Using Weather to Explain Variation in State-level Food Insecurity: A Panel Data Approach

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MPP Essay

submitted to

Oregon State University

in partial fulfillment of
the requirements for the degree of

Master of Public Policy

Presented 14 March 2011

Kristin Chatfield for the degree of Master of Public Policy presented on 14 March 2011.
Title: Using Weather to Explain Variation in State-level Food Insecurity: A Panel Data Approach

Abstract Approved:

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Most research on U.S. hunger and food insecurity is at the household level, where it occurs. Because policy to address food insecurity is created and implemented at the national and state level, hunger research at the state level provides important contextual information. By including weather data with state level economic and demographic characteristics, this study attempts to explain the variation in food insecurity rates at the state level. Using ordinary least squares regression analysis, this research estimated the relationships between state-level food insecurity rates and explanatory variables which include demographic characteristics as well as weather-related variables.

Including the July Residential Energy Demand Temperature Index in the model, a "cool or eat" effect was shown to exist at the state level. High energy demand in July, associated with comparatively warmer weather, has a positive effect on food insecurity at the state level. This analysis was unable to capture a definitive "heat or eat" effect at the state level. One model using the deviation in December Heating Degree Days showed that in colder December weather, food insecurity increases, suggesting that a "heat or eat" effect exists at the state level. However, when a "December Shock" variable capturing the effect of the coldest years was included in the model, food security improved with more severe weather. The unexpected negative relationship between a cold shock in December and food security could be due to the success of programs in place to mitigate the effects of extreme weather. Innovative state programs coordinating LIHEAP and SNAP benefits hold promise to improve food security and bring more federal money to low-income people.

ACKNOWLEDGEMENTS

I am grateful for the support I have received in the process of completing this essay. My committee, Mark Edwards, Roger Hammer, and especially my chair Bruce Weber: you all have helped me become a better student, thinker, economist, and SAS programmer. Thank you for your time, patience, knowledge, and commitment to this project.

Robert Sahr was not formally on my committee, but was always willing to let me think aloud and offer advice when I asked for it. I also deeply appreciate Carol Tremblay's invaluable help with some of the early SAS programming. Brent Steel cannot go unmentioned; he has been supportive of my many endeavors in graduate school.

Outside of the University, Mark Nord of the USDA Economic Research Service was graciously willing to share his time and insight. Melissa Torgerson, MPP graduate and energy policy expert at Oregon Housing and Community Services provided enlightening discussions that helped shape my policy recommendations. Christopher Brierley, atmospheric physicist and climate scientist of Yale University took time over Christmas to help me with the climate data with unflinching kindness.

And last, but certainly not least, my friends and peers in the MPP and Economics Departments for offering spreadsheet tricks, tea, and laughter just when I needed it. I am thankful to have many dear friends who sweeten my life and who have helped me maintain some degree of sanity during my research, but I want to especially thank Kirsten Winters and Laurel Moulton for their warm hospitality.

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INTRODUCTION:

Food security means having access to enough food for an active, healthy life. Unfortunately, since the recent economic downturn the prevalence of food insecurity is the highest it has been since the USDA began collecting food security data in 1995(USDA 2011a). Outright starvation in the United States is rare, so the USDA uses the food security continuum to describe the problem for the US. A household is considered food secure if it did not report any problems with access or food limitations, or if it reported some anxiety about sufficiency of food in the house, but showed no indications of reduced intake in that year. A household is considered food insecure if it reports reduced quality of diet, but shows little indication of reduced food intake. Very low food security means that the household reported multiple indications of disrupted eating patterns and reduced food intake. Until recently, very low food security was referred to as food insecurity with hunger, or simply "hunger" and these terms are used interchangeably in this paper (USDA 2011b).

Although food insecurity is experienced at the household level, the prevalence rate or percent of the households experiencing food insecurity is often used to describe the magnitude of the issue at the state and national level. Using multivariate analysis, this paper estimates the relationships between state-level economic, demographic, and weather characteristics and food insecurity using panel data.

Using state level economic and demographic characteristics to predict and explain variation in hunger rates should provide insight into how to best address the problem of food insecurity and hunger with policy. Although a different combination of factors may be responsible in each state that has a high prevalence of food insecurity (Tapogna et al. 2004), the extent to which state level characteristics explain differences in state hunger rates can be estimated.

Food insecurity research is particularly pertinent in Oregon, a largely rural state in the Pacific Northwest, because it has had some of the highest rates of food insecurity and hunger in the United States, despite average poverty rates. Researchers have tried to explain this trend across socioeconomic and demographic characteristics, such as the rural-urban continuum. Yet little of Oregon's high hunger rate appears to be due to its population composition as Oregon has higher rates of hunger among almost all demographic groups (Edwards and Weber 2003). One source of explanation for state level differences not yet examined is differences in climate and the associated energy costs faced by low income families. By including weather data with cross-sectional time-series data of state level economic and demographic characteristics, this research may help further explain the variation in food insecurity rates at the state level.

LITERATURE REVIEW:

The federal food stamp program, now called the Supplemental Nutrition Assistance Program (SNAP) is a cornerstone of the federal safety net serving over 35 million people each month (USDA 2010c) and is the core policy to mitigate and prevent food insecurity. At the household level, the program intends to ensure that low-income households have access to an adequate and nutritious diet. Policy analysts and academic researchers have been interested in the impacts of this large, centralized program which serves a geographically and demographically diverse population. There is a wide range of research questions, mostly centered on the efficacy or success of the program. Does SNAP reduce food insecurity and increase access to an adequate and nutritious diet for low-income households? Does the program successfully provide assistance across the demographic differences of recipients such as urban or rural, household type, race, family size? This analysis does not focus on measuring specific impacts of policy, but rather on the complex problem that SNAP hopes to mitigate: food insecurity and hunger.

The core policy of the food stamp program is to keep low-income households from going hungry by supplementing their ability to purchase nutritious food. To measure performance and assess the level of need for food assistance programs the USDA uses standardized measures to survey the food security of all households in the US annually (Tapogna et al. 2004). The food security scale is at the core of food insecurity statistics. Nord et al. (2002) discuss the USDA food security scale and the importance of understanding both the frequency and severity of food insecurity. Examining food insecurity in the United States they find that about two-thirds of the households classified as food insecure experience the condition as recurring, with approximately 20 percent as a chronic condition.

Many studies have recognized timing issues in food security data because the survey data typically used asks about experiences in the previous year, so that increasing food insecurity or impact of income and budget shocks are not seen in the month they occur. While other studies have struggled to address this issue, Nord and Golla (2009) address the adverse selection issue by investigating self-selection and the effect on food insecurity using month-by-month panel data over two consecutive years. This approach showed that food security deteriorated in the six to eight months prior to receiving SNAP benefits and improved shortly after. Although the study did not conclusively measure the level of increased food security, it did demonstrate that households self-select into SNAP when they are more severely food insecure and that benefits reduce very low food security by one-third for new entrants. As with earlier studies, Nord and Golla's study also struggles with completely untangling self-selection and amelioration effects because a true random assignment experiment cannot be performed to discern the "treatment effect" of food stamps on food security.

Most research is dedicated to understanding hunger and food insecurity at the household level, where it occurs. But policy to address food insecurity is created and implemented at the national and state level, so hunger research at the state level provides important contextual information. Tapogna et al. (2004) attempt to link household-level food insecurity indicators to state-level characteristics, such as poverty, unemployment rate, and ethnic diversity. They examine the effect of state-level demographic and economic characteristics on state-level food insecurity and hunger.

