5-23-2016

Three Essays on the Economics of Climate Change and Productivity, Food Supply, and Land Resource Conservation

Lingqiao Qi
qilingqiaow@gmail.com

Three Essays on the Economics of Climate Change and Productivity, Food Supply, and Land Resource Conservation

Lingqiao Qi, Ph.D.

University of Connecticut, 2016

Abstract

This dissertation addresses food security problem from three alternative perspectives. The first essay analyzes the total factor productivity and climatic effects on milk production in Wisconsin dairy farms. This essay employs a recent developed stochastic production frontier method to quantify the impacts of seasonal factors and longer-term adaptive effects on output, which is a novel contribution to the literature. What is more, based on the results from generalized true random effects model, this essay employs a total factor productivity index and its six components to evaluate the competitiveness between farms and to explore strategies to increase productivity for milk production. The second essay identifies the barriers for buyers and non-buyers in the local food market. Using a multiviate probit model to capture the latent heterogeneity between consumers, the second essay contributes to the literature with a comprehensive analysis about consumers' perception of price, quality, availability, and other barriers in local food market. The third essay extend a standard stated preference method to incorporate both land parcel attributes and cultural ecosystem services into a utility function to identify individuals' preference. The third essay makes methodological contributions to develop a production index for perceived services and to demonstrate respondents' choices are influenced by perceived services. These three essays contribute to fill the gap between climate change and food security problem in literature.

Three Essays on the Economics of Climate Change and Productivity, Food Supply, and Land Resource Conservation

Lingqiao Qi

B.S., Liaoning University, **2009**

M.S., Renmin University of China, **2011**

M.S., University of Connecticut, **2013**

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

2016

APPROVAL PAGE

Doctor of Philosophy Dissertation

Three Essays on the Economics of Climate Change and Productivity, Food Supply, and Land Resource Conservation

Presented by

Lingqiao Qi

Major Advisor ______________________

Boris E. Bravo-Ureta

Associate Advisor ______________________

Stephen K. Swallow

Associate Advisor ______________________

Benjamin L. Campbell

Associate Advisor ______________________

Victor E. Cabrera

University of Connecticut

[2016]

ACKNOWLEDGMENTS

This dissertation records my life in UConn and all the help and support from people who have made this possible. I would like to first express my heartfelt gratitude to my major advisor Dr. Bravo-Ureta for his advice, mentorship and guidance that he has graciously provided throughout my Ph.D. study. I would like to thank him for all his assistance and everything without mentioning details during the process of finishing the dissertation, especially for teaching me the meaning of hard-work and professionalism that will benefit my whole career life.

I would like to extend my grateful appreciation to my advisor Dr. Campbell, an outstanding advisor from whom I always can obtain helpful guidance, encouragement and support. Moreover, Dr. Campbell and Dr. Bravo-Ureta's assistantship funding support helped to pave my way into finishing my dissertation. Thank you Dr. Swallow for being a wonderful teacher and for giving me valuable comments. Thanks to Dr. Cabrera and Dr. Rabinowitz for being there to answer my questions and for their support with my dissertation. Special thanks to Dr. Shah for his support, inspiration and encouragement for my research and life.

I am grateful for being a student of the ARE department led by Dr. Lopez. I am really grateful for the wonderful time of working as a teaching assistant with Professor Deepak Joglekar, Professor Joseph Bonelli, and Professor Marilyn Altobello. And special appreciation goes to Karen Nye and Claire Bazzano for providing the best support during my study in UConn.

I would like to acknowledge my friends: Xiu Zhai, Xun Chen, Madiha Zaffo, Chakrabarti Anwesha, Hualu Zheng, Qiushuo Yu, Pengfei Liu, Guanlong Fu and many others. Finally, thanks to my family for its unconditional love and support. It is because of you, all my beloved professors, collogues and friends, that UConn has become my second home town with thousands of happy memories.

This work is dedicated to my family.
To my parents Guang Qi and Xiulan Zhang
for instilling in me a love of life,
and to my husband Sining Wang
for all of his love, support, and company.

Table of Contents

Overview of the Dissertation

Given that climatic factors are direct inputs to agricultural production, the agricultural sector is more vulnerable to climate change than other sectors. Comprehensive analyses of land conservation, food production and food market are important to generate the information needed for the agricultural sector to address food security challenges. This dissertation presents three essays to quantify climatic impacts on milk production as well as to explore solutions to increasing local food sales and to protect open spaces.

The first essay conducts an analysis of total factor productivity and climatic factors for Wisconsin dairy farms. Given that economic research focusing on the impact of adaptations on milk production is very limited, this study fills this literature gap by using the recently developed generalized true random effects (GTRE) model, to quantify the impacts of seasonal climatic factors and adaptive strategies for dairy farms. Essay 1 identifies the GTRE model as the most robust method to analyse milk production for the dairy farm data utilized. Moreover, the GTRE model makes it possible to evaluate both transient and persistent TE levels while also addressing unobserved time invariant farm-level heterogeneity.

Results of Essay 1 indicate that increasing temperature has adverse impact on output, but increase precipitation is beneficial. The adaptive strategies can significantly reduce the output lost caused by increasing temperature and decreasing precipitation. Notably, incorporating the effects of adaptive strategies captured by longer-term climatic variables in production models, is an important contribution of this study to the literature. Another key result of Essay 1 is that, on average, climate change will lead to a 2.4% to 7.7% reduction of annual output over the mid-term (2020-2039). Weather shocks under a mitigated climate change scenario have lower negative effects than under a dramatic climate change scenario. Essay 1 reveals technological

progress is the most important contributor to productivity growth. Although small farms had lower productivity levels between 1997 and 2000, their productivity growth was faster than for larger farms. Thus, the results indicate that small farms have become relatively more competitive in Wisconsin.

In order to understand consumer decisions associated with the purchasing of local foods, Essay 2 examines the barriers in the local food market that prevent current local food buyers from purchasing more local food or prevent non-buyers from entering the market. Based on an on-line survey, essay 2 examines buyers and non-buyers' perception toward eight barriers. High price is a major barrier for both buyers and non-buyers groups. Consumers in buyers groups more likely concern about product availability problem relative to non-buyers groups. Further, essay 2 employs a multivariate probit (MVP) model to estimate the effects of consumers' demographic, purchasing behaviour, health indicators, shopping location and zip-code characteristics on these eight barriers. To our best knowledge, using a MVP model to examine consumers' perception of local food barriers is a novel contribution of this essay, especially the combination of a control function method with MVP model contributes to solve the potential endogeneity problem between local food expenditure and barriers.

Essay 2 indicates that consumers with higher healthy diet scores are more likely to be concerned about local food availability problems, highly-educated consumers indicated a lack of local food labelling as a barrier, and high income consumers pay more attention to local food diversity than price. Providing specific products that are wanted by buyers is a more viable strategy to increasing local food purchasing than just creating additional venues for existing products. With respect to farmers' markets, increasing the number of farmers' markets in the community area leads to more difficulties for consumers to find local products they want. This

result indicates that pure increase in number of locations is not the solution but instead providing variety in the offerings available would be a strategy to increase purchases of local food.. High educated people are more likely to notice the labelling problem of local products.

The unique angle of this paper is that it investigates the barriers for consuming local food for both buyers and non-buyers, as opposed to the population as a whole (which is the standard in the current literature). The MVP model and the control function approach appropriately capture the latent heterogeneity problem and endogeneity problem in the empirical analysis.

Land is the most important resource for food production. Environmental economists have developed the stated preference method, particularly the choice experiment approach, to evaluate the valuation of open spaces. However, economists have done less work to identify how it is that various attributes might affect individual utility. Essay 3 provides a methodological contrition to the literature by solving this problem. Essay 3 extends the stated preference method by considering the impacts of both parcel attributes and cultural ecosystem services in the utility function. Notably, essay 3 develops a perceived production function to generate the perceived services index, where it quantifies three types of cultural ecosystem services including rural character, ecological or environmental quality, and sense of culture and history. Essay 3 employs a latent class logit model to capture the heterogeneity between respondents. The estimated results of production function indicates that parcel attributes are important inputs to create perceived services. The town landscape is also an important factor influences the amount of perceived services. For example, comparing to residents in Richmond (a town covered by forests), residents from the other towns in Rhode Island (Little Compton, Middletown and Portsmouth) indicate that wooded lands produce less rural character, ecological or environmental quality, and sense of culture and history for their community.

The results of utility function indicate that both parcel attributes and perceived services influence respondents' utility. Through conducting a series of statistical tests between utility functions with alternative specifications, Essay 3 demonstrates that incorporating either parcel attributes or perceived services only in the utility function can't reflect residents' preference appropriately. As for the estimated willingness-to-pay (WTP) values for different parcels, essay 3 found that respondents living in wooded area have a higher WTP for wooded land parcels than agricultural land, and as an opposite, respondents living in agricultural area have a higher WTP for working farm land. Further, respondents' WTP are also influenced by their demographic characteristics such as income, education and other factors.

These three essays provide a deeper insight into the challenges posed by climate change to food security. Although climate change exhibits a negative impact on milk production, adaptive strategies implemented by dairy farms are helpful to mitigate output losses. There are some helpful strategies for dairy farms to increase productivity, including increasing technological progress speed, increasing technical efficiency level. From the demand side, removing barriers to local food market expansion not only increases food sales but also increases consumer' welfare. Especially, rather than providing additional venues for existing products, increasing food diversity is a more effective strategy to increase local food sales. Finally, protecting the land attributes as well as cultural ecosystem services are important incentives for residents to protect open spaces. Thus, appropriate land conservation policies should be implemented to protect land resources.

Essay 1

Total Factor Productivity and Climatic Effects in Dairy Farms:

An Econometric Analysis Using Stochastic Frontiers

1.1 Introduction

The agricultural sector in the United States (U.S.), which contributes over $395 billion to the country's economy per year,[1] is more sensitive and vulnerable to climate change than any other sector (IPCC, 2014). The changing pattern of climatic factors, such as temperature and rainfall, has produced multiple effects on agricultural production in the U.S. (Deschenes and Greenstone, 2007; IPCC, 2014). Further, long-term climate change is expected to induce adaptation strategies that may lead to structural changes in farming (Mendelsohn, Nordhaus and Shaw, 1994).

The dairy industry, the fourth largest agricultural subsector in the U.S. (Calil et al., 2012), is particularly sensitive to climatic variations. Climatic conditions influence livestock productivity directly (Boyles, 2008; Mader, 2003), and also impact feed supplies by affecting the growth of silage and forage crops (Hill et al., 2004). These negative effects also push dairy farms to change management strategies to adapt to persistent climatic variations (Seo and Mendelsohn, 2008). Thus, a comprehensive analysis of climatic effects on milk production, as well as the performance of dairy farms in this changing environment, is important to ensure the availability and adequacy of food supplies in the U.S.

[1] Data available at: http://www.agcensus.usda.gov/Publications/2012/

The economic literature focusing on the effects of climatic variables on dairy farming remains quite limited. Hence, the general objective of this research is to conduct a comprehensive analysis for dairy farms with an emphasis on the relationship between climatic effects and milk production. In order to pursue this objective, the following tasks are undertaken: 1) identifying the most robust stochastic production frontier (SPF) model for milk production analysis; 2) quantifying the impact of weather shocks and adaptive strategies on milk output; 3) predicting climatic effects in the mid-term (years 2020–2039); 4) measuring the technical efficiency level of dairy farms; 5) analyzing total factor productivity (TFP) change for dairy farms by decomposing TFP change into six components (technological progress, technical efficiency (TE) change, scale and mix efficiency change, climatic effects change, unobserved heterogeneity and statistical noise change).

The major challenge facing the empirical analysis is finding the most appropriate specification for the climatic variables to reflect the effects of climatic conditions and adaptive strategies in the SPF model, which is the foundation for the scenario analysis and total productivity analysis of this study. The empirical analysis uses input-output data from Wisconsin dairy farms to explore the effects of a range of weather shocks, such as hot and humid summers and cold and snowy winters, on dairy production.

This study makes three important contributions to the literature: 1) it incorporates longer-term climatic variables into SPF models to capture the effects of adaptive strategies on output and thus determine the importance of such strategies in dairy farming; 2) it quantifies the joint and partial effects of weather shocks and adaptive strategies on milk production for the period 1996 through 2012 and then projects these to effects from 2020 through 2039; and 3) it conducts a comprehensive total factor productivity analysis to evaluate the contribution of six separate

elements on the productivity growth of dairy farms in Wisconsin.

1.2 Literature Review

The focus of this essay is dairy farming, which is the fourth largest agricultural subsector in the United States. Climatic variation can have multiple impacts on dairy production (García-Ispierto et al, 2007; Dikmen and Hansen, 2009). The impacts of climatic conditions on dairy farming can be divided into two elements: the short-run effects of weather shocks and the longer-term effects of climate change (Dell, Jones and Olken, 2014). The short-run effects usually involve the direct impacts of climatic factors such as temperature, precipitation, or humidity on milk production, which have been widely discussed in the dairy literature (Nardone et al., 2010; Capper, Cady and Bauman, 2009). The longer-term effects on milk production include dairy farms' efforts to adapt to climate change by adjusting management plans, the structure of dairy farming, and/or livestock species (MacDonald et al., 2007) over time (Dell, Jones and Olken, 2014). The term climatic effects in this study denotes the combined effect of short-run weather shocks and longer-term adaptive strategies.

According to Dell, Jones and Olken (2014), long-run climatic changes may have different impacts than short-run weather shocks, and the former may offset or augment the latter effects. In response to the changing climatic conditions, a number of adaptive strategies—including the adjustment of management plans, introducing different technologies, and even policy and institutional regulations—can be used to reduce the negative effects of weather shocks over a sufficiently long period. Thus, a short-run climate shock may have different impacts on dairy farming before and after adaptive strategies are introduced.

Therefore, one challenge of climate analysis is examining whether and how the effects of

longer-term climatic change will differ from the effects of short-run weather variations (Dell, Jones and Olken, 2014). In order to address this challenge, we conduct a literature review focusing on two aspects: 1) we identify the impacts of weather shocks and the impacts of climate change on milk production; and 2) we explore the methods that animal scientists and economists use to measure and analyze climatic effects. In fact, much of the applied literature does not make this distinction and focuses on the short-run effects of climatic variability on production or productivity. This study attempts to fill this gap by incorporating both short-run and longer-term effects, using panel data stochastic production frontier models.

Climatic Effects

There is a significant body of literature in animal and dairy science that establishes the susceptibility of dairy cows to extreme weather conditions (IPCC, 2014). This research clearly identifies the connection between weather shocks and output-related effects such as total milk output or productivity per cow. In general, dairy cows experience stress when the temperature is out of the thermo-neutral zone, since heat or cold stress requires cows to increase the amount of energy used to maintain body temperature; thus, less energy is available for milk production (West, 2003; Collier et al., 2006; Allen et al., 2013).

Heat stress influences livestock productivity by affecting feed intake, feed efficiency, milk yield, reproductive efficiency, cow behavior, and disease incidence (Cook et al., 2007; Tucker, Rogers and Shutz, 2008; Rhoads et al., 2009). It is estimated that cows' dry matter intake decreases by up to 40% when the ambient temperature is 40 C° (NRC, 2001). Heat stress may lead to losses ranging from $900 million to $1.5 billion per year in the U.S., depending on whether heat abatement systems are in place (St-Pierre, Cobanov and Schnitkey (2003).

Cold stress is another weather element that reduces output in some areas. At low temperatures, cows need more dietary energy to maintain body temperature. Cold stress causes animals to consume more feed but produce less milk, and it increases milk fat content (Young, 1981). In comparison to heat stress, cold stress is more restricted geographically but can have a significant incidence in the northern U.S. during winter months.

Adaptive Effects

Over time, dairies can employ multiple adaptive strategies to reduce persistent adverse effects from weather shocks. Examples of these strategies include building shade structures, installing cooling systems, and using altered feed mixes (Key and Sneeringer, 2014) to help livestock adapt to the warmer environment. Seo and Mendelsohn (2008) pointed out that farmers might also change livestock species and numbers to adapt to climate change. The thermo-neutral zone of livestock ranges between 5 C° and 25 C°, and it varies among different livestock species according to age, breed, feed intake, diet, current milk production level, and housing (Roenfeldt, 1998).

Despite the availability of adaptive strategies, it is hard to identify the specific strategies used by dairy farms. However, Dell, Jones and Olken (2014) have proposed a method to test adaptation econometrically, which does not require identifying specific actions taken but instead quantifies the total impact of such strategies. Given that the adaptive strategies are determined by the longer-term climatic conditions and that the main purpose of these strategies is to reduce the negative impacts of weather shocks, Dell, Jones and Olken (2014) introduced an interaction between weather shocks and the average initial climatic condition to capture adaptation.

A key assumption of the method introduced by Dell, Jones and Olken (2014) is that the

adaptation level is determined by fixed initial climatic conditions. For example, heat stress may cause more damage to a city with a lower annual temperature than a city with a higher annual temperature. Given that heat stress happens more frequently in the city with a higher annual temperature, that city is more likely to have implemented adaptation strategies. As a result, the effects of weather shocks have been mitigated. The longer-term climatic effects used by Dell, Jones and Olken (2014) is a fixed characteristic of a place (e.g., a long-run historical frequency with which a given temperature tends to occur), while in this study we use a 30-year climate normal for the period preceding each year in the data set.

Measuring Weather Shocks and Climatic Changes

There is a body of literature that reveals a variety of methods to measure weather shocks and to incorporate climatic effects on crop and livestock farming (e.g., Mendelsohn, Nordhaus and Shaw, 1994; Kelly, Kolstad and Mitchell, 2005; Schlenker, Hanemann and Fisher, 2006; Deschenes and Greenstone, 2007; Mukherjee, 2012). These methods include various indicators of temperature and precipitation, heat degree-days, and various indexes that combine different variables, such as the temperature humidity index (THI).

The THI is a widely used measure of weather shocks that is derived from ambient temperature and relative humidity (Holter et al., 1996; Kadzere et al., 2002). Key and Sneeringer (2014) and Mukherjee, Bravo-Ureta and Vries (2013) incorporated annual average THI in production frontier models and found a significant negative effect on milk production. Another widely used method relies on the value of temperature and precipitation. For example, Seo and Mendelsohn (2008) included 30-year averages for temperature and precipitation in a Ricardian model to examine how farmers choose livestock species to adapt to climate change.

The length of time used to define climatic variables differs across studies reported in the literature and, as mentioned already, we can classify these variable into short-run or longer-term measures. For short-run variables, dairy scientists usually monitor livestock productivity changes relative to daily or monthly temperature and/or humidity (Herbut and Angrecka, 2012). Economists use monthly or seasonal temperature and precipitation to examine the impacts of weather shocks on farm output (Hughes et al., 2011). Longer-term effects are widely considered in Ricardian models, where researchers usually use the climate normal, which is a 30-year moving average of temperature and/or precipitation, to reflect the effects of farmers' adaptive strategies (De Salvo, Begalli and Signorello, 2014). For example, Seo and Mendelsohn (2008) include longer-term average seasonal temperature and precipitation to examine the change in livestock species as an adaptation to climate change in Africa.

In this analysis, we consider both weather shocks and the effects of adaptation in dairy production to evaluate potential economic effects, which is in itself a contribution of the paper to the existing literature. This analysis employs seasonal values of temperature and precipitation to reflect the weather variation. The use of temperature and precipitation instead of an index like THI allows for a clear interpretation of the impact of weather elements on the dependent variable of interest. In addition, we redefine the length of each season according to the monthly average temperature in the state of Wisconsin. The adaptive effects are captured by the 30-year annual average of temperature and precipitation before the production year. For example, the 30-year annual average for year 1996 is the average annual temperature from 1966 through 1995.

1.3 Methodology

Stochastic Production Frontier (SPF) models have been used widely for over 40 years and during this period many methodological innovations have been introduced (Fried, Lovell and

Schmidt, 2008), including the ability to account for unobserved heterogeneity (Greene, 2005a and 2005b; Abdulai and Tietje, 2007; Colombi et al., 2014; Filippini and Greene, 2014; Kumbhakar, Lien and Hardaker, 2014; Tsionas and Kumbhakar, 2014; Lachaud, Bravo-Ureta and Ludena, 2015). Multiple authors have applied SPFs to analyze productivity in dairy farming in a variety of settings (e.g. Battese and Coelli, 1988; Kumbhakar and Tsionas, 2006; Tauer and Mishra, 2006; Cabrera, Solis and del Corral, 2010; Mayen, Balagtas and Alexander, 2010; Moreira and Bravo-Ureta, 2008, 2009 and 2010; Mukherjee, Bravo-Ureta and Vries, 2013; Njuki and Bravo-Ureta 2015). SPF models are in the mainstream of economic analysis, and researchers are beginning to use them to examine the relationship between climatic effects and productivity (Hughes et al., 2011; Dell, Jones and Olken, 2014; Njuki and Bravo-Ureta, 2015; Qi, Bravo-Ureta and Cabrera, 2015).

This section introduces the methodology used in the empirical analysis. We first present the basic form of the SPF model, then explore alternative specifications of climatic variables and heterogeneity terms and, finally, discuss the full specifications of the empirical models used. We then introduce the methods for calculating a number of indicators, such as technical efficiency index, climatic effects indexes, and total factor productivity change (TFPC). We go on to decompose the TFPC indicator into the six components (technological progress, technical efficiency (TE) change, scale and mix efficiency change, climatic effects change, heterogeneity and statistical noise change). Finally, we discuss the scenario analysis approach used to predict climatic effects on milk output for the period 2020 through 2039.

Stochastic Production Frontier Models

Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) introduced, independently but at roughly the same time, the stochastic frontier model, which has become

widely used in economics, generally, and agricultural economics, in particular (Battese and Coelli, 1995; Bravo-Ureta et al., 2007). The SPF model adds a one-sided error to the standard production function, which makes it possible to identify technical efficiency. The technical efficiency level reflects the fact that actual outcome lies on or below the production frontier (Aigner, Lovell and Schmidt, 1977; Zellner, Kmenta, and Dreze, 1966).

In this study, the basic stochastic frontier model, assuming a Cobb-Douglas functional form and panel data, can be written as:

$$ln\, Y_{it} = \alpha + \sum_{k=1}^{K} \beta_k\, ln\, X_{kit} + \theta_1 T_t + \nu_{it} - \mu_{it} \qquad [1]$$

where Y_{it} is output measured as milk equivalent for the i^{th} farm in period t; X_{kit} is the k^{th} input; and T denotes the time trend. α, β, γ and θ are parameters to be estimated. The composite error term $\varepsilon_{it} = \nu_{it} - \mu_{it}$, where $v_{it,}$ denotes the variation from the frontier resulting from external events such as luck, and μ_{it} captures technical efficiency that reflects managerial performance (Martin and Page, 1983; Bravo-Ureta et al., 2007; Moreira López and Bravo-Ureta, 2009). The component v_{it} has a symmetric normal distribution $v_{it} \sim N\ (0,\ \sigma_v^2)$, and μ_{it} follows a half-normal distribution $\mu_t \sim half\ N\ (0,\ \sigma_\mu^2)$. These two terms, v_{it} and $\mu_{it,}$ are assumed to be independent of each other (Aigner, Lovell and Schmidt, 1977; Jondrow et al., 1982).

We extend the basic SPF model in equation [1] by adding climatic variables to identify their effect on output. According to Dell, Jones and Olken (2014), panel data models like the ones used in this paper, can "…exploit the exogeneity of cross-time weather variation allowing for causative identification" (p. 753). As discussed in the literature review section, weather shocks and adaptive strategies determine the total climatic effects on dairy farm production.

Letting Z_{sit} denote the s^{th} ($s=1, 2, \ldots, 12$) climatic factor for farm i at time t, and adding T^2 to allow for a time variant rate of technological progress, the SPF model can be written as:

$$ln\, Y_{it} = \alpha + \sum_{k=1}^{K} \beta_k\, ln\, X_{kit} + \sum_{s=1}^{S} \gamma_s\, Z_{sit} + \theta_1 T_t + \theta_2 T_t^2 + \nu_{it} - \mu_{it} \quad [2]$$

In the empirical analysis presented below, this paper tests two alternative specifications of climatic variables. The first specification includes only seasonal weather, where we have four seasonal average values of temperature and four seasonal average values of precipitation: Z_{sit} ($s=1, 2, \ldots, 8$). The climatic term in equation [2] is written as: $\sum_{s=1}^{S} \gamma_s\, Z_{sit} = \sum_{s=1}^{4} \gamma_s\, Z_{sit} + \sum_{s=5}^{8} \gamma_s\, Z_{sit}$.

The second specification, following Dell, Jones and Olken (2014), incorporates an interaction term between weather and the 30-year climate normal to reflect adaptive effects. Weather is represented by average annual temperature Z_{sit} ($s=9$) and average annual precipitation Z_{sit} ($s=10$). The climate normal is a 30-year moving average of temperature Z_{sit} ($s=11$) and a 30-year moving average of precipitation Z_{sit} ($s=12$). Thus, the climate effects part of the model for this study can be expressed as:

$$\sum_{s=1}^{S} \gamma_s\, Z_{sit} = \sum_{s=1}^{4} \gamma_s\, Z_{sit} + \sum_{s=5}^{8} \gamma_s\, Z_{sit} + \gamma_9 Z_{9it} \times Z_{11it} + \gamma_{10} Z_{10it} \times Z_{12it} \quad [3]$$

SPF Model with Climatic Variables and Heterogeneity

After specifying the climatic variables, we turn our attention to unobserved time invariant farm level heterogeneity within the SPF model. Four alternative specifications have been introduced to deal with this problem. Greene (2005a and 2005b) proposed two approaches to modeling unobserved heterogeneity. The first approach, the “True” Fixed Effects (TFE) model,

assumes that farm specific effects (heterogeneity) are non-random while the second approach, the "True" Random Effects (TRE) model, assumes that such effects are random. The TRE model assumes that the heterogeneity term follows a normal distribution and that this term is uncorrelated with other regressors. An extension of the TRE model allows the regressors and the heterogeneity term to be correlated, and this is referred to hereafter as the TRE- Mundlak specification, or TRE-M, model (Abdulai and Tietje, 2007).

A further extension, introduced initially by Colombi (2010) and Tsionas and Kumbhakar (2014), makes it possible to separate the TE term into two components, time variant or transient TE and time invariant or persistent TE. This approach is called the Generalized True Random Effects (GTRE) model. According to Filippini and Greene (2015), the time-invariant term reflects persistent structural problems in the organization of the production process or systematic shortfalls in managerial capabilities, whereas the transient term reflects non-systematic management problems that can be addressed in the short term. A different perspective is offered by Tsionas and Kumbhakar (2014) who, based on Kumbhakar and Heshmati (1995), indicate that TE does consist of two terms: one is time-varying technical efficiency and the other is persistent technical efficiency, which is associated with farm heterogeneity.

We now present the equations for four models with alternative heterogeneity specifications. The TFE Model, which assumes that heterogeneity among different farms is fixed, includes a constant $\alpha_{i,}$ to capture the farm-specific fixed effects:

$$ln\, Y_{it} = \alpha_i + \sum_{k=1}^{K} \beta_k \, ln\, X_{kit} + \sum_{s=1}^{S} \gamma_s \, Z_{sit} + \theta_1 T_t + \theta_2 T_t^2 + \nu_{it} - \mu_{it} \qquad [4]$$

Equation [4] can be estimated by maximizing the unconditional log likelihood function directly (Greene, 2005b).

The TRE model assumes that heterogeneity between farms is randomly distributed, and that the heterogeneity term, w_i, follows a random distribution. Therefore, $w_i \sim iid\ N(0, \sigma_w^2)$ and is not correlated with all other regressors. Thus, the TRE model can be written as:

$$ln\, Y_{it} = \alpha + w_i + \sum_{k=1}^{K} \beta_k \, ln\, X_{kit} + \sum_{s=1}^{S} \gamma_s \, Z_{sit} + \theta_1 T_t + \theta_2 T_t^2 + \nu_{it} - \mu_{it} \qquad [5]$$

Equation [5] can be treated as a standard SPF model with a random constant term, and it is estimated via simulated maximum likelihood methods (Greene, 2005a and b). In order to discriminate between the TFE and the TRE we conduct a Hausman test (Hausman, 1978; Greene, 2008), which amounts to testing whether w_i is independent of the other regressors.

The TRE-M specification is used only if heterogeneity in the TRE model is found to be correlated with the other regressors. Farsi, Filippini and Kuenzle (2005) and Abdulai and Tietje (2007), following Mundlak (1978), redefine the heterogeneity term w_i in equation [5] as a function of the mean of all time-varying regressors. Given that the climate data is identical for dairy farms in a given county, we assume that the heterogeneity between farms comes only from conventional inputs; thus, the heterogeneity term is written as:

$$w_i = \sum_{k=1}^{K} \delta_k \, \overline{ln\, X_{k\iota t}} + \overline{m_\iota} \qquad [6]$$

where $\overline{ln\, X_{k\iota t}}$ represents an average of the log value of the k^{th} regressor over time T for farm i, and $\overline{m_\iota} \sim iid\ N(0, \sigma_m^2)$ is uncorrelated with all other regressors. Thus, the TRE-M can be written as:

$$ln\, Y_{it} = \alpha + \overline{m_i} + \sum_{k=1}^{K} \delta_k\, \overline{ln\, X_{kit}} + \sum_{k=1}^{K} \beta_k\, ln\, X_{kit} + \sum_{s=1}^{S} \gamma_s\, Z_{sit} + \theta_1 T_t + \theta_2 T_t^2 + \nu_{it} - \mu_{it} \qquad [7]$$

Equation [7] is estimated using a Simulated Maximum Likelihood method (Greene, 2005b).

