Averting Expenditures of Bottled Water by Rural Households During a Power Outage

THESIS

Presented in Partial Fulfillment of the Requirements for the Degree Master of Science in the Graduate School of The Ohio State University

By

Jamie L. Rice

Graduate Program in Agricultural, Environmental and Development Economics

The Ohio State University

2012

Master's Examination Committee:

Professor Elena Irwin, Advisor

Associate Professor Jay Martin
Abstract

In this paper I estimate averting expenditures of bottled water during a widespread power outage as a partial estimate of willingness-to-pay for public water supply. Willingness-to-pay is then used to calculate a partial estimate of net present value (NPV) of public water systems. I then compare NPV, the partial benefits of water supply, to costs of improvements to public water systems.

After Hurricane Ike in 2008, Ohio experienced severe wind storms which resulted in major power outages across the state, and many rural households also lost water. Using data collected as part of a national consumer panel that monitors shopping behavior, along with data on census tracts and incorporated areas, I run regression analyses using one-way fixed effects for households to estimate changes in bottled water consumption during the week before and two weeks following the storm, controlling for whether or not the household was located in a rural area. I find that bottled water expenditures increased by $2.85 per week in rural areas, and that purchases of households with incomes below 300% of the poverty guidelines (below an annual income of $51,115 for an average household in the sample), were $1.37 lower than purchases of households with incomes above 300% of the poverty guidelines.

These estimates are used to calculate willingness-to-pay for clean, reliable water. Willingness-to-pay can then be translated into the net present value of a water supply.
Using a 5% discount rate, the partial NPV in perpetuity of water supply per household is $2,959, and for all rural households in Ohio is $3.092 billion; using a 3% discount rate, the partial NPV is $4,931 per household and $5.154 billion for all rural Ohio households.

Replacement costs of public water systems, expected to last 75 years, average $7,659 per household; the partial NPV per household does not outweigh this amount unless a discount rate of 1.1% or lower is used. Further studies with access to additional data, such as data on other averting expenditures during a power and water outage including hauling water or electric generators, could provide a complete estimate of NPV, in which case the benefits may outweigh the costs.
Acknowledgments

I thank my advisor Dr. Elena Irwin for her support, guidance, and expertise over the past year, and for the many hours she has spent with me discussing this project and giving feedback. Her passion for economics is contagious. I also thank Dr. Jay Martin for serving on my committee and for his support as this project evolved.

I would also like to thank Aylin Kumcu at USDA ERS for providing us with the necessary data and for helping to solve technical problems. Also, I extend sincere thanks to David White, Kathy Pinto, Heather Raymond, and Jeremy Carroll at OEPA, who helped me to understand public water systems early on in my research.

All of my graduate school professors and TAs have been a huge factor in my success. I have been very impressed with their approachability and willingness to answer questions – as a student coming from a different academic background, I certainly had a lot of them.

Last but not least, I thank my friends and family, both new and old, for their love and support. Merci à vous tous et toutes.
Vita

June 2002 .......................................................Mount Vernon High School

2006...............................................................B.A. French, University of Pittsburgh

2006 to 2008 ..................................................Peace Corps Volunteer, Cameroon

June 2012 to present ......................................Graduate Research Associate, Department

of Agricultural, Environmental, and

Development Economics, The Ohio State

University

Fields of Study

Major Field: Agricultural, Environmental and Development Economics
# Table of Contents

Abstract........................................................................................................................................ ii

Acknowledgments................................................................................................................ vi

Vita........................................................................................................................................ v

List of Tables ........................................................................................................................ vii

List of Figures ......................................................................................................................... viii

Chapter 1: Introduction .......................................................................................................... 1

Chapter 2: Literature Review ............................................................................................... 4

Chapter 3: Estimation of Averting Expenditures................................................................. 7

Model ....................................................................................................................................... 7

Data ......................................................................................................................................... 10

Methods ................................................................................................................................. 13

Results .................................................................................................................................... 16

Comparison of Replacement Costs with Partial Benefits ................................................ 22

Chapter 4: Conclusion & Discussion .................................................................................... 25

References ............................................................................................................................. 28

Appendix: Tables and Figures ............................................................................................... 31
List of Tables

Table 1. Poverty Thresholds (in Dollars) for Different Household Sizes ......................... 36
Table 2. Sensitivity Analysis Using Different Time Periods ........................................... 37
Table 3. Sensitivity Analysis Using Different Income Thresholds ..................................... 38
Table 4. Correlation Coefficients of Regression Variables ............................................. 39
Table 5. Descriptive Statistics of Regression Variables .................................................. 40
Table 6. Regression Results using PROC PANEL with One-Way Fixed Effects ............. 41
Table 7. Sensitivity Analysis of Net Present Value of Averting Expenditures with
Different Discount Rates .................................................................................................. 42
List of Figures

Figure 1. Households with Different Incomes Will Choose Different Averting Options 31
Figure 2. Single Household Observations by Week in 2008 ........................................... 32
Figure 3. Incorporated Areas in Ohio .............................................................................. 33
Figure 4. Four Major Electric Service Providers in Ohio................................................ 34
Figure 5. Wind Speeds in Ohio During Hurricane Ike .................................................... 35
Chapter 1: Introduction

After the wind storms of Hurricane Ike in September 2008, a peak of 2.6 million households in Ohio lost electricity (Associated Press 2008). For some households the power outage lasted over a week. While households connected to a public water supply did not lose tap water, rural households with wells lost electricity to their well pumps and were obligated to find alternative sources of water during this time. The average American household with four family members uses about 400 gallons of water per day, and about 70% of this is used indoors (EPA 2008). Because households consume so much water we can expect a noticeable change in expenditures in rural households when tap water is interrupted. Ohio is an interesting state to observe during this power outage because unlike Texas and other states in the South, it did not experience flooding or other disasters that would cause many people to leave their homes.

If a rural household knew the storm was coming and anticipated a power outage, which many did since the incoming storm received lots of media coverage, they could take preemptive measures such as filling the bathtub with water for bathing or flushing toilets, filling pitchers for drinking water, or purchasing bottled water. After the power outage, rural households without electricity, if they chose to stay at home, could purchase
water, haul water from other households that did not lose electricity, or use electric generators to keep well pumps running.

Households that took these actions following the storm engaged in a form of “averting behavior.” Averting behavior occurs when a consumer compensates for a decrease in quality of one good by purchasing a substitute good. In the case of tap water, a non-market good, consumers engage in averting behavior by purchasing bottled water, a market good, when tap water is no longer available. The quality of tap water essentially decreases to zero. Measuring the expenditures of this market good substitute provides a means of quantifying the value that households place on a public good, a reliable supply of clean water, including drinking water.