State level food insecurity statistics have received considerable attention in the Northwest where food insecurity rates are some of the highest in the nation despite the lack of demographic and economic indicators, such as high poverty or unemployment rates, that could be linked to high hunger rates. Because poor households have higher rates of food insecurity, and food insecurity is more prevalent in certain regions, including the Pacific Northwest (Nord et al. 2002), it seems intuitive that characteristics such as poverty could be used to predict and explain state-level food insecurity. The models used by Tapogna et al. (2004) showed that although poverty had a strong impact on food insecurity, removing it from the model resulted in a statistically significant relationship with unemployment, so disentangling the independent effects of poverty and unemployment on food insecurity is difficult. Using data from the 2000 census, the regression models were able to help explain why Oregon has a low state-level poverty rate, yet one of the highest rates of food insecurity in the country. The results suggest that cost of living, specifically the percent of the population spending more than 50 percent of income on rent and income shocks associated with high mobility help explain the prevalence of hunger in Oregon. These results are consistent with earlier research regarding the higher cost of living in the Pacific Northwest. Furthermore, higher than average cost of living only stands to exacerbate income shocks such as unemployment and high mobility.

Just as with income shocks, a budget shock can put a household at risk of food insecurity or hunger. Bhattacharya et al. (2002) examine the effects of cold weather periods on household budgets and nutritional outcomes in poor American families. The authors do not discuss their findings in terms of food insecurity, but instead analyze detailed nutrition related data such as calorie consumption and vitamin deficiencies. They find that both rich and poor families respond to unusually cold weather – a 10 degree Fahrenheit drop below normal – by increasing fuel expenditures, but that poor families reduce food expenditures by roughly the same amount as the fuel expenditure increase. Because some states are colder and/or more prone to temperature shocks, including temperature data as part of state-level characteristics that predict high hunger rates, such as poverty and employment, may be useful in explaining variations in state hunger rates.

Focusing on low-income elderly, Nord and Kantor (2006) also find there are seasonal effects of home heating and cooling on hunger. Their research shows that in "high-heating" states hunger, or very low food security, is higher in the winter. They also find that in "high-cooling" states the odds of very low food security are higher in the summer.

Including temperature data as an explanatory variable could help explain variation in state level food insecurity and hunger rates. This research could yield particularly interesting results in Oregon which is a high cost of living state and many of the state's coldest counties are nonmetro. Cost of living in nonmetro areas is generally accepted to be lower in terms of housing costs, though the literature is inconclusive in terms of food costs, so it is unlikely that higher than average cost of living explains all of the variation in Oregon's high hunger rate. Oregon has a uniquely rural composition, but resists fitting into national averages with higher rates of hunger among almost all demographic groups. These groups include counterintuitive groups such as two-parent families with children and households with no unemployed adults (Edwards and Weber 2003). Edwards and Weber study six explanatory variables, including metro-nonmetro designation and find that Oregon's hunger rate is high for all household categories and that hunger rates were identical for urban and rural areas (2003). Still, Nord and Leibtag (2005) find that, on average, "cost of enough food" is 11 to 14 percent lower in nonmetropolitan areas, but comparing food costs between states shows that highest food costs are in the Pacific Northwest. Further, in three western states the authors find that food costs were higher in nonmetro than in metro areas. "Cost of enough food" is a subjective measure as it reflects socially formed expectations of what an adequate diet comprises, but it is still a useful tool for comparison, particularly for inter-regional comparisons.

Contrasting Nord and Leibtag's (2005) findings, other literature points to higher food prices, in absolute terms, in rural areas. Using ZIP code analysis, Kaufman (1999) explains that the rural poor have less access to supermarkets and large grocery stores where prices average 10 percent lower than other grocery stores. Due to insufficient accessibility of supermarkets, low- income rural households rely on smaller grocery stores, and therefore face generally higher prices. It is important to note that Kaufman's study focused on three states in the South, a region with high poverty rates, but also with lower food and housing costs.

DATA:

In this analysis I use cross sectional time-series data of state level economic and demographic characteristics based on the Tapogna et al. (2004) model. I augment the model with weather related data to predict and explain variation in state level food insecurity and hunger rates. By using time-series data, I hope to capture the impact of budget shocks due to years with higher energy use. In this section I describe the variables as well as report the means and standard deviations in Table 1. at the end of the section.

In order to obtain a balanced data set, and the most accurate results, Hawaii and Alaska were removed from the analysis as weather data was not available for these states. The data set was further restricted to the years 2002-2008 so that both versions of rent burdened could be included in the models in turn. Although I did not have access to the data from the year 2000 to replicate the results from the Tapogna et al. (2004) model, I expect the relationships between the explanatory variables and hunger to be similar to those that Tapogna et al. found.

<u>Share of households experiencing low food security and very low food security:</u> The Census Bureau, DataFerret. The food security continuum is divided into four ranges, but for the purpose of this research I focus on two that fall into the general category of food insecure. A household has low food security if it reports a diet of reduced quality, variety, or desirability; there is little or no indication of reduced food intake. A household is considered to be experiencing very low food security if it reports multiple indications of disrupted eating patterns as well as reduced food intake. These

data came from a special tabulation of the Census Bureau's Current Population Survey Food Security Supplements for December 2002-2008, so they are single-year estimates as opposed to the two- or three-year averages generally reported. Interestingly, the only dramatic year-to-year variation in state level food insecurity estimates comes in 2008, the beginning of the recent economic downturn, suggesting that single year estimates are capturing important year-to-year variations in food insecurity. In 2008, there was a nearly 25 percent increase in the average prevalence of food insecurity.

Peak unemployment rate: Bureau of Labor Statistics, Local Area Unemployment Statistics. Peak unemployment rates for each year, for each state, were computed from monthly unemployment data for each state from 2002 to 2008. As in the Tapogna et al. model, the peak unemployment rate, as opposed to the average unemployment rate, is included to capture the worst economic conditions. The peak unemployment rate is a proxy for income shocks associated with job loss. High unemployment is likely associated with high food insecurity.

Residential Energy Demand Temperature Index (REDTI): National Oceanic and Atmospheric Administration (NOAA), National Climatic Data Center. Residential energy consumption is highly correlated with heating and cooling degree days, so the REDTI is used to measure year-to-year fluctuations in energy demand for residential heating and cooling. The index is on a scale of 0 to 100 and is based on population weighted heating and cooling degree days, with 100 assigned to the year with the greatest population-weighted degree day average, and zero to the smallest. REDTI is considered a better indication of energy demand than temperature alone because it represents temperature deviations in heavily populated areas, as opposed to extreme temperatures impacting remote areas (Weurtz and Wallis 2003). The REDTI for every month from 1895 to 2010, as well as the annual average for each year for each state came from a special extract from Dr. Christopher Brierley of Yale University. As a proxy for budget shocks, I expect the REDTI to have a positive relationship with hunger and food insecurity.

Heating Degree Days (HDD): National Oceanic and Atmospheric Administration (NOAA), National Climatic Data Center. This is a quantitative index which reflects energy demand to heat both homes and businesses. It is derived from daily temperature observations, with 65°F as the base for computations of degree days. Heating degree days at the state level for each month are population weighted summations of negative differences between the mean daily temperature and the base. This means that if the mean temperature is 60°F or 30°F, the heating degree day would be 5 and 35, respectively. Each month as well as the annual amount for each year for each state came from a special extract from Dr. Christopher Brierley of Yale University. As with the Residential Energy Demand Temperature Index, a positive relationship with hunger is expected.