As indicated, the GTRE model assumes that the technical efficiency term μ_{it} in equation [5] can be separated into two parts: time-invariant persistent technical efficiency (η_i) and time-varying technical efficiency (μ'_{it}) (Colombi et al., 2014). According to Filippini and Greene (2015), the GTRE model is written as:

$$ln\, Y_{it} = \alpha + w_i - \eta_i + \sum_{k=1}^{K} \beta_k\, ln\, X_{kit} + \sum_{s=1}^{S} \gamma_s\, Z_{sit} + \theta_1 T_t + \theta_2 T_t^2 + \nu_{it} - \mu'_{it} \qquad [8]$$

where η_i follows a half normal distribution with variance σ_h^2. Then, the four disturbance terms in in equation [8] can be combined into two elements: a time invariant element ($w_i - \eta_i$), and a time varying element ($\nu_{it} - \mu'_{it}$). Thus, the GTRE model can be estimated as a SFP model where each of the two elements follows a skew normal distribution (Filippini and Greene, 2015).

Climatic Effect Index

According to Hughes et al. (2011), the Climatic Effect Index (CEI) measures the joint effect of climatic factors on output. A weakness of the method Hughes et al. (2011) is that it ignores the possible impact of adaptive strategies. The total CEI for farm *i* at time *t*, based on equation [2] and the estimated parameters $\hat{\gamma}$, can be written as:

$$CEI_{it} = exp\left(\sum_{s=1}^{S} \hat{\gamma}_s\, Z_{sit}\right) = CEIW_{it} \times CEIADP_{it} \qquad [9]$$

where $CEIW_{it}$ represents weather shocks to farm i at time t and is equal to $CEIW_{it} = exp(\sum_{s=1}^{8} \hat{\gamma}_s Z_{sit})$. The adaptive effect index, $CEIADP_{it}$, is written as $CEIADP_{it} = exp(\sum_{s=9}^{10} \hat{\gamma}_s Z_{sit})$. Notably, when *CEI* has a value greater than 1 climatic conditions have a positive effect on output and the opposite is true when the value less than 1.

The $CEIW_{it}$ has four seasonal partial indexes denoted as: CEISPR for spring ($CEISPR_{it} = exp(\hat{\gamma}_1 Z_{1it} + \hat{\gamma}_5 Z_{5it})$); CEISUM for summer ($CEISUM_{it} = exp(\hat{\gamma}_2 Z_{2it} + \hat{\gamma}_6 Z_{6it})$); CEIAUT for autumn ($CEIAUT_{it} = exp(\hat{\gamma}_3 Z_{3it} + \hat{\gamma}_7 Z_{7it})$); and CEIWIN for winter ($CEIWIN_{it} = exp(\hat{\gamma}_4 Z_{4it} + \hat{\gamma}_8 Z_{8it})$). Thus, *CEIWit* is equal to:

$$CEIW_{it} = CEISPR_{it} \times CEISUM_{it} \times CEIAUT_{it} \times CEIWIN_{it} \quad [10]$$

$CEIW_{it}$ can be also decomposed into two partial annual effects, namely, CEIT for temperature ($CEIT_{it} = \sum_{s=1}^{4} \hat{\gamma}_s Z_{sit}$) and CEIR for precipitation ($CEIR_{it} = \sum_{s=5}^{8} \hat{\gamma}_s Z_{sit}$). Thus, $CEIW_{it} = CEIT_{it} \times CEIR_{it}$.

Technical Efficiency

We use the Jondrow, Lovell, Materov, and Schmidt (JLMS) estimator (Jondrow et al., 1982) to calculate the expected value of technical efficiency term μ_{it} for our models. According to Battese and Coelli (1988), the TE level based on μ_{it} is written as:

$$TE_{it} = exp(-\mu_{it}) \quad [11]$$

The GTRE model in equation [8] contains a transient technical efficiency term μ'_{it} and a persistent technical efficiency term η_i. Thus, the TE level of farm i at time t for this model is:

$$TE_{it} = TE\ transient_{it} \times TE\ persistent_{it} = exp(-\mu'_{it}) \times exp(-\eta_i) \quad [12]$$

Total Factor Productivity

According to Jorgenson and Griliches (1967), total factor productivity is defined as the ratio of aggregate output Q to aggregate input X, where Q and X are nonnegative, non-decreasing, linearly-homogeneous functions. The TFP of farm *i* at time *t* is:

$$TFP_{it} = Q_{it}/X_{it} \qquad [13]$$

O'Donnell (2010 and 2012) and O'Donnell and Nguyen (2013) proposed a multiplicatively complete total factor productivity change index by defining $TFPC_{jsit}$ as the ratio of TFP of farm *i* at time *t* relative to TFP of farm *j* at time *s*:

$$TFPC_{jsit} = \frac{TFP_{it}}{TFP_{js}} = \frac{Q_{it}/X_{it}}{Q_{js}/X_{js}} \qquad [14]$$

By choosing any TFP index (for example, TFP_{js} in equation [14]) as a reference point, the TFPC index makes it possible to compare changes of TFP across farms and years.

TFPC Decomposition

For an output-oriented GTRE model with Cobb-Douglas functional form and climatic variables, TFPC can be decomposed into six components as follows O'Donnell (2016):

$$TFPC_{jsit} = \frac{TFP_{it}}{TFP_{js}} = \left(\frac{TP_t}{TP_s}\right)\left(\frac{TE_{it}}{TE_{js}}\right)\left(\frac{SME_{it}}{SME_{js}}\right)\left(\frac{CEI_{it}}{CEI_{js}}\right)\left(\frac{SNI_{it}}{SNI_{js}}\right)\left(\frac{HET_i}{HET_j}\right) \qquad [15]$$

TFP_t^* and TFP_s^* in the first component of the right hand side of equation [15] are maximum TFP that is possible using the technology at time *t* and time *s*, and the component TP_t/TP_s measures technological progress from time *s* to time *t* (TP_{ts}). The second component, TE_{it}/TE_{js}, measures technical efficiency change. SME_{it} and SME_{js} are scale-mix efficiency levels for farm *i* at time *t* and for farm *j* at time *s*, respectively; and the ratio SME_{it}/SME_{js} reflects the scale-mix efficiency change. The fourth component, CEI_{it}/CEI_{js}, denotes climatic effects for farm *i* at time

t relative to farm *j* at time *s*. The component SNI_{it}/SNI_{js} is the statistical noise change, and the last component (HET_i/HET_j) reflects the heterogeneity between farm *i* and farm *j*, and the number is constant over time.

The TFPC derived from the GRTE model shown in equation [8] is expressed as:

$$TFPC_{jsit} = \frac{exp\left(\hat{\theta}_1 t_i + \hat{\theta}_2 {t_i}^2\right)}{exp\left(\hat{\theta}_1 t_s + \hat{\theta}_2 {t_s}^2\right)} \cdot \frac{exp(-\hat{\eta}_i - \hat{\mu}'_{it})}{exp\left(-\hat{\eta}_j - \hat{\mu}'_{js}\right)} \cdot \left[\prod_{k=1}^{K} \left(\frac{X_{kit}}{X_{kjs}}\right)^{\hat{\beta}_k\left(1-\frac{1}{RTS}\right)}\right] \cdot \frac{exp\left(\sum_{s'=1}^{S} \hat{\gamma}_{s'} Z_{s'it}\right)}{exp\left(\sum_{s'=1}^{S} \hat{\gamma}_{s'} Z_{s'js}\right)} \cdot \frac{exp(\hat{v}_i)}{exp\left(\hat{v}_j\right)} \cdot \frac{exp(\hat{w}_i)}{exp\left(\hat{w}_j\right)} \quad [16]$$

where $RTS = \sum_{k=1}^{K} \hat{\beta}_k$ denotes the returns to scale value.

In the empirical analysis, we select the farm with the lowest TFP value in year 1996 as a reference point, defined as TFP_{j1996}. The TFPC value of farm *i* at time *t* is calculated as the ratio of TFP_{it} to TFP_{j1996}.

The annual growth rate in TFP provides a measure of the evolution in the performance of a dairy farm from 1996 through 2012 relative to itself or any other benchmark farm. Specifically, for time *t*, the annual growth rate in TFPC is given by:

$$TFPC\ annual_{it} = \frac{TFPC_{jsit+1} - TFPC_{jsit}}{TFPC_{jsit}} \quad [17]$$

Scenario Analysis

Predicting the potential impact of future climate change is an important objective of this study. Using the estimates for the SFP models, we conduct scenario analyses to examine the possible impact of climate change on dairy farm output from 2020 through 2039. For this

purpose, we use climate data derived from different IPCC emission scenarios. Each emission scenario is obtained by assuming different rates of population growth, economic growth, agricultural production, energy demand, and industrial output. Then, combining several models, including Integrated Assessment Models (IAMs), Carbon-cycle Models, General Circulation Models, and Earth System Models, scientists can calculate precipitation and surface temperature for each scenario (NCAR[2]).

Around 40 emission scenarios have been created for IPCC climate change analysis, from environmentally friendly scenarios to rapid growth and high energy-use scenarios (IPCC, 2007). GIS maps data for the latest IPCC report (2013) is not available, so we used the data for the fourth IPCC report (2007). This study focuses on two emission scenarios. One is the "commitment (CMT) scenario," which assumes that the concentration of pollutants in the atmosphere is fixed at the year 2000 levels. Given that the current greenhouse emission level is higher than the 2000 level, the CMI scenario denotes a situation in which the global warming problem is mitigated; thus, this could be characterized as an optimistic scenario in terms of emissions. The second is the "high A2 (HA2) scenario," which assumes that the world undergoes high population growth, moderate gross domestic product (GDP) growth, high energy use, medium to high land use changes, low resource availability (mainly oil and gas), and slow technological change. This HA2 scenario reflects "dramatic" climate change.

Assuming inputs, heterogeneity, technology, technical efficiency, and the stochastic noise are held constant at 2012 levels, the annual effect of CEI on output over the period 2020-2039 relative to 2012 is:

[2] https://gisclimatechange.ucar.edu/

$$\Delta Y_{i2012t} = \frac{Y_{it} - Y_{i2012}}{Y_{i2012}} = \frac{CEI_{it} - CEI_{i2012}}{CEI_{i2012}} \quad [18]$$

1.4 Data

Wisconsin is one of the largest dairy producing areas in the U.S. According to the National Agricultural Statistics Service (NASS[3]), total milk production in Wisconsin was 27,572 million pounds in 2013, accounting for nearly 14% of the U.S. total milk output. The empirical analysis uses input-output data from Wisconsin dairy farms, as well as historical and forecasted county-level climate data.

Input-output Data

The input-output data contains 8,573 observations for 938 dairy farms scattered around 48 Wisconsin counties (see Figure 1, counties in green and purple) over a 17-year period from 1996 through 2012. This data consists of detailed farm-level information on dairy farms participating in the Agricultural Financial Advisor (AgFA[4]) program of the University of Wisconsin-Madison Center for Dairy Profitability,[5] as well as high-quality financial and production information for dairy farms in the State of Wisconsin.

In this study we use a balanced panel composed of 53 farms located across 10 counties (see Figure 1, counties in purple), which produces a total of 901 observations over the 17-year period. Descriptive statistics for output, inputs and climatic variables are presented in Table 1.

On average, there were 99 head of adult cows per farm, and the total milk equivalent produced by a farm was 1,220 metric tons per year. Milk equivalent units are calculated by adding total farm income and dividing that total by the average U.S. milk price for the time

[3] http://quickstats.nass.usda.gov/
[4] http://cdp.wisc.edu/agfa.htm;
[5] https://cdp.wisc.edu

period in question. We use milk equivalent units because the related independent variables are the total amount of physical inputs used by a farm. It is important to stress that the farms in our dataset are highly specialized in milk production, for which the overall average milk revenue is 82% percent of total farm income.

Regarding inputs, there were 6,323 hours of labor used per year. The labor variable includes the total hours of family paid and unpaid labor and management, and hired labor. Concentrate feed is the total amount of 16% protein dairy concentrate feed purchased per year, which was 616 metric tons. Capital cost per year includes depreciation of breeding livestock, machinery, equipment, and buildings. Depreciation was around $78,539 per year per farm in 2012 dollars. Annual animal expense was $35,194, which includes the total expenditure for veterinary care and medicine, breeding fees and other livestock expenses. Average annual crop expense was around $85,917 in 2012 dollars. Crop expenses were composed of chemical, fertilizer, seeds and plants, gas and fuel, rented machinery, etc. Expenditure on crops is a widely used variable in dairy production studies, such as Cabrera, Solis and del Corral (2010), Moreira and Bravo-Ureta (2010), Theodoridis and Psychoudakis (2008), and Lawson et al. (2004). The time trend denotes technological progress.

According to the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS[6]), the average number of adult cows per Wisconsin farm is 61 between 1996 and 2012, which is lower than the number (99 head) presented in Table 1. The reason for this discrepancy may be that larger dairy farms are more likely to enroll in the AgFA program. We acknowledge the fact that potential bias may arise from excluding small farms from our dataset,

[6] http://quickstats.nass.usda.gov/

and our results may be suitable only for dairy farms with characteristics similar to those in our sample.

Climate Data

Climate data from 1996 through 2012 was obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) maps.[7] We use the spatial join method, a Geographic Information System (GIS) technique, to combine the climate data map with the county map in order to generate monthly mean temperature and precipitation for each county and year. The two data sets (input-output and climate) are merged based on county and year identifiers, so that all farms within a county share the same climatic data.

Table 1 lists the seasonal,[8] annual, and 30-year annual average values of temperature and precipitation in Wisconsin from 1996 through 2012. The average monthly temperatures were -4.32C° in winter and 19.13C° in summer. The average monthly precipitation was 9.01cm in summer, which is higher than in all other seasons. The average monthly precipitation was only 3.99cm in winter. In order to check the robustness of climate data, we compared our climate data from PRISM to climatic records of the National Oceanic and Atmospheric Administration (NOAA[9]), which were collected from the land-based weather stations in the 10 relevant counties in Wisconsin. We found no significant differences between the values of observations in these two data sets, rather only a small numerical difference in the average temperature in winter, which was a bit lower in the NOAA dataset.

[7] http://www.prism.oregonstate.edu/recent/
[8] According to the 17-year average monthly temperatures over 1996 through 2012 (December 4.60C°, January -7.57C°, February -5.31C°, March 0.30C°, April 7.25C°, May 13.06C°, June 18.66C°, July 21.44C°, August 20.33C°, September 16.11C°, October 9.32C°, November 2.70C°), this study redefines the seasons in Wisconsin as follows: summer - June through September; autumn - October and November; winter – December through March; and spring - April and May.
[9] http://www.ncdc.noaa.gov/cdo-web/

Climate data for 2020 through 2039 was generated by the National Center for Atmospheric Research (NCAR) GIS program for the fourth IPCC Assessment Report. The NCAR GIS maps include temperature and precipitation projections over the period from 2000 to 2099.[10] In this study we use the projected data from 2013-2039 and converted the GIS maps into county-level monthly temperature and precipitation data. We calculated monthly averages and then seasonal and annual temperature and precipitation values for the CMT and HA2 scenarios. Regarding the data used for calculating 30-year climate normal over 2020 through 2039, the data for years 1990 through 2012 was from the PRISM dataset and the data for years 2013 to 2038 was from the NCAR dataset.

The summary statistics for climate data for the CMT scenario from 2020 through 2039 are presented in the top part of Table 3. The average annual temperature from years 2020 to 2039 is 1C° higher than for the period 1996 through 2012. Even though the CMT scenario represents a situation in which global warming is mitigated, the average temperature still increases over the next three decades, with an average temperature in summer of 21.07 C°, which is 1.94C° higher than for years 1996 through 2012. The average temperature projected from 2020 to 2039 in winter (-4.12C°) is almost the same as the value as for the 1996 – 2012 period. Thus, higher temperatures in summer may become more harmful for dairy farms in the future. Compared to 1996 through 2012, there is less precipitation in spring, summer, and autumn between 2020 and 2039. Thus, water shortage may become a serious problem for dairy farms, perhaps even for the entire agricultural sector.

The summary statistics for the climate data for the HA2 scenario are presented in the bottom part of Table 2. The average summer temperature is 22.08C°, which is 1.01C° higher

[10] https://gisclimatechange.ucar.edu/gis-data

than the value in the CMT scenario and 2.95C° higher than the value over years 1996 through 2012. The precipitation in spring, summer and autumn is higher than precipitation in the CMT scenario, but lower than for years 1996 through 2012. Thus, dairy farms are more likely to face warmer and drier conditions in the future. The temperature values for all seasons over all selected years in the HA2 scenario are higher than in the CMT scenario, but the values for precipitation in the CMT scenario are even higher.

1.5 Results and Analysis

The estimates of the standard SPF model, followed by the TFE, TRE, TRE-M, and GTRE models with alternative climatic variables, are presented in Tables 3-5. Specifically, Table 3 contains the estimation results for the five models without climatic variables, Table 4 presents the results with seasonal climatic variables, and Table 5 shows the results with seasonal climatic variables and the longer-term adaptive effects. In general, the null hypothesis that all coefficients are zero is rejected in every case. The estimated coefficients of the six conventional inputs are mostly significant, and all of them in all models have the expected positive sign and values (i.e., between 0 and 1).

We apply a series of tests to identify the most robust model. We first conduct a likelihood ratio test on the climatic variables in Table 3 and 4, and the results lead to the rejection of the hypothesis that the coefficients of the climatic variables are jointly zero. Thus, climatic variables should be included in the specification of the production frontier model. Turning to heterogeneity, we conduct a Hausman test between the TFE and TRE models to evaluate the null hypothesis that unobserved heterogeneity is independent of the other explanatory variables. The chi-square value between the TFE and TRE models in Table 4 is -31.45, which indicates that we cannot reject the null hypothesis that the TRE regressors are uncorrelated with the heterogeneity

term (Stata Manual, 2013). Similarly, the chi-square value between the TFE and TRE models in Table 5 is 20.25 (Prob>chi2 = 0.3192), which again indicates that the TRE regressors are uncorrelated. Thus, the TRE-M models in Tables 4 and 5 become redundant. Finally, we compare the TRE and GTRE results, and the significant coefficient for persistent TE indicates that the GTRE is the most robust model in this study. The statistical tests to compare the various models are summarized in Table 6.

Another task before proceeding with the analysis is to identify the most appropriate climatic variables to be included. The GTRE model in Table 4 incorporates only the seasonal weather shocks, and the GTRE model in Table 5 includes both weather shocks and the longer-term adaptive effects. The coefficients of conventional inputs and seasonal temperatures are similar across the two GTRE models, but the signs of the precipitation coefficients are opposite. The GTRE results in Table 5 reveal that more precipitation is beneficial, which is consistent with findings reported by other authors, indicating that higher precipitation will likely bring greater crop production and better quality of feeds to promote milk productivity (von Keyserlingk et al., 2013; Powell and Russelle, 2009). Thus, the analysis that follows is based on the GTRE model with seasonal climatic factors and longer-term adaptive effects, and we refer to this model hereafter as GTRE-Full.

Results for the GTRE-Full model

According to the results for the GTRE-Full model in Table 5, changes in conventional inputs, technical progress, climatic factors, and adaptation strategies all have significant impacts on milk output. Given the Cobb-Douglas specification, the coefficients for the conventional inputs represent partial elasticities of production (PEP). Herd size is the major contributor to output (PEP=0.592), followed by concentrate feed (PEP=0.133) and crop expenses (PEP=0.111).

The partial elasticities for labor, depreciation and animal expenses are 0.311, 0.044 and 0.038, respectively. The value of returns to scale for the GTRE-Full model is 0.949,[11] indicating that the dairy farms in the sample exhibit decreasing return to scale.

Increasing temperatures in summer and autumn have a negative impact on milk production. A 1C° increase in summer leads to a 6% reduction in output, and a 1C° increase in autumn reduces annual output by 3.8%. The coefficients of spring and winter temperature are positive but not significant. Increasing precipitation in all seasons has positive and significant effects on dairy output. Specifically, a 1cm increase in precipitation in summer leads to a 3.3% increase in milk output.

The coefficients of the seasonal climatic factors in the GTRE-Full model indicate that increasing temperature and decreasing precipitation are harmful for dairy farming in Wisconsin. The interaction terms ATEMP*30TEMP and APREP*30PREC reflect the effects of adaptive strategies on mitigating adverse climatic shocks. A positive coefficient for the temperature interaction term indicates that adaptive strategies have had a positive impact on output; thus, adaptations can reduce the damage of higher annual temperatures on dairy farms. A negative coefficient for the precipitation interaction term indicates that the adaptive strategies would reduce output; however, adaptive strategies corresponding with a decreasing 30PREC have a positive effect on output These results are consistent with the findings regarding seasonal climactic factors, which indicate that higher temperature and less precipitation are harmful for dairy farming. Given the expectations of higher temperature and lower precipitation in the future (Table 2), adaptive strategies will play an increasingly important role in milk production as we move forward in time.

[11] The value is obtained by adding up the coefficients of conventional inputs in the GTRE model.

Climatic Effect Indexes

Based on the estimated GTRE-Full model, we calculate the CEI values, which combine various climatic effects, and present them in Table 7. We first compute the CEI terms for each farm and year, and then use these values to calculate average annual CEIs. The annual average CEI values reflect the aggregate effects of all climatic factors and adaptive strategies on output. A decreasing trend in CEI values from 1996 through 2012 implies that climatic conditions for dairy farming in Wisconsin worsened over that period. The best climatic conditions for milk production was in 1996 (CEI=0.316), while the worst occurred in 2005 (CEI=0.273). The average CEI value between 1996 and 2012 is 0.293.CEI value in this study is lower than the CEI value calculated by Hughes et al. (2011) for Australian farms (CEI=0.95), and it is also lower than the mean CEI value (CEI=0.35) in Latin America and the Caribbean countries (Lachaud, Bravo-Ureta, and Ludena, 2015).

In Table 7, the CEIW and CEIADP terms reflect the effects of weather shocks and adaptations on output. The CEIT and CEIR show the aggregated effects of temperature and precipitation on output, respectively. Regarding the seasonal climatic conditions (CEISPR, CEISUM, CEIAUT, and CEIWIN), the results show positive average effects on production in winter and spring, while the effects in summer and autumn are negative.

Technical Efficiency Estimates

Table 8 presents average annual technical efficiency and persistent and transient technical efficiencies estimated from the GTRE-Full model from 1996 through 2012. Average TE is 88%, which is the same value reported by Cabrera, Solis and Corral (2010) using a cross-sectional sample of 273 Wisconsin dairy farms. Average persistent TE equals 94.4% while transient TE

varies between 91.4% and 95.2%, with an average value equal to 93.2%, which is very close to the persistent value.

Total Factor Productivity Analysis

Table 9 presents the summary statistics for TFPC and its six components, with the corresponding annual growth rate listed in italics. $TFPC_{j1996it}$ is the total factor productivity change of farm i at time 1 relative to farm j in 1996, where the TFP value of farm j is the 1996 baseline value. The average annual TFPC for all farms is 1.85, indicating the TFPC value of an average farm is 1.85 times larger than the value of farm j at year 1996. The average annual growth rate of $TFPC_{j1996it}$ is 2.9%. The TFPC values presented in Table 9 exhibit a slightly increasing trend from 1996 through 2012, showing that a growing productivity of dairy farms. The largest TFPC value occurred in 2012, which means dairy farms' productivity reached the highest level in year 2012. The lowest TFPC value occurred in year 1996. The TFPC annual growth rate fluctuated widely from 1996 through 2012. For instance, TFPC grew 13.9% from 2005 to 2006, but decreased by 16.8% from 2006 to 2007.

TFPC consists of six components that provide us with multiple perspectives in analyzing the factors that influence dairy farm productivity. As mentioned earlier, these six components are: technological progress (TP_{1996t}), technical efficiency change ($TEC_{j1996it}$), scale and mixed efficiency change ($SEC_{j1996it}$), climatic effect change ($CEI_{j1996it}$), heterogeneity change (HET_{ji}), and stochastic noise change ($SNC_{j1996it}$). For each component, a higher value contributes more to TFPC than a smaller one. As shown in Table 9, the average value of TP is 1.26 and this is the major factor contributing to TFPC. The values of TPC in 2010 and 2011 are higher than for 2009 and 2012, indicating that technological progress reaches the highest growth rate in 2010 and

2011. The annual average TEC rate is 1.21%, and is slightly increasing over the time period analyzed.

Figure 2 presents the TFPC value for dairy farms from 1996 through 2012. The blue dots denote the TFPC values from 1996 through 1999, and the orange dots are the TFPC value for years 2008 through 2012. The dairy farms are sorted by average number of cows per farm on the horizontal axes. According to the first graph in Figure 2, only three out of 53 farms had an average number of cows greater than 200. Large farms were more likely to have a higher TFPC value than small farms from 1996 through 1999. However, the TFPC values of small farms grew faster than those of large farms. In years 2008 through 2012, some small farms had even higher TFPC values than large farms. The second graph in Figure 2 shows the TFPC value of dairy farms with average number of cow lower than 200 heads per year.

Figure 3 presents the TEC values of dairy farms from 1996 through 2012. The first graph shows that large farms were more likely to maintain a higher technical efficiency level than small farms. The second graph shows that small farms with fewer than 200 cows per year. The TEC values of small farms varied widely over years

Figure 4 presents the CEIC for the 10 Wisconsin counties represented in the data from 1996 through 2012. Oneida County had the best climatic conditions and Ozaukee County had the worst, which indicates that counties in northern Wisconsin have better climatic conditions for dairy farming than southern counties.

Finally, Figure 5 presents average annual TFPC rates from 1996 through 2012. Large farms tend to show lower growth rates than small farms. According to Figure 2, although large farms have higher productivity levels in 1996, productivity levels for small farms are equal or

even higher in 2012. Thus, small farms have become relatively more competitive than larger farms in Wisconsin.

Scenario Analysis

Table 10 presents the values of CEI for the two IPCC emission scenarios discussed earlier, the commitment (CMT) and High Emission (HA2) scenarios, over the period 2020-2039. The CEIs values for 2012 serve as the baseline. The CEICMT and CEIHA2 terms are the annual climatic effects on output, and ΔYCMT (%) and ΔYHA2 (%) reflect annual milk output changes relative to output in 2012. CEIWCMT and CEIWHA2 denote the annual effects of weather shocks on output, and CEIADPCMT and CEIADPHA2 are the annual effects of adaption on output.

The CMT scenario reflects a situation where climatic change is mitigated and the average value of CEI is 0.306, which is 0.07 lower than the baseline. On average, average annual output change caused by climatic effects is -2.4%. Thus, climatic conditions become adverse for milk production even if climate change is mitigated. Notably, the annual values of the CEIs reveal a slight upward trend over the years 2030 through 2039, indicating that the climatic conditions for milk production may improve slightly in the future. Further, all the CEIWCMT values are lower than the baseline, which means a worsening of the weather shocks to dairy production in the future. The average CEIWCMT value is 0.348. On the other hand, adaptive strategies play a more important role in mitigating negative weather shocks in the future. The average CEIADPCMT value of 0.888 is higher than the baseline, which indicates that adaptation strategies become more effective in the future.

The HA2 scenario reflects a more dramatic future climate change. Under the HA2 scenario, the average CEIHA2 value (0.289) is lower than the baseline, indicating that the climatic condition worsens from 2020 through 2039. The annual CEI value reveals a slight downward trend during this period, indicating that climatic conditions become worse over those years. Regarding output change, on average, annual climatic effects reduce milk production by 7.7% per year. Thus, weather shocks cause more damage to milk production, but adaptive strategies become more effective.

The CMT scenario denotes a relatively positive situation in which climate change has been mitigated, and the HA2 scenario represents an adverse situation in which climate change becomes more dramatic in the future. The CEIWHA2 value is lower than CEIWCMT value, indicating the weather shocks under the HA2 scenario lead to more negative impacts on output. On the contrary, the CEIADPHA2 value is larger, showing that adaption to climate change plays an increasingly beneficial role.

1.6 Summary and Concluding Remarks

As global warming continues, understanding the effect of climatic variables on total factor productivity is critical to the future of dairy farming and to many other productive sectors in agriculture. Economic research using data from operating commercial dairy farms focusing on the impact of climate change on milk production is very limited. To fill this gap, we have tested several panel data stochastic production frontier models incorporations various specifications of climatic variables. This analysis indicates that quantifying the impacts of climatic factors alone may not adequately reflect the overall climatic effect, as farmers may implement adaptation strategies to cope with this adverse and evolving new reality. Thus, incorporating the effects of

adaptive strategies in production models is an important contribution of this study to the literature.

This essay also contributes to the literature by exploring alternative SPF models for dairy production. We found that a recently developed model, the generalized true random effects model, is the most robust method for the dairy farm data utilized. This model makes it possible to evaluate both transient and persistent TE levels while also addressing unobserved time invariant farm-level heterogeneity.

The evidence reveals that, in Wisconsin, higher summer and autumn temperatures are harmful to dairy production, but more precipitation is beneficial. Moreover, the climatic conditions for Wisconsin dairy farming worsened over the 1996-2012 period, but adaptive strategies have diminished the adverse effects of increasing temperature and decreasing precipitation. Our results highlight the important role of adaptive strategies in reducing the impact of adverse climatic effects.

Climatic conditions for dairy farming from 2020 through 2039 become worse compared to 2012 under two very different scenarios, the commitment (CMT) and High Emission (HA2) scenarios. On average, holding all other factors at the 2012 level, climatic effects reduce milk output by 2.4% per year under the CMT scenario. Notably, although climatic conditions become worse than the baseline under the CMT scenario, they improve slightly from 2030 to 2039. The annual output reduction caused by climatic variations under the HA2 scenario is 7.7%. These results demonstrate that even under mild projections of adverse climatic conditions, dairy farming experiences a decline in output.

Implementing adaptive strategies plays an important role in reducing negative climatic effects on dairy farms. Our scenario analysis emphasizes that adaptive strategies are more effective in the HA2 scenario than the CMT scenario. Thus, research and extension efforts are needed to promote suitable adaptation strategies in the future.

