*** (0.0068)	
Advanced	-0.0207 (0.0365)	-0.0182 (0.0368)	-0.0053 (0.0339)	0.0005 (0.0342)	
Snowfall	0.0219*** (0.0050)	0.0220*** (0.0050)	0.0154** (0.0051)	0.0150** (0.0051)	
Snowmaking	0.1306*** (0.0144)	0.1286*** (0.0148)	0.1252*** (0.0175)	0.1244*** (0.0175)	
Distance			-0.0011 (0.0049)	-0.0008 (0.0049)	
Dummy_NE			-1.1437 (1.8511)	-2.0618 (1.9923)	
Dummy_MA			2.5239 (2.1599)	1.9346 (2.2104)	
Dummy_SE			5.3124* (2.6744)	4.7847 (2.7067)	
Dummy_MW			-9.9180*** (2.0336)	-10.5294*** (2.0913)	
Dummy_RM			-4.2527** (1.3950)	-4.5633** (1.4166)	
Tax1		8.7491 (14.4813)		17.7840 (14.3089)	
(1-Tax)*Size					0.1804*** (0.0067)
(1-Tax)*Advanced					0.0037 (0.0335)
(1-Tax)*Snowfall					0.0155*** (0.0051)
(1-Tax)*Snowmaking					0.1265*** (0.0176)
(1-Tax)*Distance					0.0004

[14] [14] The dependent variable in Model 3 is $(1 - Tax)(Price\ of\ Weekend\ Lift\ Ticket)$.

					(0.0049)
(1-Tax)*NE					-2.5601 (1.9054)
(1-Tax)*MA					1.4849 (2.1824)
(1-Tax)*SE					4.5214* (2.7065)
(1-Tax)*MW					-11.0041*** (2.0577)
(1-Tax)*RM					-4.7397*** (1.3928)
R Squared	0.6381	0.6383	0.7044	0.7051	0.7117

Table 2.B7
Semi-Log Models Estimated using OLS
Under the Assumption that Snowmaking is Exogenous

	Model 1	Model 1A	Model 2	Model 2A	Model 3A
Dependent Variable: Log of the Price of Weekend Lift Ticket					
Intercept	3.1695*** (0.0483)	3.1486*** (0.0593)	3.2625*** (0.0536)	3.2265*** (0.0610)	23.7263*** (2.4547)
Size	0.0033*** (0.0002)	0.0033*** (0.0002)	0.0033*** (0.0002)	0.0033*** (0.0002)	
Advanced	0.0011 (0.0009)	0.0011 (0.0009)	0.0014 (0.0009)	0.0015 (0.0009)	
Snowfall	0.0007*** (0.0001)	0.0007*** (0.0001)	0.0005*** (0.0001)	0.0005*** (0.0001)	
Snowmaking	0.0038*** (0.0004)	0.0037*** (0.0004)	0.0037*** (0.0005)	0.0037*** (0.0005)	
Distance			-0.0001 (0.0001)	-0.0001 (0.0001)	
Dummy_NE			-0.0356 (0.0489)	-0.0596 (0.0526)	
Dummy_MA			0.0624 (0.0570)	0.0469 (0.0584)	
Dummy_SE			0.1441* (0.0706)	0.1302 (0.0715)	
Dummy_MW			-0.2094*** (0.0537)	-0.2254*** (0.0552)	
Dummy_RM			-0.0664 (0.0368)	-0.0746* (0.0374)	
Tax		0.2238 (0.3680)		0.4658 (0.3779)	40.1513*** (14.2877)
(1-Tax)*Size					0.1961*** (0.0074)
(1-Tax)*Advanced					-0.0044 (0.0374)
(1-Tax)*Snowfall					0.0173*** (0.0056)
(1-Tax)*Snowmaking					0.1381*** (0.0193)
(1-Tax)*Distance					-0.0004 (0.0054)
(1-Tax)*NE					-1.8554 (2.2037)