Other studies in the literature have also calculated averting expenditures following a change in tap water quality. Many of these studied the effects of a drinking water contamination on bottled water consumption and hauling and/or storing water. Abrahams et al. (2000) and Abdalla et al. (1992) included changes in bottled water consumption along with purchases of a filter or home water treatment system. Laughland et al. (1993) and Abdalla et al. (1992) calculated the opportunity cost of time for behaviors such as boiling and/or hauling water. There is a gap in the literature for averting expenditures by households during a power and water outage. During a contamination, households can choose whether or not to engage in averting behaviors, but during a power outage a household’s water supply is cut off and they are obligated to seek water elsewhere. This leads to very different results.
I estimate the partial averting expenditures as a result of the loss of water supply in rural areas by examining the changes in bottled water consumption in rural area households during the week before and two weeks after the wind storm. To do this, I use data on household-level bottled water consumption to run regression analyses controlling for differences between individual households, and find that bottled water expenditures in rural households increased by $2.85 per week as a result of the storm. These estimates are used to calculate partial willingness-to-pay for clean, reliable water, and are then used to estimate the partial net present value of a water supply. Using a 5% discount rate, the partial NPV in perpetuity of water supply per household is $2,959, and for all rural households in Ohio is $3.092 billion; using a 3% discount rate, the partial NPV is $4,931 per household and $5.154 billion for all rural Ohio households. I then compare these partial benefits with average replacement costs for a public water system. Replacement costs, expected to last 75 years, average $7,659 per household; the partial NPV per household does not outweigh this amount unless a low discount rate of 1.1% or lower is used.

Both rural households using groundwater wells and urban households connected to a public water system pay a low price for clean, reliable drinking water relative to the value they place on it. Knowing how much households value tap water can help decision-makers evaluate whether or not it is cost-effective to connect a household to a public water system.
Many environmental economists have studied averting expenditures to measure how much people value environmental goods and services such as clean drinking water, for which the price consumers pay does not reflect its true value. Around the world, communities are involved in debates over the price of drinking water, which can be expensive to treat and provide, but is a basic need for human life. Knowing how much consumers spend on averting expenditures during a contamination or a shortage can help decision makers with cost-benefit analyses for potential improvements to drinking water.

Agudelo (2001) gives an overview of valuation of water goods and services, including reasons for treating water as an economic good and the resulting implications. Effects of charging a price for water related to its value include recovering the cost of providing water, funds for future development, and environmental benefits from reducing demand for water. While this might be a better method in terms of efficiency, in equity it requires poor households to spend a higher portion of their incomes on drinking water since demand for drinking water is inelastic.

Many studies have looked at averting expenditures as a result of water contamination. Abdalla, Roach, and Epp (1992) estimate the averting expenditures by
household in a Southeastern Pennsylvania community after long-term groundwater contamination. To do this, they use a survey including questions on expenditures and lost leisure time to measure the costs associated with new or increased purchases of bottled water, home water treatment systems, hauling water, and boiling water. They find that 43.7% of households who were aware of the contamination continued to drink the contaminated water, and the rest engaged in at least one form of averting behavior. Averting behaviors included increased bottled water consumption, home water treatment systems, hauling water, and boiling water. The authors find that knowledge of the contamination and perception of the risk are two factors influencing whether or not a household would engage in averting behaviors, and income levels and the presence of young children affect the level of averting behaviors.

Laughland, L. Musser, W. Musser, and Shortle (1993) estimate the opportunity cost of time and averting costs from a giardia contamination in Milesburg, PA. Averting behaviors included boiling water, hauling water from safe sources, or purchasing bottled water, and respondents to their survey reported whether or not they engaged in one or more of these actions as a result of the contamination. The authors find that using different values for the opportunity cost of time produce very different results.

Abrahams, Hubbell, and Jordan (2000) model averting behaviors in response to a contamination in Georgia. Averting behaviors included purchasing bottled water or purchasing a water filter. They find that bottled water purchases overestimate the level of averting expenditures because bottled water reduces risk from the contamination and also enters into the consumer’s utility function, meaning that consumers gain more utility
from drinking bottled water than from drinking tap water; and that water filter expenses are a better estimate of averting expenditures.

Pattanayak, Yang, Whittington, and Kumar (2005) look at averting expenditures in Kathmandu, Nepal, where there were frequent public water shortages and contaminations. Households used five common coping behaviors: collecting water from a source outside the household, pumping water from a private well, treating water by boiling or filtering, storing water at home, and purchasing water from vendors or neighbors. Higher income families spent less time on coping behaviors with higher opportunity costs of time, such as collecting and pumping water. Contingent valuation is estimated through a survey of whether or not a household would be willing to pay a certain amount for clean, safe, reliable water services.

I am not aware of any research on averting expenditures as a result of a drinking water shortage in households in the U.S. since most of the averting expenditures studies for drinking water have been focused on contamination of public water supplies.
Chapter 3: Estimation of Averting Expenditures

Model

The wind storms are an exogenous shock to the affected communities, and it is assumed that differences between communities affected by the wind storms are randomly distributed (i.e., the wind storm was an unusual event, and was not more likely to affect one community over another).

Abrahams et al. (2000) used a theoretical framework to model averting behavior, originally from Courant and Porter (1981), that I will apply using averting expenditures on bottled water. Abrahams et al., who were interested in averting expenditures following a drinking water contamination, considered the following consumer utility function,

\[
U = U(X_1, X_2, X_3, Z, H^*, q_1, q_2, q_3)
\]

where \(U\) is consumer utility, \(X_j\) is consumption of different types of water (1 = tap water, 2 = bottled water, 3 = filtered water), \(Z\) is a composite consumption good, \(H^*\) is the perceived health level, and \(q_j\) is a vector of quality attributes. Since during a power outage, tap water and filtered water are not options, the utility function is reduced to

\[
U = U(X_2, X_4, X_5, Z)
\]
where $X_2$ is bottled water, $X_4$ is stored or hauled water, and $X_5$ is well water from using a generator. If we assume that all water types are perfect substitutes and the same quality, which are reasonable assumptions since the quality of water has not changed as it would during a contamination\(^1\), then quality vectors and perceived health level are also eliminated.

Households will maximize utility subject to a budget constraint,

\[
(3) \quad Y = p_2X_2 + p_4X_4 + p_5X_5 + C + Z
\]

where $Y$ is disposable income and $p_j$ is the price of each type of water. The price of bottled water, $p_2$, is the price at which it is sold at the store (most papers have assumed zero opportunity cost of time, since bottled water can be purchased at the same time as other grocery goods); the price of hauled water, $p_4$, is the opportunity cost of time required to store or haul the water; the price of well water from using a generator, $p_5$, is the price of gasoline and the opportunity cost of time required to operate the generator; and $C$ is the cost of a generator.

Demand for each type of water can be estimated from the following function using quantity, price, and household characteristics.

\[
(4) \quad X_j = f(p_j, Y, \text{household preferences})
\]

Households with different incomes have different opportunity costs of time, so the price of hauled water for low income households is lower than the price for high income households (Abdalla et al. 1992). This means that low income households are more likely to haul water than high income households, and high income households are more

\footnote{Olson (1999) found that bottled water is not necessarily any safer than most tap water.}
likely to purchase bottled water than low income households. This is illustrated in Figure 1 in the Appendix, where consumption for both low income and high income households is a corner solution. Households with low incomes will be less likely to purchase bottled water during the water shortage than households with high incomes.

In rural areas the price of water is close to zero, and since the price of all averting expenditures is greater than zero, it is expected that households will consume less water. With the higher price of substitutes and expectations that electricity and water supply will soon return, it is also likely that households will forego some water-intensive activities, such as watering plants or cleaning, until their water supply returns. Demand for these activities is more elastic than demand for drinking water. Since demand for drinking water is inelastic, households may substitute other beverages for drinking water, but they are not expected to significantly decrease the amount of drinking water consumed.