Total factor productivity is an important indicator of competitiveness for dairy farms. The average annual TFP growth rate of Wisconsin dairy farms was 2.9% from 1996 through 2012. This figure is lower than the number reported by Brümmer, Glauben and Thijssen (2002), who used a distance function framework to examine the TFP growth of dairy farms in Northern Germany, Poland and The Netherlands during 1991 to 1994. The respective TFP growth rates were 6%, 5% and 3%. Most of the small dairy farms had lower TFP values than large farms in 1996. However, those small farms experienced faster development during the following17 years, and their TFP values were even higher than those of large farms in 2012. Our results indicate that small farms have become more competitive in Wisconsin, and increasing farm size is not an effective strategy to increase TFP.

TFP was decomposed into six elements, which made it possible to provide a detailed analysis of dairy farm performance. Technological progress is the major factor contributing to TFP increase while, technical efficiency change also improves TFP, but scale-and-mixed efficiency changes had negative effects.

Finally, policies that promote technological progress appear to be the most effective way to increase TFP. Since dairy farmers are likely to face worsening climatic conditions in the future, more efforts are needed to promote adaptive strategies. However, weather shocks may be severe, if extrapolations of weather variations go beyond historical experience (Dell, Jones and Olken, 2014). In that case, the estimated parameters in this study might no longer be suitable for

scenario analysis if the temperature became too high or too low. This issue is an important topic for future research. One possible solution may be to examine the impact of the milk output lost because of severe weather shocks, and then combine it with the results from the SPF production function to estimate the total output change.

References

Abdulai, A. and Tietje, H. (2007). Estimating technical efficiency under unobserved heterogeneity with stochastic frontier models: Application to northern German dairy farms. *European Review of Agricultural Economics* 34: 393-416.

Aigner, D., Lovell, C. K. and Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6: 21-37.

Allen, J. D., Anderson, S. D., Collier, R. J. and Smith, J. F. (2013). Managing Heat Stress and its Impact on Cow Behavior. Western Dairy Management Conference. Reno, NV.

Battese, G. E. and Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics* 38: 387-399.

Battese, G. E., and Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics* 20: 325-332.

Bravo-Ureta, B. E., Moreira López, V. H., Arzubi, A., Schilder, E. D., Álvarez, J. and Molina, C. (2008). Technological change and technical efficiency of dairy farms in three southern cone countries. *Agricultura Técnica* 68(4): 360-367.

Boyles, S. (2008). Heat stress and beef cattle. Available from: http://agnr.osu.edu/sites/agnr/files/imce/pdfs/Beef/HeatStressBeefCattle.pdf (March 20, 2016).

Bravo-Ureta, B. E., Solís, D., Moreira López, V. H., Maripani, J. F., Thiam, A. and Rivas, T. (2007). Technical efficiency in farming: A meta-regression analysis. *Journal of Productivity Analysis* 27: 57-72.

Brümmer, B., Glauben, T., and Thijssen, G. (2002). Decomposition of productivity growth using distance functions: the case of dairy farms in three European countries. *American Journal of Agricultural Economics*, 84: 628-644.

Cabrera, V. E., Solis, D. and del Corral, J. (2010). Determinants of technical efficiency among dairy farms in Wisconsin. *Journal of Dairy Science* 93: 387-393.

Calil, J., Silvester, A., Stelzl, K., Wissel-Tyson, C. and Frew, J. (2012). The Effect of Climate Change on the Production Costs of the Dairy Industry in the United States. Bren School of Environmental Science and Management, University of California, Santa Barbara, CA.

Capper, J. L., Cady, R. A. and Bauman, D. E. (2009). The environmental impact of dairy production: 1944 compared with 2007. *Journal of Animal Science* 87: 2160-2167.

Collier, R. J., Zimbelman, R. B., Rhoads, R. P., Rhoads, M. L. and Baumgard, L. H. (2006). A Re-evaluation of the Impact of Temperature Humidity Index (THI) and Black Globe Humidity Index (BGHI) on Milk Production in High Producing Dairy Cows. Western Dairy Management Conference. Reno, NV

Colombi, R. (2010). A Skew Normal Stochastic Frontier Model for Panel Data. The 45-th Scientific Meeting of the Italian Statistical Society.

Colombi, R., Kumbhakar, S. C., Martini, G. and Vittadini, G. (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis* 42: 123-136.

Comin, D. (2006). Total factor productivity. An Eponymous Dictionary of Economics. Elgar Publishers, Ltd.

Cook, N. B., Mentink, R. L., Bennett, T. B. and Burgi, K. (2007). The effect of heat stress and lameness on time budgets of lactating dairy cows. *Journal of Dairy Science* 90: 1674-1682.

Dell, M., Jones, B. F. and Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature* 52: 740-798

De Salvo, M., Begalli, D. and Signorello, G. (2014). The Ricardian analysis twenty years after the original model: Evolution, unresolved issues and empirical problems. *Journal of Development and Agricultural Economics* 6: 124-131.

Deschenes, O. and Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *The American Economic Review* 97: 354-385.

Dikmen, S. and Hansen, P. J. (2009). Is the temperature-humidity index the best indicator of heat stress in lactating dairy cows in a subtropical environment? *Journal of Dairy Science* 92: 109-116.

Farsi, M., Filippini, M. and Kuenzle, M. (2005). Unobserved heterogeneity in stochastic cost frontier models: An application to Swiss nursing homes. *Applied Economics* 37: 2127-2141.

Filippini, M. and Greene, W. (2015). Persistent and transient productive inefficiency: A maximum simulated likelihood approach. *Journal of Productivity Analysis* 45: 1-10.

Fried, H. O., Lovell, C. K. and Schmidt, S. S. (Eds.). (2008). *The Measurement of Productive Efficiency and Productivity Growth*. New York: Oxford University Press.

García-Ispierto, I., López-Gatius, F., Bech-Sabat, G., Santolaria, P., Yániz, J. L., Nogareda, C., De Rensis, F. and López-Béjar, M. (2007). Climate factors affecting conception rate of high producing dairy cows in northeastern Spain. *Theriogenology 67*: 1379-1385.

Greene, W. (2005a). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis* 23: 7-32.

Greene, W. (2005b). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics* 126: 269-303.

Greene, W. (2008). *Econometric Analysis*. 6th ed. Englewood Cliffs, NJ: Prentice Hall.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica* 46: 1251-1271.

Herbut, P. and Angrecka, S. (2012). Forming of temperature-humidity index (THI) and milk production of cows in the free-stall barn during the period of summer heat. *Animal Science Papers and Reports* 30: 363-372

Hill, M. J., Donald, G. E., Hyder, M. W. and Smith, R. C. (2004). Estimation of pasture growth rate in the south west of Western Australia from AVHRR NDVI and climate data. *Remote Sensing of Environment*, 93: 528-545.

Holter, J. B., West, J. W., McGilliard, M. L. and Pell, A. N. (1996). Predicting ad libitum dry matter intake and yields of Jersey cows. *Journal of Dairy Science*, 79: 912-921.

Hughes, N., Lawson, K., Davidson, A., Jackson, T. and Sheng, Y. (2011). Productivity Pathways: Climate-adjusted Production Frontiers for the Australian Broadacre Cropping Industry. ABARE Research Report 11.5, Canberra.

IPCC. (2014). Climate Change 2014: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press.

IPCC. 2007. Fourth Assessment Report. Available at:
http://www.ipcc.ch/publications_and_data/publications_and_data_reports.shtml

Jondrow, J., Lovell, C. K., Materov, I. S. and Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* 19: 233-238.

Jorgenson, D. W. and Z. Griliches. (1967). The explanation of productivity change. *The Review of Economic Studies*, 34(3): 249-283.

Kadzere, C. T., Murphy, M. R., Silanikove, N. and Maltz, E. (2002). Heat stress in lactating dairy cows: A review. *Livestock Production Science* 77: 59-91.

Kelly, D. L., Kolstad, C. D. and Mitchell, G. T. (2005). Adjustment costs from environmental change. *Journal of Environmental Economics and Management* 50: 468-495.

Key, N. and Sneeringer, S. (2014). Potential effects of climate change on the productivity of US dairies. *American Journal of Agricultural Economics* 96: 1136-1156.

Kumbhakar, S. C. and Heshmati, A. (1995). Efficiency measurement in Swedish dairy farms: An application of rotating panel data, 1976–88. *American Journal of Agricultural Economics* 77: 660-674.

Kumbhakar, S. C., Lien, G. and Hardaker, J. B. (2014). Technical efficiency in competing panel data models: A study of Norwegian grain farming. *Journal of Productivity Analysis* 41: 321–337.

Kumbhakar, S. C. and Tsionas, E. G. (2006). Estimation of stochastic frontier production functions with input-oriented technical efficiency. *Journal of Econometrics* 133: 71-96.

Lachaud, M., Bravo-Ureta, B. and Ludena, C. (2015). Agricultural productivity growth in LAC and other world regions: An analysis of climatic effects, convergence and catch-up. *Inter-American Development Bank Working Paper* No. 607, Washington DC.

Lawson, L. G., Agger, J. F., Lund, M. and Coelli, T. (2004). Lameness, metabolic and digestive disorders, and technical efficiency in Danish dairy herds: A stochastic frontier production function approach. *Livestock Production Science* 91: 157-172.

MacDonald, J. M., McBride, W. D., O'Donoghue, E., Nehring, R. F., Sandretto, C. and Mosheim, R. (2007). Profits, Costs, and the Changing Structure of Dairy Farming. USDA-ERS Economic Research Report.

Mader, T. L. (2003). Environmental stress in confined beef cattle. *Journal of Animal science* 81: E110-E119.

Martin, J. P. and Page, J. M. (1983). The impact of subsidies on X-efficiency in LDC industry: Theory and an empirical test. *The Review of Economics and Statistics* 65:608-617.

Mayen, C. D., Balagtas, J. V. and Alexander, C. E. (2010). Technology adoption and technical efficiency: Organic and conventional dairy farms in the United States. *American Journal of Agricultural Economics* 92: 181-195.

Meeusen, W. and van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, 18: 435-444.

Mendelsohn, R., Nordhaus, W. D. and Shaw, D. (1994). The impact of global warming on agriculture: A Ricardian analysis. *The American Economic Review*, 84: 753-771.

Moreira, V. H., and Bravo-Ureta, B. E. (2010). Technical efficiency and metatechnology ratios for dairy farms in three southern cone countries: A stochastic meta-frontier model. *Journal of Productivity Analysis* 33: 33-45.

Moreira López, V. and B. E. Bravo-Ureta. (2008). Technological change and technical efficiency for dairy farms in three countries of South America. *Chilean Journal of Agricultural Research* 68-4: 360-367.

Moreira López, V. H., and Bravo-Ureta, B. E. (2009). A study of dairy farm technical efficiency using meta-regression: An international perspective. *Chilean Journal of Agricultural Research*, 69:214-223.

Mukherjee D. (2012) Agricultural Sustainability in the Face of Climatic Change: Challenges and Opportunities. Ph. D. Dissertation, University of Connecticut.

Mukherjee, D., Bravo-Ureta, B. E. and De Vries, A. (2013). Dairy productivity and climatic conditions: Econometric evidence from South-eastern United States. *Australian Journal of Agricultural and Resource Economics* 57: 123-140.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica* 46: 69-85.

National Research Council (NRC). (2001). Nutrient Requirements of Dairy Cattle. 7th rev ed. Washington, DC: National Academy Press.

Nardone, A., Ronchi, B., Lacetera, N., Ranieri, M. S. and Bernabucci, U. (2010). Effects of climate changes on animal production and sustainability of livestock systems. *Livestock Science* 130: 57-69.

Njuki, E. and Bravo-Ureta, B. E. (2015). The economic costs of environmental regulation in US dairy farming: A directional distance function approach. *American Journal of Agricultural Economics* 97: 1087-1106.

O'Donnell, C. J. (2010). Measuring and decomposing agricultural productivity and profitability change. *Australian Journal of Agricultural and Resource Economics* 54: 527-560.

O'Donnell, C. J. (2012). Nonparametric estimates of the components of productivity and profitability change in US agriculture. *American Journal of Agricultural Economics* 94: 873-890.

O’Donnell, C. J. and Nguyen, K. (2013). An econometric approach to estimating support prices and measures of productivity change in public hospitals. *Journal of Productivity Analysis* 40: 323-335.

O’Donnell, C. J. (2016). Using information about technologies, markets and firm behaviour to decompose a proper productivity index. *Journal of Econometrics* 190: 328-340.

Powell, J. M. and Russelle, M. P. (2009). Dairy heifer management impacts manure N collection and cycling through crops in Wisconsin, USA. *Agriculture, Ecosystems and Environment* 131: 170-177.

Qi, L., Bravo-Ureta, B. E. and Cabrera, V. E. (2015). From cold to hot: Climatic effects and productivity in Wisconsin dairy farms. *Journal of Dairy Science* 98: 8664-8677.

Rhoads, M. L., Rhoads, R. P., VanBaale, M. J., Collier, R. J., Sanders, S. R., Weber, W. J. and Baumgard, L. H. (2009). Effects of heat stress and plane of nutrition on lactating Holstein cows: I. Production, metabolism, and aspects of circulating somatotropin. *Journal of Dairy Science* 92: 1986-1997.

Roenfeldt, S. (1998). You can’t afford to ignore heat stress. *Dairy Manage* 35: 6-12.

Schlenker, W., Hanemann, W. M. and Fisher, A. C. (2006). The impact of global warming on US agriculture: An econometric analysis of optimal growing conditions. *Review of Economics and Statistics* 88: 113-125.

Seo, S. N. and Mendelsohn, R. (2008). Measuring impacts and adaptations to climate change: A structural Ricardian model of African livestock management. *Agricultural Economics* 38: 151-165.

St-Pierre, N. R., Cobanov, B. and Schnitkey, G. (2003). Economic losses from heat stress by US livestock industries. *Journal of Dairy Science* 86: E52-E77.

Stata Manual. (2013). Accessed available: http://www.stata.com/manuals13/rhausman.pdf

Tauer, L. W. and Mishra, A. K. (2006). Can the small dairy farm remain competitive in US agriculture? *Food Policy* 31: 458-468.

Theodoridis, A. M. and Psychoudakis, A. (2008). Efficiency measurement in Greek dairy farms: Stochastic frontier vs. data envelopment analysis. *International Journal of Economic Sciences and Applied Research* 1: 53-67.

Tsionas, E. G. and Kumbhakar, S. C. (2014). Firm heterogeneity, persistent and transient technical inefficiency: A generalized true random-effects model. *Journal of Applied Econometrics 29*: 110-132.

Tucker, C. B., Rogers, A. R. and Schütz, K. E. (2008). Effect of solar radiation on dairy cattle behaviour, use of shade and body temperature in a pasture-based system. *Applied Animal Behaviour Science* 109: 141-154.

von Keyserlingk, M. A. G., Martin, N. P., Kebreab, E., Knowlton, K. F., Grant, R. J., Stephenson, M. and Smith, S. I. (2013). Invited review: Sustainability of the US dairy industry. *Journal of Dairy Science* 96: 5405-5425.

West, J. W. (2003). Effects of heat-stress on production in dairy cattle. *Journal of Dairy Science* 86: 2131-2144.

Young, B. A. (1981). Cold stress as it affects animal production. *Journal of Animal Science 52*: 154-163.

Zellner, A., Kmenta, J. and Dreze, J. (1966). Specification and estimation of Cobb-Douglas production function models. *Econometrica* 34: 784-795.

1.7 Tables and Figures

Table 1. Summary statistics of input-output data and climatic data (1996-2012)

Variable	Mean	Std. Dev.	Min	Max
Output/farm per year				
Milk equivalent, metric ton	1,220	1,503	142	18,543
Conventional inputs/farm per year				
Cow, head	99	99	21	1,162
Labor, hour	6,323	6,450	1,298	69,686
Concentrate feed, metric ton	616	907	11	8,695
Depreciation, \$[a]	78,539	98,502	465	1,196,189
Animal expenses, \$[a]	35,194	53,392	283	642,433
Crop expenses, \$[a]	85,917	76,487	2,666	979,827
Seasonal factors				
Spring temperature, C°	10.16	1.48	5.37	12.71
Summer temperature, C°	19.13	0.95	15.7	21.02
Autumn temperature, C°	6	1.45	0.36	8.83
Winter temperature, C°	-4.32	2.08	-10.87	0.73
Spring precipitation, cm	8.66	2.61	3.89	16.11
Summer precipitation, cm	9.01	2.3	4.87	18.69
Autumn precipitation, cm	5.32	1.74	2.09	9.81
Winter precipitation, cm	3.99	1.08	1.93	6.9
Annual factors				
ATEM[b], C°	7.63	1.21	2.96	9.92
APREC[b], cm	6.66	0.75	5.09	8.88
Climate normal				
30YrTEM[b], C°	7.28	0.83	4.28	8.08
30YrPREC[b], cm	6.69	0.16	6.37	7.01

a. The numbers have been deflated to 2012 dollars.

b. ATEM: Annual temperature; APREC: Annual precipitation; YrTEM: 30-year temperature; 30YrPREC: 30-year precipitation.

Table 2. Summary statistics of climate data from two IPCC scenarios (2020-2039)

Climatic variable	Mean	Std. Dev.	Min	Max
Scenario: commitment emission				
Seasonal factors				
Spring temperature, C°	12.26	0.93	8.45	14.4
Summer temperature, C°	21.07	0.95	17.96	23.15
Autumn temperature, C°	5.66	0.92	2.02	7.35
Winter temperature, C°	-4.12	1.07	-8.37	-1.99
Spring precipitation, cm	6.06	1.82	2.53	10.68
Summer precipitation, cm	4.66	1.53	1.75	8.16
Autumn precipitation, cm	4.65	1.41	2.08	7.76
Winter precipitation, cm	5.53	1.29	2.43	9.15
Annual factors				
ATEM, C°	8.64	0.7	5.68	9.89
APREC, cm	5.18	0.95	3.11	7.48
Climate normal				
30YrTEM[a], C°	8.25	0.66	5.28	9.02
30YrPREC[a], cm	5.9	0.36	4.97	6.75
Scenario: high A2 emission				
Seasonal factors				
Spring temperature, C°	12.99	1.83	6.68	17.14
Summer temperature, C°	22.08	1.39	18.89	26.52
Autumn temperature, C°	7.16	1.22	3.62	9.46
Winter temperature, C°	-3.17	2.2	-9.04	2.98
Spring precipitation, cm	6.62	1.4	2.53	9.69
Summer precipitation, cm	5.14	0.93	2.79	7.19
Autumn precipitation, cm	5.04	1.01	2.57	7.29
Winter precipitation, cm	5.5	0.68	3.59	7.29
Annual factors				
ATEM[a], C°	9.66	1.08	6.43	13.6
APREC[a], cm	5.49	0.64	3.11	7.26
Climate normal				
30YrTEM[a], C°	8.61	0.72	5.39	9.74
30YrPREC[a], cm	5.97	0.34	5.03	6.69

a. ATEM: Annual temperature; APREC: Annual precipitation; YrTEM: 30-year temperature; 30YrPREC: 30-year precipitation.

Table 3. Estimation results of SFP models without climatic variables.

Variable	SFP	TFE	TRE	TRE-M	GTRE
Conventional inputs					
Cow	0.691***	0.707***	0.689***	0.707***	0.685***
Labor	0.038	0.034	0.032	0.033	0.031*
Concentrate feed	0.090***	0.078***	0.086***	0.077***	0.088***
Depreciation	0.025***	0.021**	0.022**	0.021**	0.023***
Animal expenses	0.039***	0.024*	0.044***	0.025*	0.043***
Crop expenses	0.087***	0.069***	0.090***	0.069***	0.088***
Time	0.030***	0.032***	0.029***	0.032***	0.030***
Time square	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
Return to Scale	0.970	0.933	0.963	0.932	0.958
Average conventional inputs					
Average cow				-0.268*	
Average labor				0.078	
Average concentrate feed				0.056	
Average depreciation				0.038	
Average animal expenses				0.078**	
Average crop expenses				0.089	
Constant	1.395***		1.222***	-0.392	1.178***
Persistent technical efficiency					0.138***
Sigma_u	0.014	0.070	0.096	0.088	0.096
Sigma_v	0.012	0.095	0.091	0.094	0.091
Lambda	1.194	0.738	1.049	0.938	1.057

Table 4. Estimation result of SFP models with seasonal climatic variables

Variable	SFP	TFE	TRE	TRE-M	GTRE
Conventional inputs					
Cow	0.609***	0.615***	0.608***	0.620***	0.600***
Labor	0.038	0.033	0.032	0.035	0.031*
Concentrate feed	0.129***	0.123***	0.126***	0.120***	0.132***
Depreciation	0.044***	0.041***	0.042***	0.040***	0.043***
Animal expenses	0.029**	0.020	0.033**	0.020	0.033***
Crop expenses	0.110***	0.099***	0.111***	0.096***	0.117***
Time	0.050***	0.051***	0.048***	0.049***	0.049***
Time square	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
Seasonal climatic factors					
Spring temperature	0.006	0.008*	0.007	0.007	0.008*
Summer temperature	-0.045***	-0.046***	-0.044***	-0.042***	-0.046***
Autumn temperature	-0.029***	-0.030***	-0.029***	-0.028***	-0.031***
Winter temperature	0.019***	0.018***	0.018***	0.018***	0.018***
Spring precipitation	-0.006***	-0.006***	-0.006**	-0.006**	-0.006**
Summer precipitation	-0.002	-0.003	-0.003	-0.003	-0.002
Autumn precipitation	0.003	0.003	0.003	0.003	0.003
Winter precipitation	-0.016***	-0.016***	-0.016***	-0.015***	-0.017***
Return to Scale	0.959	0.931	0.952	0.931	0.956
Average conventional inputs					
Average cow				-0.132	
Average labor				0.022	
Average concentrate feed				0.007	
Average depreciation				0.046	
Average animal expenses				0.081***	
Average crop expenses				0.056	
Constant	2.251***		2.060***	0.710	1.940***
Persistent technical efficiency					0.120***
Sigma_u	0.014	0.081	0.091	0.090	0.092
Sigma_v	0.010	0.082	0.082	0.082	0.082
Lambda	1.452	0.996	1.111	1.100	1.126

Table 5. Estimation result of SFP models with seasonal climatic variables and adaptive effects

Variable	SFP	TFE	TRE	TRE-M	GTRE
Conventional inputs					
Cow	0.596***	0.611***	0.594***	0.613***	0.592***
Labor	0.038	0.031	0.034	0.031	0.031*
Concentrate feed	0.135***	0.126***	0.133***	0.125***	0.133***
Depreciation	0.046***	0.042***	0.044***	0.042***	0.044***
Animal expenses	0.032**	0.021*	0.036***	0.021*	0.038***
Crop expenses	0.110***	0.097***	0.113***	0.096***	0.111***
Time	0.051***	0.052***	0.050***	0.050***	0.049***
Time t square	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
Seasonal climatic factors					
Spring temperature	-0.003	0.00003	0.002	-0.003	0.003
Summer temperature	-0.070***	-0.062***	-0.062***	-0.070***	-0.060***
Autumn temperature	-0.041***	-0.038***	-0.039***	-0.042***	-0.038***
Winter temperature	-0.001	0.003	0.004	-0.005	0.006
Spring precipitation	0.011	0.015	0.018*	0.011	0.011**
Summer precipitation	0.036	0.041	0.046**	0.032	0.033***
Autumn precipitation	0.021*	0.024*	0.027**	0.019*	0.020***
Winter precipitation	0.020	0.027	0.032	0.018	0.018*
Adaptation					
ATEMP*30TEMP[a]	0.009***	0.007	0.006**	0.010***	0.005***
APREC*30PREC[a]	-0.017*	-0.019	-0.022**	-0.015*	-0.016***
Return to Scale	0.957	0.928	0.954	0.928	0.949
Average conventional inputs					
Average cow				-0.281*	
Average labor				0.171	
Average concentrate feed				0.006	
Average depreciation				0.013	
Average animal expenses				0.081***	
Average crop expenses				0.080*	
Constant	2.279***			0.255	2.24***
Persistent technical efficiency					0.067***
Sigma_u	0.011	0.084	0.096	0.093	0.097
Sigma_v	0.010	0.081	0.080	0.081	0.080
Lambda	1.172	1.040	1.210	1.155	1.213

a. ATEM: Average annual temperature; APREC: Average annual precipitation; 30TEM: 30-year average temperature; 30PREC: 30-year average precipitation.

Table 6. Statistical test results across models

Hypothesis	Test	Result
All coefficients are jointly equal to zero for all models in Tables 3-5.	F test: Prob > chi2 = 0.0000 for all models.	Reject the hypothesis
The coefficients of climatic variables are jointly zero for the models in Table 4 and 5.	F test: Prob > chi2 = 0.0000 for all models.	Reject the hypothesis.
	Likelihood ratio test between corresponding models in Table 3-5: Prob > chi2 = 0.0000 for all models.	Adding climatic variables results in a statistically significant improvement in model fit.
The coefficients of the longer-term adaptive effects are jointly zero for the models in Table 5.	F test: Prob > chi2 = 0.0000 for all models.	Reject the hypothesis.
	Likelihood ratio test between corresponding models in Table 4 and 5: (1) Prob > chi2 = 0.00008 for GTRE models; (2) Prob > chi2 = 0.0000 for all other models.	Adding longer-term adaptive effects results in a statistically significant improvement in model fit.
The unobserved heterogeneity in the TRE model is independent from other explanatory variables.	Hausman test: (1) chi2 = -31.45 in Table 4; (2) chi2 = 20.25 (Prob > chi2 = 0.3192) in Table 5.	Cannot reject the hypothesis.
The coefficients of persistent technical efficiency in the GTRE models in Table 4 and 5 are zero.	Z-test: Prob |z|>Z*= 0.0000	Reject the hypothesis.

Table 7. Annual climatic effect indexes (CEI) from the GTRE model (1996-2012)

Year	CEI	CEIW	CEIADP	CEIT	CEIR	CEISPR	CEISUM	CEIAUT	CEIWIN
1996	**0.316**	0.488	0.652	0.282	1.73	1.095	0.448	0.974	1.019
1997	**0.315**	0.467	0.679	0.278	1.676	1.085	0.468	0.880	1.042
1998	**0.288**	0.412	0.702	0.238	1.734	1.125	0.399	0.846	1.086
1999	**0.283**	0.442	0.644	0.245	1.804	1.175	0.448	0.806	1.041
2000	**0.297**	0.495	0.604	0.262	1.885	1.151	0.486	0.853	1.036
2001	**0.277**	0.432	0.647	0.236	1.826	1.171	0.435	0.823	1.029
2002	**0.301**	0.452	0.680	0.256	1.752	1.132	0.404	0.942	1.044
2003	**0.303**	0.444	0.684	0.259	1.713	1.135	0.407	0.945	1.015
2004	**0.281**	0.469	0.602	0.257	1.820	1.209	0.423	0.867	1.058
2005	**0.273**	0.364	0.756	0.225	1.614	1.086	0.370	0.876	1.033
2006	**0.312**	0.450	0.693	0.262	1.718	1.155	0.394	0.929	1.066
2007	**0.274**	0.408	0.674	0.235	1.738	1.109	0.417	0.839	1.053
2008	**0.276**	0.480	0.576	0.257	1.875	1.126	0.453	0.891	1.057
2009	**0.301**	0.460	0.654	0.270	1.707	1.130	0.419	0.929	1.048
2010	**0.293**	0.479	0.621	0.244	1.957	1.142	0.486	0.850	1.014
2011	**0.275**	0.440	0.626	0.242	1.823	1.141	0.428	0.863	1.045
2012	**0.313**	0.432	0.728	0.256	1.688	1.145	0.365	0.952	1.087
Average	**0.293**	0.448	0.660	0.253	1.768	1.136	0.426	0.886	1.046
Minimum annual value	**0.273**	0.364	0.576	0.225	1.614	1.085	0.365	0.806	1.014
Maximum annual value	**0.316**	0.495	0.756	0.282	1.957	1.209	0.486	0.974	1.087
Lowest individual value	0.260	0.347	0.442	0.214	1.548	1.066	0.344	0.770	0.987
Highest individual value	0.344	0.698	0.797	0.344	2.282	1.231	0.657	1.158	1.125

Note: CEI: climatic effect index;
CEIW: climatic effect index for weather shocks;
CEIADP: climatic effect index for adaptation;
CEIT: climatic effect index for temperature;
CETR: climatic effect index for precipitation;
CEISPR: climatic effect index for spring;
CEISUM: climatic effect index for summer;
CEIAUT: climatic effect index for autumn;
CEIWIN: climatic effect index for winter.