(1-Tax)*MA					2.1692 (2.4283)
(1-Tax)*SE					5.4323* (2.9860)
(1-Tax)*MW					-11.7403*** (2.2953)
(1-Tax)*RM					-5.0920*** (1.5398)
R Squared	0.5187	0.5190	0.5814	0.5825	0.7049

Table 2.B8
Simulation of Changes in the Price due to Changes in Snowfall[15]

Change in Snowfall	Direct Effect	Indirect Effect	Overall Effect
-7 Inches	-0.27	0.42	0.14
-13 Inches	-0.51	0.77	0.26
-20 Inches	-0.78	1.19	0.41

[15] These changes are based on the average decrease in snowfall throughout the United States over the past 30 years and use the estimated linear Model 3 under GMM estimation.

APPENDIX 2.C

FORMULAS

The formulas for calculating the direct and overall marginal values for the Snowfall factor and the direct marginal value for the Snowmaking factor are given below. Note that the formula depends on the functional form of the estimated model. The formulas for calculating the price change which occurs as the Snowfall factor changes are also given below.

Marginal Value Formulas:

Linear Models 1, 1A, 2, and 2A[16]

$$Direct\ Marginal\ Value\ of\ Snowfall = \beta_{Snowfall}$$

$$Overall\ Marginal\ Value\ of\ Snowfall = \beta_{Snowfall} + \beta_{Snowmaking}\gamma_{Snowfall}$$

$$Marginal\ Value\ of Snowmaking = \beta_{Snowmaking}$$

Semi-Log Models 1, 1A, 2, and 2A

$$Direct\ Marginal\ Value\ of\ Snowfall = \mu_{Price}\beta_{Snowfall}$$

$$Overall\ Marginal\ Value\ of\ Snowfall$$

$$= \mu_{Price}\beta_{Snowfall} + \mu_{Price}\beta_{Snowmaking}\gamma_{Snowfall}$$

$$Marginal\ Value\ of Snowmaking = \mu_{Price}\beta_{Snowmaking}$$

[16] $\beta_X = The\ coefficient\ of\ explanatory\ variable\ X\ in\ the\ main\ hedonic\ price\ function.$
γ_X

Linear Model 3[17]

$$Direct\ Marginal\ Value\ of\ Snowfall = \beta_{(1-Tax)*Snowfall}$$

$$Overall\ Marginal\ Value\ of\ Snowfall$$
$$= \left(\beta_{(1-Tax)*Snowfall}\right) + \left(\beta_{(1-Tax)*Snowmaking}\right)\gamma_{Snowfall}$$

$$Marginal\ Value\ of Snowmaking = \beta_{(1-Tax)*Snowmaking}$$

Semi-Log Model 3A[18]

$$Direct\ Marginal\ Value\ of\ Snowfall = \mu_{Price}\left(\beta_{(1-Tax)*Snowfall}\right)/\beta_{Tax}$$

$$Overall\ Marginal\ Value\ of\ Snowfall$$
$$= \mu_{Price}\left(\beta_{(1-Tax)*Snowfall}\right)/\beta_{Tax}$$
$$+ \left(\mu_{Price}\left(\beta_{(1-Tax)*Snowmaking}\right)/\beta_{Tax}\right)\gamma_{Snowfall}$$

$$Marginal\ Value\ of Snowmaking = \mu_{Price}\left(\beta_{(1-Tax)*Snowmaking}\right)/\beta_{Tax}$$

Price Change Formulas:

$$Direct\ Price\ Change = \beta_{(1-Tax)*Snowfall}(Change\ in\ Snowfall)$$

$$Indirect\ Price\ Change = \beta_{(1-Tax)*Snowmaking}\gamma_{Snowfall}(Change\ in\ Snowfall)$$

$$Overall\ Price\ Change$$
$$= \left(\beta_{(1-Tax)*Snowfall}\right.$$
$$\left. + \beta_{(1-Tax)*Snowmaking}\gamma_{Snowfall}\right)(Change\ in\ Snowfall)$$

