ESSAYS IN STATE-LEVEL CLIMATE CHANGE POLICIES

By

Gi-Eu Lee

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ABSTRACT

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For decades climate change has been a key issue that concerns many people, as it can impact the economy and, to some extent, endanger human lives. Articles about climate change policies have been plentiful, but some aspects of the state-level policy analysis are still sparse because most policies have only been proposed within the past decade. The primary research goal of this dissertation, comprised of three essays, is to analyze state-level climate policies which have been less discussed and to provide better understanding of climate change policy analyses.

The first essay identifies the influence of complex temperature patterns on public support for government involvement in a regional agricultural sector's adaptation to climate change. This essay takes advantage of an unexpected warm spell that occurred during the period of the public support survey. A set of identification strategies are developed to identify the complex effects of temperature abnormality, resulting from temporal patterns as well as the interdependence of these patterns and other attributes of the abnormality. This study finds that, contrary to popular belief and most existing findings, when the general public experiences a more pronounced temperature abnormality, public support for the climate change adaptation policies does not increase and may even decrease. Our results provide better understandings of how temperature affects public opinions as well as an alternative explanation of the inconsistency between the fluctuating attitudes toward climate change and the growing body of scientific evidence.

The second essay measures the local acceptance of a biorefinery. The siting and operation of a biorefinery can have both positive and negative externalities for the host community. Given the externalities, local acceptability is a key factor affecting biorefinery location decisions and the likely success of this type of mitigation investment. Numerous articles discuss the economic impact of biofuels, but there is little systematic analysis of local acceptability of biofuel production facilities. Essay 2 explores factors that influence community attitudes toward biofuel facilities. It also assesses the strength of local acceptability or opposition by estimating the local community's willingness to pay (WTP) either to support or to oppose a proposed biorefinery. Essay 2 verifies the potential inconsistency between public support and net social welfare change and finds that, conditional on the respondents' baseline attitudes toward the biorefinery, the WTPs provide a more comprehensive picture of local acceptability. County level socio-economic characteristics are found to significantly influence the respondents' attitudes as well as the WTPs.

The third essay improves on a modeling method for the estimation of greenhouse gas emissions resulting from a local food policy, as buying foods locally may reduce food-miles and the associated transportation green gas emissions. This essay shows how the existing extended input-output lifecycle analysis (EIO-LCA) method used to estimate the transportation greenhouse gas emissions of the food systems may lead to biased results. We develop a modified EIO-LCA model that corrects this problem. This essay illustrates the approach and demonstrates to what extent the results might be biased if these issues are not corrected. As the biases can be large, this finding and the modified method are meaningful and informative for local food policy makers and researchers who wish to assess the impact of local foods on greenhouse gas emissions.

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Finally, I reserve my special appreciation to my family and to my mentor, Dr. Chang-Erh Chou. Without their emotional support and encouragement from Taiwan, I could not have overcome the challenges during my trip to pursue my doctoral degree.

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KEY TO SYMBOLS

Essay 1:

A_V: dependent variable, public attitudes toward the adaptation policy V

V: adaptation policies. G= general adaptation policy; A~D denote agricultural policies

A=state gov., corn and soybeans; B=state gov., fruits and vegetables,

C=national gov., corn and soybeans; D=national gov., fruits and vegetables

j: denotes the attitudes. 1=strongly agree), 2=somewhat agree), 3=don't know/refuse to answer, 4=somewhat disagree, and 5=strongly disagree

P(.): the log-odds ratio in which the probability that the respondent chooses j compares to the probability of base option being chosen.

***X**: a set of demographic variables*

Temp: the temperature abnormality

$\boldsymbol{\beta_{Vj}}, \gamma_{Vj}$*: coefficients estimated*

Essay 2:

Y: a dummy variable represents the WTP response

t_s: the bid value offered to the respondent conditional on the attitude.

S: indexes the attitude towards the biorefinery.

Z is a set of individual characteristics and socio-economic variables.

SQ: Square

Essay 3:

i and *j*: denote the producing (row) and buying (column) industries, respectively.

Z_{ij} : represents the value of the commodity produced by industry *i* and used as the intermediate inputs by industry *j*;

F_i : is the final demands for sector *i*,

Q_i : is total sector output for sector *i*.

a_{ij} : technical coefficient

I: identical matrix

D:is the diagonal matrix of the food-miles coefficients

g: is CO_2 coefficient (CO_2 equivalent per mile).

t: transportation mode

Im_{ij} : is the use of imported commodities as the intermediate input

Int_j: is value added component

FIm_i: is the value of imported commodity *i* consumed by the institutional sector.

M_i: is the row sum of imported commodity *i*.

ESSAY 1: PUBLIC ATTITUDES TOWARD AGRICULTURAL CLIMATE CHANGE ADAPTATION POLICIES AND THE INFLUENCE OF A WARM SPELL: A CASE STUDY FROM MICHIGAN

1.1 Introduction

Policies responding to climate change need public support (Urwin and Jordan, 2008), and an understanding of the attitudes of the general public can help form feasible action plans (Shwom et al., 2010). [1] Yet, the public attitudes toward climate change issues are not consistent with scientific findings of climate change. While the evidence of climate change is incremented, the level of belief in climate change / global warming[2] in the U.S. has been fluctuating (Borick and Rabe, 2014; Brulle et al., 2012; Leiserowitz et al., 2015; Nisbet and Myers, 2007; Poortinga et al., 2011; Ratter et al., 2012; Saad, 2015; Scruggs and Benegal, 2012; Weber and Stern, 2011). Short term temperature change are found to be a possible factor that influence public attitudes (e.g., Egan and Mullin, 2012).

The existing studies discussing temperature effects mostly use simpler strategies that only identify one or two aspects relating to temperature or its abnormality. In general, one of the following identification strategies is used in a study to capture the short term temperature effects: daily temperature or daily temperature departure from normal level (Brooks et al., 2014; Egan and Mullin, 2012; Goebbert et al., 2012; Hamilton and Stampone, 2013; Scruggs and Benegal, 2012; Zaval et al., 2014); the density or fraction of the days with abnormal temperature given a specific window (Deryugina, 2012); or categorizing temperature into a set of bins and calculating

[1] This essay is co-authored with members of my dissertation committee, Dr. Scott Loveridge and Dr. Julie Winkler.
[2] Global warming is one of the well-known aspects of climate change, and it was used more often than climate change in early public dialog about the issue. We use climate change as it refers to a broader sense of the phenomena (Zaval et al., 2014).

the days of each bin within a period (Deschênes and Greenstone, 2011; Ranson, 2014). These strategies either capture the effects of temperature's absolute level, its departure from normal level or comfortable level, or accumulated temperature impacts within a period.

The temporal attributes of temperature, such as the temperature fluctuation or continuous abnormality (a warm spell), have rarely been explored. One exception is Egan and Mullin (2012), who explore the effect of a heat wave.[3] To our knowledge, no study explores temperature fluctuation. Neither does the interaction among those temporal attributes and temperature deviation or other attributes. In fact, there is no conclusion about how temperature may influence public opinion. For instance, while Egan and Mullin (2012) as well as Scruggs and Benegal (2012) show that temperature within a short term window (7 days) has a statistically significant effect, Deryugina's (2012) study finds the variables capturing temperature records within shorter windows are not significant and those including records within longer windows are. As there are disagreements regarding if some of the simpler strategies exactly identify the weather effects that the scholars are interested in or identify the effects due to other non-weather factors (Jacobsen and Marquering, 2009), strategies that can capture different temperature attributes may help to understand complex effects and improve the effectiveness of temperature analyses.

Unlike the existing temperature effect studies, which explore the public opinions with regard to generic climate change issues such as perception, belief, or concern as they discuss the temperature effect (e.g., Brody et al., 2008; Brooks et al., 2014; Goebbert et al., 2012), we explore how the temperature influences public attitudes toward agricultural adaptation policy. Public opinion about the generic issues may not be a comprehensive predictor of public support to climate change policies since risk assessment and the expected impacts could vary across

[3] As a heat wave includes two attributes, continuity and abnormal heat, what Egan and Mullin (2012) identify is the marginal effect of continuity only. We will discuss it in section 2.

subpopulations (Scheraga and Grambsch, 1998). Understanding the public opinions on adaptation is informative to policy makers, especially when only few studies have measured the public's opinion about such policies (Nisbet and Myers, 2007; Palutikof et al., 2004).

How the general public support adaptation[4] policies for the agricultural sector is a topic that has not drawn enough attention (Nisbet and Myers, 2007). Adaptation is inevitable for the agricultural sector since its productivity can be quite sensitive to climate (Kurukulasuriya and Rosenthal, 2013; Mendelsohn and Dinar, 1999; Rose, 2015; Schlenker and Roberts, 2009). Existing studies mostly discuss policy makers' or farmers' perspectives rather than the general public's opinions on the policies for agricultural adaptation (see e.g., Deressa et al., 2009; Kurukulasuriya and Rosenthal, 2013). The public and agricultural producers may have divergent interest with respect to climate change policies. While farmers would tend to view it through the lens of effects on their incomes, climate change could impact the general public through food price increases or through the agriculture sector's spillover effects on the local economy (Hornbeck and Keskin, 2015). Thus, non-farmers' opinions should be informative during policy formation process. We use a survey to analyze Michigan resident's opinions about government action to support agricultural adaptation.

To explore the influence of temperature, we take the advantage of an unseasonal warm spell that occurred during our survey period and develop identification strategies to capture the complex effects due to the temperature departure from normality, the temporal patterns of the abnormality, and their interdependence.

Out analysis of the temperature abnormality shows that the influence is not continuous across the whole space of abnormality and that the effects of temperature abnormality and other

[4] Policies that aim to moderate the vulnerability or seek benefits in the context of climate change, according to IPCC (Intergovernmental Panel on Climate Change), may be classified as adaptation (IPCC, 2014), although in practical terms any action may also have attributes with regard to mitigation.

attributes are interdependent. We also find that, unlike what the existing literature may predict, increasing to some extent, the experience of longer warm spell, might lead to more opponents and fewer supporters around political interventions. In addition, our findings imply that the analyses of temperature effects on other contexts or areas may learn more about the effects through advanced identification strategies; to date these analyses adopt simpler strategies.