Table 8. Annual technical efficiency in the GTRE model (1996-2012)

Year	TE	TE persistent	TE transient
1996	0.871	0.944	0.923
1997	0.882	0.944	0.935
1998	0.879	0.944	0.931
1999	0.898	0.944	0.952
2000	0.885	0.944	0.937
2001	0.873	0.944	0.925
2002	0.876	0.944	0.929
2003	0.894	0.944	0.947
2004	0.862	0.944	0.914
2005	0.886	0.944	0.939
2006	0.881	0.944	0.934
2007	0.863	0.944	0.915
2008	0.886	0.944	0.939
2009	0.887	0.944	0.940
2010	0.868	0.944	0.919
2011	0.885	0.944	0.938
2012	0.879	0.944	0.932
Average	0.880	0.944	0.932
Minimum annual value	0.862	0.944	0.914
Maximum annual value	0.898	0.944	0.952
Lowest individual value	0.729	0.935	0.773
Highest individual value	0.930	0.948	0.982

Table 9. Total factor productivity (top number) and annual growth rate (bottom number in italics from the GTRE-Full model (1996-2012)

Year	$\mathbf{TFPC_{j1996it}}$	TP_{1996t}	$TEC_{j1996it}$	$SMEC_{j1996it}$	$CEIC_{j1996it}$	HET_{ji}	$SNC_{j1996it}$
1996	**1.52**	1.00	1.19	0.95	1.03	2.96	0.47
	--	--	--	--	--	--	--
1997	**1.66**	1.05	1.21	0.95	1.03	2.96	0.49
	9.3%	*4.6%*	*1.3%*	*-0.1%*	*-0.2%*	--	*3.6%*
1998	**1.56**	1.09	1.20	0.95	0.94	2.96	0.48
	-5.9%	*4.2%*	*-0.4%*	*-0.4%*	*-8.5%*	--	*-1.1%*
1999	**1.75**	1.13	1.23	0.95	0.93	2.96	0.53
	11.7%	*3.9%*	*2.2%*	*-0.1%*	*-1.8%*	--	*8.9%*
2000	**1.78**	1.17	1.21	0.95	0.97	2.96	0.50
	1.8%	*3.6%*	*-1.5%*	*0.1%*	*4.9%*	--	*-5.2%*
2001	**1.64**	1.21	1.20	0.94	0.91	2.96	0.48
	-8.0%	*3.2%*	*-1.3%*	*-0.2%*	*-6.6%*	--	*-3.9%*
2002	**1.85**	1.25	1.20	0.95	0.98	2.96	0.49
	13.3%	*2.9%*	*0.4%*	*0.1%*	*8.5%*	--	*1.1%*
2003	**2.04**	1.28	1.23	0.94	0.99	2.96	0.51
	9.9%	*2.6%*	*2.0%*	*-0.1%*	*0.5%*	--	*5.5%*
2004	**1.71**	1.31	1.18	0.94	0.92	2.96	0.47
	-16.0%	*2.3%*	*-3.5%*	*-0.4%*	*-7.1%*	--	*-8.8%*
2005	**1.85**	1.33	1.22	0.94	0.89	2.96	0.50
	8.1%	*1.9%*	*2.8%*	*-0.1%*	*-2.8%*	--	*6.6%*
2006	**2.11**	1.35	1.21	0.94	1.02	2.96	0.49
	13.9%	*1.6%*	*-0.6%*	*0.2%*	*14.0%*	--	*-0.6%*
2007	**1.75**	1.37	1.18	0.94	0.89	2.96	0.47
	-16.8%	*1.3%*	*-2.0%*	*-0.3%*	*-12.1%*	--	*-4.8%*
2008	**1.94**	1.38	1.22	0.94	0.90	2.96	0.50
	10.9%	*1.0%*	*2.6%*	*0.0%*	*0.7%*	--	*6.1%*
2009	**2.16**	1.39	1.22	0.94	0.98	2.96	0.51
	10.9%	*0.6%*	*0.0%*	*0.2%*	*9.1%*	--	*1.7%*
2010	**1.96**	1.40	1.19	0.94	0.96	2.96	0.48
	-9.0%	*0.3%*	*-2.1%*	*-0.2%*	*-2.4%*	--	*-5.4%*
2011	**1.95**	1.40	1.21	0.94	0.90	2.96	0.50
	-0.7%	*0.0%*	*2.0%*	*-0.1%*	*-6.2%*	--	*4.2%*
2012	**2.19**	1.39	1.21	0.94	1.02	2.96	0.50
	12.2%	*-0.3%*	*-0.7%*	*0.0%*	*13.9%*	--	*-0.1%*
Average	**1.85**	1.26	1.21	0.94	0.96	2.96	0.49

Note: the annual growth rates are listed in italics. The baseline is the values of farm j at 1996

Table 10. Climatic effects under CMT and HA2 scenarios in the GTRE model (2020-2039)

Year	Commitment (CMT) Scenario				High A2 (HA2) Scenario			
	CEI CMT	CEIW CMT	CEIADP CMT	ΔYCMT (%)	CEI HA2	CEIW HA2	CEIADP HA2	ΔYHA2 (%)
Baseline (2012)	0.313	0.432	0.728		0.313	0.432	0.728	
2020	0.312	0.365	0.856	-0.4%	0.259	0.337	0.773	-17.3%
2021	0.289	0.313	0.927	-7.9%	0.275	0.306	0.901	-12.4%
2022	0.298	0.306	0.978	-4.8%	0.301	0.306	0.986	-4.0%
2023	0.275	0.301	0.916	-12.2%	0.290	0.343	0.848	-7.4%
2024	0.303	0.335	0.907	-3.4%	0.264	0.306	0.866	-15.7%
2025	0.307	0.358	0.862	-1.9%	0.253	0.273	0.931	-19.1%
2026	0.297	0.317	0.942	-5.2%	0.280	0.347	0.810	-10.7%
2027	0.290	0.331	0.878	-7.6%	0.286	0.325	0.883	-8.7%
2028	0.323	0.386	0.839	3.0%	0.337	0.377	0.898	7.7%
2029	0.334	0.348	0.962	6.5%	0.298	0.338	0.884	-5.0%
2030	0.274	0.347	0.792	-12.6%	0.282	0.333	0.848	-10.1%
2031	0.299	0.385	0.780	-4.7%	0.264	0.288	0.919	-15.9%
2032	0.320	0.391	0.822	2.2%	0.328	0.364	0.902	4.6%
2033	0.295	0.323	0.919	-5.7%	0.297	0.339	0.877	-5.3%
2034	0.325	0.357	0.914	3.8%	0.315	0.340	0.931	0.7%
2035	0.344	0.445	0.775	9.7%	0.245	0.257	0.956	-21.9%
2036	0.302	0.339	0.893	-3.7%	0.315	0.328	0.966	0.5%
2037	0.300	0.309	0.977	-4.1%	0.307	0.276	1.121	-1.9%
2038	0.313	0.322	0.978	0.0%	0.303	0.330	0.923	-3.3%
2039	0.319	0.384	0.833	1.7%	0.289	0.304	0.955	-7.7%
Average	0.306	0.348	0.888	-2.4%	0.289	0.321	0.909	-7.7%

Note:
CEICMT: climatic effect index under commit under commitment scenario;
CEIWCMT: climatic effect index for weather shocks under commitment scenario;
CEIADPCMT: climatic effect index for adaptation under commitment scenario;
ΔYCMT: Annual output change relative to 2012 under commitment scenario;

CEIHA2: climatic effect index under high A2 scenario;
CEIWHA2: climatic effect index for weather shocks under high A2 scenario;
CEIADPHA2: climatic effect index for adaptation under high A2 scenario;
ΔYHA2: Annual output change relative to 2012 under high A2 scenario.

Figure 1. Research Area in Wisconsin Counties

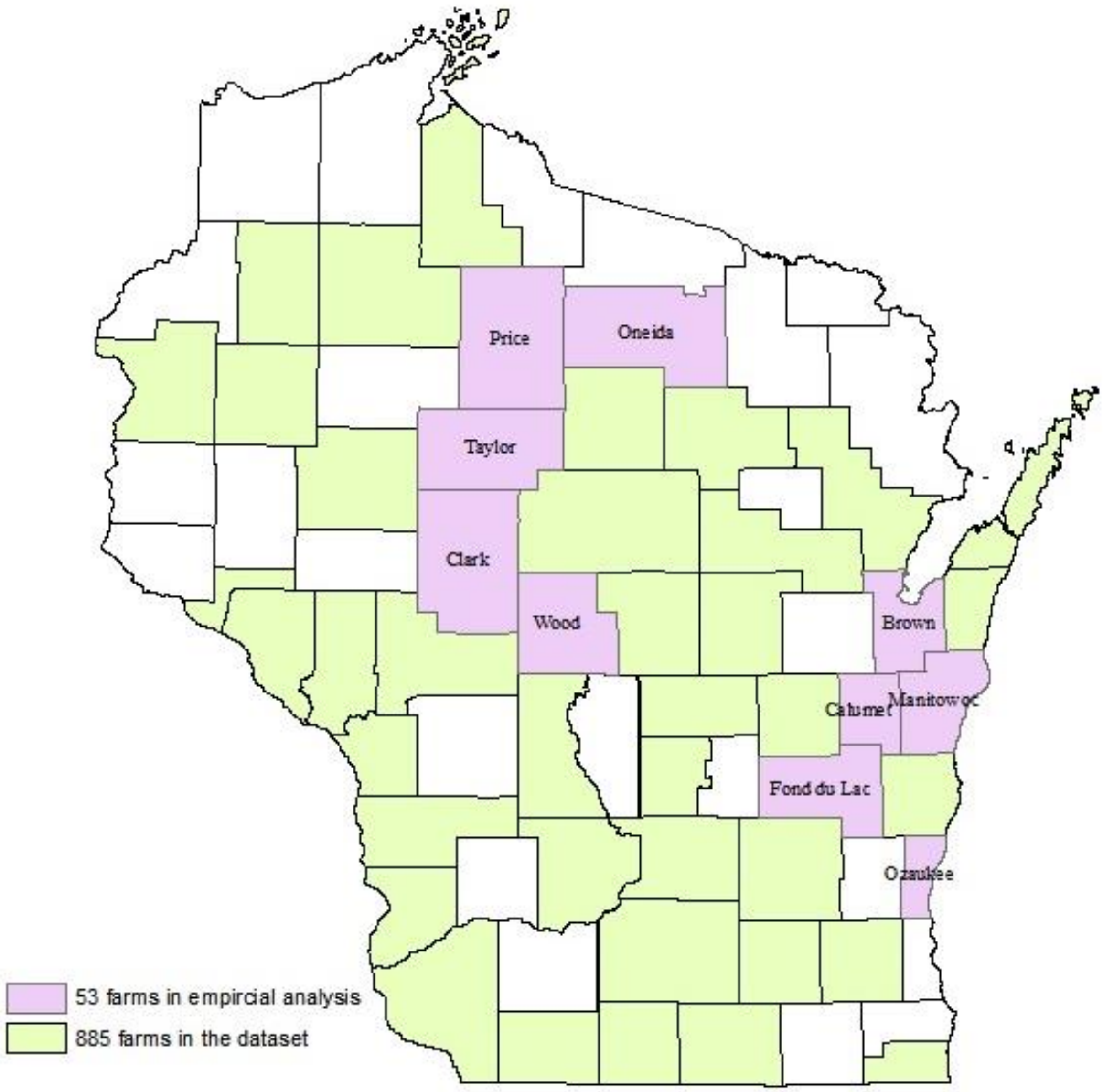
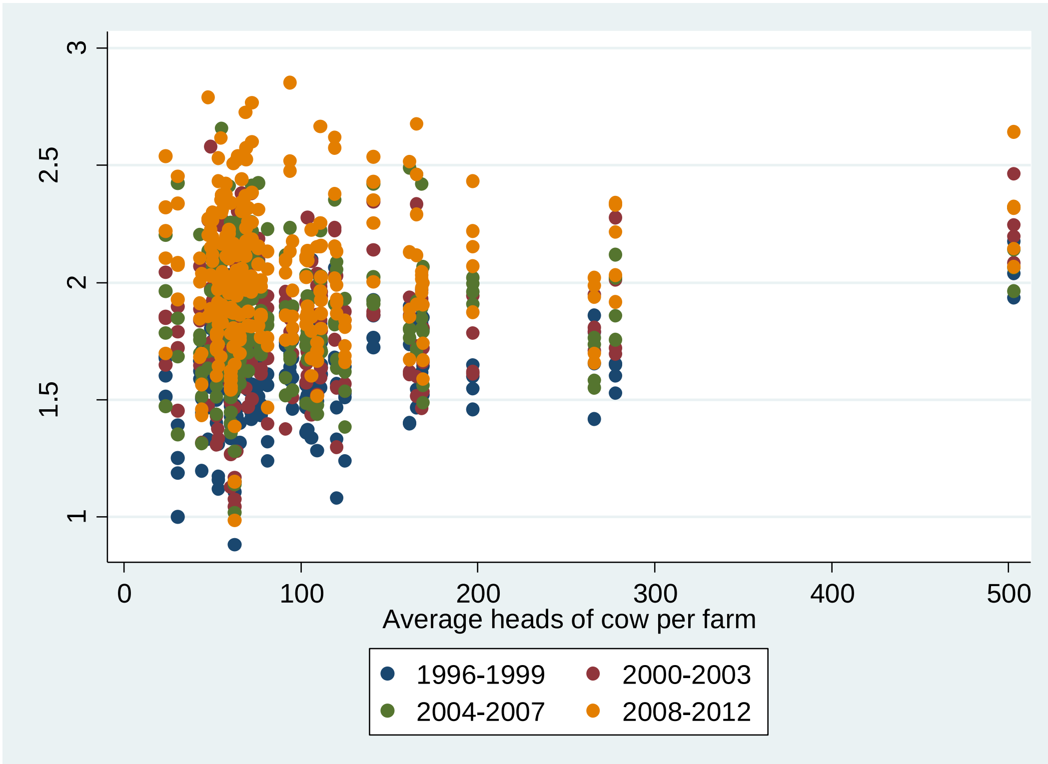


Figure 2. Total factor productivity of dairy farms in the GTRE model (1996-2012)



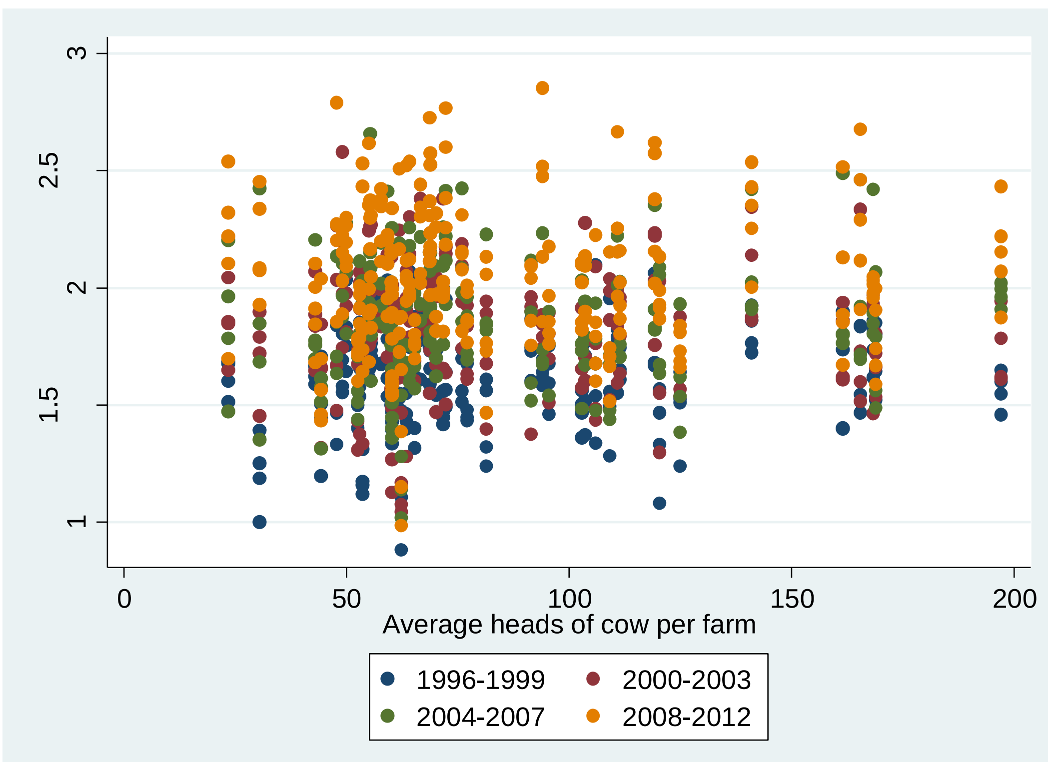
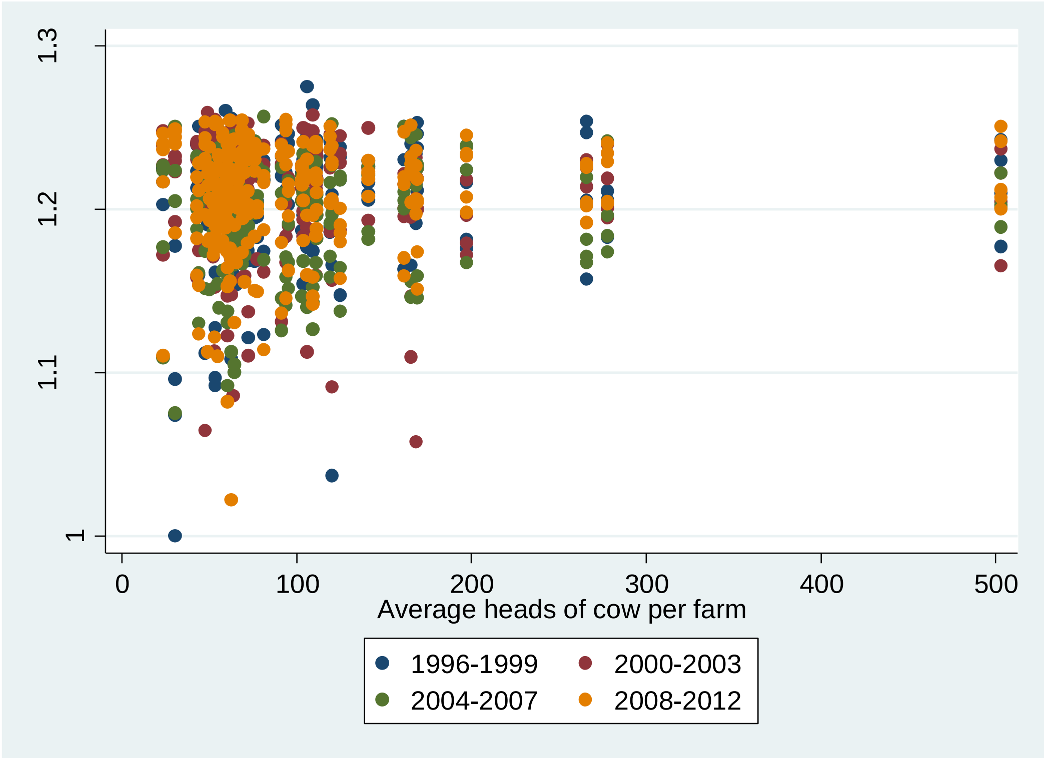


Figure 3. Technical efficiency of dairy farms in the GTRE model (1996-2012)



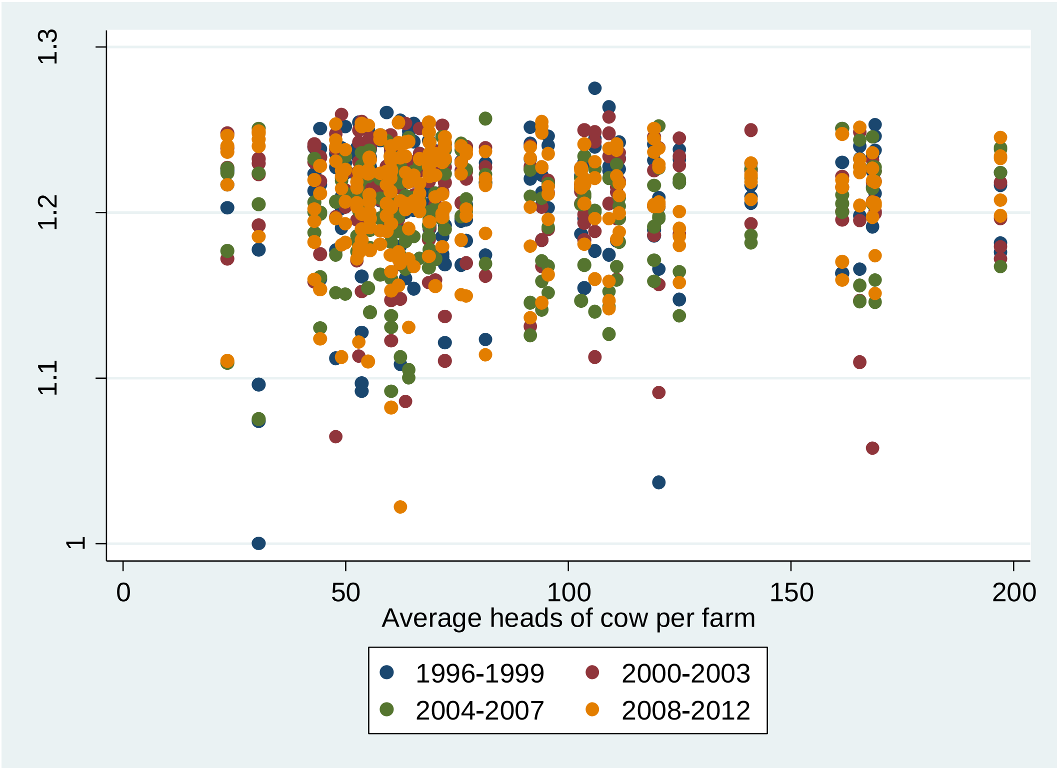


Figure 4. Climatic conditions in Wisconsin counties form the GTRE model (1996-2012)

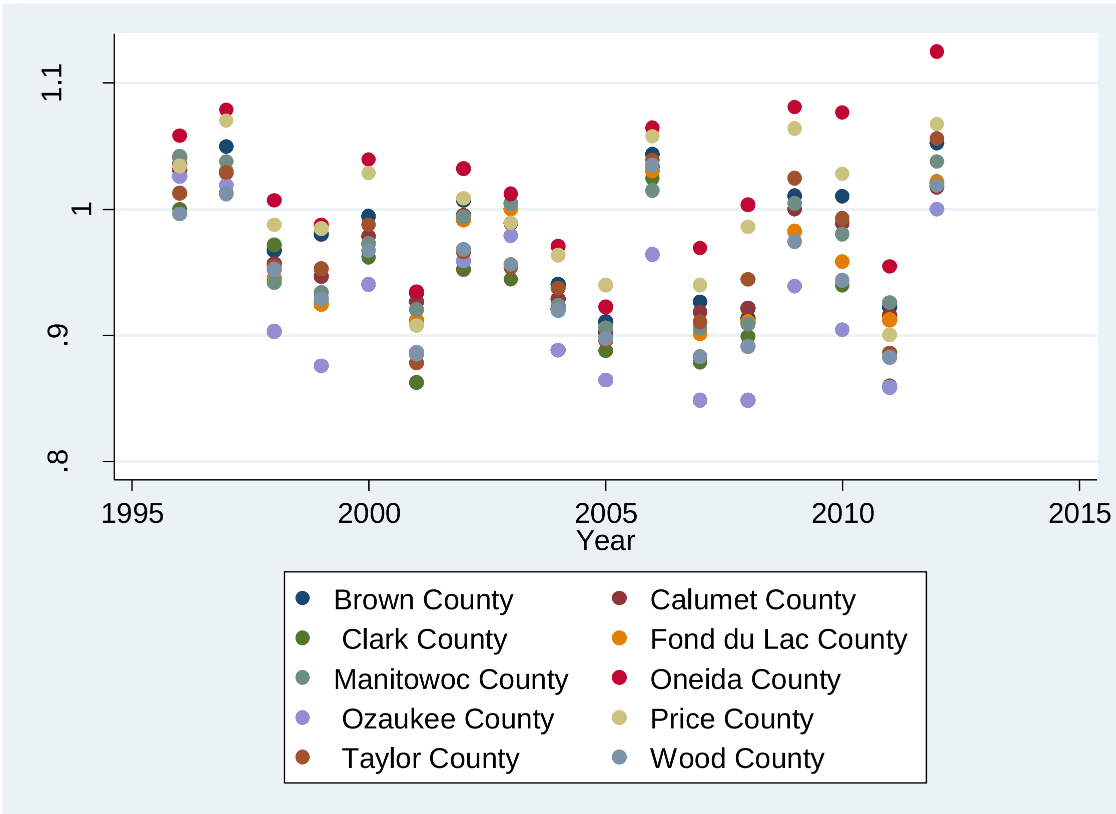
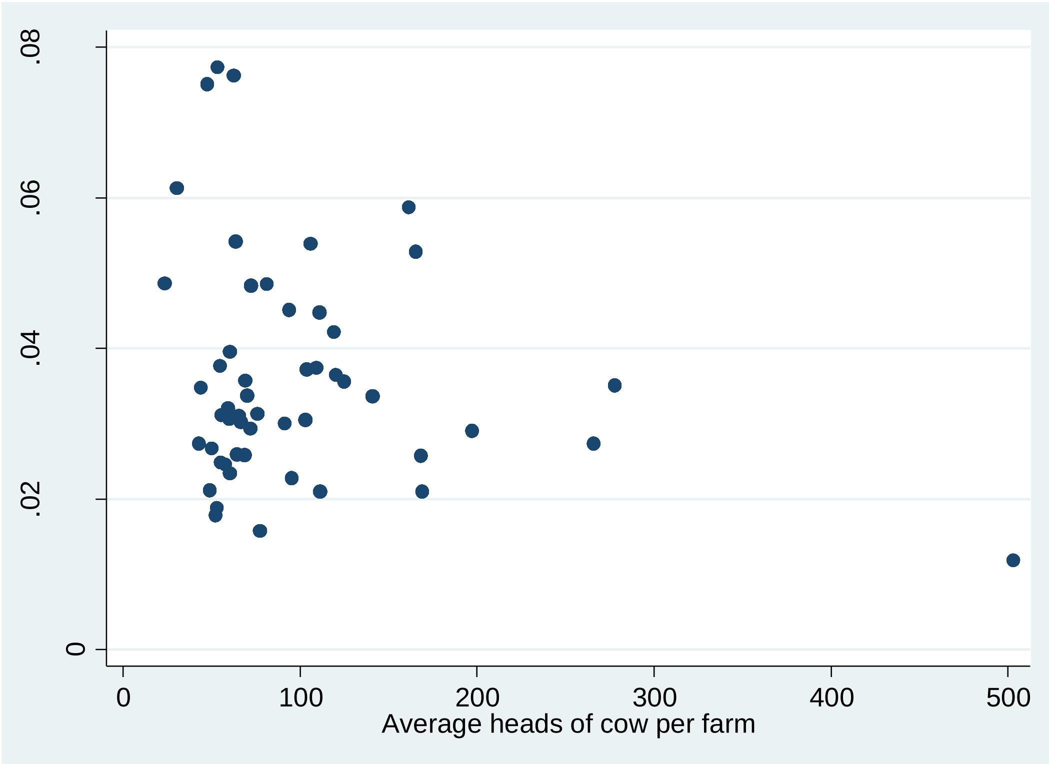
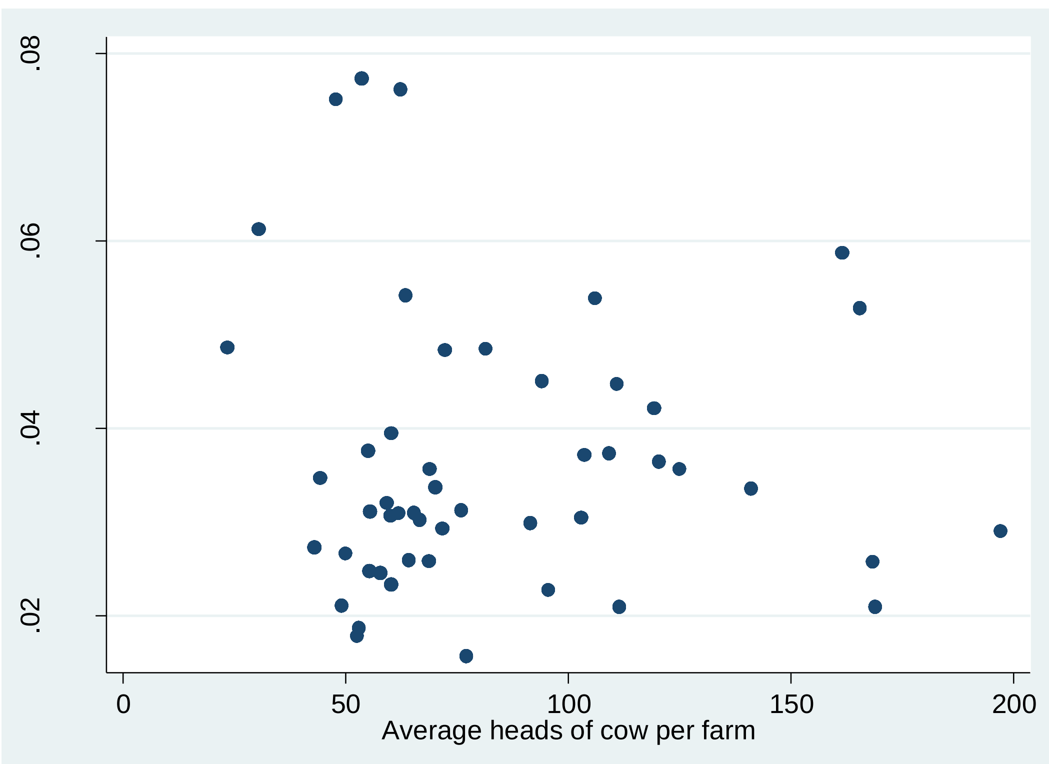


Figure 5. TFPC average annual growth rate form the GTRE-Full model over 1996 through2012





Essay 2

Buyer and Non-Buyer Barriers to Purchasing Local Food

2.1 Introduction

Local food is not a new concept within the U.S. food system. As noted by Martinez *et al.* (2010), nearly 80% of respondents surveyed indicated they either occasionally or always purchase produce from growers. There are a plethora of reasons why consumers are making the decision to purchase locally grown food, such as freshness, supports the local community, and environmental benefits (Seyfang, 2006; Darby *et al.*, 2008; Durham, King and Roheim, 2009; Hand and Martinez, 2010; Onozaka, Nurse and McFadden, 2010; Sharp *et al.*, 2011).

However, even with consumers claiming to purchase local foods and touting its' benefits, local food is only a small percentage of total agricultural sales within the U.S. Low and Vogel (2011) found the market for local foods (direct-to-consumer and intermediated channels) in 2008 was $4.8 billion, compared to over $1 trillion in total food sales. Local foods also make up only a small portion of overall agricultural sales, approximately 1.2% in 2008, yet there is continued interest in increasing both consumption and production of "local" products. Federal, state, local governments have perhaps been the most visible in terms of shifting policies to increase local consumption. For instance, the 2008 Food, Conservation, and Energy Act (2008 Farm Act) defines *"locally or regionally produced agricultural food product" is less than 400 miles from its origin, or within the State in which it is produced."* (H.R. 6124 2008). Further, as noted by Onken and Bernard (2010), all states have implemented some type of local promotional activities. The state level activities vary from strict regulations to informational materials to promote local products.