Temperature: National Oceanic and Atmospheric Administration (NOAA), Climate at a Glance, measured in degrees Fahrenheit. The climatological mean for each state is based on the 30-year average using data from 1971-2000 which comes from NOAA's climatology index. The January average for each year from 2002 to 2008, for each state is also from NOAA. Based on the research of Bhattacharya et al. (2002) cold temperatures are expected to be associated with higher food insecurity.

Except for weather related data, food insecurity variables, unemployment rate, and share of renters paying more than 50 percent of income on *gross* rent, the data came from Integrated Public Use Microdata Series (IPUMS). The IPUMS data used are from the American Community Surveys of 2002-2008 which consist of a series of compatible-format individual-level representative samples of the United States.

Share of the population under age 18: Integrated Public Use Microdata Series (IPUMS), Variable: Age. This variable reports each person's age in whole years. For a few years in this data series, PUMS files may not be representative for the 65+ population at individual ages due to Census Bureau disclosure avoidance techniques which resulted in implausible sex ratios. It is unlikely that these discrepancies will create a problem for the purpose of this paper where the data are simply used to compute a percentage of the population for each state, and not analyze individuals. Because previous research indicates that large households with children have higher hunger rates, Tapogna et al. (2004) hypothesized that as the share of the population under age 18 rose, so would that state's food insecurity rate.

Share of the population non-Hispanic white: Integrated Public Use Microdata Series (IPUMS), Variables: Race and Hispan. The concept of race is now considered a socio-politically constructed concept as opposed to a scientific or anthropological one. Beginning in 2000, respondents were allowed to report as many races as they felt necessary to describe themselves, whereas in earlier surveys only one response was coded. This has allowed more accuracy, particularly in terms of those who report Hispanic origin, who had previously reported that they were in the "other race" category. The Census Bureau does not consider Hispanic/Latino to be a race group, but instead classifies individuals by their country of origin. Also, beginning in 2000, respondents were asked to answer both the race and Hispanic origin question. The variable share of the population non-Hispanic white was derived for each state using both race and Hispanic origin variables. Tapogna et al. (2004) included this variable in their model without a hypothesized expectation about what effect it may have on state hunger rates.

Share of renters paying more than 50 percent of income on gross rent: US Census Bureau American FactFinder, American Community Survey 1-year estimates, Table B25070. Amounts are expressed in contemporary dollars. Renters for whom rent is not computed, such as pastors, are removed from the total before dividing households who spend 50 or more of income on gross rent by the total number of renters. Tapogna et al. expected greater rent burden to be associated with higher food insecurity.

Share of renters paying more than 50 percent of income on contract rent: Integrated Public Use Microdata Series (IPUMS), Variables: Rent, FTOTINC and Adjust. Rent reports the households monthly contract rent payment, which may or may not include some utilities. FTOTINC reports the total pre-tax money income earned by the respondent's family from all sources for the previous year. Because these data are from ACS surveys and respondents are surveyed throughout the year, amounts do not reflect calendar year dollars. The Census Bureau provides an adjustment factor which adjusts dollar amounts to the amount that they would have been had they been earned entirely during the calendar year. RENT was multiplied by 12 then divided by FTOTINC*ADJUST to find renters paying more than 50 percent of their income on contract rent. Amounts are expressed in contemporary dollars. The share of the population spending more than 50 percent of income on contract rent is also expected to have a positive effect on hunger. This variable is also intended to identify those who are rent burdened, but at the same time disentangle the relationship between the utilities paid in the *gross* rent variable from the budget shocks represented by the weather-related variables.

Share of population in a different house: Integrated Public Use Microdata Series (IPUMS), Variable: MIGRATE1. Persons who moved from a foreign country, state, county, or place of their previous residence in the previous year are in the category "different house." Those who did not move, or who returned to their earlier residence within the year are considered non-movers and are included in the category "same house." For each state the share of the population in a different house is calculated from the category "different house" in MIGRATE1. Tapogna et al. (2004) included this variable as a proxy for income shocks and therefore expected a positive relationship with hunger.

State poverty rate: Integrated Public Use Microdata Series (IPUMS), Variable: POVERTY. This variable describes federally established poverty status with a reference period of the previous 12 months. The variable POVERTY treats respondents who live in families collectively; expressing each family's total income for the previous year as a percentage of the poverty thresholds established by the Social Security Administration, adjusted for inflation. POVERTY does not include those living in group quarters and assigns all members of each family - not each household - the same code. The percentage of families at or below the poverty line for each state is computed to give the state poverty rate. Tapogna et al. anticipated that higher state poverty rate would put upward pressure on the prevalence of food insecurity and hunger.

Table 1.
Descriptive Statistics: State-level Food Insecurity and Related Variables 2002-2008[1]

Variables	Mean	Standard Deviation
Share of population experiencing low food security	0.114	0.028
Share of population experiencing very low food security	0.041	0.013
Share of population in poverty	0.117	0.029
Share of population under age 18	0.249	0.017
Share of population non-Hispanic white	0.756	0.135
Share of population in a different house	0.166	0.026
Share of renters paying more than 50 percent of income on gross rent	0.227	0.028
Share of renters paying more than 50 percent of income on contract rent	0.206	0.035
Peak unemployment rate	0.058	0.013
January temperature	31.9	11.6
Annual REDTI	40.3	16.6
July REDTI	47.2	22.2
December HDD	925.3	300.5

N=336

[1] This analysis gives each state equal weight as an individual observation, in each year. So a less populous state, such as Idaho, is given the same weight as a more populous state, like New York. Therefore, these figures do not represent the U.S. average, which would entail weighting the states by their population.

METHODS:

Using SAS, a series of multivariate regression models were estimated using ordinary least squares (OLS) regression analysis to assess the relationship between state-level food insecurity rates and explanatory variables which include demographic characteristics as well as weather-related variables. To control for temporal fixed effects in the panel models, year dummy variables were included.

$$y = a_1 + \beta x + e$$

The base model is constructed using the Tapogna et al. (2004) econometric model which analyzes data for the year 2000. Although these exact data were not available to reproduce the 2000 model, the model was replicated for each year from 2002 to 2008 as well as estimated as a panel model for both hunger and food insecurity. The key difference between the variables in the Tapogna model and this model is that Tapogna et al. used three-year averages for both the unemployment rate and food insecurity variables. In the Tapogna model, the peak unemployment rate and the food insecurity rate was an average of the rates for 1999, 2000, and 2001. By contrast, in my model food insecurity and peak unemployment rate are simply the rate for each respective year. The results are included in the tables below.

Table 2.