1.2 Literature Review

Contemporaneous temperature may influence public opinions about climate change issues in various ways. Temperature, especially abnormal temperature, has been well-recognized as a key attribute of climate change (IPCC, 2014) and may be seen as the signal of future risk due to climate. The discipline of psychology also suggests that temperature might influence one's attitude through a priming mechanism[5] (IJzerman and Semin, 2009; Johnson et al., 2010; Joireman et al., 2010; Williams and Bargh, 2008), as personal experience is a key factor determining an individual's opinion (Swim et al., 2009). Temperature can influence one's utility function (Deschênes and Greenstone, 2011) or the demand of other goods, so as air conditioning service approximated by appliances and energy use (Parti and Parti, 1980). As one's welfare is thus changed by temperature, her opinions about climate change policies may be affected.

Temperature can influence human activities in various areas. Ambient temperature moving toward comfortable level can increase one's satisfaction level. Seeing desirable temperature as a good, people consume it indirectly through other goods such as clothes, air conditioning (Deschênes and Greenstone, 2011), or travel to places with comfortable temperature. Exposure to undesirably high temperature can lead to loss of human lives

[5] Psychology studies have shown that temperature influences an individual's behavior (see e.g., Anderson, 1989; McCarthy, 2014; Vrij et al., 1994).

(Deschênes and Greenstone, 2011) or loss of labor productivity (Pilcher et al., 2002). Temperature may also change one's risk preference and influence the evaluation of investments with uncertainty, as people tend to be more aggressive at extreme temperature (Anderson, 1989; Baron and Bell, 1976; Howarth and Hoffman, 1984). Thus, temperature abnormality may influence stock market returns (Cao and Wei, 2005; Floros, 2008) and the crime rate (Ranson, 2014). The experience of past temperature can also update one's subjective recognition about the probability distribution of temperature abnormality (Deryugina, 2012).

Temperature can also have impacts on industry production, such as agriculture sector. Agriculture productivity is often a function of temperature (Schlenker and Roberts, 2009). The change of supply curve due to temperature will lead to the change of consumer surplus. If one is associated with the agricultural sector (such as a farmer or farmer's household) or lives in area where agriculture is important, temperature may directly affect local income or indirectly cast its influence through spillover effect (Hornbeck and Keskin, 2015). All these effects suggest temperature's influence on public opinions with respect to climate change and agricultural adaptation.

Early studies regarding the temperature influence on public attitudes mostly discuss the subjectively perceived temperature or the memory of temperature conditions (see Krosnick et al., 2006; Li et al., 2011; Palutikof et al., 2004). These subjective perceptions and images, however, are likely to be biased by inaccurate memory or other issues such as the respondents' choice of clothing on the day of the survey.

More recently, emerging studies explore how the belief in, or, concern of, climate change is affected by the actual temperature through various measures of temperature and its abnormality (Borick and Rabe, 2014; Brooks et al., 2014; Brulle et al., 2012; Deryugina, 2012;

Donner and McDaniels, 2013; Egan and Mullin, 2012; Hamilton and Keim, 2009; Hamilton and Stampone, 2013; Joireman et al., 2010; Zaval et al., 2014). The influences of temperatures are not consistent among all the studies, but, in general, these studies find the correlations between the attitudes and the temperature variables. The inconsistency might be due to the intricacy of temperature effects as the effects are likely to be composed by several attributes of temperature, such as the temporal patterns, and its abnormalities, such as deviation from normal level. If only one or two attributes are considered in an empirical model, its results will show limited parts of a whole picture.

While the non-opinion studies of temperature effect, such as stock market return (Cao and Wei, 2005) or crime rate (Ranson, 2014), often use actual temperature per se to identify the effect, temperature departure from the normal level and the average of that departure within a certain period are the more common strategies used to identify the effect on public opinions. Scruggs & Benegal (2012) and Egan & Mullin (2012) explore the impact of global warming belief through the 7 day average of daily temperature deviation and they both find a positive effect of temperature departure. Hamilton & Stampone (2013) test the belief in anthropogenic climate change by using daily temperature derivation as well as its average within a short term. They find the short term abnormality has a positive effect on belief. Zaval et al. (2014) use both perceived and actual short term temperature deviations to test several hypotheses with regard to the belief in global warming and find the actual temperature departures are not significant at 10% level. Brooks et al., (2014) discuss the effect of daily temperature deviation on the concern level of climate change and find that the effect is U shaped. Borick & Rabe (2014) examine the influence of seasonal temperature departure and find its effect is conditional on the respondent's political party.

These strategies might not be ideal as other attributes relating to temperature or its abnormalities are not well taken into consideration. While the mean of temperature deviations include more prior information of the abnormality, it might also reduce the variability as temperatures above normal and below normal could cancel out each other. The non-averaged departure of temperature does not have this drawback, but the historical information or accumulated level of abnormality several days prior is not captured by such a variable. Furthermore, temperature deviation may not distinguish normal variation of the temperature from the abnormal departure.

Some other strategies are developed for better exploring the temperature effects. Deryugina (2012) uses standardized temperature deviation to take the normal variation into account. This study also uses fraction of days with abnormal temperature within a window to explore impacts of the cumulative experience of temperature abnormality, and it finds that the fraction of the abnormal days may have statistically significant influence if the window is longer (mostly more than 14 days). However, this method measures the temperature abnormality regardless how the occurrences of abnormality are scattered.

The temporal patterns of abnormal temperature may also be influential. For instance, when the abnormal temperature happens in a consecutive pattern as a heat wave or a warm spell, it may have a stronger effect. Egan & Mullin (2012) discuss the effect of a heat wave by indexing heat wave experience as the respondents who experienced the temperatures at least 10 degrees above normal for 7 consecutive days in a 21-day window prior to the survey date. As they are interested in the marginal effect of one of a heat wave's attribute, continuity, Egan & Mullin (2012) compared the estimates from the respondents who experienced a heat wave with those who also experienced at least 7 days of, not consecutive however, abnormal temperature within the same window. The heat wave experience index, not comparing to others, however, includes impacts due to both continuity and abnormal heat. Egan & Mullin (2012) also modified their specification by adding a variable which counts the days between the survey date and the conclusion of the heat wave to identify how long the heat wave effect may lapse. But this coefficient is not significant although the predicted values of the dependent variable are significant when the value of lapse used is smaller than 4 days.

The above strategies, still, do not capture the fluctuation of short term temperature or the potential interdependence among temporal patterns and abnormalities. If the temperature drops from extremely hot to unusual cold, such fluctuation may be considered as a climate change phenomena, regardless it is actually caused by the changing climate or not. In an unusually cold or hot spell, may be more pronounced to the general public as the unusual spell may draw more attentions to weather. Thus, we develop strategies to capture more temperature attributes and the interdependence to contribute to the understanding of the temperature effects.

1.3 Data

1.3.1 Survey and Questionnaire Design

The measures of the public attitudes are based on a poll in spring 2012[6] supplemented with information from secondary sources. We construct five questions to elicit public opinions about adaptation, and to explore whether agricultural adaptation may be different from the adaptation policy for the overall economy (here after, general adaptation) and the extent to which opinions depend on crop type and government level as some crops are more regionally planted. Hereafter, the question about state government's role in helping corn and soybean farmers is

[6] It is the State of the State Survey (SOSS) conducted by Michigan State University. Please see Appendix A.1 in the supplemental document for the details of the five dependent variables, questionnaire design, and survey method.

denoted as SGCS, and that in helping fruit and vegetable farmers is denoted as SGFV. Similarly, the questions about national government's role in helping the two types of farmers are denoted as NGCS and NGFV, respectively.

Michigan has one of the most diverse agricultural sectors in the U.S. (Michigan Department of Agriculture and Rural Development, 2013). Corn and soybean production is important in terms of value as well as cropping areas in national ranks (USDA, 2014), while fruit and vegetable farms are locally important and additionally provide amenity services used by the state government to bolster the important tourism sector (Michigan Department of Agriculture and Rural Development, 2012). Thus, one question measures the public opinion about governmental help for employers to adapt without specifying the industry sector, and four agricultural adaptation questions are constructed by level of government (state or national) and crop types (corn-soybeans compared to fruit-vegetables).

The five questions were included in a stratified random sample telephone survey of 963 Michigan adults conducted from mid-February to mid-April in 2012. At the beginning of the survey, we use the cheap talk method to elicit the true attitudes as stated preference research would do (Kling et al., 2012) although these questions are not designed for estimating willingness to pay. The survey included standard questions about the respondent's demographic information. These data are used for individual variables in the regression model. Due to the stratification scheme, the survey provides information to weight the sample so that the results can represent the proper distribution in terms of population, age, gender, etc.

1.3.2 Secondary Data

The daily records of maximum temperature are obtained from National Climatic Data Center (NCDC)'s first order Automated Surface Observing System (ASOS) stations in Michigan. The records of daily normal temperature with regard to the chosen stations are from National Oceanic and Atmospheric Administration (NOAA). NOAA defines the normal temperature by the average of 30-year (1981-2010) daily records (Arguez et al., 2012).[7] NOAA's definition is more often used in the analyses although there are alternative definitions. The standard deviation of daily temperature is also obtained from NOAA. Similar to Perdinan & Winkler (2015), we employed Euclidean distance, and each respondent's county-of-residence was mapped onto closest ASOS.