[17] $\overline{Tax} = The\ mean\ of\ the\ Tax\ variable = .0942$

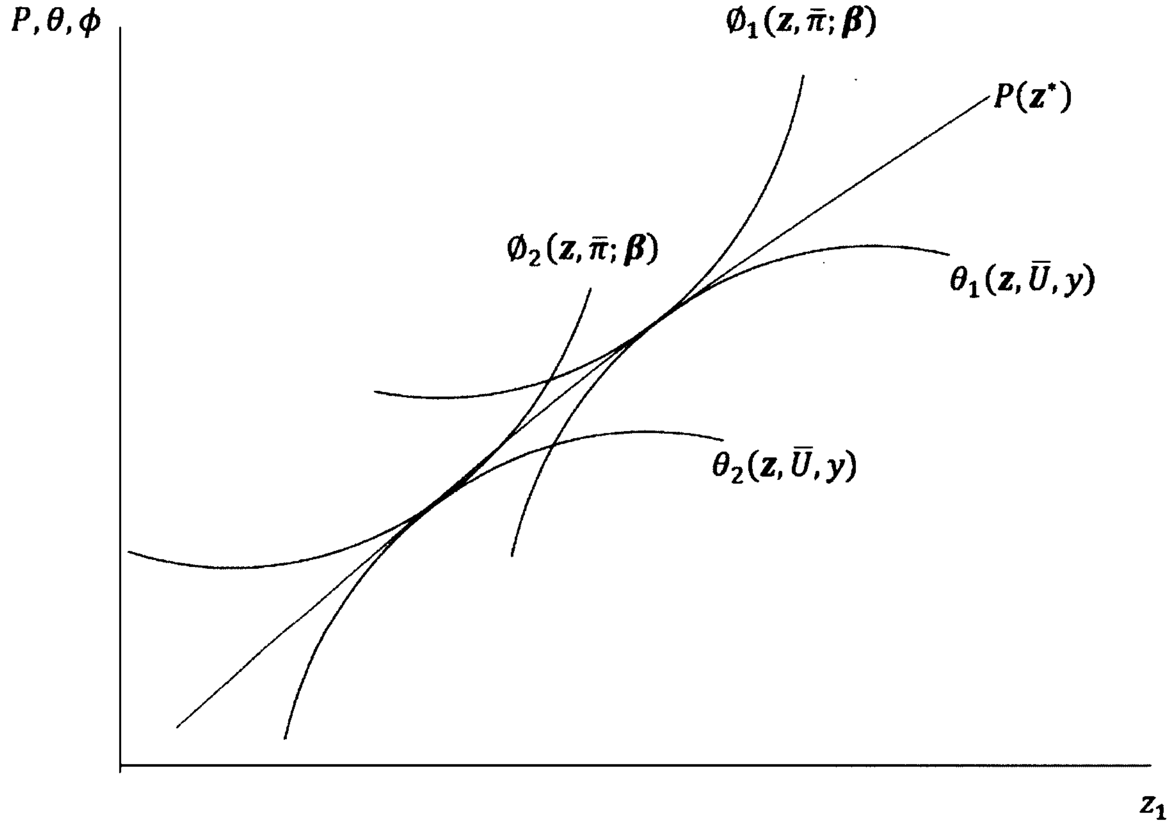
[18] $\mu_{Price} = The\ mean\ of\ the\ \ln(Weekend\ Lift\ Tickets)$

APPENDIX 2.D

FIGURES

The theoretical foundation for the hedonic valuation method relies on the interaction between consumers and firms. Figure 2.D1 presents a two-dimensional depiction of the interactions between consumers and firms in perfectly competitive markets. Under this scenario, the hedonic price function consists of all of the equilibrium points at which the consumer's willingness to pay function is tangent to the producer's willingness to accept function.

Figure 2.D1:
Interaction of Consumer and Firm Behavior



CONCLUSION

The goal of this dissertation has been to advance the field of Environmental Economics and to inspire a new methodology for examining one of the greatest negative externalities to ever influence our economies and our world; climate change. This new methodology includes more rigorous examination of all avenues through which climate change can affect an industry. Further, it provides opportunities for better measurements of the costs of climate change which stem from changes in the value of the climatic goods sold in these industries.