Since I do not have data on averting expenditures besides bottled water, this model will provide a partial estimate of averting expenditures for bottled water and look at differences between high and low income households. I then use the estimates of averting expenditures to calculate a partial willingness-to-pay for water supply and a partial net present value of public water systems. These estimates will be lower-bound estimates since, as noted above, during the short-term water outage, households do not completely switch to tap water alternatives since they expect water service to return.
Data

Nielsen HomeScan data obtained from ERS provides household-level information on bottled water consumption in Ohio in 2008.\textsuperscript{2} In the HomeScan program, participating households re-scan their grocery purchases at home, providing a wide array of information such as purchase date, price, coupon used, quantity, product information, store type, etc. The dataset also contains household characteristics including 2000 census tract, income, race, and household size. Like the surveys used in previous studies this data is also dependent on what the consumer reports, but unlike the previous studies this data was not requested in the context of a survey about water quality. While the data may still contain some errors and biases if the consumer does not wish to record all purchases, these errors are uncorrelated with the wind storm events.

The bottled water data were extracted from a larger dataset containing all dry goods purchased in 2008 all across the United States. Of the original 25,868 observations for Ohio, 96 observations were deleted because they lacked census tract info, 73 observations were deleted because the price before a coupon (if any) was zero, and 469 observations were deleted because the price was more than two standard deviations from the mean. Deleting observations with high prices is reasonable because it is likely to eliminate “luxury” bottled water, which is not a good substitute for tap water during a

\textsuperscript{2} Two dissertations from Texas A & M University used the Nielsen HomeScan data to estimate consumer demand for bottled water (Pittman, 2004 and Dharmasena, 2010). They were very helpful in understanding how the data were organized, and factors influencing bottled water purchases such as season and household demographic characteristics.
water shortage. The data were then aggregated by household purchases per week, leaving 18,575 observations. Of these, 423 observations were deleted because there was only one observation per household since the model I estimate requires at least two observations per household. Due to errors in the Nielsen data, 681 observations did not match up with the 2000 census tract data and were deleted. The final dataset contained 17,471 observations.

Data on purchases per day contained the price of each type of bottled water. Price varies by brand. Aggregating the data from daily household purchases to weekly household purchases made it necessary to create a variable for the average price per fluid ounce of bottled water purchased per week since some households purchased more than one type of bottled water per week.

Using Ohio census tract and incorporated area shapefiles from the 2000 Census, I used ArcMap to calculate the ratio of incorporated area to tract size of each census tract as a proxy for whether or not the census tract was served by a public water system. Households served by a public water system usually cannot also use a private well. Many public water systems are managed at a city level, so it is a reasonable assumption that the boundaries of these public water systems will roughly follow incorporated area boundaries. For example, the boundaries of the City of Columbus public water system covered the incorporated areas of Columbus and its suburbs. It is not a perfect estimate since some unincorporated areas are served by public water systems, and vice versa, but

---

3 See Figure 2 in the Appendix for an explanation why I do not think deleting these observations will be a problem.
data on water service was not available for all areas. This map can be found in Figure 3 in the Appendix.

The power outage was included using a dummy variable, 1 if the purchase occurred during the week before or two weeks following the wind storm, 0 otherwise. After trying different ways of specifying the length of time, it was found that the period from one week before the wind storm to two weeks following the storm had the most significant effect on bottled water consumption. The effect during the week before the storm could be due to households stocking up on bottled water supplies in anticipation of a power outage. The effect during the first week following the storm is understandably the effect of the power outage. The effect in the second week could be due to households re-scanning their purchases from the first week after electricity was restored, or replenishing a stock of bottled water used up in the first week. Electricity was restored to most households within one week.

I digitized maps to match census tracts with the four largest electric service providers in Ohio – AEP, Dayton Power and Light, First Energy, and Duke Energy – to attempt to control for any differences in length of power outages. The maps for each of these service providers came from their company websites. The service areas for these electric service providers overlapped, so some census tracts are served by more than one provider, and other census tracts were not served by any of these providers. There are several smaller, regional electric service providers that were not accounted for. This map can be found in the Appendix in Figure 4.

---

4 See Table 2 in the Appendix for a sensitivity analysis using different periods of time.
I also digitized a map of wind speeds during the storm to proxy for damage caused by the storm and assigned a wind speed to each census tract. Each census tract was assigned a wind speed from 50 to 75 mph based on the wind speed of the largest area covered by the wind speed map. The original map was from Duke Energy. The digitized map with census tracts can be found in the Appendix in Figure 5.

Previous research on bottled water purchases as averting expenditures indicated that there is an income effect, so using the HHS Poverty Guidelines (2008) I created new variables for households using household income and household size (1 if the household was below a percentage of the poverty guidelines, 0 otherwise) for 100%, 200%, 250%, 300%, and 350% of poverty guidelines (corresponding to incomes below $17,038, $34,077, $42,596, $51,115, and $59,634, respectively, for average size households in the study). Table 1 in the Appendix gives the guidelines for different household sizes. To best specify the threshold at which households change their behavior from other averting expenditures to purchasing bottled water, I experimented with different thresholds and found that the income threshold with the most significant effect on bottled water consumption after the wind storm was 300% of the poverty guidelines.  

Methods

I chose to use PROC PANEL with one-way fixed effects to control for household effects. Fixed effects are a method of controlling for unobserved, time-constant variation that is associated with the data and that otherwise could bias the statistical estimates. In

---

5 See Table 3 in the Appendix for a sensitivity analysis using different income thresholds.
my case, many differences in households were observed in the data, including income, race, household size, etc., but there are many unobserved differences such as preferences that have an effect on bottled water consumption. It is possible that some of these unobserved effects would be systematically correlated with a household’s bottled water consumption. For example, a household that purchases bottled water every week because they do not like the taste of their tap water will have higher consumption in every time period compared to other households. In the data, the minimum quantity purchased per household per week was 8 ounces, and the maximum was 5,604 ounces. For this reason I accounted for differences in households not by using the HomeScan data on household characteristics but instead by including fixed effects for each household, which will account for observed differences such as income and unobserved differences such as preferences.

These household fixed effects eliminate the overestimation problem encountered by other researchers such as Abrahams et al. (2000). In other studies with only one observation per household, it is not possible to include fixed effects for each household, which control for the difference in utility gained by one household, which prefers bottled water, compared to another household which is indifferent to bottled water or tap water. This leads to an overestimation of averting expenditures since some households are purchasing bottled water for reasons other than averting expenditures. In this study, having more than one observation per household allows us to include fixed effects which control for these differences in utility, which will resolve the overestimation problem.
Time effects were not controlled for by week but instead by season, which explained more variation. The first season, Winter1, was defined as weeks in January and February. Spring was defined as weeks in March, April, and May. Summer was defined as weeks in June, July, and August. Autumn was defined as weeks in September, October, and November. The second winter, Winter2, was defined as weeks in December.