One example of a state level program is in Connecticut, where like many other states, legislators have defined a goal of increasing consumption of food within the defined geographic boundaries of the state. Connecticut, in contrast to other states, has legislated that by 2020, 5% of total food expenditures need to be from local food (Governor's Council for Agricultural Development, 2011). As noted by Warner *et al.* (2012), local food purchasing in CT accounted for only 2.5% of total food expenditures in 2010.

As state governments try to increase consumption of local food a central tenet is to increase demand. A critical gap in many of these endeavors is to understand the barriers associated with consumers consuming more local food. Notably, recommendations tend to concentrate on the population as a whole instead of understanding the differences in barriers between buyers and non-buyers. This paper attempts to fill this gap in the literature by examining barriers associated with buyers purchasing more local food and non-buyers beginning to purchase local food. Through understanding the barriers to purchasing, policymakers and other interested parties can make more informed decisions on how to increase consumption of local foods.

2.2 Literature Review

There are many factors that influence a consumers' motivation for purchasing local food. Demographic characteristics have been shown to be an important factor in local purchasing. Studies have also shown that high income consumers are more likely to purchase local while gender and education have had mixed effects (Jekanowski, Williams and Schiek, 2000; Brown 2003).

In addition to demographic and economic variables, consumer behavior also influences purchasing of goods. Local foods are perceived as being healthier (Sims, 2009) and thus it is important to consider factors about health. This includes BMI[12] as well as methods of computing a healthy eating index Teratanavat and Hooker (2006) and Verbeke and López (2005). Additionally, literature has measured a person's aversion to new food through the computation of a food neophobia score Pliner and Hobden (1992) which has implications for one's likelihood to purchase a variety of products.

With respect to barriers to purchasing local food, Conner *et al.* (2010) identified five barriers for underrepresented populations in visiting farmers markets, notably price, inability to find, lack of time, and lack of skill to prepare. Further, as noted by Chambers *et al.* (2007), price and inconvenience were found to be key barriers to local purchasing. A lack of product choices, as well as limited accessibility, make local food more difficult for consumers to find satisfactory products (Hardesty, 2008). Furthermore, consumers are less likely to purchase sustainable products if they believe these products are less available (Vermeir and Verbeke, 2006). As these studies, and others have found, barriers do prevent consumers buying local food in the market.

However, few studies go further to explore the barriers facing different consumer groups such as the buyers and non-buyers of local foods. The barriers for influencing purchasing decisions of buyers and non-buyers are most likely not the same, where barriers prevent non-buyers from entering the market for local food, while barriers prevent buyers already in the market from purchasing more local food. By understanding the factors that influence barriers in these two groups, stakeholders interested in increasing the purchase of local food can target marketing activities to overcome these barriers. This provides us with motivation for this paper.

---

[12] $\text{BMI} = [\text{weight (lb)} / \text{height (inch)}^2] \times 703$; Underweight: $\text{BMI} < 18.5$; Overweight: $25.0 \leq \text{BMI} < 29.9$; Obese: $\text{BMI} \geq 30.0$

2.3 Data

This study was part of a larger project designed to investigate consumer demand for local and organic products in Connecticut. An online survey was conducted during the fall 2013 to assess these objectives. Advantages of online surveys are that they are less expensive, faster to conduct and generate more accurate information while potentially allowing for a larger number of surveys to be collected, relative to mail or fax surveys (McCullough, 1998; Cobanoglu, Warde and Moreo, 2001; Dillman, Smyth and Christian, 2009). However, a potential disadvantage to online surveys is that consumers without internet access are not included in the sample (Bethlehem, 2010). If our sample is representative of the population, discussed below, then the potential biases of not including non-internet users should be minimized and we can feel more comfortable about the results being generalizable to the population as a whole.

Using the panel database from Global Market Insight, Inc. (GMI), potential participants were emailed an invite to take part in the survey. Those agreeing to take part were directed to a survey link. To participate, respondents had to be 18 years of age or older and a resident of Connecticut. GMI reported the total incidence rate of the survey was 85%. There are a total of 1,820 panelists that clicked the link to agree to participate the survey. The first two questions that potential participants were asked was their age and zip code as these were the two criteria for participation in the survey. Participants were required to be 18 or older and residents of Connecticut. Among the 1,820 panelists, 2 panelists reported their ages as under 18 and 412 panelist reported ZIP codes not belonging to Connecticut. Thus, 414 panelists were immediately disqualified from the survey leaving 1,406 qualified participants.

Notably, panelist did not know the content of the survey until they started answering questions, so their decision to participate was independent of the survey content. This process is

helpful to reduce the occurrences of self-selection among buyers and non-buyers of local foods. Respondents were asked a variety of demographic, purchasing behavior, eating habit, and health questions (Table 1). Zip codes were matched to the 2011 American Community Survey and 2010 U.S. Census Bureau estimates in order to match a respondent with the population density, household income, median age, and percent female, Caucasian, and African American for the area they live. Zip codes were also matched with the number of farmers' market within each zip code area in order to assess the impact of access to farmers markets on barriers to purchasing more local food. In order to calculate BMI, respondents were asked to provide their height and weight which were then transformed into a BMI. For the analysis we then categorized each respondent as underweight, normal, overweight or obese based on their BMI scores.

From the 1,406 qualified participants there were 51 respondents who did not answer any question in the survey. Another 219 observations have some missing values in the sample: 41 observations have a missing value for only the income variable, 30 observations have a missing value for only some of the food neophobia questions, 56 observations with missing values for some of the healthy diet questions, 1 observation with missing value of race, and 90 observations have missing values for more than 1 variable. For the buyers group, we keep only the observations without any missing values. For the non-buyer group, we imputed the missing values for the observations with only one missing value, and dropped observations with more than one missing value. Our final sample contains 985 observations in the buyer group, and 173 observations in the non-buyer group.

As noted in Table 1, our sample tended to be older (sample = 52 for buyers and 46 for non-buyers vs. U.S. Census = 40) and have a higher income for buyers than the average Connecticut resident (sample = $93,000 for buyers and $71,000 for non-buyers vs. U.S. Census

= $69,461). Thereby, any generalizations of results to the population as a whole needs to keep this caveat in mind.

Purchasing behavior questions revolved around identifying the shopping location where consumers buy local and non-local food and the amount of dollars spent on local food. For the question of primary interest to this paper we asked respondents "What are the barriers to your purchasing more locally produced foods? (check all that apply)". Respondents were then given a list of barriers that are frequent in the literature and/or frequently occur in discussions with producers, policymakers, and other interested parties.

The descriptive statistics and the t-test of the means between buyers and non-buyers groups in Table 1 provide us with basic profiles of these two types of consumers. Demographic questions consisted of age, gender, race, household income, number of children and adults in the household. Health questions include BMI and dietary habits. There is a larger proportion of female consumers in the buyers group than non-buyer group. The average household income in the buyers group is higher than non-buyers group. There is a higher proportion of people with a master's degree or higher education in the buyers group. Regarding dietary habit, local food buyers have a healthier dietary habit and are more likely to try new food relative to non-buyers. Consumers from the two groups have significantly different preference with respect to shopping locations. Finally, most of the zip code characteristics are also different between the two groups indicating a differentiated geographic dispersion between buyer and non-buyers of local foods.

Participants' perceptions about barriers in local food markets are collect by a multi-response question in the survey, where we present 8 barriers that may influence purchasing behaviors. As shown in Table 2, the list of barriers included high prices, lack of products available that I want, quality issues, and shops do not carry local products, among others.

Respondents were also given the option to select the "other" option for barriers that were not listed or to indicate they perceive local as a "marketing gimmick."

Examining the barriers impacting buyers and non-buyers of local food we see notable differences between the two groups (Table 2). We utilize a t-test to compare differences of the mean number of respondents identifying a specific barrier as a limitation to purchasing or purchasing more local foods. First, buyers are more likely to indicate that availability is an issue. When asked whether shops carry local products they want, 37% responded this was a barrier to buying more local while only 15% of non-buyers indicated this was a concern. Further supporting concerns about available, 28% of buyers responded that shops do not carry local products, compared to 18% of non-buyers. Respondents felt, to a lesser degree, that a lack of unique local products were available, with 11% buyers choosing that barrier and only 6% of non-buyers. Quality issues are more likely to be an issue for buyers while some other barrier is most likely an issue for non-buyers. There are 16% non-buyers concerned about other barriers not listed in the survey, which encourages us to explore those barriers in future studies. As one might expect, and consistent with previous literature, price is the biggest barrier to buying more local food with over half of respondents indicating high prices for local foods is a barrier to increasing their purchases.

2.4 Empirical Model

To assess the demographic, purchasing behavior, health indicator, and zip-code characteristics impact on barriers to purchasing local foods, we utilized a multivariate probit model (MVP) whereby the dependent variables were binary with one being if a respondent marked a barrier as a reason for purchasing less local food and zero otherwise. Edwards and Allenby (2003) proposed a MVP model to deal with multiple response data that arise in the study

of consumer behavior. One advantage of using a multivariate probit model is that it allows for the correlation between alternatives, as opposed to a multivariate logit (MVL) model that assumes alternatives are independent (Aurier and Mejía, 2014).

As can be seen in Table 1 many of the characteristics of buyers were significantly different than for non-buyers; thereby, we analyzed the buyers and non-buyers in separate models. Furthermore, to model the choice of increasing local food consumption depends on whether one already buys local foods or not. Effectively this means that for buyers we are interested in the barriers that prevent them from increasing local food consumption, given they are already in the market. For non-buyers we are interested in the barriers for entering the market for local foods, or increasing their local food consumption from zero.

Assuming the total number of observations is n, and y_{it}^{*} represents the perception of respondent i for barrier j (j=1, 2, …, 8). Consumers' perception on barrier is impacted by a set of factors, such as consumer demographics, purchasing behavior including expenditure, and health, in a vector of X_i, and a random term ϵ_{ij}. Thus, consumer's perception of barrier j is written is:

$$y_{ij}^{*} = \beta_j' X_{ij} + \epsilon_{ij} \qquad [1]$$

where error term ϵ_{ij} distributed as multivarite normal distribution with a mean of zero, and a variance-covariance matrix must be symmetric ($\rho_{jk} = \rho_{kj}$, for k =1, 2, …, 8) and have ones on its diagonal. X_{ij} is a vector of independent variables of observation *i* in the equation of barrier *j*.

y_{ij} is a binary response taking the value of one if the respondent thinks j is a barrier, otherwise y_{ij} equals to zero. Thus, y_{ij} is written as:

$$y_{ij} = \begin{cases} 1 & if\ respodent\ i\ choses\ item\ j\ is\ a\ barrier\ (y_{ij}^{*} > 0) \\ 0 & otherwise \end{cases} \qquad [2]$$

Then the joint log-likelihood function of 8 barriers (J= 1,2, …8) for a total number of n observations is written as:

$$L = \sum_{i=1}^{n} log\, \Phi_8(\mu_i, \Omega) \qquad [3]$$

where Φ_8 follows multivariate normal distribution. The argument μ_i is:

$$\mu_i = (K_{i1}\beta_1' X_{i1}, K_{i2}\beta_2' X_{i2}, \dots, K_{i8}\beta_8' X_{i8}) \qquad [4]$$

where $K_{ik} = 2\mathrm{y}_{\mathrm{ik}} - 1$ for k = 1, 2, …8, and the Ω is a matrix consist of Ω_{jk} elements which is written as:

$$\Omega_{jk} = \begin{cases} 1 & \text{if } \mathrm{j} = \mathrm{k} \\ \Omega_{kj} = K_{ik}K_{ij}\rho_{jk} & \text{if } j \neq k \end{cases} \qquad [5]$$

According to Cappellari and Jenkins (2003), this log-likelihood function can be estimated by simulated maximum likelihood using STATA.

After estimating the coefficients, we calculated the marginal effects for each explanatory variable. The marginal effect for a continuous variable represents the probability of perceiving a barrier as an issue given a one-unit change of the explanatory variable. For a dummy variable the marginal effect represents the probability change of perceiving a barrier is an issue given a move from the base to the dummy variable of interest. Particularly, we are interested in the marginal effects of each explanatory variable on the success probability, namely, the probability of dependent variable $y_{ij} = 1$.

Assuming all the independent variables are holding at their mean values, the marginal effect for a continuous explanatory variable x_{ij} is calculated by:

$$\textit{marginal effect of } x_{ij} = Pr(y_{ij} = 1 | x_{ij} = x_{ij} + 1) - Pr(y_{ij} = 1 | x_{ij} = x_{ij}) \qquad [6]$$

The marginal effect of a dummy variable x_{ij} is calculated by:

$$marginal\ effect\ of\ x_{ij} = Pr\left(y_{ij} = 1 \middle| x_{ij} = 1\right) - Pr\left(y_{ij} = 1 \middle| x_{ij} = 0\right) \quad [7]$$

Further, in order to check the significance level of average marginal effect, we applied a bootstrapping method to calculate means and standard errors for the marginal effects. Over 50 replications, we create a bootstrap sample by randomly drawing data from original dataset, where the bootstrap sample size is the same as original sample size. The average value of marginal effects for the buyer group and non-buyer groups are presented in Tables 3 and 4.

Endogeneity

It is possible that there are some unobserved factors that affect consumers' perception of barrier *j* that might be correlated with their expenditures on local food. Therefore, we use control functions to address the potential endogeneity of expenditure because they are straightforward to incorporate into consumer choice models (Petrin and Train, 2010).

We decompose the endogenous variable, expenditure exp_{ij}, such that it is expressed as the sum of a liner combination of exogenous instruments Z_{ij} and an unobserved expenditure shock η_{ij}:

$$exp_{ij} = \theta_j' Z_{ij} + \eta_{ij} \quad [8]$$

The endogeneity of expenditure on local food arises if η_{ij} and ϵ_{ij} are correlated. The control function approach handles the potential endogeneity problem by decomposing the error term ϵ_{ij} into two parts: the part that can be explained by a general function of η_{ij}, the unobserved factors that is known to consumers when they are making choices but unknown to econometricians, and the residual:

$$\epsilon_{ij} = CF(\eta_{ij}, \lambda_j) + \widetilde{\epsilon_{ij}}, \qquad [9]$$

where $CF(\eta_{ij}, \lambda_j)$ denotes the control function with parameter λ_j. The simplest approximation is to specify the function to be linear in η_{ij}: $CF(\eta_{ij}, \lambda_j) = \lambda_j \eta_{ij}$. Then the choice model with the control function is then:

$$y_{ij}^{*} = \beta_j' X_{ij} + \lambda_j \eta_{ij} + \widetilde{\epsilon_{ij}} \qquad [10]$$

where error term $\widetilde{\epsilon_{ij}}$ is distributed as multivariate normal distribution with a mean of zero.

The instruments chosen for each barrier j, Z_{ij}, are consumers' all other perceptions. For example, in the equation that specifies prices as a barrier, the instruments are all other barriers not including prices. The intuition is that one consumer's perception of other barriers, such as lack of products available and local not labeled, should be correlated to their total expenditures on local food. However, these perceptions of other barriers are less likely to affect their perception of higher prices.

2.5 Results and Discussion

Buyers of Local Food

Looking at Table 3 we can see the results for the multivariate probit model assessing the demographic, purchasing behavior, and health indicators impact on consumers already buying local foods and indicating a barrier to increasing their local food purchases. With respect to price as a barrier we see that young, lower income, and Caucasian consumers are more likely to indicate price as a barrier. Consumers were 0.1% less likely to say high prices are a barrier when average household income increases by $1,000. Caucasian consumers were 10.6% more likely to say high prices are a barrier relative to other races. Overweight and obese consumers were also

more likely to indicate price was an issue. A potential reason for this finding is that overweight and obese consumers consume more processed foods which are more likely to be cheaper than foods traditionally sold as local (e.g. fresh fruits, vegetables). Consumers' dietary habit is another important factor influencing their perception of price as a barrier. A 1 unit increased in food neophobia score leads to 3.1% higher probability of indicating high prices as a barrier. After controlling for endogeneity, we find that consumers that spend less on local food are more likely to indicate price as a barrier. However, shopping at warehouse clubs and discount stores increases the likelihood of perceiving price as a barrier to purchasing more local foods. A potential reason for this finding is that these retailers tend to have lower prices and seek lower cost options which are not typical of local foods.

Now focusing on the barrier that no local food products are available that they want, females and older consumers were more likely to perceive this as a barrier to increased purchasing. Consumers with one more child in household are 3.8% more likely to indicate no products available was an issue. Interestingly, consumers that have a higher healthy diet score are 6.4% more likely to indicate the lack of available products are a barrier. From a policy perspective the finding that shopping at a farmers market indicates the lack of available products they want as a barrier is very enlightening. This suggests that consumers may feel constrained by the lack of *variety* in products available at these locations. To further support this, as the number of farmers markets increase in a zip code consumers are more likely to say they cannot find the products they want. Based on these two findings the policy of increasing access or the number of farmers markets may not make a large difference in increasing local food consumption. Our results indicate that identifying the specific products that are wanted by consumers is a more viable strategy to increasing local food purchasing than just creating

additional venues for existing products. Besides, consumers shopping at mass merchandiser stores also are more likely to indicate they are unable to find local products they want.

With respect to quality as a barrier, we see that consumers with higher household income were less likely to worry about quality. Obese people are 6.6% more likely to be concerned about the quality problem. One of the few community characteristics that are statistically significant is the percent female, where a 1% higher proportion of females in the community leads to a 1% higher probability of indicating quality is a barrier for local food purchasing.

Consumers that value local food rely on labeling to identity local goods; however, as noted in Table 2, 25% of buyers indicate lack of labeling as an issue in purchasing more local food. According to the estimate result in Table 3, Caucasian and higher educated consumers were more likely to say lack of labeling is an issue. For instance, a Caucasian consumer was 8.1% more likely to indicate labeling as an issue while having a bachelor degree resulted in 11.6% increase and having a master's degree or higher resulted in a 13.9% increase. Furthermore, consumers shopping at ethnic and specialty health stores were 9.4% more likely to say labeling was an issue. However, consumers shopping at a roadside stand or CSA are less likely to perceive labeling as an issue most likely due to the expectation that these locations provide only local foods.

Lack of unique local products was more likely to be a barrier for high-income consumers, which indicates that consumers with high income payed more attention to local food diversity but less on price. Education level also influenced consumers' perception: individuals with some college education were 4.4% less likely to indicate the lack of unique local product as a barrier, while individuals with master's or higher degrees were 6.3% less likely to worry about lack of unique local products. This finding is similar to the findings by Conner et al. (2010) that shows

high educated consumers were less likely to think "Large variety of products available" is an important factor. The more children a family has, the less likely they indicate lack of unique products is a barrier for them.

Consumers also shop in some stores that do not carry local products which ultimately prevents consumers from purchasing more local products. Higher educated consumers such as those with a bachelor's or master's or higher degrees indicated that shops that do not carry local products is a barrier to purchasing more local. However, older consumers were less likely to indicate this as an issue. Consumers with a higher healthy-diet habit index were more likely to indicate no local products are available in their shopping location. Thus, increasing local food availability is important for this type of consumer.

What is more, as local food expenditures increase by $100, consumers are 4.6% more likely to identify shops do not carry local as a barrier to purchasing more local food. These results provide an interesting insight with regards to supply constraints, thus to increase purchasing of local foods one must address supply issues for consumers that purchase larger amounts of local. Consumers who shop at supermarket and grocery stores as well as ethnic and specialty health stores are more likely to say shops do not carry local products is a barrier to increasing local food purchases. Thus, increasing local food supply in these shopping locations may be also benefit local food buyers. Interestingly, shopping at a farmers market also increases the likelihood of identifying no local food available which is consistent with the finding that shopping at a farmers market increases the likelihood of a barrier of no products being available that are wanted by the consumer. This highlights a concern that consumers may not be aware of the origin of products and thus do not know if a given product is locally produced or not. The State of Connecticut Department of Agriculture has recently started to address this issue by

making available point of purchase material that not only indicates it is CT Grown but also the farm name and town where it was grown.

With respect to the additional barriers, local food is not a marketing gimmick for most consumers. For example, consumers with more children in the household were less like to think local foods are a marketing gimmick. Also of interest is that consumers having larger family size (more children or more adults in household) were less like to indicate other barriers may exist to prevent local food purchasing. While we do not know what "other" implies for these consumers, a few possibilities based on anecdotal evidence suggest it might be related to the stigma that is associated with buying local foods, the desire for ethnic foods, or the lack of local access at a variety of retailers in these neighborhoods.

Non-Buyers of Local Food

Some consumers either do not know they purchase local or do not purchase local food. In either case, there is a need to understand who these consumers are to target them to become local food buyers. However, we have a relatively smaller sample size at 173 and less variability within the independent variables both of which make running the same 8 equation MVP impossible. Therefore, we only analyze three barriers (price, local not labeled, and shops do not carry local products) for the non-buyer group. We also drop variables of roadside stand/CSA, percent African American in zip-code area, supermarket & grocery, as well as farmers' market variables in relative equations due to issues of collinearity in this sample.

For non-buyers, the shopping location plays an important role in the price barrier. Non-buyers that shop at supermarkets/grocery stores are more likely to indicate price as a barrier, but non-buyers shopping at 'other' places (those not asked) are less likely to worry about the price.

Alternatively, non-buyers in zip codes where there are more farmers markets are less likely view price as a barrier to purchasing local.

Examining the labeling barrier we see that consumers shopping at supermarkets/grocery stores, warehouse clubs, and ethnic/health stores are less likely to indicate lack of labeling as a barrier. However, Caucasian consumers and consumers with a healthier diet are more likely to perceive labeling as an issue. With one more adult in the household, there was 22.2% higher probability for a participant in the non-buyer group to perceive local products not labeled as a barrier.

Perceived lack of local food availability is an issue for higher educated non-buyers. For instance, non-buyers with some college education were 51.3% more likely to notice shops do not carry local products, the probability for non-buyers with bachelor degree is 43.5%; and the probability for non-buyers with master's or higher degree is 61.7%.

2.6 Conclusion

Many states and communities are striving to increase local food production and consumption. To accomplish this, policymakers and value chain members generally implement one size fits all strategies. However, our results indicate that a one size fits all approach may not have the desired effects as buyer and non-buyers of local food have differing barriers to purchasing more local food or entering the market for local food. One example where this is apparent is with buyers who shop in ethnic/specialty grocery stores. These consumers are more likely to view no local availability as a barrier, yet non-buyers who shop in these same stores are less likely to perceive no local availability as a barrier. This highlights the differing levels of awareness of local foods by buyers and non-buyers and the importance of properly identifying

through research if consumers are in the market for local foods. Furthermore, strategies that focus on increasing availability or products available will impact current buyers more than non-buyers. However, focusing on different barriers will move non-buyers to buyers.

Non-buyers indicating that price is a barrier in conjunction with the buyer results that price is a barrier indicates that retailers charging premiums for local foods may be limiting increased sales. As has been noted in numerous studies, consumers are willing to pay price premiums for local foods (Gracia, Barreiro-Hurlé, and Lȯpez-Galán, 2014). However, our results indicate that premiums over non-local food are a barrier to non-buyers and limit purchasing by buyers. This presents a conundrum to retailers and policymakers as retailers strive for increased profits which premiums on local might deliver; however, from a social justice/sustainability perspective consuming local is not about profits but rather helping the local community/environment which occurs through eating more local.

Further, demographics, purchasing behaviors, health, and community characteristics play a role in a consumer's barriers to purchasing more local food. Notably for local food buyers, local food has been described by popular media outlets (e.g. cnn.com) as a possible solution to the obesity epidemic within the U.S. (Pollan 2006; Gustafson 2010; Nordahl 2013). However, our results indicate that obese consumers perceive high prices as an issue to purchasing local food. Without counteracting (perception of) higher local food prices, local food will most likely have little impact on obesity. Further, we see that buyers that spend more on local food are less likely to perceive price as a barrier but more likely to say that shops not carrying local products is a barrier. So policies that focus only on price will not increase purchasing by consumers that are already spending a large amount on local, rather a focus on expanding the supply of local foods is more important.

References

Aurier, P., and Mejía, V. (2014). Multivariate logit and Probit models for simultaneous purchases: Presentation, uses, appeal and limitations. *Recherche et Applications en Marketing (English Edition)* 29: 75-94.

Bethlehem, J. (2010). Selection bias in web surveys. *International Statistical Review* 78: 161-188.

Brown, C. (2003). Consumers' preferences for locally produced food: A study in southeast Missouri. *American Journal of Alternative Agriculture* 18: 213-224.

Cappellari, L. and Jenkins, S. P. (2003). Multivariate probit regression using simulated maximum likelihood. *The Stata Journal* 3: 278-294.

Chambers, S., Lobb, A., Butler, L., Harvey, K., and Traill, W. B. (2007). Local, national and imported foods: a qualitative study. *Appetite* 49: 208-213.

Cobanoglu, C., Warde, B., and Moreo, P. J. (2001). A comparison of mail, fax and web-based survey methods. *International Journal of Market Research* 43: 441-452.

Conner, D., Colasanti, K., Ross, R. B., and Smalley, S. B. (2010). Locally grown foods and farmers markets: Consumer attitudes and behaviors. *Sustainability* 2: 742-756.

Darby, K., Batte, M. T., Ernst, S., and Roe, B. (2008). Decomposing local: a conjoint analysis of locally produced foods. *American Journal of Agricultural Economics* 90: 476-486.

Dillmann, D. A., Smyth, J. D., and Christian, L. M. (2009). Internet, Mail, and Mixed-mode Surveys: The Tailored Design Method. Hoboken: John Wiley and Sons, Inc., NJ.

Durham, C. A., King, R. P., and Roheim, C. A. (2009). Consumer definitions of" locally grown" for fresh fruits and vegetables. *Journal of Food Distribution Research* 40: 56-62.

Edwards, Y. D., and Allenby, G. M. (2003). Multivariate analysis of multiple response data. *Journal of Marketing Research* 40: 321-334.

Gracia, A., Barreiro-Hurlé, J., and Galán, B. L. (2014). Are local and organic claims complements or substitutes? A consumer preferences study for eggs. *Journal of Agricultural Economics* 65: 49-67.

Governonor's Council for Agricultural Development. (2011). Internet Site: http://www.ct.gov/doag/cwp/view.asp?a=3595&q=423842 (Accessed on June, 3, 2015)

Gustafson, E. (2010). Solving the world's hunger and obesity crisis together. Internet Site: http://www.cnn.com/2010/OPINION/08/10/gustafson.hunger.obesity/ (Accessed on June 4, 2015).

Hand, M. S., and Martinez, S. (2010). Just what does local mean. Choices 25: 13-18.

Hardesty, S. D. (2008). The growing role of local food markets. *American Journal of Agricultural Economics* 90: 1289-1295.

Jekanowski, M. D., Williams, D. R., and Schiek, W. A. (2000). Consumers' willingness to purchase locally produced agricultural products: an analysis of an Indiana survey. *Agricultural and Resource Economics Review* 29: 43-53.

Low, S. A., and Vogel, S. J. (2011). Direct and intermediated marketing of local foods in the United States. *USDA-ERS Economic Research Report* 128.

Martinez, S., et al. (2010). Local food systems: concepts, impacts, and issues. *USDA-ERS Economic Research Report* 97. Internet Site: http://www.ers.usda.gov/media/122868/err97_1_.pdf (Accessed on May, 13, 2014).

McCullough, D. (1998). Web-based market research: The dawning of a new age. *Direct Marketing* 61: 36–38.

Nordahl, D. (2013). Solving obesity crisis: strawberries in parking lots. Internet Site: http://www.cnn.com/2013/07/12/world/solving-obesity-crisis-strawberries/ (Accessed on June 4, 2015).

Onken, K. A., and Bernard, J. C. (2010). Catching the "Local" bug: A look at state agricultural marketing programs. *Choices* 25: 1-7.

Onozaka, Y., Nurse, G., & McFadden, D. T. (2010). Local food consumers: How motivations and perceptions translate to buying behavior. *Choices* 25: 1-6.

Petrin, A., and Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research* 47: 3-13.

Pliner, P., and Hobden, K. (1992). Development of a scale to measure the trait of food neophobia in humans. *Appetite* 19: 105-120.

Pollan, M. (2006). The Omnivore's Dilemma: A Natural History of Four Meals. The Penguin Group. New York, NY.

Seyfang, G. (2006). Ecological citizenship and sustainable consumption: Examining local organic food networks. *Journal of rural studies* 22: 383-395.

Sharp, J. S., Clark, J. K., Davis, G. A., Smith, M. B., and McCutcheon, J. S. (2011). Adapting community and economic development tools to the study of local foods: The case of Knox County, Ohio. *Journal of Extension* 49: 1-12.

Sims, R. (2009). Food, place and authenticity: local food and the sustainable tourism experience. *Journal of Sustainable Tourism* 17: 321-336.

Teratanavat, R., and Hooker, N. H. (2006). Consumer valuations and preference heterogeneity for a novel functional food. *Journal of Food Science* 71: S533-S541.

Verbeke, W., and Poquiviqui López, G. (2005). Ethnic food attitudes and behaviour among Belgians and Hispanics living in Belgium. *British Food Journal* 107: 823-840.

Vermeir, I., and Verbeke, W. (2006). Sustainable food consumption: Exploring the consumer "attitude–behavioral intention" gap. *Journal of Agricultural and Environmental ethics* 19: 169-194.

Warner, T., Lopez, R. A., Rabinowitz, A., and Campbell, B. (2012). *Estimates of consumption of locally-grown aricultural products in Connecticut* (No. 10). University of Connecticut, Department of Agricultural and Resource Economics, Charles J. Zwick Center for Food and Resource Policy. Report available at: http://purl.umn.edu/153402 (Accessed on June, 3, 2015).

2.7 Tables and Figures

Table 1. Descriptive statistics of variables used in the model.