Tapogna Model: Food Insecurity

	Tapogna et al.	2002	2003	2004	2005	2006	2007	2008	Panel
Intercept	-0.164 *	-0.083 -1.14	0.042 0.69	-0.135 -2.09*	-0.010 -1.26	-0.031 -0.57	0.085 1.14	-0.008 -0.10	-.0032 -0.12
Peak unemployment rate	0.187	0.513 1.31	0.185 0.59	0.454 1.20	0.766 2.37*	0.608 2.23*	0.833 2.28*	0.076 0.31	0.505 4.43*
Poverty rate	0.360 *	0.462 4.36*	0.424 4.56*	0.588 6.00*	0.490 3.85*	0.486 5.60*	0.234 2.18*	0.475 3.78*	0.44 11.33*
Share of population White non-Hispanic	0.014	-0.007 -0.28	-0.031 -1.37	-0.003 -0.12	0.030 1.03	-0.015 -0.75	-0.03 -1.16	-0.019 -0.69	-0.011 -1.17
Share of population in a different house	0.280 *	0.203 1.54	0.360 2.93*	0.158 1.38	0.193 1.55	0.146 1.46	0.188 1.36	0.190 1.23	0.184 3.87*
Share of population under age 18	0.434 *	0.448 1.97	0.095 0.50	0.630 3.14*	0.353 1.60	0.238 1.40	-0.045 -0.21	-0.002 -0.01	0.220 2.82*
Share of population rent burdened	0.276 *	-0.166 -1.06	-0.238 -1.95	-0.124 -0.81	-0.145 -1.08	-0.090 -0.83	-0.177 -1.29	0.293 1.86	-0.084 -1.66
R-squared Adjusted R-squared	0.736 0.700	0.590 0.530	0.591 0.531	0.681 0.634	0.614 0.557	0.676 0.629	0.374 0.283	0.480 0.404	0.580 0.564

*p<.05

Table 3.

Tapogna Model: Hunger

	Tapogna et al.	2002	2003	2004	2005	2006	2007	2008	Panel
Intercept	-0.069 *	0.013 0.35	0.027 0.94	-0.016 -0.46	-0.024 -0.58	-0.014 -0.45	-0.018 -0.42	0.009 0.20	0.015 1.04
Peak unemployment rate	0.314 *	0.282 1.38	0.005 0.03	0.149 0.72	0.323 1.88	0.319 1.98	0.223 1.03	0.181 1.34	0.236 3.85*
Poverty rate	0.034	0.041 0.75	0.072 1.61	0.189 3.52*	0.121 1.79	0.230 4.49*	0.044 0.69	0.139 1.99	0.117 5.50*
Share of population White non-Hispanic	0.011	-0.012 -0.85	-0.004 -0.34	-0.0002 -0.02	0.008 0.54	-0.005 -0.46	0.017 1.13	0.005 0.35	0.0006 0.11
Share of population in a different house	0.132 *	0.128 1.85	0.135 2.29*	0.111 1.77	0.118 1.79	0.053 0.89	0.131 1.60	0.168 1.95	0.108 4.24*
Share of population under age 18	0.112 *	0.009 0.07	-0.046 -0.51	0.113 1.03	0.075 0.64	0.037 0.37	0.0006 0.01	-0.144 -1.09	-0.002 -0.05
Share of population gross rent burdened	0.130 *	-0.074 -0.91	-0.039 -0.66	-0.101 -1.21	-0.060 -0.84	-0.013 -0.45	0.043 0.53	0.091 1.04	-0.027 -1.00
R-squared Adjusted R-squared	0.638 0.588	0.250 0.141	0.213 0.098	0.414 0.328	0.383 0.293	0.547 0.480	0.167 0.045	0.327 0.228	0.437 0.416

*p<.05

The variables that represent economic characteristics in the Tapogna model largely serve as proxies for income shocks (poverty rate, unemployment rate, percent of the population in a different house). To better capture the impact of budget shocks related to unusually high utility bills, various weather-related variables were added to the Tapgona model. According to Bhattacharya et al. (2002) and Nord and Kantor (2006), a “heat or eat” dilemma exists. That is, poor households often have to make tradeoffs between expenditures on food and other necessities. In order to find the effect that weather, specifically cold weather might have on hunger, weather-related data were added to the Tapogna model. These models, for both food insecurity and very low food security, are included in the next section under *Weather Related Models*.

Due to the milder winter weather of the South, OLS regressions using the same equations were also applied separately to non-Southern states and Southern states. An example of these results is included in the appendix.

RESULTS AND ANALYSIS:

Base model:

Applying the 2000 Tapogna et al. (2004) model to this data, by individual year for 2002-2008, and to the panel model with all years combined, yielded unexpected results. There were disparities in significance levels, magnitudes, and signs of the coefficients when comparing Tapogna et al.'s model to the individual year models and the panel model. Replicating the original model by running OLS regressions of the panel data by individual year further highlighted these differences, revealing year to year fluctuation of independent variables and the model's explanatory power. Tapogna et al. reported an unadjusted R^2 of 74 percent of the variation of state rates of food insecurity, and 64 percent of the variation in state rates of hunger, or very low food security. The panel model from this research resulted in an unadjusted R^2 of 58 percent for food insecurity, but the individual year models had a range of 68 percent in 2004 down to 37 percent in 2007. The panel model for very low food insecurity resulted in an unadjusted R^2 of 44 percent, with the individual year models ranging between 55 percent in 2006 down to 17 percent in 2007.

Peak unemployment rate

Tapogna et al. found that states with high unemployment rates also tended to have high poverty rates; therefore disentangling their independent effects was difficult. They found that peak unemployment was not statistically significant in predicting food insecurity. Analyzing the panel data by year resulted in three of seven years (2005-2007) having statistically significant relationships between peak unemployment rate and food insecurity. The panel model found a strong relationship (t=4.43) between food insecurity and peak unemployment rate with a coefficient of 0.505. This means that a one percentage point increase in peak unemployment is associated with a 0.51 percentage point increase in food insecurity at the state level.

Although Tapogna et al. did not find a strong association of peak unemployment rates with food insecurity rates they did find a statistically significant relationship between peak unemployment rates and hunger, or very low food security. In the yearly analysis of panel data, only two years were statistically significant, 2005 and 2006. Still, in the panel model peak unemployment rate showed strongly statistically significant (t=3.85) relationship with hunger with a coefficient of 0.236.

Poverty rate

In terms of the poverty rate with respect to food insecurity, the panel model, including individual year regressions are in agreement with Tapogna et al.'s model, as expected. The poverty rate is statistically significant in all models. The panel model resulted in a coefficient of 0.44 (t=11.33).

By contrast, Tapogna et al. did not find a statistically significant relationship between hunger, or very low food security, and the percent of a state's population living in poverty. They assert that persistently poor households may have developed ways to avoid hunger by relying on local institutions or their social network. In this research, three of seven individual year regressions show a statistically significant relationship between hunger and state poverty rates. The panel model resulted in a statistically significant relationship (t=5.50) with a coefficient of 0.117, which is a much smaller magnitude than in the food insecurity model, but level of very low food security is also much smaller than food insecurity resulting in a nearly proportional relationship.

Share of population White non-Hispanic

Tapogna et al. found a weak and not statistically significant relationship between both food insecurity and hunger and the share of a state's population that is White non-

Hispanic. This research also found a weak and non-statistically significant relationship between both food insecurity and hunger and the share of the population White non-Hispanic.

Share of population in a different house

The share of the population in a different house, or mobility variable, is a proxy for economic shocks, often due to family disruptions. Tapogna et al. find that this variable had the most robust and consistent relationship with both state hunger and food insecurity rates. Although there is a strong positive relationship (t=3.87) in the panel model, in only one of the seven individual year models (2003) is there a statistically significant relationship between food insecurity rates and mobility. Very low food security follows the same pattern as food insecurity: in the panel model there is a strong statistically significant relationship (t=4.24) which can be interpreted to mean that a one percentage point increase in the state mobility rate is associated with a 0.11 percentage point increase in a state's hunger rate.

Share of population under age 18

For both hunger and food insecurity Tapogna et al. found a statistically significant positive relationship with the share of the population under age 18. However, in this analysis the panel model results are different for food insecurity and hunger. In the food insecurity panel model, the share of the population under age 18 has a statistically significant positive effect. Yet in only one of the seven individual year models is this variable statistically significant (2004). Share of the population under age 18 is statistically non-significant in all of the models in relation to very low food security.