The model including all variables is below:

\[
(5) \quad \text{HHIDTotal} = \alpha + \beta_{1t}\text{Ike} + \beta_{2ht}\text{Ike}*\text{Poverty300} + \beta_{3ht}\text{Ike}*\text{Rural} + \\
\beta_{4ht}\text{Ike}^*\text{HHSize} + \beta_{5ht}\text{Ike}^*\text{Wind} + \beta_{6ht}\text{Ike}^*\text{AEP} + \beta_{7ht}\text{Ike}^*\text{Duke} + \\
\beta_{8ht}\text{Ike}^*\text{FirstEn} + \beta_{9ht}\text{Ike}^*\text{Dayton} + \beta_{10t}\text{Winter} + \beta_{11t}\text{Spring} + \beta_{12t}\text{Summer} + \\
\beta_{13t}\text{Winter2} + \beta_{14ht}\text{AvgPrice} + \beta_{19h}\text{HHFixedEffects} + \mu_{ht}
\]

- \( t \) = time
- \( h \) = household

Variable Descriptions:

- **HHIDTotal**: total fluid oz. of bottled water purchased by a household in a given week
- **Ike**: 1 if week before or 2 weeks after wind storm, 0 otherwise
- **Poverty300**: 1 if household income is below 300% of 2008 Ohio poverty guidelines, 0 otherwise
- **Rural**: 1 if household is in a rural census tract, 0 otherwise
- **HHSize**: Number of people in household
- **Wind**: Wind speed during wind storm
- **AEP**: 1 if household is located in AEP service area, 0 otherwise
- **Duke**: 1 if household is located in Duke Energy service area, 0 otherwise
- **FirstEn**: 1 if household is located in First Energy service area, 0 otherwise
- **Dayton**: 1 if household is located in Dayton Power & Light service area, 0 otherwise
- **Winter**: 1 if purchase occurred in January or February, 0 otherwise
- **Spring**: 1 if purchase occurred in March through May, 0 otherwise
- **Summer**: 1 if purchase occurred in June through August, 0 otherwise
- **Autumn**: 1 if purchase occurred in September through November, 0 otherwise (dropped)
- **Winter2**: 1 if purchase occurred in December, 0 otherwise
- **AvgPrice**: Average price per fluid ounce of bottled water purchased by a household
- **HHFixed Effects**: Fixed effects for 1906 households (one household is dropped)

Please see Table 4 in the Appendix for correlation coefficients and Table 5 for descriptive statistics of variables. The highest correlation coefficient was 0.46 between Ike and Autumn, which is expected since the wind storms occurred during this season. It is not correlated enough to result in issues with multicollinearity.

In estimating the model, it is necessary to omit one of the seasons and one of the household fixed effects because including all variables would be redundant and would result in the econometric problem of multicollinearity. By omitting Autumn, it becomes the base group against which the four other seasonal variables are compared. For example, the coefficient for Summer will show the intercept difference between Summer and Autumn. The same applies for households – by dropping one household, this household becomes the base group against which all other households are compared. The model will produce the same results no matter which variable is dropped – the only difference is the base group against which other variables are compared.

**Results**

The results of the estimation are reported in Table 6 (see the Appendix). In comparing two different specifications of the model, Model 1 is the preferred model because it has the most significant values, but both models provide interesting insights. Model 2 is interesting because it supports the evidence of significant variables in Model 1.
The $R^2$ values for both models signify that the models have explained 47% of the variance in weekly household purchases of bottled water. I was not expecting a larger $R^2$ value since there are many things not accounted for that could influence the amount of bottled water purchased by a consumer, and previous studies also resulted in low values.

In both models, the coefficients for the interaction terms Ike*Rural and Ike*HHSize are positive and significant, as expected. The seasonal effects also have the expected signs since bottled water consumption is higher in warmer seasons and lower in colder seasons. The negative sign for AvgPrice is also reasonable since an increase in price will result in a decrease in bottled water consumption.

The insignificant coefficients for Wind, AEP, Duke, FirstEn, and Dayton suggest that these variables were not good indicators of storm damage and length of power outages, or that there is not a significant variation between them.

I have included the results of the second model to show the robustness of the interaction variables with Ike and Poverty300, Rural, and HHSize. Although Ike*Poverty300 is not significant at the 10% level, it is significant at the 15% level and its magnitude does not change much in either model. It is a weak result but since the coefficient was also negative, but not as significant, at other income thresholds, I am confident that the sign of this coefficient is correct, even though its magnitude may not be entirely accurate. The significance and magnitude of Ike*Poverty300 and Ike*HHSize also remain fairly constant in the two models. These results are consistent with expectations that bottled water consumption during a power outage decreases with lower

---

6 See Table 3 in the Appendix for a sensitivity analysis using different income thresholds.
incomes (the opportunity cost of time for other averting behaviors is lower for households with lower incomes), increases for rural households (water supply is shut off if the household relies on well water), and increases with household size.

The coefficient for the time period, \( I_{ke} \), changes significantly between the two models. While it is important to include it in the model to account for variation during the time period, it will not be used in the following analysis.

To interpret the interaction terms using Model 1, during the week before and two weeks following the wind storm, rural households with incomes below 300% of the poverty guidelines with one family member increased bottled water consumption by 30.9 ounces per week (15.54 + 51.64 - 36.30). For every additional family member, bottled water consumption increased by 15.54 ounces. Rural households with incomes above 300% of the poverty guidelines with one family member increased bottled water consumption by 67.2 ounces (51.64 + 15.54), and increased consumption by 15.54 ounces for each additional family member.

If the coefficient for \( I_{ke} \times Poverty300 \) is not considered significant, then bottled water consumption for all households, regardless of income level, increased by 67.2 ounces for households with one family member, plus 15.54 ounces for each additional family member.

To calculate the averting expenditures for bottled water of households in rural areas, we can plug the mean values into the model and multiply by the average price of bottled water. Of the total 1906 households, 1525 were in rural areas. 47.21% of rural households were below the 300% poverty level, and the average household size was
2.6892. The average price of bottled water during the two weeks after the wind storm was $0.0373 per ounce.

Model 1:

\[ HHIDTotal = \alpha + \beta_{11}Ike + \beta_{23}Ike*Poverty300 + \beta_{33}Ike*Rural + \beta_{43}Ike*HHSize + \beta_{53}Ike*Wind + \beta_{10t}Winter + \beta_{11t}Spring + \beta_{12t}Summer + \beta_{13t}Winter2 + \beta_{14t}AvgPrice + \beta_{ht}HHFixedEffects + \mu \]

(6)

\[ \Delta HHIDTotal / \Delta Ike = -36.3039(0.4721) + 51.63527(1) + 15.53612(2.6892) \]

(7) \[ \Delta HHIDTotal / \Delta Ike = 76.28 \text{ ounces} \]

(8) Averting Expenditures = (\Delta HHIDTotal / \Delta Ike) * Price

Averting Expenditures = 76.28 * 0.0373 = $2.85 / week

Using the same process, I calculated averting expenditures for households above and below the 300% poverty level.

(9) \[ \Delta HHIDTotal_{Below300} / \Delta Ike = -36.3039(1) + 51.63527(1) + 15.53612(2.6892) \]

\[ \Delta HHIDTotal_{Below300} / \Delta Ike = 57.11 \text{ ounces} \]

(10) Averting Expenditures_{Below300} = (\Delta HHIDTotal_{Below300} / \Delta Ike) * Price

Averting Expenditures_{Below300} = 57.11 * 0.0373 = $2.13 / week

(11) \[ \Delta HHIDTotal_{Above300} / \Delta Ike = 51.63527(1) + 15.53612(2.6892) \]

\[ \Delta HHIDTotal_{Above300} / \Delta Ike = 93.42 \text{ ounces} \]

(12) Averting Expenditures_{Above300} = (\Delta HHIDTotal_{Below300} / \Delta Ike) * Price

Averting Expenditures_{Above300} = 93.42 * 0.0373 = $3.48 / week

The difference in averting expenditures between the two groups is $1.35 per week.
It is likely that these results would be even better controlling for length of the power outage for each household; since the proxy variables using electric providers and wind speeds were not significant, I was not able to do this.