Variables	Sample	Buyers	Non-Buyers	t-test significance of the means (buyers vs. non-buyers)
Observations	1,158	985	173	
Female	0.62	0.63	0.57	*
Age	51	52	46	***
Household income in 2012 ($1,000)	90	93	71	***
Caucasian	0.89	0.90	0.87	
Education				
Some college	0.27	0.27	0.29	
Bachelor	0.32	0.32	0.31	
Master's or higher	0.27	0.28	0.23	*
No. of children	0.45	0.45	0.48	
No. of adults	2.10	2.10	2.12	
Underweight	0.02	0.02	0.02	
Overweight	0.37	0.37	0.35	
Obese	0.26	0.25	0.29	
Food neophobia index	3.37	3.31	3.75	***
Healthy-diet habit index	4.54	4.60	4.19	***
Local expenditure ($1,000)	1.11	1.31	--	***
Shopping Location (can select multiple locations)				
Supermarket & Grocery	0.94	0.95	0.93	
Farmers market	0.33	0.38	0.03	***
Roadside stand/Community supported agriculture	0.22	0.26	0.01	***
Warehouse Clubs	0.39	0.40	0.30	***
Ethnic and specialty health grocery store	0.15	0.17	0.06	***
Discount grocery store	0.13	0.14	0.08	**
Merchandiser	0.14	0.14	0.16	
Other	0.06	0.06	0.05	
Zip Code Characteristics				
Population density	1.91	1.84	2.31	***
Percent female	0.51	0.51	0.51	**
Percent Caucasian	0.85	0.85	0.83	
Percent African American	0.09	0.08	0.09	
Household income (2012) ($1,000)	100	101	95	**
Median age	41	41	40	***
No. of farmers market	0.65	0.63	0.71	

*, **, *** represent significance at the 0.1, 0.05, and 0.01 levels.

Table 2. Breakdown of barriers to purchasing more local by buyers and non-buyers.

Barriers	Buyers	Non-Buyers	t-test significance of the means
High prices	54%	61%	*
Lack of products available that I want	37%	15%	***
Shops do not carry local products	28%	18%	***
Local not labeled where I shop	25%	27%	
Lack of unique local products	11%	6%	**
Quality issues	11%	5%	***
Other	10%	16%	***
Consider local a marketing gimmick	3%	7%	**

*, **, *** represent significance at the 0.1, 0.05, and 0.01 levels.

Table 3. Marginal effects associated with barriers for local food buyers purchasing more local food.

Variables	Price	*P-value*	No Products Available I Want	*P-value*	Quality	*P-value*	Local not Labeled	*P-value*	Lack of Unique Local Products	*P-value*	Shops do not carry local products	*P-value*	Gimmick	*P-value*	Other	*P-value*
Female	0.036	0.321	**-0.099**	0.016	-0.012	0.577	0.033	0.304	-0.018	0.410	0.026	0.456	-0.018	0.138	0.020	0.135
Age	**-0.003**	0.068	**0.003**	0.012	-0.0003	0.752	-0.001	0.639	-0.0001	0.904	**-0.003**	0.007	-0.0001	0.552	-0.0003	0.637
Income($1,000)	**-0.001**	0.001	0.0003	0.305	**-0.0004**	0.098	0.0001	0.817	**0.0002**	0.098	0.0002	0.518	-2.E-06	0.972	-0.0002	0.205
Caucasian	**0.106**	0.040	0.010	0.857	-0.038	0.272	**0.081**	0.077	-0.046	0.316	0.043	0.491	-0.012	0.386	0.012	0.676
Some college	0.065	0.277	0.019	0.771	0.001	0.961	0.024	0.587	**-0.044**	0.054	0.091	0.136	-0.012	0.144	-0.006	0.813
Bachelor	0.095	0.126	-0.016	0.798	-0.035	0.183	**0.116**	0.011	-0.023	0.383	**0.142**	0.017	-0.011	0.284	-0.013	0.618
Master's or higher	0.059	0.280	-0.080	0.185	-0.018	0.562	**0.139**	0.020	**-0.063**	0.022	**0.201**	0.002	0.0002	0.987	-0.005	0.868
No. of children in household	0.034	0.186	**0.038**	0.020	0.003	0.823	-0.006	0.729	**-0.022**	0.033	0.015	0.429	**-0.005**	0.077	**-0.025**	0.020
No. of adults in household	0.027	0.305	-0.001	0.953	-0.0004	0.974	0.015	0.429	-0.0001	0.994	0.026	0.221	-0.004	0.145	**-0.016**	0.064
Underweight	-0.052	0.699	-0.094	0.385	0.146	0.203	0.074	0.566	0.047	0.672	0.140	0.248	0.077	0.448	-0.028	0.549
Overweight	**0.063**	0.066	-0.023	0.602	0.031	0.206	-0.006	0.857	0.020	0.361	0.023	0.543	-0.002	0.686	0.002	0.905
Obese	**0.069**	0.064	-0.054	0.206	**0.066**	0.047	0.006	0.886	0.019	0.481	-0.030	0.450	0.0005	0.946	-0.006	0.702
Food neophobia index	**0.031**	0.096	0.014	0.401	0.008	0.393	-0.003	0.867	0.002	0.853	0.012	0.439	0.001	0.839	0.002	0.800
Healthy-diet habit index	0.029	0.148	**0.064**	0.006	-0.005	0.678	-0.005	0.783	0.002	0.894	**0.040**	0.044	-0.001	0.779	-0.007	0.445
Local expenditure	**-0.506**	0.000	0.199	0.349	0.345	0.143	-0.003	0.986	0.240	0.286	**0.454**	0.012	0.007	0.871	0.380	0.106
Supermarket & Grocery	0.117	0.172	0.103	0.103	-0.043	0.423	0.009	0.876	0.024	0.402	**0.100**	0.078	-0.007	0.605	-0.026	0.520
Farmers market	0.013	0.750	**0.130**	0.000	0.008	0.688	-0.002	0.957	0.020	0.334	**0.098**	0.010	-0.002	0.638	-0.004	0.803
Roadside stand/CSA	-0.015	0.680	0.059	0.118	-0.014	0.544	**-0.056**	0.063	0.019	0.427	-0.0003	0.993	-0.013	0.101	0.029	0.138
Warehouse Clubs	**0.086**	0.014	0.021	0.501	0.014	0.495	-0.032	0.270	0.015	0.367	0.042	0.197	0.001	0.803	-0.008	0.498
Ethnic and specialty health grocery store	-0.022	0.649	0.035	0.300	0.0004	0.990	**0.094**	0.046	0.041	0.209	**0.091**	0.038	0.002	0.787	-0.018	0.296
Discount grocery store	**0.134**	0.008	-0.006	0.920	0.026	0.451	0.021	0.636	0.043	0.108	-0.002	0.960	0.005	0.663	-0.021	0.328

Merchandiser	-0.002	0.964	**0.103**	0.014	-0.003	0.915	-0.009	0.796	0.042	0.230	0.036	0.431	-0.001	0.945	-0.004	0.890
Other	-0.072	0.351	0.124	0.103	-0.010	0.754	-0.039	0.547	0.028	0.542	-0.066	0.303	--	--	0.020	0.605
Population density	-0.004	0.764	0.010	0.561	-0.0001	0.993	-0.008	0.467	-0.002	0.848	-0.014	0.211	-0.0002	0.956	0.005	0.430
Percent female (1% increase)[a]	0.0002	0.984	0.007	0.474	**0.010**	0.096	-0.004	0.571	0.008	0.119	0.003	0.763	0.002	0.345	-0.003	0.348
Percent Caucasian (1% increase) [a]	-0.001	0.807	0.0001	0.972	0.001	0.734	-0.001	0.637	0.002	0.299	0.001	0.788	-0.0002	0.788	0.002	0.406
Percent African American (1% increase)	-0.003	0.461	-0.005	0.376	0.0001	0.977	-0.002	0.708	0.0002	0.947	-0.001	0.862	-0.0004	0.542	0.003	0.234
Household income (2012)	0.0001	0.917	0.0001	0.729	0.0003	0.181	-0.00003	0.945	-0.0002	0.491	-0.0001	0.726	-0.00003	0.642	-0.0001	0.765
Median age	-0.006	0.322	-0.001	0.820	-0.001	0.638	-0.002	0.660	-0.003	0.238	-0.002	0.738	0.001	0.395	-0.001	0.699
No. of farmers market	0.013	0.608	**0.041**	0.098	0.007	0.486	0.013	0.511	0.011	0.415	-0.010	0.656	0.001	0.831	-0.004	0.698

Note: (1) We included the term for correct endogeneity in the multivariate probit model, but didn’t report it in the marginal effect table.

(2) Bold indicates significance at the 0.10 level or less.

Table 4. Marginal effects associated with barriers for non-local food buyers purchasing more local food.

Variables	Price	*P-value*	Local not Labeled	*P-value*	Shops do not carry local products	*P-value*
Female	0.119	*0.247*	0.067	*0.369*	0.046	*0.366*
Age	-0.003	*0.488*	0.003	*0.255*	0.001	*0.588*
Income	-0.001	*0.334*	0.001	*0.438*	0.0003	*0.608*
Caucasian	-0.087	*0.531*	**0.165**	*0.008*	-0.026	*0.738*
Some college	0.158	*0.281*	-0.002	*0.988*	**0.513**	*0.020*
Bachelor	0.101	*0.459*	0.125	*0.375*	**0.388**	*0.093*
Master's or higher	0.229	*0.121*	0.292	*0.120*	**0.511**	*0.030*
No. of children in household	-0.028	*0.677*	-0.011	*0.786*	0.014	*0.607*
No. of adults in household	-0.053	*0.337*	**0.222**	*0.009*	0.022	*0.344*
Underweight	-0.021	*0.949*	0.117	*0.678*	0.169	*0.591*
Overweight	0.057	*0.646*	0.055	*0.546*	-0.036	*0.343*
Obese	0.145	*0.251*	-0.090	*0.269*	-0.052	*0.204*
Food neophobia index	-0.041	*0.541*	-0.025	*0.507*	-0.005	*0.795*
Healthy-diet habit index	-0.026	*0.706*	**0.201**	*0.047*	0.098	*0.204*
Local expenditure						
Supermarket & Grocer	**0.353**	*0.071*	**-0.541**	*0.036*	--	--
Farmers market	--	--	-0.090	*0.244*	0.163	*0.504*
Roadside stand/CSA	--	--	--	--	--	--
Warehouse Clubs	0.163	*0.238*	**-0.150**	*0.060*	-0.071	*0.159*
Ethnic and specialty health grocery store	0.185	*0.322*	**-0.134**	*0.032*	-0.047	*0.275*
Discount grocery store	0.019	*0.925*	-0.045	*0.736*	0.004	*0.959*
Merchandiser	0.109	*0.407*	-0.022	*0.816*	0.021	*0.748*
Other	**-0.387**	*0.087*	0.113	*0.633*	-0.006	*0.939*
Population density	-0.063	*0.282*	0.035	*0.438*	0.018	*0.563*
Percent female (1% increase)	-0.014	*0.676*	-0.016	*0.458*	0.002	*0.819*
Percent Caucasian (1% increase)	-0.014	*0.197*	0.011	*0.152*	0.005	*0.320*
Percent African American (1% increase)	--	--	--	--	--	--
Household income (2012)	0.001	*0.656*	-0.001	*0.458*	0.0004	*0.541*
Median age	0.008	*0.706*	-0.011	*0.478*	-0.003	*0.639*
No. of farmers market	**-0.127**	*0.069*	0.113	*0.124*	0.012	*0.661*

*Bold indicates significance at the 0.10 level or less.

Essay 3

Open Space Conservation Perceived: Parcel Attributes versus Production of Cultural Ecosystem Services

3.1 Introduction

Open space provides ecosystem goods and services for human well-being, such as creating fertile soil, cleaning air, capturing carbon, protecting agricultural land, providing protection against floods or storms (Morandin and Winston, 2006; MEA, 2005); and provides sites for leisure or cultural services (Wu et al., 2000) that increase the quality of life for a community's residents. However, with the fast pace of urbanization, the total amount of undeveloped land is decreasing across the United States (Burchell et al., 2002; Livanis et al., 2006). According to American Farmland Trust (AFT), around 41 million acres of rural land, including crop, pasture, forest, and other undeveloped land, were converted to developed uses between 1982 and 2007 (AFT, 2010). Open space loss associated with damage to ecosystem services takes a toll on the health of plant, animal, and human populations (Moore, 2002). Thus, open space conservation is a critical environmental protection task concerning a variety of ecological resources and services in the United States (Arendt, 2012).

Environmental economists have developed the stated preference method, particularly the choice experiment approach, to enable the valuation of attributes of environmental quality that provide benefits outside of common market transactions (Adamonwicz et al. 1998; Louviere et al. 2000; Johnston, Swallow and Bauer, 2002). However, economists have done less work to identify how it is that various attributes might affect individual utility. Some bio-physical attributes of the environment may rightly be modeled as direct inputs to individual's utility. However, it is possible individuals perceive that a subset of attributes create a service that the

individual judges will contribute an unobserved good that provides utility directly. We explore this possibility within the context of land conservation actions that may provide cultural ecosystem services, such as contributing to the rural character of a community. The perception of a service like rural character may differ between individuals within or across communities.

Identifying services provided by nature resources is the foundation of nature resource evaluation and environmental performance assessment (Boyd and Banzhaf, 2007), and it is especially challenging for open space evaluation. The attributes of open spaces can benefit human beings directly; they can also combine with other factors to create new services for humans (Johnson et al., 2013; Boyd and Banzhaf, 2007; Johnston and Russell, 2011; Boyd and Krupnick, 2013).

Johnston et al. (2013) defined the ecosystem attributes that directly enhance the utility of humans by providing either use or nonuse benefits as "final services"; and they defined the attributes used to produce "final services" as intermediate services. An attribute can be either an intermediate service, a final service, or both. Thus, a challenge for understanding what drives the value of open space lands is to identify the final services that people seek, particularly when individuals make choices based on integrating relatively observable attributes or intermediate services to compose a perceived or intangible final service. To evaluate land parcels, Johnson et al. (2013) considered a situation for which a final service consists of three intermediate services, and included both this type of final service and all other final services in the utility function.

One contribution of this study is to consider a specific type of final service that influences individuals' preference for open space land. In this context, we name this type of final service as a "perceived service" and assume the services are individuals' perception of cultural ecosystem

services[13]. Our application uses a stated preference survey involving choice among land parcels to preserve as open space. The perceived services are not included in the choice questions directly, but are created subjectively by individuals based on their perception and the land attributes in the question. Thus, this study makes three main methodological contributions to the literature: (1) the first contribution is examining whether we can develop an index for perceived services; (2) the second contribution is exploring whether modeling the perceived services can explain a substantial share of the respondents' preference for protecting nature resources; (3) the third contribution is identifying whether perceived services influences respondents' choices even if the perceived services questions were not in the survey. In other words, this study contributes to identifying whether the addition of the perceived services questions change the estimation of respondents' preferences in the stated preference model. To our best knowledge, considering perceived services and using the stated production function to measure the level of perceived services are novel contributions of this study.

This general objective involves: 1) developing a perceived production function to generate indexes of perceived services by quantifying the magnitudes of parcel attributes and town landscapes that contribute to the level of perceived services; 2) applying a utility function to examine impacts of parcel attributes and perceived services on utilities for both a treatment group and a control group; 3) comparing the full utility function model with nested models to test whether perceived services are factors that affect individuals' choices; 4) comparing the results from the treatment and control groups to identify whether perceived services questions cause individuals to change their choices or preferences. Finally, we also calculate individuals' willingness-to-pay for alternative attributes and land parcels.

[13] According to Millennium Ecosystem Assessment (2006)'s categories of ecosystem services, ecosystem services include provisioning services, regulating services, and cultural services. Cultural Services have spiritual and religious values, aesthetic values, and recreation and ecotourism.

The rest of the paper is structured as follows. Section 2 conducts a brief literature review. Section 3 describes survey design, outlines hypotheses, and discusses theoretical and empirical methodology. Section 4 summarizes statistics of the data sets, and the estimation results are in section 5. Finally, we discuss policy implications and conclude in section 6.

3.2 Literature review

Open space conservation programs are developing within the U.S. (Wu, Xu and Alig, 2015), with extensive federal and state land conservation planning associated with nearly 800 open-space referenda initiatives that have been passed between 1998 and 2003, raising over $21 billion (Kotchen and Powers, 2006). In 2007, the United States Forest Service released an open space conservation strategy (USDA, 2007).

Given that conservation cost is constrained by government budgets (Wu, 2014), environmental economists' efforts on evaluating open space provide critical information for policy makers, public interest groups, and other organizations to identify favorable cost-benefit strategies (Brander and Koetse, 2011). Because open space values cannot be obtained from markets directly, economics models such as a stated preference model, hedonic method, and cost-benefit analysis are widely used to estimate the value of open spaces and other nature resources (e.g. Bateman et al., 2003; Anderson and West, 2006).

The stated preference (**SP**) methods are widely used to estimate the value of non-market ecosystem services (e.g. McConnell and Walls, 2005; Swallow and McGonagle, 2006; Johnston and Duke, 2007). SP method is a survey-based method through which economists can identify individuals' preferences of goods and services provided by ecosystems. In order to avoid estimation bias, a survey needs to list all services relevant to a choice, and those services should be presented in a manner that respondents would understand (Heal et al., 2005).

Identifying all services is particularly difficult for open space evaluation. As discussed above, not only do land parcels provide multiple attributes, but also we have to consider the individuals' preference for perceived services. Some parcel attributes providing final service are also inputs to produce perceived services. For example, woods provide a beautiful landscape to residents; and they function also as an inputs that combines with water and soil to create wildlife habitat. In this case, landscape and wildlife habitat are final services that influence residents' utility directly.

This study considers three perceived services, namely, rural character, ecological or environmental quality, and sense of culture and history, which are hypothetically available for individuals through the protection of undeveloped land parcels as open space. The level of perceived service is created by an individual's judgment of parcel attributes and the combination of parcel type and town landscape. A body of literature found that people would like to protect for these cultural ecosystem services. For example, Lokocz, Ryan, and Sadler (2011) found that residents' attachment to the rural landscape is a strong motivation for them to protect rural places. Home sale prices increased with closer proximity to parks, lakes, wetland, or tree cover (Doss and Taff, 1996; Sander and Polasky, 2009). De Groot et al (2010) indicated that factual knowledge is linked to the amount of ecological service supply. Cultural landscapes are significantly correlated with the identity of an individual, a community, or a society (Benson et al., 1998). Johnston, Swallow and Weaver (1999) and Johnston, Swallow and Bauer (2002) found that residents specifically were willing to pay more for watershed management plans that contributed to "rural character" defined as a presence-absence attribute.

3.3 Methodology

Survey design

This study is based on data derived from a land conservation survey conducted in Rhode Island in 2002. At that time, 3899 surveys were mailed to residents in four towns of Rhode Island, and 1132 people returned completed surveys. Particularly, 339 respondents came from Little Compton, 193 from Middletown, 178 from Portsmouth, and 420 respondents from Richmond. Two respondents didn't provide residency locations so that we removed them from our sample.

The survey contains a series of questions on respondents' demographic information and their perceptions about their living environment. The main part of the survey presented "land conservation" questions, where each question asked respondents to evaluate attributes of two parcels, and to make a choice to preserve one parcel or to choose to protect neither. Choice questions were created using a fractional factorial main effects design[14]. The empirical analysis of this paper focuses on 4 questions in the survey: Questions 1 and 2 (e.g. Question 1 in Figure 1a) let respondents to make decisions without considering conservation cost, whereas Questions 3 and 4 (e.g. Question 3 in Figure 2) involved the same type of choice but included a conservation cost.

The land parcel attributes are described by six categorical characteristics, including parcel description, size (acreage), most common wildlife, most common sounds, human elements, and land use of the surrounding area. Regarding each characteristic, there are 3-6 alternative attributes assigned to each parcel (see Table 1). For example, the parcel description category includes six alternative attributes: (1) farmland with nursery/ornamental plants, (2) wooded parcel with wetlands, (3) wooded parcel with mixed pine and hardwoods, (4) farmland with turf/sod, (4) farmland with cows horses or other livestock, or (6) cropland.

[14] The factorial design was provided by Stat Design, Inc., in Evergreen, CO.

We assumed respondents' perception of cultural ecosystem services is affected by the town's landscape where the respondent lives. Residents may differ in their perceptions on different services given that town landscapes are different. This specification helps to identify whether a parcel generates a larger amount of perceived service if the land type is consistent with town landscape. Given that the four towns in Rhode Island have different landscapes, such as forestland, farmland, mixed forestland and farmland area, and urban area (Figure 3), it's an ideal region for our empirical analysis. Based on parcel description category, we created two dummy variables to categorize the parcel types as wooded land or working farmland (as identified in Table 1). Then, we create interaction terms of the parcel type and town location dummy in the perceived production function.

Parcel attributes are dummy variables coded by effects coding using the values of -1, 0, and 1. Effects coding (e.g. Adamowicz, Louviere, and Williams, 1994; McGonagle and Swallow, 2005) for categorical attributes establishes a dummy variable for each attribute in the category, and then omitting one corresponding to the baseline variable. If the attribute of the parcel corresponds to the baseline, then the value for the baseline variable equals one and the other variables identifying this attribute equal negative one. If the variable doesn't correspond to the baseline, then the value for the attribute variable equals to one, and the remaining variables take the value of zero (McGonagle and Swallow, 2005).

The survey included two versions, which were assigned randomly to half of the mailing list, creating a control group and a treatment group. We have 598 respondents in the treatment group and 534 respondents in the control group. The version for the treatment group included three additional perceived services questions (e.g. Figure 1b) in Questions 1 and 2, while the control group received a version that did not include any of the additional questions. The

responses to perceived services in Question 1 and 2 are used to estimate the perceived production function for the services, and responses to Question 3 and 4 are used for estimating the utility function.

The difference between the treatment and control groups is that, respondents in the treatment group were reminded in Question 1 and 2 that the potential perceived services may benefit their community, but respondents in control groups did not receive questions that explicitly stimulated consideration of the perceived services. Thus, we can compare results from the treatment and control groups to examine respondents' preferences with and without explicit prompting regarding the three perceived services of rural character, ecological or environmental quality, or sense of culture and history.

Hypotheses

This study tests the following hypotheses:

Hypothesis 1: Parcel attributes are inputs of perceived services. Through testing significance level of coefficients in a perceived production function, we can identify key components of perceived services.

Hypothesis 2: Perceived services significantly influence respondents' choices in the treatment group. We test the significance level of perceived services indexes in the utility function for treatment groups.

Hypothesis 3: Perceived services significantly influence respondents' choices, even if respondents were not prompted to consider the perceived services. We first examine the significance level of the perceived services indexes in the utility function for control groups.

Then, we conduct likelihood ratio tests to whether perceived services should be incorporated into the estimated utility function.

Hypothesis 4: The perceived services questions in the treatment group cause respondents to change their choices of land parcels to protect. We again employ a likelihood ratio test.

Theoretical model

For our application to open space, we posit that individuals may identify or perceive that land protected from development may create three perceived services affecting the quality of life in their town: rural character, ecological quality, and cultural character. There is no literature that clarifies how to quantify these perceived services (Tilt, Kearney, and Bradley, 2007). The present study developed a perceived production method to address this problem.

The perceived production function used in this analysis is analogous to household production. The basic idea of the household production model is that people sometimes don't directly consume commodities that they purchase from markets, but transform them into goods through a household production process (e.g. Becker 1965; Rosenzweig and Schultz, 1983). We adopt a similar idea by assuming individuals develop a perceived service that derives from parcel attributes and town landscapes. A latent-class logit model is used to capture the heterogeneity of respondents' perceptions of services. Assuming respondents can be divided into Q classes, if a respondent i is in class q, a perceived production function for perceived service p is defined as:

$$Prod_{ijtpq} = Prod\left(X_{ijt}, Z_i, \beta_q\right) = F_{ijpq}\left(X_{ijt}, Z_i, \beta_q\right) + \varepsilon_{ijtq} \qquad [1]$$

where X_{ijt} is a vector of attributes of land parcel j in question t answered by individual i. Z_i is a vector of dummy variables for town location. $F_{ijpq}(X_{ijt}, Z_i, \beta_q)$ is a perceived production function of perceived service p, β_q is a vector of corresponding coefficients for individuals in class q, and ε_{ijtq} follows Weibull distribution.

For respondent i in class q, he/she was presented T questions, and there are J alternatives in a question. The probability of choosing parcel j in question t is a monotonic transformation of perceived production function $F_{ijpq}(X_{ijt}, Z_i, \beta_q)$, which is written as:

$$Prob(parcel\ j\ is\ chosen\ by\ i\ in\ question\ t\ for\ service\ p\ |class\ q)$$

$$= \frac{exp\left(F_{ijpq}(X_{ijt}, Z_i, \beta_q)\ \right)}{\sum_{k=1}^{J} exp\left(F_{ikpq}(X_{ikt}, Z_i, \beta_q)\ \right)} \qquad [2]$$

The likelihood of respondent i's choice across T questions is:

$$Prob(respondent\ i's\ choices\ for\ service\ p\ |class\ q) = P_{ip}\left(X_{ijt}, Z_i, \beta_q\right)$$

$$= \prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{exp\left(F_{ijpq}(X_{ijt}, Z_i, \beta_q)\right)}{\sum_{k=1}^{J} exp\left(F_{ikpq}(X_{ikt}, Z_i, \beta_q)\right)}\right)^{y_{ijt}} \qquad [3]$$

where, y_{ijt} equals one if individual i chose parcel j in question t, otherwise y_{ijt} equals zero.

Assuming that the probability of individual i in class q depends on a vector of the respondent's demographic characteristics S_i such as gender and education, then this probability can be written as:

$$Prob(\ i\ in\ class\ q) = \pi_i\left(S_i, \theta_q\right) = \frac{exp\left(S_i, \theta_q\right)}{1 + \sum_{m=1}^{q-1} exp\left(S_m, \theta_q\ \right) + \sum_{m=q+1}^{Q} exp\left(S_m, \theta_q\ \right)} \qquad [4]$$

where θ_q is a vector of corresponding parameters, and the joint log likelihood function of a total number of I respondents is:

$$ln\, L(\beta, \theta) = \sum_{i=1}^{I} ln \sum_{q=1}^{Q} \pi_i\left(S_i, \theta_q\right) P_{ip}\left(X_{ijt}, Z_i, \beta_q\right) \qquad [5]$$

The utility function reflects an index of happiness or preference value that an individual receives from protecting land parcels. Assuming all of the respondents belong to *G* classes, then the utility for individual *i* in class *g* answering question t is defined as:

$$Utility_{ijtg}(\alpha_g) = U(X_{ijt}, \hat{F}_{ij}, C_{ijt}, S_i, \alpha_g) \quad [6]$$

C_{ijt} is the conservation cost for individual *i* to protect parcel *j* in question *t*. $\hat{F}_{ij}$ is a vector of perceived service p (p=1,2,…P) of parcel j for respondents i. The value of perceived services is calculated using the estimated parameters of perceived production function. Based on the estimated coefficients of $\hat{\beta}_q$ and $\hat{\theta}_q$ in the perceived production function and the probability of respondent i being in class q, combining equations [1] and [4], the value of $\hat{F}_{ijt}$ for parcel *j* is:

$$\hat{F}_{ijt} = \sum_{q=1}^{Q} \pi_i(S_i, \hat{\theta}_q)\, F_{ijtq}(X_{ijt}, Z_i, \hat{\beta}_q) \quad [7]$$

Assuming α_g is a vector of corresponding parameters, then equation [6] can be expressed as:

$$Utility_{ijtg}(\alpha_g) = U(X_{ijt}, \hat{F}_{ijt}, C_{ijt}, S_i, \alpha_g) = V(X_{ijt}, \hat{F}_{ijt}, C_{iijt}, S_i, \alpha_g) + \delta_{ijtg} \quad [8]$$

where $V(X_{ijt}, \hat{F}_{ijt}, C_{ijt}, S_i, \alpha_g)$ represents the utility function used in empirical analysis, and δ_{ijtg} also follows the Weibull distribution. Similarly, the probability function that is a monotonic transformation of utility function $V(X_{ijt}, \hat{F}_{ijt}, C_{ijt}, S_i, \alpha_g)$. Then, we can conduct a latent class model to estimate the parameters of equation [8].

Empirical model

We adopt a linear functional form for the perceived production function and the utility function as a first-order approximation. For a respondent i belonging to class q, a perceived production function (PPF) is:

$$F_{ijtq}\left(X_{ijt}, Z_i, \beta_q\right) = \beta_{Pq}(ParcelAttributes) + \beta_{TLq}(TownDummy \times LandType) \qquad [9]$$

where the interaction term between town dummy variables and land type (i.e. working farmland or wooded land) allows the model to capture various perceptions of perceived services among residents in different towns.

The utility function with perceived services and attributes (UF_Full) used for empirical analysis is written as:

$$V\left(X_{ijt}, \hat{F}_{ijt}, C_{iit}, S_i, \alpha_g\right) = \alpha_{Ng}(NeitherParcel) + \alpha_{Cg}(Cost) + \alpha_{Pg}(ParcelAttributes)$$

$$+\alpha_{Percg}(PerceivedServices) + \alpha_{LPg}(LivingEnvironment \times ParcelType)$$

$$+\alpha_{RCg}(Demographic \times NeitherParcel) \qquad [10]$$

In the utility function, *NeitherParcel* is a dummy variable that equals one for the alternative that protects neither A nor B, otherwise it equals zero. *Cost* represents the money to be paid to protect the corresponding parcel. *ParcelAttributes* denotes the six categorical characteristics of the parcel described in the survey, and *PerceivedServices* are indexes ($\hat{\mathrm{F}}_{\mathrm{ijt}}$) obtained from perceived production function. *LivingEnvironment* reflects the respondents' perception of their living environment. In the survey, we asked respondents to indicate whether their town provides a wooded landscape view or not, and whether their town provides a farm landscape view or not. *Demographic* in the utility function is a vector of variables that describe respondents' demographic information such as age, education level, and income level. The

interaction term *Demographic*×*NeitherParcel* serves as a baseline to quantify the respondent's utility from protecting neither parcel A nor B.