County level data are retrieved from U.S. government sources. County level unemployment rate is obtained from Bureau of Labor Statistics, United States Department of Labor. The agricultural sales data is obtained from the 2012 Census of Agriculture (USDA, 2014). The urbanization level is from USDA's 2013 Rural-Urban Continuum Codes (USDA, 2013), which is the closest version to our survey year. There are nine different levels of urbanization. We combine the two smallest metro adjacent and the two smallest non-metro adjacent codes[8] so that each level has enough observations for analysis.

1.4 Empirical Methods

1.4.1 The Possible Aspects of Temperature Abnormality

During our survey period, two significant temporal patterns of temperature might be correlated with the abnormality (Figure 1.1). Figure 1.1 only shows how the daily maximum

[7] NOAA does not have 30 year average temperature for February 29 (leap year), so we average the adjoining days.
[8] The definition of each code can be found at: http://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation.aspx.

temperature deviated[9] from normal daily temperature during our survey period, since the daily maximum temperature per se is almost parallel to its deviation. We can find that, there was a warm spell (continuity) occurring during our survey period with fluctuation.

In March 2012, the northern states, including Michigan, in the Midwest experienced almost record breaking high temperature (NOAA National Climatic Data Center, 2012). For 16 consecutive days, the daily temperature deviation was higher than normal by at least 10.6^{o} F. The mean departure during this warm spell was 26^{o} F. The respondents surveyed on different days during the warm spell had different numbers of consecutive days temperature abnormality. While Egan & Mullin (2012) explored the influence of a 7-day heatwave, we can explore the effect when the consecutively abnormal heat lasts longer. The length of the warm spells allows us to explore what happens when residents experience abnormal heat for more than a week.

For some days within or beyond the warm spell, the temperature fluctuated significantly. By fluctuation, we define it as the difference of temperature between two consecutive days. Our definition reflects the temporal change of temperature, and this gives an more intuitive idea about fluctuation than Deryugina's (2012) idea that the fluctuation is defined by the departure from normal temperature. Even in the warm spell, there was dramatic temperature change between two days. Thus, there could be composite effects due to the interdependence of temperature departure, consecutive heat, and the fluctuations.

[9] The data is averaged from the chosen stations in Michigan to represent the abnormality of the state.

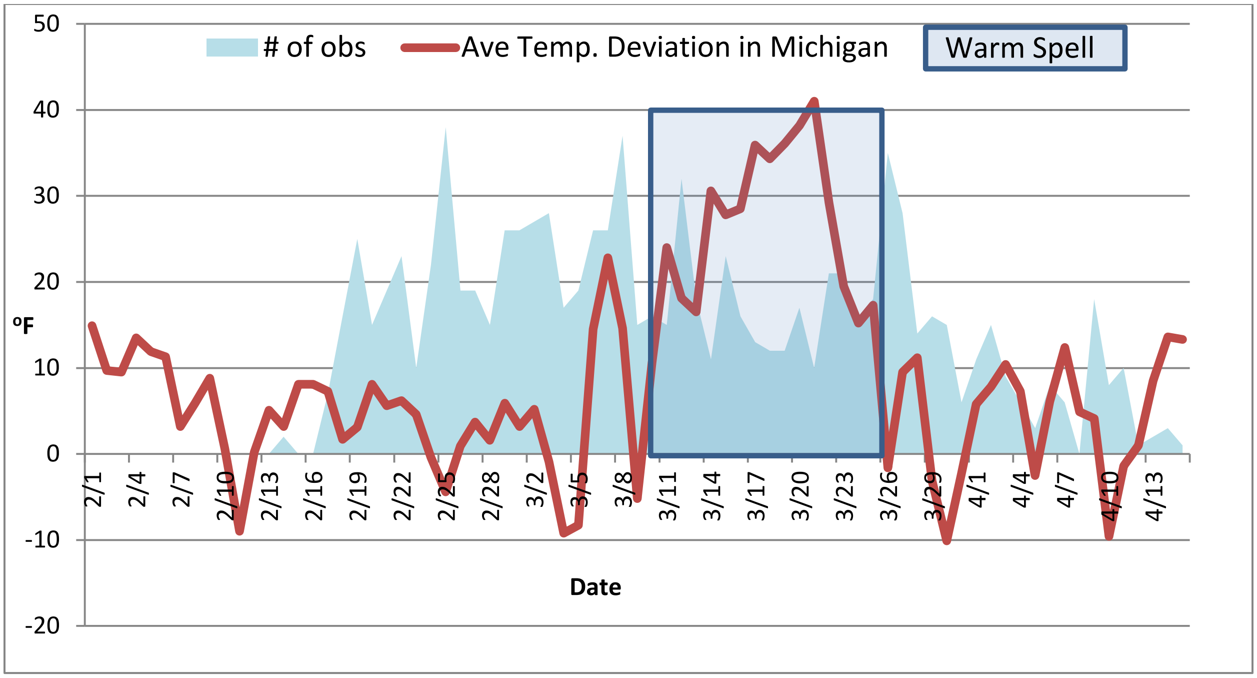

Figure 1.1 Deviations of Daily Maximum Temperature Deviations from 30 Year Normal and Number of Survey Observations.

For some days within or beyond the warm spell, the temperature fluctuated significantly. By fluctuation, we define it as the difference of temperature between two consecutive days. Our definition reflects the temporal change of temperature, and this gives an more intuitive idea about fluctuation than Deryugina's (2012) idea that the fluctuation is defined by the departure from normal temperature. Even in the warm spell, there was dramatic temperature change between two days. Thus, there could be composite effects due to the interdependence of temperature departure, consecutive heat, and the fluctuations.

1.4.2 Strategies for Daily Fluctuation and Longer Warm Spell

As the existing strategies cannot capture the temporal patterns of temperature and the complex effects due to interdependence, we develop strategies to identify these effects.[10] To capture the effect due to temperature fluctuation, we constructed a variable by subtracting the daily temperature deviation one day prior the respondent's survey date from that of the survey date. This variable captures the change between two days as daily temperature and temperature deviation are almost parallel, and the temperature deviation further captures the difference from long term mean value.

$$\begin{aligned} &Temperature\ Deviation\ Fluctuation_{d,s} \\ &\qquad = (Daily\ Temperature\ _{d,s} - Daily\ Normal\ Temperature_{d,s}) \\ &\qquad - (Daily\ Temperature\ _{d-1,s} - Daily\ Normal\ Temperature_{d-1,s}) \end{aligned}$$

In above equation, date is represented by d and s denotes the weather station. The fluctuation can also be approximated by percentage change by taking natural logarithm on the two daily maximum temperatures as the following:

$$Temperature\ Fluctuation\ in\ \%_{d,s} = ln\ Max\ Temperature_{d,s} - ln\ Max\ Temperature_{d-1,s}$$

To identify the effect due to a longer experience with the warm spell, we propose warm spell time index variables and 3-day index variables. We also construct interaction terms among the time index variables, temperature deviation, and the fluctuation. Since we want to explore the effect due to the experience of longer consecutively abnormal heat, instead of using one index variable to represent the whole warm spell, we create a set of dummy variables that represent the first half (8 days for each half) and second half of the warm spell as well as before and after the

[10] We adopt two types of strategies in the literature for comparison and robustness check. Details about the conventional strategies can be found in Appendix 1.A.2.

warm spell.[11] We define March 10 ~ 25 as the warm spell.[12] We assume no respondent travelled away from the state during our analysis period. Since Egan & Mullin's (2012) definition of heatwave experience is 7 consecutive days abnormal heat which happened at most 21 days prior to the survey date and our definition is simply time dummy variables, to avoid confusion, we distinguish the two terms although both terms describe a period of hot days.

The advantage of this strategy is that all effects due to the abnormal temperature can be captured by the time dummy variables. While the temperature effect can be a composition of temperature deviation, temporal continuity of abnormal heat, the fluctuation, etc., time index variables capture all the related effects during the sub-period. In fact, other effects during that period, if not controlled by other variables, can also be captured by time index variables. This may raise concerns if we include the effects other than temperature. However, in practice the issue seems inconsequential since our survey period is relatively short making other types of shocks unlikely.

In addition, the time dummy variables can also capture different accumulated levels of abnormal warm spell experiences. Respondents surveyed during the second half of warm spell experienced the first half of warm spell, and those surveyed after the warm spell have the experience of the whole warm spell. Thus, we can capture the partial effect of more warm spell experience by comparing the dummy variables.

To have higher resolution of the composite effect due to temperature, we further construct a set of time index dummy variables to represent every 3 days in the survey period. The 3-day dummy variables provide a closer look at the influence of the warm spell and we can

[11] According to NOAA National Climatic Data Center (2012), except for the west coast, the rest continental U.S. was experiencing the warm spell. So if there was such incompliance, it should not be a serious issue.
[12] We also moved the window of the warm spell one or two days forward or backward for robustness check of the definition of warm spell. In general we find similar results.

differentiate the effect of accumulated experience to the level of three days. The later the respondents were surveyed, the more abnormal temperature they were likely to have experienced. Three days is the shortest span of time dummy variables we can construct without causing practical issues due to too few observations for certain dummies, as the number of observations on each day is not evenly distributed.

While using the time dummy variables has the advantage of including all the uncontrolled effects varying across time, the disadvantage is that, among the different temperature effects, we cannot isolate the effect due to temperature deviation, or due to fluctuation. Thus, we construct interaction terms between the warm spell time index variables and the temperature deviation to model the composite effect due the complex interaction of temperature effects. In the representation of the interaction strategy, WS_p denotes the warm spell dummy variable, p, in temporal order, denotes the four warm spell sub-periods from that before warm spell (p = 0) to that after warm spell (p = 3), *TD* denotes temperature deviation, and *TF* denotes temperature fluctuation in percentage change as *d* and *s* denote date and weather station, respectively.