Share of population rent burdened

Perhaps the most counterintuitive results come from the share of renters paying 50 percent or more of income on gross rent. Tapogna et al. anticipated that those with high rents relative to income would be particularly vulnerable to food insecurity. As expected, Tapogna et al. found a statistically significant relationship showing that the share of the population spending more than 50 percent of income on gross rent puts upward pressure on both food insecurity and hunger rates. On the contrary, the panel models in this research result in negative estimates of small magnitudes that are statistically significant at the 90 percent level for food insecurity, while hunger does not have a statistically significant relationship with rent burden. And again, there is some year-to-year variation in the models. For hunger, in none of the models is there a statistically significant relationship with the share of the population that is rent burdened. Results from the food insecurity models are more perplexing still. Two of the individual year models result in coefficient magnitudes that are very similar to the Tapogna et al. model are significant at the 90 percent level of confidence, yet in 2003 it is a negative relationship, and in 2008 it is positive. In the panel model for food insecurity, this rent burden variable is also significant at the 90 percent level (t=-1.66), though with an unexpected negative relationship.

Weather Related Models:

Table 4.

Weather Models: Food Insecurity

	Tapogna et al.	January Temperature	REDTI July with Contract Rent
Intercept	-.0032 -0.12	-0.032 -1.19	-0.031 -1.22
Peak unemployment rate	0.505 4.43*	0.522 4.67*	0.445 4.21*
Poverty rate	0.44 11.33*	0.399 9.76*	0.442 9.54*
Share of population White non-Hispanic	-0.011 -1.17	0.012 1.06	-0.004 -0.45
Share of population in a different house	0.184 3.87*	0.142 2.98*	0.187 3.93*
Share of population under age 18	0.220 2.82*	0.282 3.61*	0.239 3.10*
Share of population gross rent burdened	-0.084 -1.66	-0.113 -2.25*	
Share of population contract rent burdened			-0.010 -0.28
January temperature		0.0005 3.83*	
REDTI July			0.0001 1.89
R-squared Adjusted R-squared	0.580 0.564	0.598 0.582	0.581 0.564

N=336, *p<.05

Table 5.

Weather Models: Hunger

	Tapogna et al.	January Temperature	REDTI July with Contract Rent
Intercept	0.015 1.04	-0.017 -1.17	0.007 0.50
Peak unemployment rate	0.236 3.85*	0.242 3.97*	0.216 3.78*
Poverty rate	0.117 5.50*	0.100 4.49*	0.115 4.59*
Share of population White non-Hispanic	0.0006 0.11	0.008 1.42	0.003 0.54
Share of population in a different house	0.108 4.24*	0.094 3.60*	0.109 4.25*
Share of population under age 18	-0.002 -0.05	0.019 0.45	0.004 0.09
Share of population gross rent burdened	-0.027 -1.00	-0.037 -1.36	
Share of population contract rent burdened			-0.005 -0.24
January temperature		0.0002 2.44*	
REDTI July			0.00002 0.85
R-squared Adjusted R-squared	0.437 0.416	0.447 0.425	0.437 0.414

N=336, *p<.05

January Temperature

Including mean January temperature in the panel model yielded a similar R^2 to the base model, explaining 60 percent of the variation in state food insecurity rates compared to 58 percent in the base model. The most notable difference from the base model to the model with January temperature is the coefficients of the percent of the population that is rent burdened. Again, the rent burden variable has a counter-intuitively negative relationship with food insecurity, meaning that as the proportion of the population rent burdened increases, food insecurity decreases. But in this model it is statistically significant (t= -2.25) and the coefficient has a larger magnitude than the other models (-0.113). This suggests that a one percentage point increase in the percent of the population that is rent burdened leads to a 0.11 percentage point decrease in food insecurity.

The added variable, January temperature, is significant in this model (t= 3.83) and has positive relationship with food insecurity. This positive relationship was unexpected as it was hypothesized that cold temperature shocks increase food insecurity, as opposed to warmer winters being associated with higher food insecurity. Assuming that the mild winter weather of the South[2] obscured the effect that extreme cold might have on states with moderate or cold winter weather, the South was removed from the data, and the model re-run. The same positive, statistically significant relationship held (see appendix).

Adding January temperature to very low food security model did not yield dramatic changes from the base model. As with the food insecurity model, the R^2 value is slightly higher (.45 as opposed to .44) and January temperature has a statistically significant positive relationship with food insecurity.

Annual Residential Energy Demand Temperature Index (REDTI)

Instead of just a "heat-or-eat" dilemma creating a financial burden, a "cool or eat" dilemma as Nord and Kantor (2006) found, may exist. By using annual REDTI I hope to capture the impact that temperature shocks can have at any time of the year – modeling for "heat or eat" and/or "cool or eat" effects on food insecurity and hunger concurrently. Two models were run with annual REDTI using a different measure of rent burdened. Because gross rent, from the Tapogna et al. model, also captures the portion of the budget spent on utilities, the contract rent variable may allow for the true impact

[2] The average January temperature for the South in this data set is 43.6°F, while average January temperature outside the South was 27.8°F. Both figures are two degrees higher than the 1971-2000 average for the same states.

of a temperature shock to be captured by the annual REDTI variable. Annual REDTI is not statistically significant in either model – using gross rent or contract rent burden – for hunger or food insecurity. Results for this analysis are not shown.

July Residential Energy Demand Temperature Index (REDTI)

Following up on the hypothesis that seasonally high cooling costs, or “cool or eat,” may have an effect on hunger and food insecurity at the state level, July REDTI was added to the model. Again, contract rent was used to minimize the correlation between utility expenditures in gross rent and the Residential Energy Demand Temperature Index. In the food insecurity model, including July REDTI resulted in almost identical signs and magnitudes of coefficients, with a slightly improved R^2 value compared to the base model. As hypothesized, July REDTI results in a positive relationship with food insecurity that is significant at the 90 percent confidence level (t=1.89). Results for very low food security follow a similar pattern, showing little difference between the other models, but July REDTI is not statistically significant. Removing the variables that are not statistically significant from the food insecurity model (percent of the population rent burdened and percent of the population White non-Hispanic, results not shown) creates almost no change in the model or R^2, but does increase the t-value of July REDTI so that it is statistically significant at the 95 percent confidence level (t=1.97). The REDTI is an index from 0 to 100 that is meant for year to year comparisons; years with higher energy demand have higher number. In this analysis the coefficient could be interpreted as for each one unit increase in the July Residential Energy Demand Temperature Index, there is a corresponding 0.01 percentage point increase in the food insecurity rate at the state level.

Weather Shock Models

Due to the counterintuitive results for some of the weather variables it seems likely that the model was not correctly specified to capture a weather shock. Heating Degree Days (HDD) is a quantitative index derived from daily temperature observations which reflects energy demand; it is population weighted at the state level. A shock comes from a deviation from the average. In order to generate a deviation, a 30-year average for each state was produced using HDD data from 1971-2000. These years were selected because they replicate the 30-year climatological normal NOAA uses.

Table 6.