These values provide partial estimates of the value per week that a single household places on tap water. In annual terms, the lower bound willingness-to-pay of one household for tap water is $147.94. It is possible to use this estimate to derive an aggregate willingness-to-pay for all households in the affected area. For the entire rural population in Ohio, consisting of 1.045 million households (U.S. Census Bureau, Urban and Rural Population by State 2011), the lower bound total willingness-to-pay for one year of tap water is $154.6 million.

From willingness-to-pay for tap water, we can calculate a partial net present value (NPV) of water supply. NPV puts the value of all future returns in terms of the present. This requires the choice of a discount rate, which reflects the value of the future compared to current value. A low discount rate suggests that the future is nearly as valuable as the present; a high discount rate could be used to indicate riskiness, impatience, or deterioration of infrastructure over time (a zero discount rate, for mathematical reasons, is rarely used). For private investments, the discount rate is usually equal to the market interest rate to calculate the returns possible from investing the same amount of money in other options, but for public goods such as water supply, some argue that the discount rate can be lower to reflect intergenerational equity or other benefits not measured by monetary values, such as the value of healthier communities.
from increased water consumption. NPV in perpetuity can be calculated using the following equation:

\[ \text{NPV} = \frac{R}{i} \]  

where \( R \) is the benefit per year (in this case, $147.94), and \( i \) is the discount rate.

In September 2008 at the time of the power outage, the prime interest rate was 5%, and currently it is 3.25% (Board of Governors of the Federal Reserve System 2012). Using a 5% discount rate, the partial NPV in perpetuity of water supply per household is $2,959, and for all rural households in Ohio is $3.092 billion; using a 3% discount rate, the partial NPV is $4,931 per household and $5.154 billion for all rural Ohio households. It is clear that the choice of a discount rate is very important because it can significantly change the estimates. A sensitivity analysis using different discount rates can be found in Table 7 in the Appendix.

The regression results also provide a way to estimate of the price elasticity of bottled water demand. Price elasticity is the percent change in quantity demanded due to a percent change in price. The demand curve for bottled water, holding constant all other variables that affect demand, can be written as:

\[ Q = \alpha - bp \]  

where \( \alpha \) is the quantity demanded when the price is zero, \( p \) is price, and \( b \) is the coefficient for AvgPrice estimated in the regression analysis. AvgPrice indicates the change in quantity demanded due to a change in price.

\[ Q = \alpha - 92.61p \]  

The elasticity, \( \varepsilon \), can be calculated from the following equation:
\[ \varepsilon = -b^* \left( \frac{p}{Q} \right) \]

With an average price per fluid ounce of $0.04, and an average quantity demanded of 418.23 ounces,

\[ \varepsilon = -92.61 \left( \frac{0.04}{418.23} \right) = -0.0089 \]

This means that a 1% increase in the price of bottled water will cause quantity to decrease by about 0.01%. From this we would conclude that bottled water is very inelastic in this case since the price increase results in a less than proportionate decrease in quantity.

Other estimates of elasticity in the literature vary from elastic at -1.493 (Pittman 2004) to inelastic at -0.498 (Zheng and Kaiser 2008),\(^7\) but none were this inelastic. Differences in elasticity can be caused by different models, time periods, regions, and definitions of bottled water. The difference between these estimations and mine is likely because in this case, bottled water is more of a basic necessity than a luxury good. In this study, since observations with prices above two standard deviations from the mean, or “luxury goods,” were deleted, many of the remaining types of bottled water were likely purchased out of necessity rather than a choice of beverage.

**Comparison of Replacement Costs with Partial Benefits**

Assuming that rural and urban households equally value tap water, the partial NPV calculations can be compared with estimates of replacement costs of utilities to

\(^7\)Pittman (2004) estimated the own-price elasticity of demand as -1.493; Uri (1986) estimated the own-price elasticity of demand as -0.7901; Zheng and Kaiser (2008) estimated the compensated own-price elasticity as -0.498, and uncompensated as -0.501; Dharmasena (2010) estimated the compensated own-price elasticity as -0.7190, and uncompensated as -0.7540.
determine whether the benefits of maintaining the provision of clean, safe, reliable water outweigh the costs of providing public water to rural residents. Distribution pipes that were installed in many communities 75-120 years ago are nearing the end of their lives (American Water Works Association 2001). Costs vary greatly between public water systems due to differences in size, water treatment methods, and whether the population is growing or shrinking. These costs will be funded by a combination of federal assistance, state assistance, grants, loans, and/or increased rates to consumers. The AWWA estimated replacement costs for 20 public water systems across the United States, including Cincinnati. Costs for small systems are greater than costs for large systems due to economies of scale in large systems. Also, costs to extend services to rural areas are greater because rural areas require longer lengths of pipe to reach the households. On average, the replacement cost is about $6,300 per household in 2001 dollars, or $7,659 in 2008 dollars.

Assuming that the replaced pipes have an average life of 75 years (AWWA 2001), after which the pipes would need to be replaced again, I calculated the 75-Year NPV for individual households, which can be found in Table 7 in the Appendix, using the following formula

\[
\text{NPV}(i, 75) = \sum_{t=1}^{75} \frac{R_t}{(1+i)^t}
\]

where R is equal to a household’s averting expenditures per year, $147.94, i is the discount rate, and t is the year. The partial NPV per household at a 5% discount rate is $3,030.55, and at a 2% discount rate is $5,869.83. The discount rate at which NPV equals the costs of replacement, $7,659 in 2008 dollars, is 1.1%.
The calculated partial NPV, or benefits, do not outweigh the costs unless a very low discount rate is used. With more data it would be interesting to use these results along with further analysis to estimate a total low-end willingness-to-pay and NPV of public water systems, using additional averting expenditures, which would give a higher estimate of NPV. Depending on the choice of discount rate (and, one could argue that it should be lower than the current interest rate), the benefits may outweigh the replacement costs.
Chapter 4: Conclusion & Discussion

The purpose of this study is to estimate the averting expenditures of bottled water by rural households during a power outage. Using a panel data model and controlling for differences between households such as income, location, and preferences, I was able to calculate averting expenditures and demand elasticity for bottled water.

I found that rural households purchased an average of $2.85 of bottled water per week as a result of the power outage. Households with incomes above 300% of the poverty guidelines purchased $1.37 more than households with incomes below 300% of the poverty guidelines. The difference in expenditures between these two groups is due to a lower opportunity cost of time for households with lower incomes, who are more likely to engage in time-intensive behaviors such as hauling or storing water rather than purchasing water.

This estimate was used to calculate partial willingness-to-pay for clean, reliable tap water. Aggregated to the annual level, an individual household’s partial willingness-to-pay is $147.94. In perpetuity, with a 5% discount rate this gives a partial NPV of $2,959 per household, and $3.092 billion for all rural households in Ohio; with a 3% discount rate, the partial NPV increases to $4,931 per household, and $5.154 billion for
all rural households in Ohio. It is important to note that this is a partial, low-end estimate of NPV since it was only calculated from low-end averting expenditures on bottled water; including other averting expenditures such as electric generators or the opportunity cost of time for hauling or storing water, would result in a higher estimation of NPV.