$Interaction\ Strategy$:

$$TD_{d,s} + TF_{d,s} + TD_{d,s} \cdot TF_{d,s} + \sum_{p=1}^{3} WS_p + \sum_{p=1}^{3} WS_p \cdot (TD_{d,s} + TF_{d,s} + TD_{d,s} \cdot TF_{d,s})$$

1.4.3 Empirical Model

Multinomial logit regression is used in our analysis. As the survey data are weighted, a robust form of variance is used by default in the Stata package that estimates the multinomial logit model. We choose this regression model for two reasons. First, we can make less restrictive assumptions for our analysis than ordered logit. The options of the outcome variables may be not ordered, which is reasonable as we included the “don’t know / refuse to answer” option into our analysis. The multinomial logit also allows the violation of parallel assumption required by ordered logit.[13] Second, the results of multinomial logit regression are intuitively easier to interpret than generalized ordered logit although the latter can also relax the parallel assumption. The coefficient estimated in multinomial logit regression is the effect of the corresponding control variable on the log-odds ratio of the selected and base outcomes.

There are five regression equations for each of the identification strategies as we have five dependent variables. Equation (1.1) is the simplified representation of the log odds ratio of attitude j of the v adaptation policy (A_V), which is a function of socio-economic variables $\boldsymbol{X}$ and temperature variable. The variable *Temp* denotes the identification for temperature effects. For instance, *Temp* can be the variable of temperature deviation or the set of time index dummy variables. Details about the symbols in equations can be found in Appendix 1.A.4.

$$(1.1) \quad P(A_V = j) = \alpha_{Vj} + \boldsymbol{X}\boldsymbol{\beta}_{\boldsymbol{Vj}} + \gamma_{Vj} Temp$$

The choice of control variables is based on empirical studies mentioned in the literature review except for the variables to identify the specific temperature effect. The socio-economic variables found to influence the public belief in or concern about climate change include: age, gender, race, education level, political ideology, economic status, media exposure. We adopt these variables in the regression except for the media exposure due to lack of data at the appropriate scale.[14] Still, our identification strategy of using time dummy variables may capture this unobserved effect if there was more media exposure during a certain period. We also include

[13] We test the parallel assumption and find it is violated in some variables.

[14] Some studies use the number of news reports in major TV channel to index the media exposure. But it is hard to know if this index can properly approximate media exposure across different groups or regions of Michigan.

a categorical variable which represents the urbanization level of each county to capture the unobserved regional level effects clustered at different urbanization levels.

Since local economic status may also influence public opinion, we include the local unemployment rate, as suggested in Scruggs & Benegal (2012) and Brulle et al. (2012), to capture the potential influence of local economy. While we distinguish crop types for the public attitudes by using corn and soybeans as well as fruit and vegetables, we also include the sales of these crops in the model to explore if the importance of a certain commodity in local economy would influence the public attitudes.

1.5. Results

1.5.1 Survey Response Frequencies

Survey response frequencies may provide some insight for our analysis through a non-econometric view. Table 1.1 shows how public attitudes vary through sub-periods of the survey due to extreme temperature event. Table 1.1 only provides the frequencies of the general adaptation and agricultural adaptation with regard to national government and corn / soybeans farmers as we find the attitudes toward agricultural adaptations are significantly more supportive than that of the general adaptation. The differences among the agricultural adaptations are not significant, however. The basic frequencies and patterns were broadly similar across government and crop types.[15]

The temperature has similar effect on both the general adaptation and agricultural adaptations. In both general and agricultural adaptation, as expected, during the whole warm spell the respondents were more likely to agree to the statements of adaptation (say, 72.7% for

[15] The frequencies of attitudes toward the other three agricultural adaptations can be found in Table 1.B1 in Appendix 1.B.1. The statistical tests for the differences among the measures of public opinions on the five adaptations are discussed in section 1.5.2.

NGCS) than in pre-warm-spell period (66.2% for NGCS). If we split the warm spell into two sub-periods, we find that, although the extreme temperature deviation appears to have had a strong effect on the respondents surveyed during the first half of the warm spell, in the second half of the warm spell, the proportion of agreement dropped to a level lower than that before the warm spell. After the warm spell, the support rates bounced back somewhat but were still lower than the pre-event level.

The result shows experiencing a longer warm spell did not result in higher rates of agreement on the statements. This finding is quite different from most of the existing literature that found the first derivative (or the second derivative in Brooks et al. (2014)) of temperature or its deviation on the public attitudes is non-negative (e.g., Borick and Rabe, 2014; Brooks et al., 2014; Egan and Mullin, 2012). The rate of support in second half of the warm spell dropped to the level lower than it was in pre-warm spell suggests that more experience of the abnormality neither increased the positive effect nor just vanished. There could be certain negative effect with more experience of a warm spell so that the proportion of opponents is lower than its pre-warm spell level.

Table 1.1 Michigan Residents' Attitudes toward General Adaptation and NGCS Adaptation Before, During, and After the Warm Spell (WS)

Unit: %

	Before WS	1st Half of WS	2nd Half of WS	After WS	Warm Spell	All Dates
			General Adaptation			
Strongly Agree	16.9	19.8	21.4	7.6	20.4	15.8
Somewhat Agree	32.1	41.0	24.2	41.0	34.5	35.0
Subtotal	49.0	60.8	45.6	48.6	54.9	50.8
Somewhat Disagree	32.8	28.7	27.7	26.5	28.3	29.8
Strongly Disagree	15.0	6.8	21.3	23.3	12.5	16.3
Subtotal	47.9	35.5	49.1	49.9	40.8	46.1
Don't know	3.1	3.7	5.3	1.5	4.3	3.1
			National Government Role - Corn/Soybeans			
Strongly Agree	15.9	34.0	27.5	8.7	31.4	19.1
Somewhat Agree	50.2	45.3	34.8	54.6	41.2	48.4
Subtotal	66.2	79.3	62.3	63.4	72.7	67.6
Somewhat Disagree	16.7	9.5	10.7	15.8	10.0	14.3
Strongly Disagree	12.8	7.3	22.7	16.7	13.3	13.9
Subtotal	29.5	16.9	33.4	32.5	23.3	28.3
Don't know	4.3	3.8	4.3	4.1	4.0	4.2

Source: Author calculation based on SOSS, 2012.

1.5.2 Test Differences among the Attitudes

We test if the public attitudes vary across adaptation types due to the suspect that the public support may depend on to whom is beneficial by the policy. Using the mean value of each dependent variable or the proportion of the j^{th} outcome of each dependent variable,[16] we test hypothesis 1) attitudes about the general adaptation are the same as those about the agricultural adaptations; and hypothesis 2) public attitudes about the four variations of agricultural adaptation are not different. The testing results are reported in Table 1.2. Jointly, we can reject the H_0 that

[16] We also test the cross-restrictions of the coefficients among five attitude predicting equations. We treat the five regressions as seemingly correlated regression (SUR) system so that the estimator is robust to the potential unobserved correlation among the attitudes. The results are reported in Table 1.B2 and Table 1.B3 in Appendix 1.B.2.

attitudes about the general adaptation are the same as those about the agricultural adaptations. Either the mean value or the proportion of each choice is different at 1% level of significance. Pairwise, except for the proportion of the option, “don’t know / refuse to answer” and that of “strongly disagree,” the attitudes about the general adaptation is different from that of each of the four agricultural adaptations with respect to mean value and the proportions of the options. This implies hypothesis 1 is confirmed with at least 10% level of significance.

The attitudes about the four variations of agricultural adaptation are not different except for the choice of “somewhat agree” in pairwise test of SGCS-SGFV and SGCS-NGCS. In the rests, jointly or pairwise, both the mean values and the proportions of the options are not significantly different across crop types and government levels in general. We fail to reject hypothesis 2 by these results.

Table 1.2 P-values of the Test of Difference between Adaptation Questions

	G=A=B=C=D	G=A	G=B	G=C	G=D		
Mean	0.000***	0.000***	0.000***	0.000***	0.000***		
Strongly Agree	0.000***	0.009***	0.046**	0.166	0.060*		
Somewhat Agree	0.000***	0.043**	0.002***	0.002***	0.011**		
DNRA	0.002***	0.367	0.409	0.255	0.783		
Somewhat Disagree	0.000***	0.002***	0.001**	0.000***	0.001***		
Strongly Disagree	0.000***	0.268	0.056*	0.128	0.132		
	A=B=C=D	A=B	A=C	A=D	B=C	B=D	C=D
Mean	0.355	0.228	0.868	0.774	0.551	0.316	0.433
Strongly Agree	0.513	0.283	0.250	0.458	0.717	0.885	0.345
Somewhat Agree	0.190	0.037**	0.047**	0.293	0.976	0.247	0.234
DNRA	0.765	0.758	0.711	0.717	0.887	0.430	0.469
Somewhat Disagree	0.444	0.374	0.149	0.997	0.540	0.536	0.285
Strongly Disagree	0.438	0.154	0.967	0.868	0.349	0.269	0.809

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables. DNRA: don’t know/refuse to answer

++ $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

1.5.3 Influence of Abnormality: Conventional and Fluctuation Strategies

We report the results adopting commonly used identification strategies in Table 1.B9 in Appendix 1.B.[17] Both *temperature* and *temperature deviation* can explain the log-odds ratios of "strongly agree" of the adaptation statements at mostly the 5% or 10% level for the general adaptation statement. The results also indicate temperature has a positive effect for strong opposition toward the statements of state government's role (SGCS and SGFV). When including the squared term to test for non-linearity, we find *temperature deviation* and *temperature* are non-linear in predicting the log-odds ratio of "somewhat agree" in general adaptation, and the latter is also non-linear for NGCS adaptation. Overall, the non-linearity is not pervasive and depends on the type of adaptation. *Standardized temperature deviation* should capture the effect after taking the normal variation into account and it is not significant in explaining attitudes of general adaptation at the 10% level. The *average temperature deviation* has fewer significant coefficients in predicting the attitudes toward the five adaptation statements. This reflects our concern that, when the information on short term temperature variation is averaged out, it does not perform well in explaining the attitudes when the same mean temperature deviation has different variance.