Temperature Shock Models: Food Insecurity

	Tapogna et al.	Annual HDD Deviation	December HDD Deviation	December Shock
Intercept	-.0032 -0.12	-0.026 -1.06	-0.0289 -1.15	-0.013 -0.98
Peak unemployment rate	0.505 4.43*	0.432 4.10*	0.432 4.10*	0.402 3.81
Poverty rate	0.44 11.33*	0.437 9.40*	0.442 9.53*	0.448 9.64
Share of population White non-Hispanic	-0.011 -1.17	-0.004 -0.41	-0.005 -0.50	-0.004 -0.48
Share of population in a different house	0.184 3.87*	0.185 3.88*	0.185 3.89*	0.183 3.86
Share of population under age 18	0.220 2.82*	0.247 3.19*	0.253 3.28*	0.250 3.23
Share of population gross rent burdened	-0.084 -1.66			
Share of population contract rent burdened		-0.015 -0.41	-0.012 -0.34	-0.010 -0.28
Heating Degree Day Deviation		0.000007 1.57	0.00002 1.65	-0.013 -1.64
R-squared Adjusted R-squared	0.580 0.564	0.580 0.563	0.580 0.563	0.580 0.563

N=336, *p<.05

Table 7.

Temperature Shock Models: Hunger

	Tapogna et al.	Annual HDD Deviation	December HDD Deviation	December Shock
Intercept	0.015 1.04	0.007 0.50	0.008 0.57	0.008 0.61
Peak unemployment rate	0.236 3.85*	0.217 3.83*	0.212 3.73*	0.203 3.58*
Poverty rate	0.117 5.50*	0.112 4.47*	0.115 4.59*	0.117 4.66*
Share of population White non-Hispanic	0.0006 0.11	0.003 0.70	0.002 0.49	0.003 0.56
Share of population in a different house	0.108 4.24*	0.109 4.28*	0.108 4.22*	0.108 4.23*
Share of population under age 18	-0.002 -0.05	0.006 0.16	0.007 0.16	0.007 0.17
Share of population gross rent burdened	-0.027 -1.00			
Share of population contract rent burdened		-0.006 -0.30	-0.005 -0.27	-0.004 -0.21
Heating Degree Day Deviation		0.000004 1.57	0.000003 0.49	-0.005 -1.09
R-squared Adjusted R-squared	0.437 0.416	0.440 0.417	0.436 0.413	0.437 0.415

N=336, *p<.05

Annual Heating Degree Day deviation was not statistically significant in the panel model. January HDD deviation was also included, but the results were not statistically significant (results not shown). The deviation in Heating Degree Days in December was statistically significant at the 90 percent confidence level (t=1.65), with the expected positive relationship with food insecurity – the colder than average the December, the higher the food insecurity. So for each heating degree day increase in the deviation of December Heating Degree Days, there is a corresponding 0.002 percentage point increase in the food insecurity rate at the state level. Interpreting these results in terms of temperature, if December is 60 heating degree days cooler than average that translates into each day being 2°F cooler than average. If each day was 2°F cooler than average, food insecurity would be expected to increase by 0.12 percentage points.

Concerned that these models were capturing a deviation (in either direction) but not a true cold shock, a dummy variable to represent a cold shock in December was included to the model. If there December deviation in HDD was greater than 150, then the "December Shock" dummy equals 1. The December Shock variable is arguably statistically significant (t= -1.64, critical t=1.645), but with an unexpected negative relationship with food insecurity. This means that if each day in December is at least 5°F colder than average, then food insecurity decreases.

Spatial Fixed Effects Models:

Cross-sectional variation that is unaccounted for in the model, such as SNAP participation rates, cost of living, or even predominant industrial sectors may be correlated with the other explanatory variables (particularly rent burdened and weather variables). This unobserved heterogeneity is often referred to as individual fixed effects. If fixed effects are present, but unaccounted for in the model, then the least squares estimator of β is biased and inconsistent (Greene 2003). By introducing fixed effects variables into the regression model, we can control for unobserved heterogeneity.

Table 8.

Fixed Effects Models: Food Insecurity

	Tapogna et al.	January Temperature	REDTI July with Contract Rent
Intercept	0.012 0.40	-0.022 -0.73	-0.019 -0.68
Peak unemployment rate	0.461 3.63*	0.470 3.77*	0.366 3.16*
Poverty rate	0.432 10.34*	0.382 8.79*	0.436 8.91*
Share of population White non-Hispanic	-0.016 -1.56	0.008 0.65	-0.011 -1.10
Share of population in a different house	0.199 3.90*	0.165 3.24*	0.211 4.08*
Share of population under age 18	0.169 2.01*	0.241 2.82*	0.190 2.29*
Share of population gross rent burdened	-0.086 -1.51	-0.112 -1.97*	
Share of population contract rent burdened			0.008 0.22
January temperature		0.0005 3.51*	
REDTI July			0.0001 1.66
R-squared Adjusted R-squared	0.633 0.555	0.649 0.572	0.634 0.554

N=336, *p<.05

Table 9.

Fixed Effects Models: Hunger

	Tapogna et al.	January Temperature	REDTI July with Contract Rent
Intercept	0.026 1.66	0.013 0.81	0.014 0.97
Peak unemployment rate	0.206 3.02*	0.209 3.10*	0.167 2.68*
Poverty rate	0.111 4.97*	0.092 3.92*	0.112 4.27*
Share of population White non-Hispanic	-0.004 -0.67	0.005 0.82	-0.002 -0.31
Share of population in a different house	0.118 4.97*	0.105 3.81*	0.122 4.42*
Share of population under age 18	-0.036 -0.88	-0.013 -0.28	-0.031 -0.70
Share of population gross rent burdened	-0.036 -1.18	-0.046 -1.49	
Share of population contract rent burdened			0.002 0.10
January temperature		0.0002 2.46*	
REDTI July			0.00004 1.14
R-squared Adjusted R-squared	0.517 0.413	0.527 0.424	0.512 0.411

N=336, *p<.05

This analysis uses one observation in each year for each of the 48 states, creating 336 observations. As mentioned earlier, (T – 1) year dummy variables were included in the panel models. States can contribute error in the model with unobserved heterogeneity, meaning that each state could have individual characteristics that are constant over time and correlated with the independent variables (Kennedy 1996). Including state dummy variables in the panel models will control for state or individual fixed effects (N – 1)[3].

[3] Wyoming was the reference state, simply due to its alphabetical position.

Controlling for state fixed effects by including state dummy variables resulted in little change in the other explanatory variables in both the food insecurity and hunger models. Although the results are not shown, none of the state dummy variables were statistically significant at the 95% level in the food insecurity models, and only one was significant at the 90% level. This means that unobserved heterogeneity among states does not affect food insecurity rates. By contrast, in the very low food security models, roughly half of the state dummy variables were statistically significant at the 95% level, and nearly all of them were significant at the 90% level. This means that in terms of hunger, unobserved heterogeneity among states does affect hunger rates and it is important to control for state fixed effects.

ANALYSIS AND DISCUSSION

Multiple models were run in order to discover if weather shocks affect state hunger and food insecurity rates. As discussed above, there was little variance in the R^2 between the different models for either food insecurity or very low food security. Perhaps the most interesting result of the multiple models is that the percent of the population gross rent burdened has an unexpected negative relationship with food insecurity that is statistically significant at the 90 percent confidence level in many of the models. Because this result is found in each of the specifications, it is safe to assume it is not a statistical fluke, but instead comes from more serious misspecification of the model. Perhaps households that are rent burdened have some unobserved characteristics that are related to lower food insecurity.