The NPV can be considered a partial estimate of benefits and can be compared with the costs of providing water to households. According to a study by the AWWA (2001), the average cost per household of providing water service, in 2008 dollars, is $7,659. In this study, the NPV does not equal the costs per household unless a very low discount rate of 1.1% is used.

To conduct a complete cost-benefit analysis, it would be necessary to calculate the full benefits of water supply. The full private benefits would include the benefits measured in this study along with the willingness-to-pay for water supply calculated from other averting behaviors such storing water, hauling it from other sources, or using an electric generator. Social benefits would include healthier communities as a result of adequate clean water supply.

Households connected to a public water supply must pay for the volume of water consumed but receive the benefits of a clean, reliable source of water. It is important to note that the costs to supply water from a public water system for rural households are greater than the costs for urban households due to larger distance between houses and more infrastructure needs in rural areas. It can be cost-prohibitive for public water systems to supply water to some rural households because the infrastructure needs are too high.
Even in rural areas, water is not free; owners of private groundwater wells also incur costs to access clean water such as drilling costs, maintenance costs to keep the well in working order, well pump purchases and maintenance, water softener purchases and maintenance, electricity costs, and water quality tests. While many of these are fixed costs and the variable, day-to-day costs are generally low, these costs are usually covered by the well owner, and there is risk involved with a collapsed or dried-up well or an undetected groundwater contamination. As we can see in this study, there are also significant costs to disrupted service during a power outage. With continued advances in technology, future improvements such as less expensive water distribution pipes with longer lifespans may make it more cost-effective to extend the benefits of public water service to rural areas.
References


Assuming that all averting behaviors are perfect substitutes, the indifference curves for both income groups are linear. Households gain the same utility from consuming water at any point on this line, so from a utility standpoint, they are indifferent to the source of water. They are constrained by their budgets. Low-cost options for low income households include those which require time, such as hauling or storing water, since the opportunity cost of time is lower; the opposite holds true for high income households. Low-cost options for high income households include purchasing bottled water, since the opportunity cost of time for other options is higher.
Figure 2. Single Household Observations by Week in 2008

Over 400 observations were deleted since they were from households with only one observation. The graph above presents the number of these observations per week in year 2008. While there is a small spike in the number of households purchasing bottled water in week 39, this spike does not appear to be much different than other weeks during the year. For this reason, I believe deleting these observations to be able to include household fixed effects is reasonable.
Figure 3. Incorporated Areas in Ohio
Figure 4. Four Major Electric Service Providers in Ohio
Figure 5. Wind Speeds in Ohio During Hurricane Ike
Table 1. Poverty Thresholds (in Dollars) for Different Household Sizes

<table>
<thead>
<tr>
<th>Household Size</th>
<th>100%</th>
<th>200%</th>
<th>250%</th>
<th>300%</th>
<th>350%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10,830</td>
<td>21,660</td>
<td>27,075</td>
<td>32,490</td>
<td>37,905</td>
</tr>
<tr>
<td>2</td>
<td>14,570</td>
<td>29,140</td>
<td>36,425</td>
<td>43,710</td>
<td>50,995</td>
</tr>
<tr>
<td>Average household size in study: 2.66</td>
<td>17,038</td>
<td>34,077</td>
<td>42,596</td>
<td>51,115</td>
<td>59,634</td>
</tr>
<tr>
<td>3</td>
<td>18,310</td>
<td>36,620</td>
<td>45,775</td>
<td>54,930</td>
<td>64,085</td>
</tr>
<tr>
<td>4</td>
<td>22,050</td>
<td>44,100</td>
<td>55,125</td>
<td>66,150</td>
<td>77,175</td>
</tr>
<tr>
<td>5</td>
<td>25,790</td>
<td>51,580</td>
<td>64,475</td>
<td>77,370</td>
<td>90,265</td>
</tr>
<tr>
<td>6</td>
<td>29,530</td>
<td>59,060</td>
<td>73,825</td>
<td>88,590</td>
<td>103,355</td>
</tr>
<tr>
<td>7</td>
<td>33,270</td>
<td>66,540</td>
<td>83,175</td>
<td>99,810</td>
<td>116,445</td>
</tr>
<tr>
<td>8</td>
<td>37,010</td>
<td>74,020</td>
<td>92,525</td>
<td>111,030</td>
<td>129,535</td>
</tr>
<tr>
<td>9</td>
<td>40,750</td>
<td>81,500</td>
<td>101,875</td>
<td>122,250</td>
<td>142,625</td>
</tr>
</tbody>
</table>

Source: HHS Poverty Guidelines, 2008
Table 2. Sensitivity Analysis Using Different Time Periods

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Model 1 WeekBefIke</th>
<th>Model 2 Ike (preferred)</th>
<th>Model 3 Week12Ike</th>
<th>Model 4 Week1Ike</th>
<th>Model 5 Week2Ike</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
</tr>
<tr>
<td>Intercept</td>
<td>69.16105 (174.9)</td>
<td>66.62269 (174.8)</td>
<td>66.36433 (174.8)</td>
<td>68.44231 (174.8)</td>
<td>66.91237 (174.8)</td>
</tr>
<tr>
<td>Ike_t</td>
<td>-159.765 (231.4)</td>
<td>-82.0306 (131.8)</td>
<td>-37.3465 (158.7)</td>
<td>41.36375 (219.0)</td>
<td>-117.074 (226.8)</td>
</tr>
<tr>
<td>Ike_t*Poverty_300h</td>
<td>-7.23445 (36.9938)</td>
<td>-36.3039 (24.5949)</td>
<td>-36.2175 (25.6966)</td>
<td>-34.1983 (35.6561)</td>
<td>-39.2194 (36.6305)</td>
</tr>
<tr>
<td>Ike_t*Rural_h</td>
<td>15.39507 (44.9832)</td>
<td>51.63527** (32.4944)</td>
<td>56.71084* (32.4944)</td>
<td>61.07394 (43.5374)</td>
<td>48.60176 (48.1993)</td>
</tr>
<tr>
<td>Ike_t*Wind_h</td>
<td>1.651152 (3.2288)</td>
<td>0.515982 (1.8545)</td>
<td>-0.24922 (2.2709)</td>
<td>-1.55494 (3.1536)</td>
<td>1.08948 (3.2237)</td>
</tr>
<tr>
<td>Spring_t</td>
<td>22.00834*** (7.2896)</td>
<td>25.8311*** (7.7575)</td>
<td>26.21564*** (7.5133)</td>
<td>23.09634*** (7.3031)</td>
<td>25.38767*** (7.2949)</td>
</tr>
<tr>
<td>Summer_t</td>
<td>32.01958*** (7.1277)</td>
<td>35.78453*** (7.6059)</td>
<td>36.17652*** (7.3500)</td>
<td>33.0808*** (7.1352)</td>
<td>35.38703*** (7.1273)</td>
</tr>
<tr>
<td>HH Fixed Effects_h</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>R²</td>
<td>0.4697</td>
<td>0.4700</td>
<td>0.4700</td>
<td>0.4698</td>
<td>0.4699</td>
</tr>
</tbody>
</table>