We also explore several methods of measuring respondent experience of the heat wave (Table 1.B10 in Appendix 1.B). No matter whether the abnormal heat is defined by 10^{o} F or 1.645 standardized temperature deviation, the experience of heatwave seems not to have influence. Yet, the dummy variables which index if the temperature on the survey date was higher than the thresholds, i.e. above 10^{o} F or 1.645 standardized temperature deviation, on the day, explain the probability of choosing "strongly agree" with positive and significant

[17] Results of socio-economic variables are reported in Table 1.B4 ~ Table 1.B8 in Appendix 1.B. The discussion of the results can be found in Appendix 1.B.3.

coefficients. This may be because the definition heatwave experience recognizes a long window (21 days) so that this strategy cannot distinguish respondents who had the heatwave shock yesterday and who had that shock three weeks ago.

The results of temperature fluctuation defined by percentage change are also reported in Appendix Table B10. No matter how the fluctuation is defined, the fluctuation does not explain the attitudes with significance at 10% level if our model only includes temperature fluctuation as the strategy to capture the effect of temperature.

1.5.4 Warm Spell Time Index

Using the identification strategy of the warm spell indexes mentioned above, we find that the time index dummy variables can explain the "strongly agree" choice in terms of significance as *temperature* or *temperature deviation*. The coefficients of warm spell indexes are also significant in predicting some of the log-odds ratio of "somewhat agree" and that of "strongly disagree" for some adaptation statements (Table 1.3).

The first half of the warm spell has coefficients that are mostly positive, especially when the coefficients are significant, for the non-base attitudes. By comparing its coefficients of supportive attitudes with that of strong denial, the coefficient of "strongly agree" is larger than that of "strongly disagree" in each of the adaptation statements. This implies that the first half warm spell led to lower probability of choosing mild opposition and resulted in higher probability for strong support than that for strong opposition.

The second half of the warm spell has significant coefficients in: strongly agree of NGFV (national government's role in helping fruit and vegetable farmers), somewhat agree of SGFV and NGFV, and strongly disagree of NGCS and NGFV. Similarly, all these significant coefficients are positive. While the average temperature in the second half of the warm spell was about 4^{o} F higher departure from normal level than the first half, it seems hotter and longer experience of a warm spell does not result in stronger positive effect than the first half of warm spell. In fact, second half warm spell may be associated with a negative effect. For NGFV, three coefficients of this time index are significant and positive. Since the coefficient of “strongly disagree” is larger than the two supportive attitudes, it implies that, when respondents were surveyed in this period, they had higher probability to choose this strong opposition attitude than the two supportive attitudes when considering the NGFV statement. In fact, we may draw the same conclusion if we ignore the significance, since all the coefficients of “strongly disagree” are larger than those of the supportive attitudes.

The dummy of after warm spell has significant coefficients in: “somewhat agree” of general adaptation, and “strongly disagree” of general adaptation, SGCS and SGFV. Similar to the results of second half warm spell, we may conclude that this back-to-normal period led to higher probability to choose strong opposition. Quite different from Egan & Mullin’s (2012) conclusion that the experience of heatwave effect may vanish after three days from the end of heatwave, our results suggest, after the warm spell, the effect existed and is negative.

We also construct time index variables that define the warm spell with lags of 3 days and 7 days to explore the potential lagged effect (Table 1.B11 and Table 1.B12 in Appendix 1.B). For either the first half, second half, or after warm spell, as expected, the longer the time indexes are lagged, the more the effects vanish. This result supports Egan & Mullin’s (2012) finding rather than Deryugian’s (2012) conclusion.

Table 1.3 Results of Warm Spell (WS) Identification Strategy

Dependent Variable	G	A	B	C	D
Strongly Agree					
1st Half of WS	1.154**	1.761***	1.899***	1.900***	1.137*
	(0.558)	(0.547)	(0.542)	(0.665)	(0.605)
2nd Half of WS	0.635	0.185	0.750	0.795	1.470**
	(0.589)	(0.598)	(0.594)	(0.607)	(0.575)
After Warm Spell	-0.195	0.159	0.280	-0.474	0.105
	(0.614)	(0.550)	(0.524)	(0.619)	(0.532)
Somewhat Agree					
1st Half of WS	0.722	1.416***	1.361**	0.742	0.506
	(0.455)	(0.501)	(0.529)	(0.594)	(0.566)
2nd Half of WS	0.221	0.200	1.048*	-0.028	1.302**
	(0.513)	(0.536)	(0.573)	(0.591)	(0.550)
After Warm Spell	0.999**	0.491	0.651	0.098	0.583
	(0.448)	(0.466)	(0.449)	(0.485)	(0.447)
DKRA					
1st Half of WS	0.659	2.449*	0.741	1.392	-1.483
	(0.872)	(1.291)	(0.910)	(1.088)	(0.936)
2nd Half of WS	-0.046	1.075	1.145	-2.874	-3.109
	(1.074)	(1.198)	(0.806)	(1.894)	(2.248)
After Warm Spell	-1.256	0.419	-1.444	-0.511	-1.106
	(1.216)	(0.870)	(0.952)	(0.786)	(0.920)
Strongly Disagree					
1st Half of WS	-0.237	1.635**	1.535**	0.285	-0.167
	(0.688)	(0.678)	(0.716)	(0.727)	(0.702)
2nd Half of WS	0.867	1.096	0.645	1.045*	2.274***
	(0.647)	(0.688)	(0.664)	(0.625)	(0.617)
After Warm Spell	1.083**	1.042*	1.211**	0.016	0.766
	(0.500)	(0.564)	(0.600)	(0.551)	(0.568)
N	793	793	793	793	793
P	0.000	0.000	0.000	0.000	0.000
F	24.725	9.334	38.095	26.903	20.204

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables. DNRA: don't know/refuse to answer.
++ Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1.5.5 3-Day Time Index

The results of 3-day dummy variables for all the adaptation statements are reported in Table B13. Using this set of time indexes, we can explore the composite effect of a specific time period with a higher resolution. We can thus verify if the effect after a warm spell is contributed by the first three days after warm spell through the results of 3 day time indexes. Our results show that for all the adaptation statements, the dummy variable denoting the three days right after the warm spell has no significant coefficients for "strongly disagree." Instead, its coefficients are significant for "strongly agree" in SGCS and NGCS. During the period after the warm spell, for the three statements (general adaptation, SGCS, and SGFV), the opposition mostly came from April; more 3-day variables are significant in the two weeks of April.

Figure 1.2 shows the relationship between the point estimates of the 3-day indexes for SGCS and the temperature deviation.[18] In the six days that the temperature was highest, the coefficients of the two corresponding dummy variables are not significant for all the attitudes. During the warm spell, it was the first six days and the last three days that have significant effect on the attitudes. This further confirms that more continuous days experiencing abnormal heat did not always lead to higher support of climate change adaptation. There could be other types of weather effects than temperature departure that affect the public attitudes. While the coefficients of the last 3-day dummy variable in the warm spell are significant for both strong support and opposition, the former has smaller coefficient than the latter with regard to the regressions of SGCS, NGCS and NGFV. Thus, this short period caused higher probability to choose "strongly disagree" than to choose "strongly agree" for the three statements. But for general adaptation and SGFV, this short period leads to higher probability of choosing strong support than choosing strong opposition.

[18] The coefficients of 3 day dummy variables are reported in Table 1.B13 in Appendix 1.B.

After the warm spell, positive temperature deviation seems to have a significant effect on the log-odds ratio of "strongly agree" and that of "strongly disagree." However, since the two attitudes' corresponding coefficients do not have a clear pattern of their relative scale, we cannot conclude whether the temperature deviation in this period led to higher probability of strong support or strong opposition.