The statistically significant unexpected sign on the gross rent burdened variable is possibly due to a key independent variable that was omitted from each equation, though it is difficult to discern from the literature what that variable or proxy might be. One explanation may be due to the strong positive relationship between food insecurity and poverty, because those who are poor are more likely to experience food insecurity. Perhaps those who are poor and food insecure have learned coping techniques such as utilizing housing programs they are eligible for such as Section 8, a federal program which helps families pay rent. Using a similar variable, contract rent burden, was less confounding because it was not statistically significant in any of the models. Using the alternate measure of rent burden also helped to disentangle the effect of the different weather-related variables by excluding the amount that households spend on utilities from the rent burden variable.

Cross-sectional variation in energy use and expenditures may be the key to understanding the somewhat counterintuitive results for the weather-related variables. Even states with similar weather patterns may still vary dramatically in terms of energy expenditures and types of fuels used for home heating and cooling. For example, there is a comparatively strong demand for renewable energy in Oregon where many residential customers can expect a 14.5 percent rate increase in 2011 to offset costs associated with adding wind energy and hydroelectric relicensing expenses (Oregon Public Utility Commission 2010). Some states, particularly in the Northeast, have a large proportion of households that rely on heating oil, making them more vulnerable to the volatility of petroleum prices.

Previous research has shown that a “heat or eat” effect exists at the household level; this analysis was unable to capture a definitive effect at the state level as two similar models had very different results. Using the deviation in December Heating Degree Days, this analysis showed that in colder December weather, food insecurity increases. However, when the “December Shock” variable was included to capture the effect of the coldest years, food security actually improved with more severe weather. The unexpected negative relationship between a cold shock in December and food security could be due to programs in place, such as Low Income Home Energy Assistance Program (LIHEAP), that help mitigate budget shocks from extreme weather. This analysis did, however, find a “cool or eat” effect at the state level using the Residential Energy Demand Temperature Index.

Finally, and perhaps most importantly, this research may have uncovered a sort of reverse ecological fallacy. An ecological fallacy is making the assumption or generalization that relationships or characteristics which exist as part of a group or aggregate also exist at the individual level. This research suggests that in terms of food insecurity, relationships that exist at the individual or household level cannot be generalized up to the aggregate or state level. That is to say assuming the model has not been mispecified (as theory does not directly point to an omitted variable or alternate functional form) and considering the somewhat drastic variation in the individual year models, perhaps the variables that predict household level food insecurity do not predict area food insecurity and hunger rates. The results do not suggest that households, particularly poor households, do not make tradeoffs, but that it is difficult to capture these tradeoffs at the state, or aggregate level.

CONCLUSION:

This research intended to determine the extent to which state level data – demographic, economic, and weather-related – can explain the differences in state hunger and food insecurity rates. To do so, a state level analysis for the year 2000 was selected as a base model for cross-sectional time-series data from 2002-2008. The research yielded somewhat unexpected, though interesting results. By running individual year regressions of the base model for each year of the panel data, I found that the model did not consistently explain food insecurity and hunger rates from year to year. Results varied in terms of signs and magnitudes of the coefficients, as well as the overall explanatory power of the model. Such dramatic variation suggests the group of factors that influence the prevalence of hunger vary by year. This variation could also be interpreted as a reverse ecological fallacy where the same variables used to predict household level food insecurity and hunger do not predict state level food insecurity and hunger.

Although there is outstanding research linking weather with hunger and nutrition, the literature is somewhat thin, and is mostly at the household level. By adding weather data to a state level demographic data, I hoped to contribute to the literature by capturing the effect that a weather shock had on state level food insecurity rates. The results from adding weather variables were unexpected and counterintuitive at times. Using a Heating Degree Day deviation and Heating Degree Day "shock" variable to capture a cold temperature shock produced opposing results. Adding the deviation in Heating Degree Days in December showed a "heat or eat" effect at the state level with colder weather being associated with increased food insecurity. However, when a variable to capture a more severe weather shock, defined as 150 or more Heating Degree Days above the December average, the relationship appeared to be reversed. This means that more severe December weather is associated with less food insecurity at the state level, which is counter to earlier research on food insecurity and weather at the household level.

Moving beyond the "heat or eat" effect and including the July Residential Energy Demand Temperature Index (REDTI) to the base model, a "cool or eat" effect was shown to exist at the state level. Increased energy demand in July, associated with comparatively warmer weather, was shown to have a positive effect on food insecurity at the state level. This research suggests that policy should move beyond the heat or eat dilemma, and should address energy burden throughout the year. Most federal funds for the Low Income Home Energy Assistance Program (LIHEAP) are spent during the winter (US Department of Health and Human Services 2009). In Oregon, the year round crisis program has only six percent of emergency funds left available by summer. Because households, particularly poor households, make difficult decisions regarding tradeoffs throughout the year, the social safety net should be responsive throughout the year to help mitigate the consequences of these tradeoffs. Most states do not have federal LIHEAP funds allocated for a cooling component, but typically operate a crisis fund that can be used for cooling assistance if funding is available. Other states, including Arizona, California, North Dakota and Washington, have integrated programs (US Department of Health and Human Services 2011). By creating integrated programs or setting aside some funding for cooling assistance, LIHEAP could better insulate against budget shocks for low income households that can occur at any point in the year.

The federal food stamp program, now called the Supplemental Nutrition Assistance Program (SNAP), is a cornerstone of the federal safety net, and its goal is to reduce food insecurity. This goal would be best met by working in conjunction with other programs that address the many issues low income households face. The Low Income Home Energy Assistance Program (LIHEAP) is relevant to this research, and like SNAP it is also a federally funded program administered at the state level. SNAP typically uses “standard utility allowances” as opposed to the true, fluctuating cost of utilities as part of the SNAP benefits calculation, which is often beneficial for SNAP recipients. However, some households do not receive this allowance because utilities are included in their rent. The cost of utilities is passed down to renter by the landlord, but by not receiving a standard utility allowance the household’s SNAP benefit level is reduced. By identifying households that have utilities included in rental costs and giving them a nominal annual LIHEAP payment, these households are then eligible for increased SNAP benefits. Some states, including Oregon in 2009, have already implemented this cooperative effort between SNAP and LIHEAP; states without this should consider implementing this collaboration.

This partnership helps generate additional financial resources for low-income households, but this collaboration is also beneficial in terms of a state’s ability to leverage federal funding. The Low Income Home Energy Assistance Program (LIHEAP) is a competitive block grant, so funding can vary by year or by a state’s institutional capacity to apply for funds. Including an “Energy and Eat” program as part of the LIHEAP application satisfies or bolsters required outreach and program coordination efforts for the state. A stronger LIHEAP application could bring more federal funding into the state, but an "Energy and Eat" program also helps leverage more SNAP dollars. SNAP is an entitlement program, meaning Congress authorized an open-ended appropriation bill so that those who qualify have the right receive benefits, however many people apply.

Including more state level variables in the model, such as SNAP participation rates, could strengthen this research. Future research might use spatial data to examine the relationship between climate and food insecurity; perhaps hungry people live in warmer climates. Using the published three-year food insecurity estimates in a similar model may also yield interesting results with more stable estimates of each of the variables.   Future analysis that includes types of fuel used and energy expenditures could be helpful to better understand how weather related shocks can impact food security at the state level.

Bibliography:

Bessec, Marie and Fouquau, Julien. (2008) The non-linear link between electricity consumption and temperature in Europe: A threshold panel approach. *Energy Economics.* 30: 2705-2701.