Since climatic goods are often classified as non-market goods that are sold in markets in which firm enjoy some form of pricing power, the major contribution of this dissertation has been to explore new ways to value non-market goods in imperfectly competitive markets. Until now, current methodologies have been mathematically challenging and limited by their unattainable data requirements. Together both chapters of this dissertation highlight the importance of first identifying the potential impact of changing weather patterns and then valuing these changes through the goods which they alter. Ultimately this dissertation has shown how changing weather patterns can affect the overall structure of a market or industry and how the market structure then influences the value of the goods sold in these markets. Although climate change is used as the motivation for each study in this dissertation, the contributions made to both empirical and theoretical examination of imperfectly competitive markets could be extended to several other applications within the field of Environmental Economics.

There are many more research projects which can stem from this work including the simple adaptation of the case studied industry to extensions of the second chapter of the dissertation to the second stage of the hedonic method. This dissertation only considers one particularly vulnerable industry. Although the ski industry in the U.S. is an extremely important industry and vital to the health of the economy, there are many more industries which are suffering similar fates. The first chapter of the dissertation could be easily adapted to examine the impact that changing weather patterns have had on other industries over time as well. It would also be interesting to compare the impacts to see which industries have suffered most from changing weather and this might help flow the limited resources for combatting climate change into the correct channels.

The first chapter could also be extended in the analysis. Currently, the chapter focuses on weather and weather patterns, and does not particular consider climate change. The models which include accumulated effects and the simulations at the end of the chapter help tie the results to climate change issues; however, the use of more climate change related variables in the model might help to influence policy more concretely. Other climatic variables which could be included might be the snow depth, the snowpack, the number of degree days, and deviations from averages. Including these variables in the suggested model would allow this model to be more closely related to other climate change studies.

Finally, the first chapter focuses on the effects of climate on firm's exit decisions - the impact of climate on the supply side of the market. An extension is to investigate the effects of weather conditions on the demand side of the ski industry and to derive the welfare changes of skiers when taking into account the market structure being altered by climate change. A better understanding of the links between weather conditions and individual industries can help better depict the overall economic impact of climate change. The proposed structural model of discrete time survival analysis can be applied to studying the direct and indirect effects of weather conditions on firms in other industries such as horticulture and fishing industries that can be vulnerable to climate change as well.

The first chapter of this dissertation holds its contributions in the rigorous techniques used in estimating the econometric model to ensure that the climate factors are fully accounted and controlled for. The second chapter has contributions which are mainly found in the theoretical foundation of the adapted hedonic approach. The hedonic approach has two stages and this dissertation only considers the first. This is because the market structure only affects the first stage. However, the estimates from the first stage are used in the second stage to estimate marginal willingness to pay values for changes in environmental amenities. Therefore, for this new methodology to influence policy, in future work, the adapted first stage should be used to show how the second stage will be affected as well. With these results we could begin to make recommendations to the industry on how better to combat the changing weather patterns across the country. This extension to the current analysis could be very useful again in determine how much to spend on climate related projects. The more precise first stage estimates would give the projects much less uncertainty about the overall expected benefits.

Based on the conclusions of this theoretical and empirical study it would be beneficial to improve the data in our study to be able to conduct functional form test with significant results. Knowing the correct functional form of the hedonic price equation would allow us to have a better understanding of the magnitude of the impact that reduced snowfall has had on the industry. Also, by gathering more data the study would be better equipped to estimated nonparametric models and be able to significantly determine which method of estimation might yield the most robust results.

This dissertation opens the door to more accurate measures of the damages of climate change. To fully understand the affects that climate change has had on the ski industry and many other important industries, the techniques of chapters one and two could be combined. Using pricing data going back in time and showing that climate change has been influential in decreasing the competition in the market, we can examine how climate change may have harmed consumers as the lower competition increases the pricing power of firms in various industries. The more firms are able to increase the value of their product over marginal cost, the less surplus is left for consumers. This dissertation highlights the potential costs which accrue to consumers as industries become less competitive as a result of climate change. Future investigation of this type of cost of climate change is warranted.