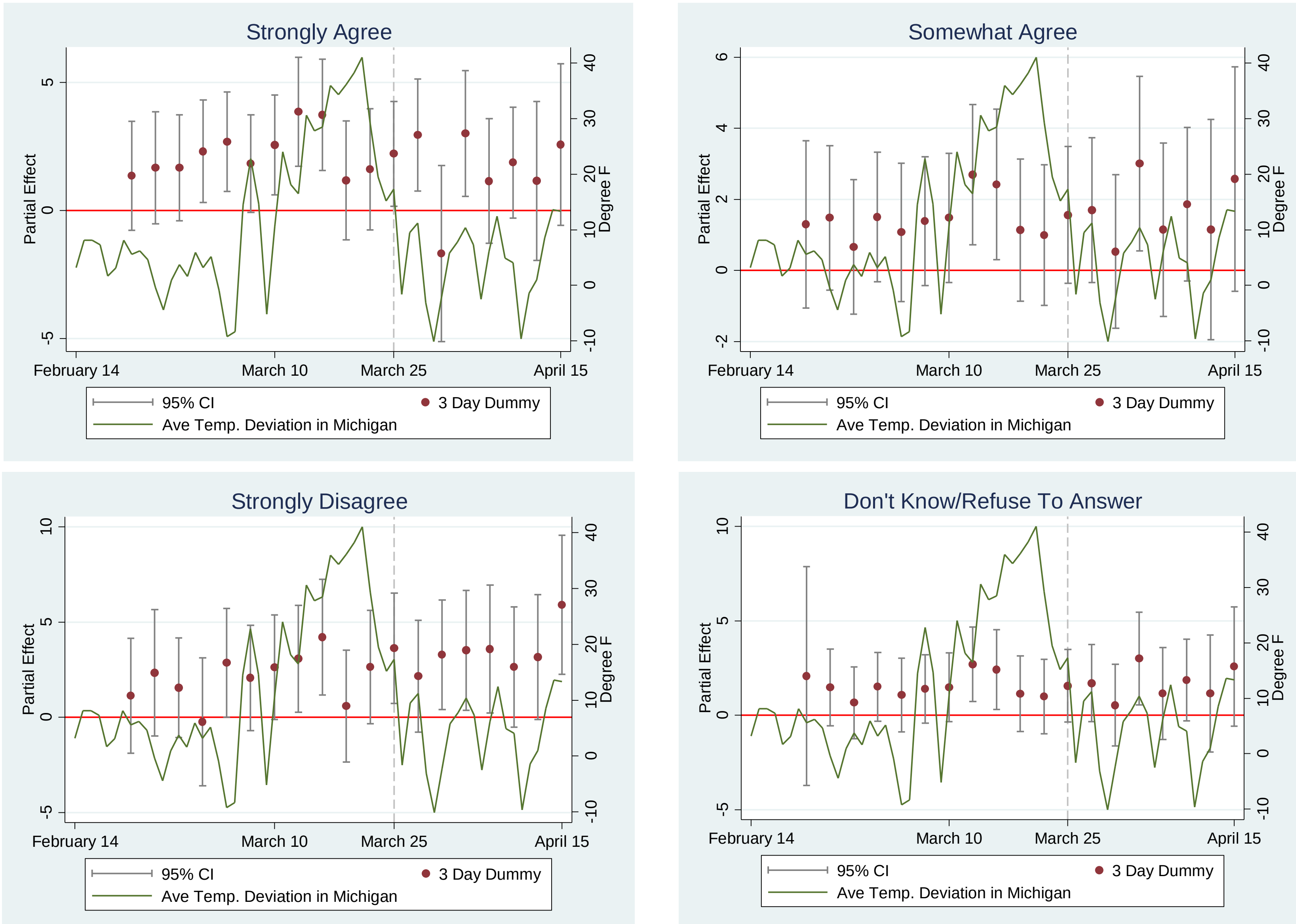

Figure 1.2 Three Day Time Index Regarding Public Attitudes toward SGCS

1.5.6 Interaction Strategy

Using the interaction strategy, we can explore the effects of two factors of abnormal temperature, deviation and fluctuation, conditional on the each of the sub-periods. The results of interaction strategy are reported in Table 1.4 and the full reports can be found in Table 1.B14 ~ Table 1.B18 in Appendix 1.B. The significance of many interaction terms implies that the effect of temperature on the public attitudes can be quite complicated. The interaction of time dummy with temperature deviation and temperature fluctuation represents the mutual dependency of temperature deviation and temperature fluctuation conditional on the time period. For instance, in first half of the warm spell, for log-odds ratio of “strongly agree” in NGCS, the marginal effect of temperature fluctuation on the log-odds ratio is different from the effect in the base period by 1.194*TD - 23.232. With this result, we should not simply conclude that the first half warm spell lead to negative temperature fluctuation effect. Actually, the mean temperature departure in the first half of the warm spell was 24^{o} F. Measured at this average value, the temperature fluctuation is more likely to have positive marginal impact than what it has in the base period (before the warm spell).

In the first half of the warm spell most coefficients of the interaction terms are significant while some time indexes are not. Thus, the influence of temperature on the probabilities of supportive attitudes is due to the temperature deviation and the temperature fluctuation in this period, but for a few adaptation statements there could be other effects not captured by the two temperature factors. The direction of the interaction term, *WS1*TD*TF*, is positive for the attitudes toward agricultural adaption statements. It implies that, in this period, the marginal effect of either temperature deviation or temperature fluctuation on the log-odds ratios mutually depends on the other variable with a positive correlation. Say, when temperature increases for

10% from yesterday, the marginal effect of temperature deviation in this period will be larger. If the temperature drops, the temperature deviation will have smaller marginal effect on predicting the probabilities. This is consistent with our daily experience that one of the temperature factors will amplify the effect of the other on the idea of climate change.

Except for SGFV and NGCS, the second half warm spell dummy variable and its interaction terms are not significant. Since the dummy variable should capture other effects not explained by temperature deviation or temperature fluctuation, its insignificance implies during that period, temperature has no effect on the public attitudes toward general adaptation, SGCS and NGFV. As to SGFV, it is the temperature deviation and some other effects that influence the probability to choose strong opposition while the corresponding coefficients are significant. For NGCS, it could be the deviation, fluctuation, and some other effects that together influence the log-adds ratios of the attitudes given that the corresponding coefficients are significant.

After the warm spell, the attitudes of "strongly agree" are explained by temperature fluctuation while its interaction term, *WS3*TF*, are all significant but the other variables are not. For the choice of "somewhat agree," this interaction term is also significant for SGFV, NGCS, and NGFV while another interaction term, *WS3*TD*, is significant for general adaptation. Thus, in this period, the log-odds for supportive attitudes are explained mostly by temperature fluctuation except that the general adaptation is explained by the deviation. For the attitude of strong opposition, all the variables in this period are not significant for the agricultural related statements. Yet, the strong opposition for general adaptation is explained by temperature fluctuation and some other effects in this period since it has significant coefficient of *WS3* and *WS3*TF*.

In short, in the first half of warm spell, the attitudes can be explained by temperature deviation, temperature fluctuation, and some other effects not captured by the two factors. In the second half of the warm spell, responses to three adaptation statements are not explained by either the time dummy variable or the two temperature factors, but are relevant for SGFV and NGCS. After the warm spell, it is the temperature fluctuation that explains most of the supportive attitudes while the attitude of strong opposition is not explained by the temperature factors or the time index.

Table 1.4 Interaction of Time Index, Temperature Deviation, and Temperature Fluctuation

	G	A	B	C	D
Str. Agg.					
WS1	0.517	3.712*	4.604**	8.360**	2.867
WS2	1.738	0.043	1.412	4.028*	-0.898
WS3	-0.126	-0.311	-0.215	-0.970	-0.334
TDTF	0.042	-0.037	-0.142*	-0.089	-0.082
WS1*TD*TF	-1.725***	0.576	1.050**	1.194**	0.832*
WS2*TD*TF	-0.239	1.636	-0.919	-1.896**	-0.565
WS3*TD*TF	0.554	-0.279	0.016	-0.407	-0.061
TF	-4.894***	0.457	2.167*	1.895	0.923
WS1*TF	43.728***	-9.481	-15.500*	-23.232*	-9.408
WS2*TF	18.907	-36.197	23.350	42.466**	14.075
WS3*TF	5.194*	-7.172**	-5.756**	-6.823**	-5.230*
TD	0.082**	0.019	0.022	0.007	0.014
WS1*TD	-0.022	-0.102	-0.153*	-0.257*	-0.102
WS2*TD	-0.117*	-0.028	-0.056	-0.100	0.073
WS3*TD	-0.008	0.141	0.094	0.165	0.101
Swh. Agg.					
WS1	0.957	5.233***	5.905***	9.140**	4.446**
WS2	1.097	0.686	-1.692	3.473*	-0.831
WS3	0.329	0.198	0.498	-0.095	-0.114
TD*TF	0.072	-0.115	-0.119	-0.208**	-0.238**
WS1*TD*TF	-1.205**	1.053**	1.036***	1.562***	1.284***
WS2*TD*TF	-0.158	1.304	0.132	-1.266	0.942
WS3*TD*TF	0.504	-0.069	-0.036	-0.056	0.297
TF	-3.966***	2.731**	2.064*	2.022	2.785*
WS1*TF	31.593**	-22.680***	-24.594***	-34.021**	-21.310***
WS2*TF	9.305	-31.126	-3.230	30.818*	-17.385
WS3*TF	1.197	-6.151**	-2.836	-6.222***	-7.813***
TD	0.073***	-0.006	0.020	0.029	0.011
WS1*TD	-0.051	-0.156**	-0.203***	-0.345***	-0.189**
WS2*TD	-0.093	-0.023	0.069	-0.136**	0.050
WS3*TD	0.153**	0.094	0.062	0.012	0.058
Str. Disagg.					
WS1	-8.022***	3.031	3.099	7.205*	2.176
WS2	1.616	0.697	-3.599*	4.738**	-0.880
WS3	1.306**	0.835	1.158	-0.002	0.402
TD*TF	0.136	-0.284*	-0.295*	-0.188	-0.203
WS1*TD*TF	-0.329	1.057**	1.502***	1.413**	1.115***
WS2*TD*TF	-1.408	1.441	1.059	-1.404	0.767
WS3*TD*TF	0.095	0.434	0.431	0.180	0.347
TF	-3.912**	0.164	0.016	1.234	1.530
WS1*TF	-9.351	-17.432	-26.080**	-33.643**	-22.385**
WS2*TF	27.029	-32.308	-17.995	32.882	-14.903
WS3*TF	7.434**	-0.374	3.995	-2.564	-1.028
TD	0.037	-0.015	0.015	0.008	-0.015
WS1*TD	0.266**	-0.053	-0.100	-0.262*	-0.092
WS2*TD	-0.060	0.013	0.115*	-0.126*	0.110
WS3*TD	0.020	-0.032	-0.056	-0.098	-0.029

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables.

++ WS1~3:1st half, 2nd half and after Warm Spell; TD: Temperature Deviation; TF: Temperature Fluctuation

++ * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1.6 Discussion and Conclusion

With an emphasis on the complex patterns of temperature, our results provide a better understanding of the complex temperature effects on public attitudes toward adaptation policies. Our model uses the interaction terms of time index, temperature deviation and temperature fluctuation to further confirm the complexity of the temperature effect. It revealed that effect of these three attributes of temperature abnormality was not constant over time and that they are interdependent. Such complicated dependency also varies across attitudes toward different adaptations.

As we analyze the effect of warm spell which had not been discussed, we find results different from the usual temperature effect in the existing literature. In the short-term, anomalous warm temperature, in general, has a positive relationship with supportive public attitudes about government action to help farmers adapt to climate change. But experiencing longer warm spell does not lead to more supportive attitude. In fact, the analysis using 3-day time index finds that other than the consecutively abnormal heat, temperature fluctuation may also take a role although it is not significant when we use only this variable to identify the effect.