Bhattacharya, Jay; DeLeire, Thomas C; Haider, Steven; & Currie, Janet. (2002) Heat or Eat? Cold Weather Shocks and Nutrition in Poor American Families. UC Los Angeles: California Center for Population Research. Retrieved from: http://www.escholarship.org/uc/item/7cw7v2kk

Edwards, Mark and Weber, Bruce (2003). *Food Insecurity and Hunger in Oregon: A New Look.* Working Paper No. AREC 03-104 R. ScholarsArchive at Oregon State University. http://ir.library.oregonstate.edu/jspui/handle/1957/9251

Greene, William H. (2003) *Econometric Analysis.* New Jersey: Prentice Hall, Inc.

Gundersen, C. (2006). Are the effects of the macroeconomy and social policies on poverty different in nonmetro areas in the United States? *Rural Sociology, 71*(4), 545-572.

Gundersen, C., & Kreider, B. (2008). Food stamps and food insecurity - What can be learned in the presence of nonclassical measurement error? *Journal of Human Resources, 43*(2), 352-382.

Gundersen, C., & Oliveira, V. (2001). The Food Stamp Program and Food Insufficiency. *American Journal of Agricultural Economics, 83*(4), 875.

Grussing, Jay and Edwards, Mark (2006) *Non-Metropolitan Hunger and Food Insecurity in the Northwest*. Rural Studies Working Paper RSP 06-02. ScholarsArchive at Oregon State University. http://ir.library.oregonstate.edu/jspui/handle/1957/9258

Hanson, Kenneth. (April 2008) *Food Stamp Benefits Provide Fiscal Stimulus*. Amber Waves. USDA Economic Research Service.

Heim, Richard R; Lawrimore, Jay H; Wuertz, David B; Waple, Anne M; & Wallis, Trevor WR. (2003) The REDTI and MSI: Two New National Climate Impact Indices. *Journal of Applied Meteorology.* 42: 1435-1442.

Hirschl, T. A., & Rank, M. R. (1999). Community Effects on Welfare Participation. *Sociological Forum, 14*(1), 155-174.

Huang, J., Guo, B. R., & Kim, Y. (2010). Food insecurity and disability: Do economic resources matter? *Social Science Research, 39*(1), 111-124. doi: 10.1016/j.ssresearch.2009.07.002

Kaufman, P. R. (1999). Rural Poor have less access to supermarkets, large grocery stores. *Rural Development Perspectives, 13*(3), 19-25.

Kennedy, Peter (1996) *A Guide to Econometrics.* Cambridge, Mass: The MIT Press.

Martin, P. L., & Lane, S. (1977). Distributional Equity of the Food Stamp Program. *American Journal of Agricultural Economics, 59*(5), 1006-1012. doi: http://www.blackwellpublishing.com/journal.asp?ref=0002-9092

McConnell, Sheena and Ohls, James. (2002). Food Stamps in Rural America: Special Issues and Common Themes. In Weber et al. (eds). *Rural Dimensions of Welfare Reform.* Kalamazoo, MI: W.E. Upjohn Institute.

McKinnish, Terra G. Model Sensitivity in Panel Data Analysis: Some Caveats About the Interpretation of Fixed Effects and Differences Estimators. University of Colorado, Department of Economics. http://stripe.colorado.edu/~mckinnis/fe053100.pdf Accessed 31 Jan 2011.

Nord, M., Andrews, M., & Winicki, J. (2002). Frequency and Duration of Food Insecurity and Hunger in US Households. [Article]. *Journal of Nutrition Education & Behavior, 34*(4), 194.

Nord, Mark and Golla, Anne Marie. (2009). *Does SNAP Decrease Food Insecurity? Untangling the Self-Selection Effect.* USDA Economic Research Service, Economic Research Report Number 85.

Nord, M. and Kantor, Linda S. (2006). Seasonal Variation in Food Insecurity Is Associated with Heating and Cooling Costs among Low-Income Elderly Americans. *Journal of Nutrition.* 136:2939-2944.

Nord, M., & Leibtag, E. (2005). Is the 'Cost of Enough Food' Lower in Rural Areas? *Review of Regional Studies, 35*(3), 291-310. doi: http://economy.okstate.edu/rrs/

Rank, M. R., & Hirschl, T. A. (1993). The Link between Population Density and Welfare Participation. *Demography, 30*(4), 607-622.

Ruggles, Steven J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

Tapogna, J., Suter, A., Nord, M., & Leachman, M. (2004). Explaining Variations in State Hunger Rates. *Family Economics and Nutrition Review, 16*(2), 12-22.

USDA. (2010a) FNS: American Recovery and Reinvestment Act 2009 http://www.fns.usda.gov/pd/SNAPsummary.htm. Retrieved 18 Feb 2010

USDA. (2010b) FNS: Legislation. http://www.fns.usda.gov/snap/rules/Legislation/default.htm. Retrieved 6 March 2010.

USDA. (2010c) FNS: Supplemental Nutrition and Assistance Program. http://www.fns.gov/FSP/. Retrieved 2 March 2010.

USDA (2011a) ERS: Food Security. http://www.ers.usda.gov/Briefing/FoodSecurity/ Retrieved 1 Feb 2011.

USDA (2011b) ERS: Food Security in the United States: Definitions of Hunger and Food Security http://www.ers.usda.gov/Briefing/FoodSecurity/labels.htm. Retrieved 1 Feb 2011

US Department of Health and Human Services (2009) LIHEAP Brochure. http://www.acf.hhs.gov/programs/ocs/liheap/brochure/brochure.html. Retrieved 5 Mar 2011.

US Department of Health and Human Services (2011) LIHEAP Clearinghouse: Percent LIHEAP Funds by Program Component. http://www.liheap.ncat.org/tables/FY2011/components.htm. Retrieved 5 Mar 2011.

APPENDICES

Appendix: No South
Model: January Temperature - No South

No South: Even after removing Southern states in an attempt to correct for the unexpected positive relationship between warmer January weather and food insecurity, the result remained the same, with little difference in the magnitude of the coefficient or t-value (3.13 as opposed to 3.83 with all states). The Southern states removed were: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia.

	January Temperature
Intercept	-0.073 -2.52*
Peak unemployment rate	0.399 2.80*
Poverty rate	0.557 9.22*
Share of population White non-Hispanic	0.031 2.68*
Share of population in a different house	0.043 0.86
Share of population under age 18	0.318 3.85*
Share of population gross rent burdened	-0.013 -0.23
January temperature	0.0005 3.13*
R-squared Adjusted R-squared	0.558 0.532

N=238, *p<.05

Appendix: Year Dummy Variables
Model: July REDTI with Contract Rent

Dummy Variables: To control for temporal autocorrelation, year dummy variables were included to each panel model. I choose the last year in the data set, 2008, as the 'reference year' and omitted it from the model. Each of the included year dummy variables is statistically significant; meaning 2002-2007 is significantly different from 2008. Analyzing SAS Proc MEANS by year showed that from 2002 to 2007 the average food insecurity was between 10 and 11 percent, but in 2008 it jumped to 13.7 percent. This increase makes sense as 2008 was the beginning of the recent economic downturn.

	July REDTI with Contract Rent
Intercept	-0.031 -1.22
Peak unemployment rate	0.445 4.21*
Poverty rate	0.442 9.54*
Share of population White non-Hispanic	-0.004 -0.45
Share of population in a different house	0.187 3.93*
Share of population under age 18	0.239 3.10*
Share of population contract rent burdened	-0.010 -0.28
REDTI July	0.0001 1.89
2002	-0.030 -7.62*
2003	-0.030 -7.69*
2004	-0.022 -5.58*
2005	-0.027 -6.92*
2006	-0.028 -6.70*
2007	-0.022 -5.28*
R-squared Adjusted R-squared	0.581 0.564

N=336, *p<.05