*** = significant at the 0.01 level  
** = significant at the 0.05 level  
* = significant at the 0.10 level

WeekBefIke = 1 if week before storm, 0 otherwise
Ike = 1 if week before storm or within two weeks of storm, 0 otherwise
Week12Ike = 1 if within two weeks following storm, 0 otherwise
Week 1 = 1 if week after storm, 0 otherwise
Week 2 = 1 if two weeks after storm, 0 otherwise
Table 3. Sensitivity Analysis Using Different Income Thresholds

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Model 1 100% of Poverty Guidelines</th>
<th>Model 2 200% of Poverty Guidelines</th>
<th>Model 3 250% of Poverty Guidelines</th>
<th>Model 4 300% of Poverty Guidelines (preferred)</th>
<th>Model 5 350% of Poverty Guidelines</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
</tr>
<tr>
<td>Intercept</td>
<td>66.61836 (174.8)</td>
<td>66.61378 (174.8)</td>
<td>66.61892 (174.8)</td>
<td>66.62269 (174.8)</td>
<td>66.62499 (174.8)</td>
</tr>
<tr>
<td>Ike_t</td>
<td>-87.3893 (131.7)</td>
<td>-89.2771 (131.8)</td>
<td>-91.2882 (131.7)</td>
<td>-82.0306 (131.8)</td>
<td>-87.8706 (131.9)</td>
</tr>
<tr>
<td>Ike_t*Poverty_h</td>
<td>-57.6033 (60.4704)</td>
<td>-21.4164 (29.5534)</td>
<td>-16.8219 (26.2943)</td>
<td>-36.3039 (24.5949)</td>
<td>-13.8989 (24.0308)</td>
</tr>
<tr>
<td>Ike_t*Rural_h</td>
<td>40.1169* (20.6356)</td>
<td>42.59942*** (21.3106)</td>
<td>43.08864** (21.7516)</td>
<td>51.63527*** (32.4944)</td>
<td>44.71958* (23.1587)</td>
</tr>
<tr>
<td>Ike_t*Wind_h</td>
<td>0.597076 (1.8532)</td>
<td>0.611008 (1.8533)</td>
<td>0.639725 (1.8524)</td>
<td>0.515982 (1.8545)</td>
<td>0.304475 (1.8546)</td>
</tr>
<tr>
<td>Spring_t</td>
<td>25.83478*** (7.7578)</td>
<td>25.85052*** (7.7579)</td>
<td>25.84844*** (7.75580)</td>
<td>25.8311*** (7.7575)</td>
<td>25.83065*** (7.7579)</td>
</tr>
<tr>
<td>Summer_t</td>
<td>35.80749*** (7.6063)</td>
<td>35.79472*** (7.6064)</td>
<td>35.78637*** (7.6064)</td>
<td>35.78453*** (7.6059)</td>
<td>35.7738*** (7.6064)</td>
</tr>
<tr>
<td>HH Fixed Effects_h</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>R²</td>
<td>0.4700</td>
<td>0.4700</td>
<td>0.4699</td>
<td>0.4700</td>
<td>0.4699</td>
</tr>
</tbody>
</table>

*** = significant at the 0.01 level
** = significant at the 0.05 level
* = significant at the 0.10 level
Table 4. Correlation Coefficients of Regression Variables

<table>
<thead>
<tr>
<th></th>
<th>hhidtotal</th>
<th>ike</th>
<th>AEP</th>
<th>DUKE</th>
<th>FIRSTEN</th>
<th>DAYTON</th>
<th>WIND</th>
<th>poverty300</th>
<th>rural</th>
<th>HHSize</th>
<th>winter</th>
<th>spring</th>
<th>summer</th>
<th>autumn</th>
<th>winter2</th>
</tr>
</thead>
<tbody>
<tr>
<td>hhidtotal</td>
<td>0.00001</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ike</td>
<td>0.00401</td>
<td>-</td>
<td>0.041</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>AEP</td>
<td>0.969</td>
<td>-</td>
<td>0.00401</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DUKE</td>
<td>0.03733</td>
<td>0.969</td>
<td>0.00401</td>
<td>0.041</td>
<td>0.990</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>FIRSTEN</td>
<td>-0.01558</td>
<td>-0.969</td>
<td>-0.00401</td>
<td>-0.041</td>
<td>-0.990</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DAYTON</td>
<td>0.0889</td>
<td>0.03733</td>
<td>0.969</td>
<td>0.00401</td>
<td>0.990</td>
<td>1</td>
<td>0.25723</td>
<td>0.03185</td>
<td>0.8939</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>WIND</td>
<td>0.0047</td>
<td>0.00807</td>
<td>0.11357</td>
<td>0.00014</td>
<td>0.00634</td>
<td>0.00192</td>
<td>0.14564</td>
<td>0.00213</td>
<td>0.0213</td>
<td>0.00623</td>
<td>0.00623</td>
<td>0.00623</td>
<td>0.00623</td>
<td>0.00623</td>
<td>0.00623</td>
</tr>
<tr>
<td>poverty300</td>
<td>-0.00101</td>
<td>-0.00812</td>
<td>0.03185</td>
<td>0.00213</td>
<td>0.00623</td>
<td>0.00623</td>
<td>0.00014</td>
<td>0.00123</td>
<td>0.00123</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
</tr>
<tr>
<td>rural</td>
<td>0.02813</td>
<td>0.00004</td>
<td>0.07129</td>
<td>0.00752</td>
<td>0.01046</td>
<td>0.01528</td>
<td>0.020777</td>
<td>0.01232</td>
<td>0.01232</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
<td>0.00014</td>
</tr>
<tr>
<td>HHSize</td>
<td>0.04538</td>
<td>-0.01416</td>
<td>0.04041</td>
<td>0.03822</td>
<td>0.00382</td>
<td>0.09762</td>
<td>0.15963</td>
<td>0.09562</td>
<td>0.15963</td>
<td>0.09562</td>
<td>0.15963</td>
<td>0.09562</td>
<td>0.15963</td>
<td>0.09562</td>
<td>0.15963</td>
</tr>
<tr>
<td>winter</td>
<td>-0.02798</td>
<td>-0.01223</td>
<td>0.00364</td>
<td>-0.00399</td>
<td>0.0077</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>spring</td>
<td>0.00022</td>
<td>-0.00007</td>
<td>0.00011</td>
<td>-0.00309</td>
<td>-0.00342</td>
<td>-0.00573</td>
<td>-0.00612</td>
<td>0.00263</td>
<td>0.27404</td>
<td>0.02844</td>
<td>0.36614</td>
<td>0.00174</td>
<td>0.00033</td>
<td>0.00844</td>
<td>0.28844</td>
</tr>
<tr>
<td>summer</td>
<td>0.03511</td>
<td>-0.01574</td>
<td>0.00433</td>
<td>0.00844</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>autumn</td>
<td>-0.01923</td>
<td>0.46645</td>
<td>0.00144</td>
<td>0.00006</td>
<td>-0.00651</td>
<td>0.00453</td>
<td>0.00283</td>
<td>0.0011</td>
<td>0.0001</td>
<td>0.00007</td>
<td>0.00007</td>
<td>0.00007</td>
<td>0.00007</td>
<td>0.00007</td>
<td>0.00007</td>
</tr>
<tr>
<td>winter2</td>
<td>0.0111</td>
<td>-0.01906</td>
<td>-0.01</td>
<td>-0.01535</td>
<td>0.00714</td>
<td>0.00177</td>
<td>-</td>
<td>-0.01282</td>
<td>-0.17129</td>
<td>0.24348</td>
<td>0.39097</td>
<td>0.00004</td>
<td>0.00004</td>
<td>0.00004</td>
<td>0.00004</td>
</tr>
<tr>
<td>averageprice</td>
<td>-0.06204</td>
<td>-0.00825</td>
<td>-0.00678</td>
<td>-0.00198</td>
<td>0.0004</td>
<td>-0.02429</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-0.011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
<td>0.0011</td>
</tr>
<tr>
<td>&lt;0.001</td>
<td>0.0528</td>
<td>0.00151</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
<td>0.00118</td>
</tr>
</tbody>
</table>