Our findings may have two implications to other studies. First, the assessments about the impact of climate change may require revision. The assessments of climate change impacts tend to be based on the scenario that long term average temperature will increase. While our study finds that the public attitudes are also influenced by other temperature patterns and their interdependence, such simple scenarios may not be sufficient to predict long term climate impacts. Specifically, the studies forecasting future impact of climate change related to individual responses, such as personal health management or farmer’s investment in adaptation, may need to verify if complex temperature effects exist in the long run.

Second, complexity of temperature effect may also exist in areas directly related to climate change. One example is the line of studies regarding the temperature effect on stock market return, in which only daily temperature or its departure as the identification strategy are used (see e.g., Cao and Wei, 2005). A simple strategy may result in dispute about the effectiveness of the identification strategies. For example, Jacobsen and Marquering's (2009, 2008) criticism about Kamstra et al.'s (2003) paper published on the American Economic Review is centered around the problem of isolating the weather effect from other seasonal effects. Our identification strategies may contribute to the discussions as different attributes of temperature abnormality are included.

Our findings provide an alternative explanation of the inconsistency between the fluctuating belief and the increasing weight of scientific evidence. As more experience of the warm spell did not lead to more support, we might not expect the public support to grow as the public experiences more short-term weather anomalies. Decision-makers should also be informed about the weather conditions, not just the temperature deviation but also other types of temperature abnormality, during polling periods as they judge whether to incorporate poll findings into their thinking about policy options. Some popularly referenced surveys, such Gallup's Environmental Poll, are only performed within a less than a one week window. Given our findings, their results might be affected due to short term abnormalities close to or during the survey. Either historical or cross-survey comparisons using these results should also aware of this potential issue.

Public attitudes toward climate change adaptation can be affected by short run temperature but the effects seem to be not just a continuous relationship across the whole space of abnormality. To understand the public attitudes better, future polls and the subsequent policies that they inform should take weather anomalies into consideration.

APPENDICES

Appendix 1.A Supplementary Information for Essay 1

1.A.1 Questionnaire Design and Survey Method

The survey was part of Michigan State University's Institute for Public Policy and Social Research (IPPSR) 61st State of the State Survey (SOSS). While IPPSR assures the quality of the data collection process, analysis of the data and interpretation are the responsibility of the authors. Further description about SOSS methods and our survey instrument can be found at http://ippsr.msu.edu/soss/. Unless otherwise stated, our analysis is based on the weighted data.

Most respondents were randomly selected by their phone number (both landline and cell phone), and a few respondents are collected from the last SOSS. If the call was not answered, IPPSR called back later so that the selection bias of absence due to work or other causes can be avoided.

There was a short introduction saying how the survey results might be referred by policy makers. The order of presentation of the four agricultural adaptation questions was randomized. We also randomly reversed the order of the options for answering the questions. These efforts can relieve the possible yes-saying issue.

We construct five variables that measure the public attitudes. There is a variable representing respondent attitudes towards the government's adaptation intervention without specifying the industry. Four agricultural adaptation variables gauge how attitudes about government adaptation assistance vary across level of government (state or national) and crop type (corn-soybeans compared to fruit-vegetables). The adaptation policies from the combinations are: state government help for local corn and soybean farmers (hereafter, SGCS), state government help for local fruit and vegetable farmers (hereafter, SGFV), national government help for corn and soybean farmers (hereafter, NGCS), and national government help for fruit and vegetable farmers (hereafter, NGFV).

The survey first asked a general question about the government's role in helping employers adjust to climate change in their operations without mentioning agriculture. The context was read before the general adaptation as: "*You may have heard about the idea that the world's temperature may have been changing over the past 100 years, a phenomenon sometimes called climate change. I would like to read you a statement about climate change and ask to what extent you agree or disagree*." And the statement for the adaptation is: "*The government has a role in helping employers adjust to the impact of climate change on their operations*." Then, the respondent may reveal their attitudes by one of the choices: "strongly agree," "somewhat agree," "somewhat disagree," "strongly disagree" and "don't know / refuse to answer."

After the general adaptation question, four agricultural adaptation questions were presented to elucidate respondents' viewpoints on state versus national involvement in assisting farmer adaptation with regard to different crop types. A context was read before the agricultural adaptation statements were presented, "*Crops are sensitive to climate. If the climate changes, farmers may need to adjust their cropping systems by using new practices or by planting different varieties. I would like to read you a statement about climate change and ask to what extent you agree or disagree*." The statement about state government and corn/soybeans adaptation is: "*The Michigan state government has a role in helping Michigan corn and soybean farmers adjust to long-term changes in the climate*." A statement with regard to national government and fruits and vegetables is read as: "*The United States government has a role in helping American fruit and vegetable farmers adjust to long-term changes in the climate.*" The underlined phrases are interchangeable with their counterparts.

1.A.2 Conventional Strategies for Temperature Abnormality

We adopt two types of strategies in the literature for comparison and robustness check. The first type of strategy is to include a variable that represents the temperature, the temperature deviation from normal level, etc. This is the most commonly applied method in studies that analyze the influence of temperature. In addition to variable of daily temperature and daily temperature deviation, we construct the standardized daily temperature deviation to take the regular variation of daily temperature into consideration and exclude the effect due to normal variation. The square term of these variables are also constructed for testing nonlinearity. In the equations, d denotes the date when the respondent was surveyed and s denotes the weather station closest to the respondent's zip code. As described in section 3.2, we adopt NOAA's definition and data of normal daily temperature, and the standard deviation is also obtained from NOAA.

$$Temperature\ Deviation_{d,s} = Maximum\ Temperature_{d,s} - Normal\ Temperature_{d,s}$$

$$Standardized\ Temperature\ Devidation_{d,s} = \frac{Maximum\ Temperature_{d,s} - Normal\ Temterature_{d,s}}{Standard\ Deviation_{d,s}}$$

In an intuitive way, this set of variables explores the influence of temperature per se or the abnormality due to the departure from normal temperature. Since the normal temperature is the average of 30 years' records of the same day, it captures the departure of the day in 2012 from the 30 year average of the same day. But it cannot recognize the abnormality due to day by day temporal patterns within a certain period.

Thus, we adopt Egan & Mullin's (2012) heat wave definition as illustrated in section 2.2 to construct a dummy variable to index the experience of heatwave as the second type of conventional identification strategy. We further modify their criterion of abnormal temperature to take the regular variation into consideration. This is because, as Egan & Mullin (2012) used 10^{o} F departure to be the threshold of a heat day, it is often less than one standard deviation of the daily temperature departure on each day of our survey period. Instead, we define the abnormal heat as the standardized temperature deviation which is above 1.645. With the assumption that the same day temperature deviation is normally distributed across years, it implies the abnormal heat is in the 5% upper tail. Note that different from Egan & Mullin's (2012) analysis compared the respondents who experienced 7 consecutive days of abnormal heat with those who experienced 7 days of abnormal heat but not consecutively in the same window, we simply include the dummy variables of heatwave in our regression and the coefficients identify the effect due to both the abnormally high temperature and its consecutive occurrence. We do not further adopt the strategy using the fraction of abnormal days since, on the one hand, a heat wave can also capture the accumulated experience, and on the other hand, the fraction strategy suffers from the drawbacks we discuss in Appendix 1.A.3.

1.A.3 Potential Drawbacks of the Strategy Using Fraction of Abnormal Days

One strategy used to identify the temperature abnormality is constructing a variable for indexing the number of days with abnormality given some window or the fraction between the days and the window length. For instance, Deryugina (2012) used this strategy. This strategy has some drawbacks, and shorter survey period may suffer more from the issues.

While number of days is an integer, small window often implies pretty discrete distribution with big range and large variation. For instance, when the window is 5 days, there are only six possible outcomes (0/5, 1/5, …, 5/5) and the 'extreme' outcomes like 0/5 or 5/5 have some non-trivial probability to occur. When the window is longer, say, 50, 100, or more days, it is much less likely to have the outcome like zero abnormal days or all the 50 days with abnormal temperature. This nature implies very different nature of the two measurements, since the distribution in a long window is closer to normal while that in a small window tend to have a uniform distribution or distributions with fat tails.

In addition, a large fraction in a small window, say, 4 abnormal days in a 5 days window, might be considered by the respondents as regular variation rather than extreme abnormality like 160 abnormal days in a 200 days window. At least, the levels of abnormality are not the same, although the fractions are identical. Further, while N fraction variables were constructed by N different lengths of window and one regression model includes just one of the fraction variables so that N regressions are performed, the comparison among the estimate results of these fraction variables may suffer from type I error. For instance, at 95% confidence level, as there are 20 or more fraction variables estimated in its own regression, there could be one or more coefficients falsely rejecting the null hypothesis. Considering these potential issues and our relatively shorter survey period, we do not adopt the strategy.

1.A.4 Empirical Model

(1.1) $P(A_V = j) = \boldsymbol{X\beta_{Vj}} + \gamma_{Vj}Temp$

A_V: dependent variable, public attitudes toward the adaptation policy V

V: adaptation policies. G= general adaptation policy; A~D denote agricultural policies

A=state gov., corn and soybeans; B=state gov., fruits and vegetables,

C=national gov., corn and soybeans; D=national gov., fruits and vegetables *j: denotes the attitudes. 1=strongly agree), 2=somewhat agree), 3=don't know/refuse to answer, 4=somewhat disagree, and 5=strongly disagree*

P(.): the log-odds ratio in which the probability that the respondent chooses j compares to the probability of base option being chosen.