We assume the utility function with parcel attributes (UF_Attribute) is:

$$V\left(X_{ijt}, \hat{F}_{ijt}, C_{iit}, S_i, \alpha_g\right) = \alpha_{Ng}(NeitherParcel) + \alpha_{Cg}(Cost) + \alpha_{Pg}(ParcelAttributes)$$

$$+\alpha_{LPg}(LivingEnvironment \times ParcelType) + \alpha_{RCg}(Demographic \times NeitherParcel) \quad [11]$$

The utility function with perceived services (UF_PS) is:

$$V\left(X_{ijt}, \hat{F}_{ijt}, C_{iit}, S_i, \alpha_g\right) = \alpha_{Ng}(NeitherParcel) + \alpha_{Cg}(Cost) + \alpha_{Percg}(PerceivedServices)$$

$$+\alpha_{Sizeg}Size + \alpha_{LPg}(LivingEnvironment \times ParcelType)$$

$$+\alpha_{RCg}(Demographic \times NeitherParcel) \quad [12]$$

We conduct a likelihood test between UF_Full and UF_Attribute models to test whether parameters of perceived services jointly equal zero; and the same test for UF_Full and UF_PS models to examine whether parameters of parcel attributes (except size) jointly equal zero.

Willingness to pay

For individual *i* in class *g* answering choice set *t*, his/her willingness to pay WTP_{ijktg} for parcel *j* over current parcel *k* can be expressed as:

$$V\left(X_{ijt}, \hat{F}_{ijt}, -WTP_{ijktg}, S_i, \alpha_g\right) = V\left(X_{ikt}, \hat{F}_{ikt}, 0, S_i, \alpha_g\right) \quad [13]$$

Assuming the parameter of an attribute m is α_{Pmg}, the marginal WTP of attribute m is:

$$\Delta WTP_m = -\alpha_{Pmg}/\alpha_{Cg} \quad [14]$$

The total WTP of individual i in class g for a parcel j is:

$$WTP_{jig} = \left(- \alpha_{Pg}/\alpha_{Cg}\right) + \left(- \alpha_{Percg}/\alpha_{Cg}\right) \times PerceivedServices + \left(- \alpha_{LPg}/\alpha_{Cg}\right)$$
$$- \left(- \alpha_{Ng}/\alpha_{Cg}\right) - \left(-\alpha_{RCg}/\alpha_{Cg}\right) \times Demographic \qquad [15]$$

3.4 Data

The treatment group responses from Questions 1 and 2 are used to estimate the perceived production function. For the total of 598 respondents, we first eliminated 29 respondents with missing values for education level or gender variables. The education and gender variables are needed to estimate the class membership function. Thus, 546 respondents are used for estimating the perceived production function. According to the summary statistics presented in Table 1, 55.3% are female, 45.3% have a bachelor degree or completed some college education, and 37.4% have a graduate degree or have some graduate school education. The four interaction terms that are town dummy variables interact with land types, where the term of Richmond or a working farm land parcel serves as a baseline in the model.

Responses to Question 3 and 4 are used to estimate the utility function. There are 561 respondents who answered Question 3 or 4 or both. Thus, the number of observations in the estimation of the perceived production function is different from the number in the estimation of the utility function. Particularly, we have 554 respondents who answered Question 3 and 558 respondents who answered Question 4. For the control group, after removing observations with missing values, we retained 503 respondents who answered Question 3 and 500 respondents who answered Question 4. The total number of respondents in the control group is 503. We present the demographic statistics of respondents in the two groups in Table 2.

In both groups, 82% of respondents have a bachelor's or higher degree. In both groups, and 56% of respondents are female. What is more, the average age of control group is

significantly older (1.5 years) than treatment group. For the treatment group, 28% of respondents indicate their annual household income is $100,000 or more, and the number of control group is 31%. The difference of household income means of two groups are significant at 10% level. In general, the differences of gender and education between the treatment and control groups are not statistically significant, but the age (1.5 years) and household income (3%) are significantly higher in the control group. Thereby, any comparison between two groups needs to keep this caveat in mind.

Table 3 presents summary statistics for responses to Question 3 and 4 for the treatment group, including perceived services, a dummy variable for choosing neither parcel, conservation cost, descriptions of the parcels, living environment, and demographic information. Similarly, Table 4 presents the statistics information for the control group. The value of perceived services indexes are calculated using the estimated parameters from the perceived production function (equation [9]) and the parcel attributes in Question 3 and 4 for both groups. Comparing Table 3 with Table 4, we can see means the perceived services indexes and the attributes are similar.

3.5 Empirical Results

We first present the results of the perceived production function in Table 5. We find that a 2-class model yields the lowest AIC, CAIC, and BIC[15] values in modeling the production functions, which supports adopting the 2-class model as most consistent with the data. In Table 5, respondents' class memberships are independently estimated between separate models addressing each of the explicit perceived services in the survey.

[15] Rural character: AIC= 1261.354; CAIC=1494.183; and BIC= 1450.183.
Ecological or environmental quality: AIC=1211.448; CAIC= 1444.195; and BIC= 1400.195.
Sense of culture and history: AIC=1106.095; CAIC=1338.679; and BIC=1294.679.

In each model, some parameters of parcel attributes are significant, which supports our Hypothesis 1 that parcel attributes are important inputs of perceived services. The result shows that parcel attributes play different roles in creating each perceived service. Finally, the negative sign of interaction terms indicate that, compared to Richmond, residents from the town with a less forested landscape indicate that wooded parcels provides less of the corresponding perceived service. Landscape is an important factor for perceived services, and wooded parcels can generate more perceived services for towns with forest landscape.

Perceived services

For the model regarding the production of rural character, 57.5% respondents are in class 1 and 42.5% respondents in class 2. Respondents with some graduate school education are more likely in class 1. Regarding the model for the perception of higher ecological or environmental quality, there are 48 percent of respondents in class 1, and 52 percent of respondents in class 2. Male respondents and respondents with college or higher education are more likely in class 1. Sense of culture and history is another perceived service, for which we have 61.9% respondents in class 1 and 38.1% respondents in class 2, and female respondents are more likely in Class 1.

Results for estimating the production of rural character (Table 5) show that individuals in class 1 tend to view wooded land as providing more rural character than agricultural land, although there is some tendency (with significance levels of only $P<0.15$) for working farms also to contribute to rural character. In contrast, individuals in class 2 significantly view farms with traditional row crops as providing rural character, while turf grass farms are not adding rural character and wooded parcels are tending ($P<0.15$) to detract from rural character. In class 1, land features such as larger acreage, deer or other small mammals, farm sounds, and stonewalls are beneficial for rural character; but wire or other metal fences reduce rural character. In class 2,

there are more features that can significantly influence rural character production than class 1: respondents indicate that turkey or other large birds, nature sounds and wind, remnants of old farms/mills and stone walls produce more rural character; but deer or other small mammals, small birds or frogs, vehicle sounds, wire or metal fences, and surrounded by wooded land would reduce rural character.

Town landscape also influences production of perceived services. In comparison with Richmond residents or working farmland parcel, Little Compton and Middletown residents in class 1 and Little Compton and Portsmouth residents in class 2 indicate that wooded parcel creates less rural character. This result wooded parcels with town forest town landscape can provide rural character.

Results suggest that respondents in both classes use only a few parcel attributes to create their perception of a parcel as contributing more in terms of ecological or environmental quality in their community. In class 1, respondents indicate that deer or small mammals improve ecological and environmental quality but farm sounds are harmful. Respondents in class 2 consider more attributes as contributing: including larger parcel acreage, small birds or frogs, sounds of farm, remnants of old farms or mills, and stone walls. However, vehicle sounds and wire/metal reduce this perceived service.

Regarding the production of ecological or environmental quality, Little Compton residents in class 2 point out that a wooded parcel significantly decreases ecological or environmental quality relative a farmland parcel or a wooded parcel in Richmond. Given that the most common landscape in Little Compton is agricultural land (Figure 3), we can infer that residents in Little Compton think working farmland, the same land type with their town landscape, are better for increasing ecological and environmental quality for the community.

Respondents in the two classes all indicate that remnants of old farms/mills contribute positively to a sense of culture and history for their community, while wire/metal fences have negative impacts. However, the opinions about the production of other attributes affecting the culture and history service are different between two classes. Comparing with farmland with nursery plants, respondents in class 1 show that wooded parcels with wetland and wooded parcels with mixed pines and hardwoods produce less culture and history character, while cropland produces more. In class 2, wetlands and a larger land parcels create more of this perceived service. Deer or small mammals, nature sounds and winds are attributes in class 1's perception of contributions to a sense of culture or history, but small birds or frogs reduce culture and history character. Respondents in class 2 indicate that a parcel surrounded by wooded land creates more of this perceive service than do parcels surrounded by a general neighborhood. Finally, among the respondents in class 2, those who live in Little Compton or Middletown make choices indicating that wooded parcels create less culture and history character for their community.

In conclusion, both town landscapes and parcel attributes are important components for a perceived service, and each attribute plays various roles in creating different perceived services. A latent class model indicates that respondents show heterogeneity in their perception of the production of perceived services. Regarding town landscapes, the estimated results indicate that land parcels that are consistent with town landscape would provide more perceived services.

Perceived services in utility function

In order to identify the most appropriate model to reflect the respondents' utility obtained from protecting land parcels, we estimate the three alternative utility functions for treatment and control groups. The results of the utility function for the treatment group are in Table 6, where

we present estimated results of UF_Full, UF_Attribute, and UF_PS models[16]. These three models and relative tests are employed to identify the most appropriate model to analyze respondents' choices for the treatment group. Table 7 presents the estimated results for the utility function of the control group.

Hypothesis 2 posits that perceived services significantly influence respondents' choices in the treatment group. The parameters of perceived services in the UF_Full models reflect that ecological or environmental quality benefit respondents in treatment group. What is more, **Hypothesis 3** posits that perceived services significantly influence respondents' choices, even if respondents were not prompted to consider the perceived services. According to the results of UF_Full models in Table 7, rural character significantly increases utility for the respondents in the control group. Notably, the choices in different groups are driven by different perceived services, which needs further analysis.

Respondents in the treatment group answered perceived services questions in Question 1 and 2. This study strives to test whether the presence of questions concerning the perceived services in the treatment group cause respondents to change their choices for protecting land parcels (**Hypothesis 4**). We employ a likelihood test with both groups to test this hypothesis.

The likelihood ratio test between UF_Full model and UF_Attribute models for the treatment group (Table 6) cannot reject the hypothesis that parameters on perceived services are jointly equal to zero (LR chi2 (6) = - 5.33). Further, the likelihood ratio test between UF_Full model and UF_PS model rejects the hypothesis that parcel attributes jointly equal to zero (LR chi2(32) = 107.62, and Prob > chi2 = 0.0001). Thus, perceived services should not be included

[16] UF_Full model: the utility function with perceived services and attributes. UF_Attribute model: the utility function with parcel attributes. UF_PS model: the utility function with perceived services.

in the model on statistical grounds, which leads to the UF_Attribute model to be the most appropriate utility function to represent respondents' choices for the treatment group.

As opposed to the treatment group, the likelihood ratio test between UF_Full model and UF_Attribute models rejects the hypothesis that perceived services are jointly zero for the control group (LR chi2(6) = 13.08, and Prob > chi2 = 0.0418). The test between UF_Full model and UF_PS model also rejects the hypothesis that parcel attributes jointly equal to zero (LR chi2(32) = 51.25, and Prob > chi2 = 0.0168). Thus, perceived services should be incorporated in the model, and the UF_Full model is the most appropriate utility function to represent respondents' choices for the control group.

The results of likelihood ratio tests indicate that perceived services play different roles in the treatment and control groups. One possible reason for this difference is that the samples are different, and another possible other reason is that the perceived services questions in Question 1 and 2 may cause respondents to more explicitly consider the named perceived services, and this may have led the treatment-group respondents to make different choices than they would have made as part of the control group. Given that means of age and income are significantly different between the two groups, we may infer that the difference drives from the additional questions (information) in treatment group. In the control group, a parcel's index for the production of rural character significantly increased a respondents' utility. However, these questions changed respondents' perception of perceived services, and indicate the three perceived services are not beneficial to their utility. Thus, Hypothesis 4 is true that perceived services questions lead respondents to change their choices.

Results of the tests of Hypotheses 2-4 indicate that: 1) perceived services are important factors to influence respondents' choices for protecting land resources; 2) but framing effects

arising from the addition perceived-service questions may lead respondents to alter their choices. What is more, through comparing the results between three models in each group, we find that adding perceived services in the model of the control group (by using the model for perceived services obtained from the treatment group to estimate an index of perceived services for the control group) does improve the model (adds statistically significant parameters to the model) for the control group. But using the index of perceived services does not add statistically significant parameters to the model for the treatment group. However, the treatment group's choices are significantly related to the indices of perceived services if the parcel attributes are removed from the model. That result suggests that perceived services are nonetheless likely to be driving choices by the treatment group, even though the best overall model may simply be to use a reduced form that only explicitly retains the parcel attributes.

Results of UF_Attribute model for the treatment group

As it is mentioned in the previous paragraph, UF_Attribute model is the most appropriate model for the treatment group. This result indicates that respondents' preferences are divided into two classes, and 35.8% of respondents are more likely in class 1 and 74.2% respondents are in class 2. The parameter of *NeitherParcel* indicates that respondents in class 1 prefer to protect neither parcel A nor B. Highly educated respondents in class 1 indicate that protecting neither parcel decreases their utility. In both classes, a higher cost decreases the utility for a respondent to choose to protect that parcel. Comparing to respondents in class 2, increases in conservation cost has a larger negative impact on utility (class 2 exhibits a higher magnitude for the marginal utility of income). What is more, only two parcel attributes can significantly influence respondents' utility in class 1. Comparing to farmland with nursery plants, wetlands increases utility but turf or sod farmland decreases respondents' utility in class 1 (Table 6).

There are more attributes significantly influencing respondents' utility in class 2. They indicate that mixed pine and hardwoods land reduces utility. However, turf or sod land and farms with cows horses or other livestock significantly increase utility. Larger land size isn't an important factor for both classes. With respect to the wild life category, the presence of turkey or large birds is a beneficial attribute for respondents in class 2. Respondents indicate the distant sounds of cars or traffic negatively affects utility, but nature sounds and farm vehicles sounds have positive contributions to utility. Human elements such as remnants of old farms/mills and stone walls benefit respondents' welfare.

The interaction term category reflects effects if the respondent's living environment matches the parcel type or not. Respondents in class 1 and 2 have the opposite preference although some of the parameters are not significant. Respondents in class 1 are willing to protect parcels that are different to their living environment, but respondents in class 2 prefer to protect parcels same as the living environment. In class 2, respondents who are living within a wooded area indicate wooded land parcels significantly increase the utility relative to respondents living in other areas or near working farmlands. Thus, respondents' heterogeneity is an important factor that determines respondents' preferences and choices.

Results of UF_Full model for the control group

UF_Full model is the most appropriate model for control group (Table 7). There are 26.1% of respondents in class 1 and 73.9% respondents in class 2. More highly educated respondents are less likely to be in class 1. In class 1, older people indicate protecting neither parcel significantly increases their utility, but we obtained an opposite result for class 2. An increase in conservation cost has larger negative impacts on respondents' utility in class 1 relative to class 2.

Both perceived services and attributes influence respondents' preference in the control group. Rural character is an important factor for respondents in class 2. A larger acreage of parcel increases utility in class 1, and respondents in class 1 also indicate that parcels with deer or small mammals are more preferred. Parcels surrounded by woods provide higher utility than parcels surrounded by neighborhoods, but those surrounded by farmlands lower utility for respondents in class 1. For respondents in class 2, crop lands and farm vehicles sounds reduce their utility. With regard to human elements, respondents in class 2 indicate that parcels with wire/metal fences significantly increase their utility.

The role of parcel attributes

This study demonstrates parcel attributes are inputs to produce perceived services and also influence utility directly. For example, turkey or large birds is an important component of rural character, and they increase respondents' utility directly in the treatment group. The presence of deer and small mammals is an important input to generate rural, ecological, and historical perceived services, but presence of these wildlife also decreases respondents' utility in the control group because these wildlife cause damage to homeowners' landscaping.

Willingness to pay to protect land parcels

In table 8, we first calculate the marginal WTP of the most appropriate model for the treatment group and control group, namely, UF_Attribute model for the treatment group and the UF_Full model for the control group. In the treatment group, the wetland attribute has the highest marginal WTP value ($83.6), and the turf/sod farmland has the lowest marginal WTP (-$122.6). The values of marginal WTP for parcel attributes range from -$599.5 to $599.5 in class 2. Regarding marginal WTP in the control group, respondents in class 2 are willing to pay $63.2

per year to protect rural character, but the corresponding value in class 1 is only $1.8. The highest value of marginal WTP from control group is $413.7 for respondents living in farmed area to protect farmland parcels.

3.6 Summary and Concluding Remarks

Perceived services are important factors influencing people's preferences. Through identifying and analyzing the perceived services, this study made contributions to explore the most appropriate model to evaluate open spaces. Specifically, as we mentioned above, this study makes three main methodological contributions to the literature. We create and estimate indexes for perceived services, and demonstrate parcel attributes are important inputs to generate perceived services. Through comparing the results of alternative utility functions, we demonstrate that perceived services can explain respondents' choices of protecting land resources. What is more, the additional information about the perceived services led respondents in the treatment group to alter their choices with respect to rural character and ecological and environmental character.

In this study, we consider three cultural ecosystem services including rural character, ecological or environmental quality, and sense of culture and history. Using a latent class logit model to capture the heterogeneity among consumers, we find that 2-class logit models are the best models for all three perceived services. The results for perceived production functions indicate that parcel attributes, such as wooded or agricultural attributes, wildlife, and human elements are important inputs for generating perceived services. What is more, town landscape is also an important factor that influences the level of perceived services. Respondents indicate that parcels that match the their town landscape, such as forest landscape and wooded parcel, generate more perceived service. Besides being inputs to perceived services, this study

demonstrates that parcel attributes can influence respondents' utility directly. For example, the presence of turkey or large birds is an important component of rural character, and also increases respondents' utility directly in the treatment group.

Parcel attributes and perceived services influence respondents' utility obtained from protecting land parcels. Heterogeneity among respondents also lead to different conservation decisions.

In conclusion, perceived services are important factors for individuals to protect open space. Developing perceived services indexes contributes to the literature by suggesting a methodology to identify and quantify the perceived services. What is more, the perceived services questions should be presented in an appropriate manner in the survey. Otherwise, it may distract respondents' attentions, and cause them to change conservation decisions. Thus, incorporating perceived services in an appropriate in the survey is a challenging research question for future study.

References

American Farmland Trust (AFT). (2010). What's Happening to Our Farmland? Accessed at March 19. 2015 http://www.farmland.org/resources/fote/

Anderson, S. T., and West, S. E. (2006). Open space, residential property values, and spatial context. *Regional Science and Urban Economics 36*: 773-789.

Arendt, R. G. (2012). Conservation design for subdivisions: A practical guide to creating open space networks. Island Press.

Bateman, I. J., Lovett, A. A., and Brainard, J. S. (2003). Applied environmental economics: A GIS approach to cost-benefit analysis. Cambridge University Press.

Becker, G. S. (1965). A theory of the allocation of time. *The Economic Journal* 75: 493-517.

Benson, E. D., Hansen, J. L., Schwartz Jr, A. L., and Smersh, G. T. (1998). Pricing residential amenities: the value of a view. *The Journal of Real Estate Finance and Economics* 16: 55-73.

Boyd, J., and Banzhaf, S. (2007). What are ecosystem services? The need for standardized environmental accounting units. *Ecological Economics* 63: 616-626.

Brander, L. M., and Koetse, M. J. (2011). The value of urban open space: Meta-analyses of contingent valuation and hedonic pricing results. *Journal of Environmental Management* 92: 2763-2773.

Burchell, R.W., Lowenstein, G., Dolphin, W. R., Galley, C. C., Downs, A., Seskin, S., Still, K. G., and Moore, T. (2002). Costs of Sprawl--2000. Transit Cooperative Research Program (TCRP) Report 74, published by Transportation Research Board, Washington. Accessed at April 10, 2016 http://onlinepubs.trb.org/onlinepubs/tcrp/tcrp_rpt_74-a.pdf

Costanza, R., Wilson, M. A., Troy, A., Voinov, A., Liu, S., and D'Agostino, J. (2006). The value of New Jersey's ecosystem services and natural capital. Accessed at July 15, 2015. http://pdxscholar.library.pdx.edu/cgi/viewcontent.cgi?article=1014&context=iss_pub

De Groot, R. S., Alkemade, R., Braat, L., Hein, L., and Willemen, L. (2010). Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. *Ecological Complexity* 7: 260-272.

Doss, C. R., and Taff, S. J. (1996). The influence of wetland type and wetland proximity on residential property values. *Journal of Agricultural and Resource Economics* 21: 120-129.

Heal, G.M., Barbier, E.B., Boyle, K. J., Covich, A. P., Gloss, S. P., Hershner, C. H., Hoehn, J. P., Pringle, C. M., Polasky, S., Segerson, K., and Shrader-Frechette, K. (2005). Valuing Ecosystem Services: Toward Better Environmental Decision Making. The National Academies Press, Washington DC.

Johnston, R. J., Swallow, S. K., and Bauer, D. M. (2002). Spatial factors and stated preference values for public goods: considerations for rural land use. *Land Economics* 78: 481-500.

Johnston, R. J., and Duke, J. M. (2007). Willingness to pay for agricultural land preservation and policy process attributes: Does the method matter? *American Journal of Agricultural Economics* 89: 1098-1115.

Johnston, R. J., Schultz, E. T., Segerson, K., Besedin, E. Y., and Ramachandran, M. (2013). Stated preferences for intermediate versus final ecosystem services: disentangling willingness to pay for omitted outcomes. *Agricultural and Resource Economics Review* 42: 98-118.

Kotchen, M. J., and Powers, S. M. (2006). Explaining the appearance and success of voter referenda for open-space conservation. *Journal of Environmental Economics and Management* 52: 373-390.

Livanis, G., Moss, C. B., Breneman, V. E., and Nehring, R. F. (2006). Urban sprawl and farmland prices. *American Journal of Agricultural Economics* 88: 915-929.

Lokocz, E., Ryan, R. L., and Sadler, A. J. (2011). Motivations for land protection and stewardship: Exploring place attachment and rural landscape character in Massachusetts. *Landscape and Urban Planning* 99: 65-76.

McConnell, V., and Walls, M. A. (2005). The value of open space: Evidence from studies of nonmarket benefits. Washington, DC: Resources for the Future.

McGonagle, M. P., and Swallow, S. K. (2005). Open space and public access: A contingent choice application to coastal preservation. *Land Economics* 81: 477-495.

Ecosystems and human well-being. Vol. 5. Washington, DC:: Island press, 2005.

Moore, T. (2002). Protecting Maryland's Green Infrastructure: The case for aggressive public policies. Maryland Department of Natural Resources, Chesapeake and Coastal Watershed Service.

Morandin, L. A., and Winston, M. L. (2006). Pollinators provide economic incentive to preserve natural land in agroecosystems. *Agriculture, Ecosystems & Environment* 116: 289-292.

Rosenzweig, M. R., and Schultz, T. P. (1983). Estimating a household production function: Heterogeneity, the demand for health inputs, and their effects on birth weight. *The Journal of Political Economy* 91: 723-746.

Sander, H. A., and Polasky, S. (2009). The value of views and open space: Estimates from a hedonic pricing model for Ramsey County, Minnesota, USA. *Land Use Policy* 26: 837-845.

Swallow, S. K., and McGonagle, M. P. (2006). Public funding of environmental amenities: contingent choices using new taxes or existing revenues for coastal land conservation. *Land Economics* 82: 56-67.

Tilt, J. H., Kearney, A. R., and Bradley, G. (2007). Understanding rural character: Cognitive and visual perceptions. *Landscape and Urban Planning* 81: 14-26.

US Department of Agriculture. (2007). Forest Service Open Space Conservation Strategy. Assessed at March 19, 2015 http://www.fs.fed.us/openspace/OS_Strategy_final_web.pdf.

Wu, B., Zhu, H., and Xu, X. (2000). Trends in China's domestic tourism development at the turn of the century. *International Journal of Contemporary Hospitality* Management 12: 296-299.

Wu, J. (2014). Public open-space conservation under a budget constraint. *Journal of Public Economics* 111: 96-101.

Wu, J., Xu, W., and Alig, R. J. (2016). How do the location, size and budget of open space conservation affect land values? *The Journal of Real Estate Finance and Economics* 52: 73-97.

3.7 Tables and Figures

Table 1. Statistic summary of Question 1 and 2 (546 respondents in treatment group)

Variables	Description	Question 1		Question 2	
		Parcel A	Parcel B	Parcel A	Parcel B
Rural character (DV)		0.572	0.428	0.473	0.527
Ecological or environmental quality (DV)		0.580	0.420	0.479	0.521
Sense of culture and history (DV)		0.529	0.471	0.453	0.547
Parcel Description (DV[1])	Working farm (nursery/ornamental plants) (Baseline) [3]	0.130	0.125	0.170	0.057
	Wooded (wetlands)[2]	0.059	0.143	0.081	0.192
	Wooded (mixed pine and hardwoods)[2]	0.313	0.112	-0.040	0.253
	Working farm (turf/sod)[3]	-0.079	0.064	0.027	-0.002
	Working farm (cows, horses or other)[3]	0.057	0.059	-0.099	0.009
	Working farm (field crops)[3]	-0.130	-0.125	0.009	0.207
Size	10 acres, 20 acres, 50 acres, 80 acres, 110 acres	72.802	62.802	60.659	66.905
Most Common Wildlife (DV[1])	Nothing of particular note (Baseline)	0.189	0.313	0.302	0.308
	Turkey/large birds	0.240	-0.059	-0.176	-0.106
	Deer/small mammals	-0.081	-0.011	0.147	-0.106
	Small birds/frogs	0.086	-0.183	-0.179	-0.018
Most Common Sounds (DV[1])	Nothing of particular note (Baseline)	0.363	0.114	0.108	0.300
	Distant cars/traffic	-0.112	0.170	0.082	-0.040
	Nature sounds and wind	-0.103	0.264	0.198	-0.101
	Farm vehicles	-0.236	0.112	0.288	-0.060
Human Elements (DV[1])	Nothing of particular note (Baseline)	0.339	0.242	0.267	0.141
	Remnants of old farms/mills	-0.048	0.150	-0.090	0.108
	Wire/metal fences	-0.216	-0.068	0.112	0.165
	Stone walls	-0.092	-0.049	-0.092	0.163
Surrounding Area (DV[1])	Neighborhoods (Baseline)	0.168	0.126	0.330	0.456
	Wooded	0.473	0.229	0.106	-0.317
	Farmed	0.022	0.392	-0.095	-0.051
Interaction term (DV)	Richmond or Working farmland (Baseline)	0.601	0.690	0.769	0.654
	Little Compton and Wooded land	0.174	0.136	0.110	0.159
	Middle Town and Wooded land	0.119	0.088	0.053	0.103
	Portsmouth and Wooded land	0.106	0.086	0.068	0.084
Female (DV)				0.553	
Bachelor degree or completed some college education (DV)				0.452	
Graduate degree or have some graduate school education (DV)				0.374	

Note: [1] Effects coding; [2] Wooded land; [3] Working farmland; DV: Dummy Variable

Table 2. Demographic statistics of treatment group, control group

Variable	treatment group (561)		control group (503)		t-test significance of the means
	Mean	Std. Dev.	Mean	Std. Dev.	
Age	52.43	13.77	54.07	15.42	***
Female (DV)	0.56	0.50	0.56	0.50	
Bachelor Degree or higher education (DV)	0.82	0.38	0.82	0.39	
$100,000<=Income (DV)	0.28	0.45	0.31	0.46	**

DV: Dummy Variable; *, **, *** represent significance at the 0.1, 0.05, and 0.01 levels.

Table 3. Statistic summary of Question 3 and 4 in the treatment group survey

Variables	Description	Question 3[4]			Question 4[5]		
		Parcel A	**Parcel B**	**Neither**	**Parcel A**	**Parcel B**	**Neither**
Choice (DV)		0.383	0.428	0.190	0.468	0.330	0.203
NeitherParcel (No parcel =1)		0	0	1	0	0	1
Cost	$25, $55, $80, $110, $155, $190, $250, $320	124.278	137.987	0	149.203	173.674	0
Perceived Services	Rural character	1.845	1.774	0	2.744	2.525	0
	Ecological or environmental quality	1.559	1.679	0	1.959	1.102	0
	Sense of culture and history	0.944	0.680	0	1.596	1.751	0
Parcel Description (DV[1])	Working farm (nursery/ornamental plants) (B)[3]	0.206	0.206	0	0.059	0.077	0
	Wooded (wetlands)[2]	0.023	0.069	0	0.181	0.170	0
	Wooded (mixed pine and hardwoods)[2]	0.108	0.060	0	0.254	0.158	0
	Working farm (turf/sod)[3]	-0.150	-0.206	0	0.145	0.097	0
	Working farm (cows, horses or other)[3]	-0.137	-0.011	0	0.124	-0.025	0
	Working farm (field crops)[3]	-0.079	-0.146	0	-0.059	0.138	0
Size	0 acres, 20 acres, 50 acres, 80 acres, 110 acres	60.181	69.603	0	71.559	57.634	0
Most Common Wildlife (DV[1])	Nothing of particular note (B)	0.170	0.186	0	0.246	0.188	0
	Turkey/large birds	0.074	0.199	0	0.125	0.011	0
	Deer/small mammals	0.211	-0.056	0	-0.118	0.183	0
	Small birds/frogs	0.036	0.114	0	0.011	0.054	0
Most Common Sounds (DV[1])	Nothing of particular note (B)	0.314	0.363	0	0.185	0.188	0
	Distant cars/traffic	-0.132	-0.137	0	0.048	-0.023	0
	Nature sounds and wind	-0.072	-0.148	0	0.070	0.115	0
	Farm vehicles	-0.052	-0.166	0	0.143	0.156	0
Human Elements (DV[1])	Nothing of particular note (B)	0.256	0.256	0	0.244	0.186	0
	Remnants of old farms/mills	-0.007	-0.132	0	-0.004	0.188	0
	Wire/metal fences	0.049	-0.013	0	-0.106	0.138	0
	Stone walls	-0.067	0.119	0	0.134	-0.072	0
Surrounding Area (DV[1])	Neighborhoods (B)	0.352	0.440	0	0.115	0.188	0
	Wooded	-0.097	-0.197	0	0.572	0.065	0
	Farmed	0.042	-0.125	0	0.084	0.371	0
Interaction term (DV)	Other area or Working farmland (B)	0.494	0.506	0	0.489	0.549	0
	Wooded area and Wooded land	0.506	0.494	0	0.511	0.451	0
	Other area or Wooded land (B)	0.578	0.587	0	0.594	0.529	0
	Farm area and Farm land parcel	0.422	0.413	0	0.406	0.471	0

Note: [1] Effects coding; [2] Wooded land; [3] Working farmland; [4] 554 respondents in Question 3; [5] 558 respondents answered Question 4; DV: Dummy Variable; B: Baseline.