Pearson Correlation Coefficients, N = 17471

Prob > |r| under H0: Rho=0
Table 5. Descriptive Statistics of Regression Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Sum</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>hhidtotal</td>
<td>17471</td>
<td>418.225</td>
<td>392.315</td>
<td>7306800</td>
<td>8</td>
<td>5604</td>
</tr>
<tr>
<td>ike</td>
<td>17471</td>
<td>0.05638</td>
<td>0.23066</td>
<td>985</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>AEP</td>
<td>17471</td>
<td>0.40301</td>
<td>0.49052</td>
<td>7041</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>DUKE</td>
<td>17471</td>
<td>0.12695</td>
<td>0.33293</td>
<td>2218</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>FIRSTEN</td>
<td>17471</td>
<td>0.38303</td>
<td>0.48614</td>
<td>6692</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>DAYTON</td>
<td>17471</td>
<td>0.1273</td>
<td>0.33331</td>
<td>2224</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>WIND</td>
<td>17471</td>
<td>71.2129</td>
<td>5.64348</td>
<td>1244160</td>
<td>50</td>
<td>75</td>
</tr>
<tr>
<td>poverty300</td>
<td>17471</td>
<td>0.44502</td>
<td>0.49698</td>
<td>7775</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>rural</td>
<td>17471</td>
<td>0.80196</td>
<td>0.39854</td>
<td>14011</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>HHSize</td>
<td>17471</td>
<td>2.66132</td>
<td>1.35664</td>
<td>46496</td>
<td>1</td>
<td>9</td>
</tr>
<tr>
<td>winter</td>
<td>17471</td>
<td>0.17755</td>
<td>0.38215</td>
<td>3102</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>spring</td>
<td>17471</td>
<td>0.25808</td>
<td>0.43759</td>
<td>4509</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>summer</td>
<td>17471</td>
<td>0.27818</td>
<td>0.44811</td>
<td>4860</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>autumn</td>
<td>17471</td>
<td>0.21544</td>
<td>0.41114</td>
<td>3764</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>winter2</td>
<td>17471</td>
<td>0.07075</td>
<td>0.25641</td>
<td>1236</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>avgprice</td>
<td>17471</td>
<td>0.04002</td>
<td>0.1236</td>
<td>699.118</td>
<td>0.00201</td>
<td>1.49911</td>
</tr>
<tr>
<td>Independent Variable</td>
<td>Model 1 (preferred)</td>
<td>Model 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------------------</td>
<td>---------------------</td>
<td>---------</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Coefficient (Std. Error)</td>
<td>Coefficient (Std. Error)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>66.62269 (174.8)</td>
<td>66.6434 (174.8)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t</td>
<td>-82.0306 (131.8)</td>
<td>-179.863 (155.3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*Poverty300h</td>
<td>-36.3039 (24.5949)</td>
<td>-38.5523 (24.637)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*Rural_h</td>
<td>51.63527** (22.3946)</td>
<td>55.6838** (22.5132)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*HHSize_h</td>
<td>15.53612* (8.0315)</td>
<td>15.8841** (8.0383)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*Wind_h</td>
<td>0.515982 (1.8545)</td>
<td>1.94858 (2.1201)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*AEP_h</td>
<td></td>
<td>19.6283 (36.5754)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*Duke_h</td>
<td></td>
<td>-0.74595 (47.3594)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*FirstEn_h</td>
<td>-25.3235 (36.0553)</td>
<td>-33.1548 (42.3519)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ike_t*Dayton_h</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Winter_t</td>
<td>-13.1892 (8.4377)</td>
<td>-13.2071 (8.4379)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring_t</td>
<td>25.8311*** (7.7575)</td>
<td>25.8184*** (7.7576)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Summer_t</td>
<td>35.78453*** (7.6059)</td>
<td>35.7219*** (7.6062)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Winter2_t</td>
<td>-18.48* (10.8290)</td>
<td>-18.4869* (10.8295)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HH Fixed Effects_h</td>
<td>YES</td>
<td>YES</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.4700</td>
<td>0.4701</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*** = significant at the 0.01 level
** = significant at the 0.05 level
* = significant at the 0.10 level
Table 7. Sensitivity Analysis of Net Present Value of Averting Expenditures with Different Discount Rates

<table>
<thead>
<tr>
<th>Discount Rates</th>
<th>5%</th>
<th>4%</th>
<th>3%</th>
<th>2%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>For Individual Rural Households</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Averting Quantity per Week (oz.)</td>
<td>76.28</td>
<td>76.28</td>
<td>76.28</td>
<td>76.28</td>
</tr>
<tr>
<td>Averting Expenditures per Week</td>
<td>$2.85</td>
<td>$2.85</td>
<td>$2.85</td>
<td>$2.85</td>
</tr>
<tr>
<td>Averting Expenditures per Year</td>
<td>$147.94</td>
<td>$147.94</td>
<td>$147.94</td>
<td>$147.94</td>
</tr>
<tr>
<td>NPV in Perpetuity</td>
<td>$2,958.90</td>
<td>$3,698.62</td>
<td>$4,931.49</td>
<td>$7,397.24</td>
</tr>
<tr>
<td>75-Year NPV</td>
<td>$3,030.55</td>
<td>$3,651.22</td>
<td>$4,542.03</td>
<td>$5,869.83</td>
</tr>
<tr>
<td><strong>For All Affected Households in Study:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Averting Expenditures per Year</td>
<td>$225,615</td>
<td>$225,615</td>
<td>$225,615</td>
<td>$225,615</td>
</tr>
<tr>
<td>NPV of Averting Expenditures</td>
<td>$4,512,316</td>
<td>$5,640,395</td>
<td>$7,520,527</td>
<td>$11,280,790</td>
</tr>
<tr>
<td><strong>For All Rural Households in Ohio:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Averting Expenditures per Year</td>
<td>$154,620,357</td>
<td>$154,620,357</td>
<td>$154,620,357</td>
<td>$154,620,357</td>
</tr>
<tr>
<td>NPV of Averting Expenditures</td>
<td>$3,092,407,142</td>
<td>$3,865,508,927</td>
<td>$5,154,011,903</td>
<td>$7,731,017,855</td>
</tr>
</tbody>
</table>

HH = Household
Affected Households in Study: 1525
Rural Population in Ohio (Census 2000): 2,571,000
Rural Households in Ohio (population divided by average household size in Ohio): 1,045,122