Table 4. Statistic summary of Question 3 and 4 in the control group survey

Variables	Description	Question 3[4]			Question 4[5]		
		Parcel A	Parcel B	Neither	Parcel A	Parcel B	Neither
Choice (DV)		0.326	0.443	0.231	0.444	0.336	0.220
NeitherParcel (No parcel =1)		0	0	1	0	0	1
Cost	$25, $55, $80, $110, $155, $190, $250, $320	130.070	142.088	0	155.930	170.950	0
Perceived Services	Rural character	1.910	1.911	0	2.699	2.609	0
	Ecological or environmental quality	1.540	1.957	0	1.951	1.101	0
	Sense of culture and history	1.139	0.639	0	1.623	1.800	0
Parcel Description (DV[1])	Working farm (nursery/ornamental plants) (B) [3]	0.221	0.173	0	0.054	0.060	0
	Wooded (wetlands)[2]	0.010	0.149	0	0.196	0.202	0
	Wooded (mixed pine and hardwoods)[2]	0.070	0.091	0	0.236	0.164	0
	Working farm (turf/sod)[3]	-0.167	-0.173	0	0.166	0.126	0
	Working farm (cows, horses or other)[3]	-0.157	0.014	0	0.132	-0.002	0
	Working farm (field crops)[3]	-0.080	-0.119	0	-0.054	0.150	0
Size (1 acre = 3/4 football field)	0 acres, 20 acres, 50 acres, 80 acres, 110 acres	59.722	68.310	0	71.060	59.300	0
Most Common Wildlife (DV[1])	Nothing of particular note (B)	0.183	0.173	0	0.240	0.184	0
	Turkey/large birds	0.080	0.209	0	0.098	-0.002	0
	Deer/small mammals	0.175	-0.016	0	-0.080	0.220	0
	Small birds/frogs	0.014	0.115	0	0.022	0.046	0
Most Common Sounds (DV[1])	Nothing of particular note (B)	0.288	0.346	0	0.170	0.200	0
	Distant cars/traffic	-0.123	-0.087	0	0.100	-0.034	0
	Nature sounds and wind	-0.006	-0.155	0	0.082	0.126	0
	Farm vehicles	-0.024	-0.141	0	0.138	0.108	0
Human Elements (DV[1])	Nothing of particular note (B)	0.284	0.245	0	0.256	0.188	0
	Remnants of old farms/mills	-0.054	-0.127	0	-0.034	0.192	0
	Wire/metal fences	-0.004	-0.018	0	-0.122	0.138	0
	Stone walls	-0.080	0.167	0	0.132	-0.082	0
Surrounding Area (DV[1])	Neighborhoods (B)	0.362	0.414	0	0.144	0.178	0
	Wooded	-0.129	-0.157	0	0.540	0.056	0
	Farmed	0.044	-0.083	0	0.028	0.410	0
Interaction term (DV)	Other area or Working farmland (B)	0.514	0.449	0	0.483	0.552	0
	Wooded area and Wooded land	0.486	0.551	0	0.517	0.448	0
	Other area or Wooded land (B)	0.558	0.607	0	0.572	0.529	0
	Farm area and Farm land parcel	0.442	0.393	0	0.428	0.471	0

Note: [1] Effects coding; [2] Wooded land; [3] Working farmland; [4] 503 respondents in Question 3; [5] 500 respondents answered Question 4; DV: Dummy Variable; B: Baseline.

Table 5. Estimate result of production function using the treatment group data

Variable	Description	Rural character				Ecological or environmental quality				Sense of culture and history			
		Class1(57.5%)		Class2 (42.5%)		Class1(48.0%)		Class2 (52.0%)		Class1(61.9%)		Class2 (38.1%)	
		Coefficient	*P-value*	Coefficient	*P-value*	Coefficient	*P-value*	Coefficient	*P-value*	Coefficient	*P-value*	Coefficient	*P-value*
Parcel Description (DV[1])	Wooded (wetlands)[2]	2.684	*0.149*	-1.277	*0.135*	7.578	*0.111*	0.265	*0.533*	**-5.285**	*0.006*	**3.222**	*0.039*
	Wooded (mixed pine and hardwoods)[2]	**1.209**	*0.086*	-0.362	*0.535*	4.268	*0.179*	0.376	*0.249*	**-2.222**	*0.001*	0.022	*0.971*
	Working farm (turf/sod)[3]	-1.524	*0.121*	**-1.652**	*0.021*	-5.146	*0.187*	-0.651	*0.236*	0.695	*0.536*	-0.448	*0.316*
	Working farm (cows, horses or other)[3]	0.046	*0.959*	0.946	*0.121*	-2.480	*0.208*	-0.135	*0.846*	0.940	*0.457*	0.528	*0.663*
	Working farm (field crops)[3]	2.463	*0.112*	**1.905**	*0.014*	-3.020	*0.209*	0.734	*0.150*	**4.431**	*0.000*	-0.181	*0.767*
Size	10 acres, 20 acres, 50 acres, 80 acres, 110 acres	**0.068**	*0.078*	-0.009	*0.453*	0.016	*0.144*	**0.010**	*0.058*	0.021	*0.188*	**0.044**	*0.031*
Most Common Wildlife (DV[1])	Turkey/Large birds	0.217	*0.643*	**1.736**	*0.010*	-0.210	*0.746*	-0.025	*0.957*	0.793	*0.292*	0.244	*0.665*
	Deer/small mammals	**1.390**	*0.062*	**-1.086**	*0.043*	**1.015**	*0.063*	0.322	*0.425*	**0.909**	*0.088*	0.510	*0.242*
	Small birds/frogs	0.451	*0.364*	**-0.694**	*0.055*	-1.500	*0.118*	**0.725**	*0.004*	**-1.708**	*0.020*	0.326	*0.440*
Most Common Sounds (DV[1])	Distant cars/traffic	-0.453	*0.267*	**-1.346**	*0.003*	0.395	*0.670*	**-1.090**	*0.006*	0.248	*0.582*	-0.988	*0.127*
	Nature sounds and wind	0.068	*0.941*	**2.871**	*0.003*	0.970	*0.371*	0.519	*0.478*	**1.723**	*0.067*	2.538	*0.105*
	Farm vehicles	**1.303**	*0.045*	0.001	*0.997*	**-1.052**	*0.059*	**0.636**	*0.058*	0.767	*0.125*	-0.516	*0.226*
Human Elements (DV[1])	Remnants of old farms/mills	0.073	*0.870*	**1.669**	*0.001*	-1.167	*0.307*	**0.735**	*0.033*	**2.350**	*0.000*	**1.124**	*0.080*
	Wire/metal fences	**-2.232**	*0.025*	**-0.912**	*0.035*	-1.189	*0.300*	**-1.151**	*0.007*	**-2.751**	*0.008*	**-1.586**	*0.027*
	Stone walls	**0.735**	*0.075*	**0.779**	*0.024*	1.174	*0.178*	**0.673**	*0.013*	1.456	*0.137*	0.127	*0.819*
Surrounding Area (DV[1])	Wooded	**1.631**	*0.093*	**-0.814**	*0.056*	1.557	*0.133*	0.059	*0.860*	-0.918	*0.329*	**1.329**	*0.039*
	Farmed	-0.051	*0.911*	0.758	*0.154*	-1.191	*0.181*	0.240	*0.388*	0.210	*0.720*	-0.233	*0.658*
Interaction term (DV)	Little Compton and Wooded land	**-1.545**	*0.021*	**-2.291**	*0.014*	0.599	*0.723*	**-1.140**	*0.014*	0.196	*0.782*	**-2.150**	*0.082*
	Middle Town and Wooded land	**-1.280**	*0.077*	-0.684	*0.461*	-1.357	*0.214*	-0.392	*0.502*	0.556	*0.438*	**-2.220**	*0.064*
	Portsmouth and Wooded land	-0.755	*0.237*	**-2.213**	*0.040*	-1.615	*0.137*	-0.752	*0.160*	-0.522	*0.594*	-1.138	*0.286*
Class membership variables	Female (DV)	0.113	*0.680*	0	*0*	**-0.843**	0.079	0	*0*	**0.665**	0.028	0	*0*
	Bachelor degree or completed some college education (DV)	0.045	*0.899*	0	*0*	**1.337**	0.018	0	*0*	-0.712	0.138	0	*0*
	Graduate degree or have some graduate school education (DV)	**1.034**	*0.015*	0	*0*	**1.500**	0.015	0	*0*	-0.830	0.116	0	*0*
	Constant	-0.134	*0.750*	0	*0*	-0.819	0.259	0	*0*	0.783	0.142	0	*0*

[1] Effects coding; [2] Wooded land; [3] Working farmland; DV: Dummy Variable; * Bold indicates significance at the 0.10 level or less.

Table 6. Estimated result of utility function for treatment group

Variable	Description	UF_Full				UF_Attribute				UF_PS			
		Class 1 (54.5%)		Class 2 (45.5%)		Class 1 (25.8%)		Class 2 (74.2%)		Class 1 (70.4%)		Class 2 (29.6%)	
		Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
NeitherParcel (DV)	No parcel (=1), Parcel A or B (=0)	2.231	0.234	**-3.193**	0.006	**2.914**	0.070	-3.367	0.177	-0.2	0.805	14.874	0.955
Cost	$25, $55, $80, $110, $155, $190, $250, $320	**-0.008**	0.004	**-0.006**	0.000	**-0.018**	0.000	**-0.002**	0.002	**-0.002**	0.017	**-0.015**	0.004
Perceived Services (Continuous)	Rural character	0.131	0.471	-0.039	0.796					0.107	0.013	0.097	0.592
	Ecological or environmental quality	-0.358	0.220	**0.604**	0.000					0.054	0.231	0.236	0.209
	Sense of culture and history	0.141	0.648	-0.209	0.343					0.005	0.887	**0.269**	0.094
Parcel Description (DV[1])	Working farm (nursery/ornamental plants) (B) [3]	0.126		0.440		0.364		-0.164					
	Wooded (wetlands)[2]	1.243	0.474	**-2.289**	0.035	**1.504**	0.041	-0.548	0.204				
	Wooded (mixed pine and hardwoods)[2]	1.116	0.355	**-2.601**	0.001	0.332	0.678	**-1.027**	0.022				
	Working farm (turf/sod)[3]	-0.593	0.553	**1.739**	0.015	**-2.206**	0.026	**0.509**	0.082				
	Working farm (cows, horses or other)[3]	0.285	0.65	**1.483**	0.004	0.65	0.295	**0.896**	0.001				
	Working farm (field crops)[3]	**-2.176**	0.088	1.227	0.129	-0.644	0.420	0.335	0.265				
Size	0 acres, 20 acres, 50 acres, 80 acres, 110 acres	**0.033**	0.018	-0.002	0.814	0.014	0.145	0.011	0	0.004	0.153	**0.03**	0.053
Most Common Wildlife (DV[1])	Nothing of particular note (B)	0.161		-0.399		-0.49		-0.422					
	Turkey/Large birds	0.463	0.201	**0.598**	0.033	-0.012	0.986	**0.555**	0.001				
	Deer/small mammals	0.421	0.289	-0.379	0.182	0.571	0.113	-0.042	0.744				
	Small birds/frogs	**-1.044**	0.019	0.181	0.529	-0.068	0.859	-0.091	0.516				
Most Common Sounds	Nothing of particular note (B)	-0.394		-0.662		-0.739		-0.433					
	Distant cars/traffic	-0.394	0.242	-0.111	0.675	0.476	0.365	**-0.285**	0.073				

(DV[1])	Nature sounds and wind	0.237	*0.649*	0.544	*0.165*	0.673	*0.111*	**0.411**	*0.000*				
	Farm vehicles	0.551	*0.117*	0.229	*0.317*	-0.41	*0.300*	**0.307**	*0.081*				
Human Elements (DV[1])	Nothing of particular note (B)	0.5		-0.887		-0.088		-0.372					
	Remnants of old farms/mills	0.005	*0.994*	0.745	*0.132*	0.139	*0.751*	**0.226**	*0.063*				
	Wire/metal fences	**-1.316**	*0.052*	0.231	*0.596*	-0.489	*0.276*	-0.241	*0.149*				
	Stone walls	**0.811**	*0.025*	-0.089	*0.722*	0.438	*0.219*	**0.387**	*0.012*				
Surrounding Area (DV[1])	Neighborhoods (B)	-0.918		0.471		0.256		-0.061					
	Wooded	**0.981**	*0.066*	**-0.95**	*0.000*	0.038	*0.932*	-0.023	*0.812*				
	Farmed	-0.063	*0.833*	**0.479**	*0.007*	-0.294	*0.563*	0.085	*0.457*				
Interaction term (DV)	Other area and working farmland (B)	-1.304		-0.453		0.852		-1.199		-0.543		2.833	
	Wooded area and Wooded land parcel	**1.304**	*0.081*	0.453	*0.474*	-0.852	*0.317*	**1.199**	*0.044*	0.543	*0.166*	**-2.833**	*0.024*
	Other area and Wooded land (B)	-1.972		0.725		0.199		-0.085		-0.674		3.869	
	Farmed area and Working farmland parcel	**1.972**	*0.067*	-0.725	*0.211*	-0.199	*0.814*	0.085	*0.874*	0.674	*0.102*	**-3.869**	*0.013*
Age (Continuous)*NeitherParcel		**0.078**	*0.024*	-0.008	*0.522*	-0.013	*0.454*	0.017	*0.686*	-0.015	*0.114*	**0.079**	*0.078*
Bachelor Degree or higher education (DV) *NeitherParcel		**-8.399**	*0.000*	**3.019**	*0.000*	**-1.949**	*0.039*	-1.392	*0.339*	**1.507**	*0.001*	-43.958	*0.915*
Income (DV)>= $100,000*NeitherParcel		0.529	*0.615*	**-0.643**	*0.058*	-0.160	*0.783*	1.344	*0.251*	**-2.957**	*0.000*	25.145	*0.954*
Class membership variables	Female (DV)	-0.251	*0.336*			0.059	*0.802*			0.123	*0.669*		
	Bachelor degree or some education (DV)	**0.897**	*0.019*			-0.168	*0.626*			-0.056	*0.891*		
	Graduate degree or some education (DV)	**1.239**	*0.003*			-0.584	*0.104*			-0.178	*0.640*		
	Constant	**-0.567**	*0.049*			**-0.807**	*0.005*			**0.999**	*0.000*		

[1] Effects coding; [2] Wooded land; [3] Working farmland; (DV): Dummy Variable; * Bold indicates significance at the 0.10 level or less. (B): Baseline

Table 7. Estimated result of utility function for control group

Variable	Description	UF_Full				UF_Attribute				UF_PS			
		Class 1 (26.1%)		Class 2 (73.9%)		Class 1 (24.8%)		Class 2 (75.2%)		Class 1 (24%)		Class 2 (76%)	
		Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*	Coefficient	*p-value*
NeitherParcel (DV)	No parcel (=1), Parcel A or B (=0)	8.363	*0.976*	0.395	*0.724*	11.177	*0.972*	-0.141	*0.923*	-2.695	*0.406*	0.542	*0.612*
Cost	$25, $55, $80, $110, $155, $190, $250, $320	**-0.049**	*0.000*	**-0.003**	*0.000*	**-0.041**	*0.000*	**-0.003**	*0.000*	**-0.036**	*0.000*	**-0.003**	*0.000*
Perceived Services (Continuous)	Rural character	0.088	*0.801*	**0.181**	*0.079*					**0.330**	*0.092*	**0.080**	*0.067*
	Ecological or environmental quality	-0.149	*0.737*	0.058	*0.564*					0.218	*0.276*	0.056	*0.186*
	Sense of culture and history	-0.660	*0.312*	0.230	*0.114*					-0.256	*0.125*	0.045	*0.209*
Parcel Description (DV[1])	Working farm (nursery/ornamental plants) (B) [3]	-7.809		0.451		-7.667		-0.092					
	Wooded (wetlands)[2]	15.179	*0.957*	0.177	*0.816*	17.121	*0.957*	-0.071	*0.888*				
	Wooded (mixed pine and hardwoods)[2]	17.460	*0.951*	-0.199	*0.744*	17.567	*0.956*	-0.466	*0.352*				
	Working farm (turf/sod)[3]	-11.207	*0.937*	0.342	*0.459*	-10.985	*0.945*	0.078	*0.802*				
	Working farm (cows, horses or other)[3]	-7.082	*0.960*	0.273	*0.449*	-8.267	*0.958*	**0.628**	*0.039*				
	Working farm (field crops)[3]	-6.541	*0.963*	**-1.044**	*0.067*	-7.769	*0.961*	-0.077	*0.823*				
Size	0 acres, 20 acres, 50 acres, 80 acres, 110 acres	**0.061**	*0.008*	-0.001	*0.777*	**0.038**	*0.027*	0.013	***0.000***	**0.023**	*0.030*	**0.007**	*0.003*
Most Common Wildlife (DV[1])	Nothing of particular note (B)	-2.401		0.499		-2.505		-0.084					
	Turkey/Large birds	0.369	*0.675*	-0.182	*0.348*	0.371	*0.702*	0.119	*0.407*				
	Deer/small mammals	**1.646**	*0.056*	-0.320	*0.101*	0.844	*0.216*	0.178	*0.151*				
	Small birds/frogs	0.385	*0.669*	0.003	*0.984*	1.291	*0.316*	**-0.212**	*0.098*				
Most Common	Nothing of particular note (B)	-1.445		0.552		-0.215		-0.182					

Sounds (DV[1])	Distant cars/traffic	-1.033	*0.240*	0.208	*0.241*	-1.004	*0.208*	-0.021	*0.892*				
	Nature sounds and wind	1.832	*0.166*	-0.311	*0.253*	0.947	*0.319*	**0.363**	*0.001*				
	Farm vehicles	0.646	*0.357*	**-0.449**	*0.021*	0.272	*0.650*	-0.161	*0.333*				
Human Elements (DV[1])	Nothing of particular note (B)	1.266		-0.164		1.195		-0.100					
	Remnants of old farms/mills	-0.340	*0.820*	-0.309	*0.303*	-1.226	*0.254*	0.227	*0.052*				
	Wire/metal fences	-1.565	*0.272*	**0.782**	*0.021*	-0.437	*0.600*	-0.188	*0.248*				
	Stone walls	0.638	*0.411*	-0.308	*0.101*	0.468	*0.502*	0.061	*0.663*				
Surrounding Area (DV[1])	Neighborhoods (B)	0.652		0.085		0.819		-0.120					
	Wooded	**1.547**	*0.099*	-0.063	*0.669*	1.522	*0.232*	0.061	*0.519*				
	Farmed	**-2.200**	*0.020*	-0.022	*0.856*	**-2.341**	*0.061*	0.059	*0.573*				
Interaction term (DV)	Other area and working farmland (B)	4.709		-0.487		3.818		-0.480		-0.818		-0.433	
	Wooded area and Wooded land parcel	**-4.709**	*0.006*	0.487	*0.326*	**-3.818**	*0.038*	0.480	*0.332*	0.818	*0.822*	0.433	*0.249*
	Other area and Wooded land (B)	-20.416		0.130		-21.423		0.052		-2.612		-0.294	
	Farmed area and Working farmland parcel	20.416	*0.962*	-0.130	*0.815*	21.423	*0.964*	-0.052	*0.935*	2.612	*0.404*	0.294	*0.451*
Age (Continuous)*NeitherParcel		**0.136**	*0.000*	**-0.036**	*0.034*	**0.094**	*0.001*	-0.021	*0.299*	**0.112**	*0.001*	**-0.032**	*0.040*
Bachelor Degree or higher education (DV) *NeitherParcel		-1.709	*0.122*	-0.891	*0.157*	-0.515	*0.533*	-1.145	*0.185*	-0.221	*0.761*	**-1.582**	*0.089*
Income (DV)>= $100,000*NeitherParcel		-0.149	*0.841*	-1.277	*0.109*	-0.604	*0.584*	**-1.184**	*0.097*	-0.069	*0.945*	-0.540	*0.381*
Class membership variables	Female (DV)	0.153	*0.543*			0.069	*0.784*			0.215	*0.409*		
	Bachelor degree or some education (DV)	-0.214	*0.513*			-0.287	*0.411*			-0.421	*0.230*		
	Graduate degree or some education (DV)	**-0.665**	*0.065*			**-0.789**	*0.040*			**-0.893**	*0.022*		
	Constant	**-0.811**	*0.008*			**-0.762**	*0.021*			**-0.791**	*0.017*		

[1] Effects coding; [2] Wooded land; [3] Working farmland; (DV): Dummy Variable; * Bold indicates significance at the 0.10 level or less. (B): Baseline

Table 8. Marginal willingness-to-pay of perceived services and parcel attributes

Variable	Description	UF_Attribute				UF_Full			
		Class 1 (25.8%)		Class 2 (74.2%)		Class 1 (26.1.5%)		Class 2 (73.9%)	
		Coefficient	Δ*WTP*	Coefficient	Δ*WTP*	Coefficient	Δ*WTP*	Coefficient	Δ*WTP*
NeitherParcel (DV)	No parcel (=1), Parcel A or B (=0)	**2.914**	*161.9*	-3.367	*-1683.5*	8.363	*169.5*	0.395	*137.4*
Cost	$25, $55, $80, $110, $155, $190, $250, $320	**-0.018**		**-0.002**		**-0.049**		**-0.003**	
Perceived Services (Continuous)	Rural character					0.088	*1.8*	**0.181**	*63.2*
	Ecological or environmental quality					-0.149	*-3.0*	0.058	*20.1*
	Sense of culture and history					-0.660	*-13.4*	0.230	*80.2*
Parcel Description (DV[1])	Working farm (nursery/ornamental plants) (B) [3]	0.364	*20.2*	-0.164	*-82.0*	-7.809	*-158.2*	0.451	*156.9*
	Wooded (wetlands)[2]	**1.504**	*83.6*	-0.548	*-274.0*	15.179	*307.6*	0.177	*61.6*
	Wooded (mixed pine and hardwoods)[2]	0.332	*18.4*	**-1.027**	*-513.5*	17.460	*353.8*	-0.199	*-69.2*
	Working farm (turf/sod)[3]	**-2.206**	*-122.6*	**0.509**	*254.5*	-11.207	*-227.1*	0.342	*119.1*
	Working farm (cows, horses or other)[3]	0.65	*36.1*	**0.896**	*448.0*	-7.082	*-143.5*	0.273	*95.2*
	Working farm (field crops)[3]	-0.644	*-35.8*	0.335	*167.5*	-6.541	*-132.5*	**-1.044**	*-363.7*
Size	0 acres, 20 acres, 50 acres, 80 acres, 110 acres	0.014	*0.8*	0.011	*5.5*	**0.061**	*1.2*	-0.001	*-0.5*
Most Common Wildlife (DV[1])	Nothing of particular note (B)	-0.49	*-27.2*	-0.422	*-211.0*	-2.401	*-48.6*	0.499	*173.6*
	Turkey/Large birds	-0.012	*-0.7*	**0.555**	*277.5*	0.369	*7.5*	-0.182	*-63.5*
	Deer/small mammals	0.571	*31.7*	-0.042	*-21.0*	**1.646**	*33.4*	-0.320	*-111.3*
	Small birds/frogs	-0.068	*-3.8*	-0.091	*-45.5*	0.385	*7.8*	0.003	*1.2*
Most Common Sounds (DV[1])	Nothing of particular note (B)	-0.739	*-41.1*	-0.433	*-216.5*	-1.445	*-29.3*	0.552	*192.2*
	Distant cars/traffic	0.476	*26.4*	**-0.285**	*-142.5*	-1.033	*-20.9*	0.208	*72.4*
	Nature sounds and wind	0.673	*37.4*	**0.411**	*205.5*	1.832	*37.1*	-0.311	*-108.2*
	Farm vehicles	-0.41	*-22.8*	**0.307**	*153.5*	0.646	*13.1*	**-0.449**	*-156.4*
Human Elements (DV[1])	Nothing of particular note (B)	-0.088	*-4.9*	-0.372	*-186.0*	1.266	*25.7*	-0.164	*-57.3*
	Remnants of old farms/mills	0.139	*7.7*	**0.226**	*113.0*	-0.340	*-6.9*	-0.309	*-107.7*
	Wire/metal fences	-0.489	*-27.2*	-0.241	*-120.5*	-1.565	*-31.7*	**0.782**	*272.4*
	Stone walls	0.438	*24.3*	**0.387**	*193.5*	0.638	*12.9*	-0.308	*-107.4*
Surrounding Area (DV[1])	Neighborhoods (B)	0.256	*14.2*	-0.061	*-30.5*	0.652	*13.2*	0.085	*29.6*
	Wooded	0.038	*2.1*	-0.023	*-11.5*	**1.547**	*31.4*	-0.063	*-22.1*
	Farmed	-0.294	*-16.3*	0.085	*42.5*	**-2.200**	*-44.6*	-0.022	*-7.5*
Interaction term (DV)	Other area and working farmland (B)	0.852	*47.3*	-1.199	*-599.5*	4.709	*95.4*	-0.487	*-169.7*
	Wooded area and Wooded land parcel	-0.852	*-47.3*	**1.199**	*599.5*	**-4.709**	*-95.4*	0.487	*169.7*
	Other area and Wooded land (B)	0.199	*11.1*	-0.085	*-42.5*	-20.416	*-413.7*	0.130	*45.3*
	Farmed area and Working farmland parcel	-0.199	*-11.1*	0.085	*42.5*	20.416	*413.7*	-0.130	*-45.3*
Age (Continuous)*NeitherParcel		-0.013	*-0.7*	0.017	*8.5*	**0.136**	*2.8*	**-0.036**	*-12.6*
Bachelor Degree or higher education (DV) *NeitherParcel		**-1.949**	*-108.3*	-1.392	*-696.0*	-1.709	*-34.6*	-0.891	*-310.3*
Income (DV)>= $100,000*NeitherParcel		-0.16	*-8.9*	1.344	*672.0*	-0.149	*-3.0*	-1.277	*-444.7*

[1] Effects coding; [2] Wooded land; [3] Working farmland; (DV): Dummy Variable; (B): Baseline

Figure 1. An example of Question 1 and 2

Question 1. Please indicate which of the following parcels, if any, you would vote to preserve in **your** community if these were the only choices. Assume preservation funds are already available in your town budget, but only enough for conservation on **<u>one</u>** of **these** parcels.

	Parcel A	**Parcel B**	**Neither Parcel**
Parcel Description	Wooded: mixed pine and hardwoods	Working farm (nursery/ornamental plants)	Both parcels remain available for potential development.
Size (1 acre = 3/4 football field)	50 Acres	50 Acres	
Most Common Wildlife	Nothing of particular note	Deer/small mammals	
Most Common Sounds	Nothing of particular note	Distant cars/traffic	
Human Elements	Wire/metal fences	Stone walls	
Surrounding Area	Wooded	Farmed	

Based on your preferences
VOTE FOR THE OPTION YOU PREFER
(choose one)

☐ I vote to preserve PARCEL A

☐ I vote to preserve PARCEL B

☐ While I support preservation in general, I vote to preserve NEITHER PARCEL

☐ I vote to preserve NEITHER PARCEL

Figure 1a,

In your opinion, **<u>which parcel is better</u>**, if preserved in its current use, for each of the following:

Contributing to your community's **Rural Character**	☐ Parcel A	☐ Parcel B
Contributing to your community's **Ecological or Environmental Quality**	☐ Parcel A	☐ Parcel B
Contributing to your community's **Sense of Culture and History**	☐ Parcel A	☐ Parcel B

Figure 1b.

Figure 2. An example of Question 3 and 4

Question 3. Please vote as if this were an actual referendum. Assume none of the previous parcels were preserved and please indicate which of the following parcels, **if any**, you would vote to preserve in **your** community **<u>if theses were the only choices</u>**. Assume preservation and associated tax changes would begin this year.

	Parcel A	**Parcel B**	**Neither Parcel**
Parcel Description	Working farm (nursery/ornamental plants)	Working farm (cows, horses, or other)	Both parcels remain available for potential development. Your money remains available for other uses.
Size (1 acre = 3/4 football field)	110 Acres	50 Acres	
Most Common Wildlife	Deer/small mammals	Large birds (turkeys, herons)	
Most Common Sounds	Farm vehicles	Nature sounds/wind	
Human Elements	Nothing of particular note	Nothing of particular note	
Surrounding Area	Neighborhoods	Wooded	
Cost to your household (covers cost of bond issue)	Your annual town taxes would increase by $155 for 5 years ($775 over 5 years)	Your annual town taxes would increase by $110 for 5 years ($550 over 5 years)	

As in an actual referendum:
VOTE FOR THE OPTION YOU PREFER
(choose one)

☐ I vote to preserve **PARCEL A**
($155×5 years = $775 in new taxes)

☐ I vote to preserve **PARCEL B**
($110×5 years = $550 in new taxes)

☐ While I support preservation in general, in this case, I vote to preserve **NEITHER PARCEL**

☐ I vote to preserve **NEITHER PARCEL**

Figure 3. Land use of four towns in the State of Rhode Island (2004).