$\boldsymbol{X}$*: a set of demographic variables*

Temp: the temperature abnormality

$\boldsymbol{\beta_{Vj}}, \gamma_{Vj}$*: coefficients estimated*

Appendix 1.B Supplementary Results for Essay 1

1.B.1 Statistics of Public Attitudes

Table 1.B1 Michigan Residents' Attitudes towards SGCS, SGFV, and NGFV Adaptation Before, During, and After the Warm Spell (WS)

Unit: %

	Before WS	1st Half of WS	2nd Half of WS	After WS	Warm Spell	All Dates
			State Government Role - Corn/Soybeans			
Strongly Agree	25.5	26.1	22.1	13.8	24.5	22.3
Somewhat Agree	40.5	47.4	37.0	47.3	43.4	43.1
Subtotal	66.0	73.6	59.1	61.2	67.9	65.5
Somewhat Disagree	20.9	8.3	15.4	17.2	11.1	16.8
Strongly Disagree	10.2	14.4	18.0	17.6	15.9	13.8
Subtotal	31.1	22.7	33.5	34.8	26.9	30.7
Don't know	2.9	3.7	7.4	4.0	5.1	3.9
			State Government Role – Fruits/Vegetables			
Strongly Agree	18.6	29.1	22.3	13.4	26.5	19.9
Somewhat Agree	47.9	47.2	48.4	50.6	47.7	48.5
Subtotal	66.5	76.3	70.7	64.0	74.1	68.4
Somewhat Disagree	19.2	8.5	9.3	17.2	8.8	15.4
Strongly Disagree	9.6	13.2	6.9	17.4	10.7	11.9
Subtotal	28.8	21.7	16.2	34.6	19.5	27.2
Don't know	4.7	2.0	13.1	1.3	6.3	4.4
			National Government Role - Fruits/Vegetables			
Strongly Agree	18.6	29.4	26.4	12.4	28.2	20.2
Somewhat Agree	42.8	46.4	38.4	52.8	43.3	45.4
Subtotal	61.4	75.8	64.9	65.2	71.5	65.6
Somewhat Disagree	22.4	14.2	4.8	15.3	10.5	16.8
Strongly Disagree	12.0	7.4	25.8	17.3	14.6	14.1
Subtotal	34.4	21.5	30.6	32.6	25.1	31.0
Don't know	4.2	2.7	4.6	2.2	3.4	3.4

Source: Author calculation based on SOSS, 2012.

1.B.2 Results of Testing Difference among Types of Adaptations

Because the five dependent variables all measure the attitudes about the climate change issues, we treat the five regressions as a seemingly uncorrelated regression system[19] for testing cross-equation restrictions and dealing with the possible correlation due to the errors in each of the equation with robust variance. As the survey data are weighted, a robust form of variance is used by default of the Stata package which estimates the multinomial logit model.

To test the hypotheses in term of predicted probability, we test the cross-equation restrictions among five attitudes regressions (Equation 1.1). The model adopts temperature deviation to capture the effect of temperature. As the direction and significance of the control variables in other models that adopt different temperature identification strategies in general are similar, here we use this specification as the basic model to test the cross-equation restrictions. Table 1.B2 and Table 1.B3 show the results of testing hypothesis 1 and 2 mentioned in section 1.5.2, respectively. Conditional on the variables such as age, gender, etc., the predicted log-odds ratio of a specific agreement level of the statement is likely different between the general adaptation and the four agricultural adaptations as well as different among the four agricultural adaptions. From this perspective, both hypothesis 1 and hypothesis 2 are supported. But for some demographic groups such as conservatives, the cross-equation restrictions are mostly valid since the tests cannot reject the corresponding null hypotheses about the cross-equation restrictions.

[19] We use Stata's *mlogit* command for main regressions and *suest* command to estimate the variance-covariance matrices robust to the cross-equation correlations. The robust matrices are used to test for the cross-equation restrictions.

Table 1.B2 Test of Difference of Coefficients between Adaptation Equations: General Adaptation vs. Agricultural Adaptation

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Strongly Agree: G=A=B=C=D		*	***											*		**				
Strongly Agree: G=A			**							*			**		*					
Strongly Agree: G=B			***										*		*	**	**			
Strongly Agree: G=C		*								**							**		*	
Strongly Agree: G=D	**	***	**							*			**				**		*	
Somewhat Agree: G=A=B=C=D	*	*	*											*					*	
Somewhat Agree: G=A		**				*				**		*	*			*		**		
Somewhat Agree: G=B	**	**	**							**		**		**		**		**	*	
Somewhat Agree: G=C						*				**							*	**	**	
Somewhat Agree: G=D		*	*							*								**	**	
DKRA: G=A=B=C=D	*	**	***		**						**		**	*		***	***			
DKRA: G=A			***	*							**						***			
DKRA: G=B		**	***														***			
DKRA: G=C			***	*			*									***	***			
DKRA: G=D	*	**	***				*						**	*		***	***			
Strongly Disagree: G=A=B=C=D			***					*	*	**						*				
Strongly Disagree: G=A		*						*	**	**						*			**	
Strongly Disagree: G=B	**	**	***												*	***			**	
Strongly Disagree: G=C		*	***			*			*	*									*	
Strongly Disagree: G=D		**	***																**	

+ Variable: 1. Age; 2. Age Squared; 3. Male; 4. White; 5. Conservative; 6. Conservative White Male; 7. Education less than High School; 8. Education with Some College; 9. Education at least with Bachelor Degree; 10. Income > 50k; 11. Unemployment Rate; 12. Sales of Corn and Soybeans; 13. Sales of Fruits and Vegetables; 14. ~ 19. Rural Urban Area Code 2 ~ 7; 20. Temperature Deviation.
++ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables. DNRA: don’t know/refuse to answer.
+++ * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B3 Test of Difference of Coefficients between Agricultural Adaptation Equations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Strongly Agree: A=B=C=D		*	**	*										*		***				
Strongly Agree: A=B	*	*												*		**	**	*		
Strongly Agree: A=C		*															**			
Strongly Agree: A=D	**	**		*			*										**			
Strongly Agree: B=C			**	*					*		**	*		**		***				
Strongly Agree: B=D				***			*											*		
Strongly Agree: C=D			*						*		**			*		*				
Somewhat Agree: A=B=C=D			*														*			
Somewhat Agree: A=B																	*			*
Somewhat Agree: A=C			**														**			
Somewhat Agree: A=D																	*		*	
Somewhat Agree: B=C	*		**		*				*			**		**						**
Somewhat Agree: B=D	*											**		**						*
Somewhat Agree: C=D			**						*											
DNRA: A=B=C=D	**	**			***		*			*	**		**	**		***				
DKRA: A=B	**	***								*			**				*			
DKRA: A=C					*											***				
DKRA: A=D	***	**								**	**		*	**		***		*		
DKRA: B=C	**	***			**			*		**			**			***				
DKRA: B=D							**				**		***	***		***				**
DKRA: C=D	***	***			**					**	**		*	**		*		*		
Strongly Disagree: A=B=C=D			***					**	*	*				*						
Strongly Disagree: A=B			***					**	*		*			**			*			
Strongly Disagree: A=C			***					**												
Strongly Disagree: A=D			***					**	**	*	*									
Strongly Disagree: B=C			**											**	*	**				
Strongly Disagree: B=D														**						
Strongly Disagree: C=D						*			**	**										

+ Please see the footnote of Table 1.3 for the meaning of the Equation A ~ D & Variable 1 ~ 20.

++ $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

1.B.3 Discussion of Social-Economic Variables

We discuss the effects of socio-economic variables using the results of the temperature deviation model as the estimates of their coefficients are in general similar among the regressions using different specifications of temperature variables. While all the rest control variables are all the same, our analysis in section 1.5.3 shows that, among the conventional strategies, temperature deviation is a good control for a certain effect of temperature abnormality. We report the results in Table 1.B4 ~ Table 1.B8. This section summarizes the results of socio-economic variables.

The effect of age is positive but decays slowly when age increases. The results show that age has an inverse U shape effect: the coefficient of its square term is negative and significant. Age and age-square are mostly significant for at least 5% level in explaining the “strongly agree” and “strongly disagree” attitudes of the four agricultural adaption statements.

Male respondents are more likely to agree to the five adaptation statements and less likely to hide their attitudes or to have no idea about the statements. White people tend to be mildly against the national government’s role in agricultural adaption. Respondents’ political ideology (conservative) in general has no effect. The interaction term of these three attributes gender (male) and race (white) is negative and significant in supportive options among the regressions. This result is consistent with McCright & Dunlap’s (2011) finding that conservative white males tend to “endorse denialist views” on climate change issues.

Respondents with education levels other than high school (base of education level) tend to choose a mild position against the five adaptation statements. But those with a low education level have higher probability of choosing the two supportive attitudes than to choose the attitude of strong denial. Meanwhile, when the coefficients of higher education levels are significant, their scale is smaller in “strongly agree” than in “strongly disagree” such that higher education levels lead to higher probability to choose the latter than the former. This may, to some extent, explain why Borick & Rabe (2014) and Hamilton & Stampone (2013) find a positive effect of education while Brooks et al. (2014) find it to be negative, since the overall effect of education may depend on the questionnaire design and the distribution of education groups.

Richer households (income greater than $50,000) are more likely to have mild disagreeing attitude (somewhat agree) than the strong attitude of denial or supportive attitudes. The county level economic variables (unemployment rate, corn and soybeans sales, as well as fruits and vegetables sales) are mostly not significant. This may be because they have no effect on the public attitudes or because of multicollinearity

The effects captured by urbanization indexes have no common pattern across all regions. The smaller metropolitan areas have no effect on the attitudes; non-metropolitan areas with middle population have positive effect for the supportive attitudes for general adaptation, SGCS, and SGFV. The rural areas tend to oppose the adaptation statements. This complicated result can be because these urbanization indexes captured other regional effects not controlled in the model.

Table 1.B4 Results of Multinomial Logit Regression: General Adaptation

General Adaptation	Strongly Agree	Somewhat Agree	Don't Know/No Answer	Strongly Disagree
Age	0.063 (0.066)	0.001 (0.049)	0.239 (0.057)***	0.086 (0.056)
Age2	-0.000 (0.001)	0.000 (0.000)	-0.002 (0.000)***	-0.001 (0.000)
Gender (Male=1)	1.532 (0.515)***	1.334 (0.433)***	-1.759 (1.005)*	1.098 (0.579)*
Race (White=1)	-0.695 (0.534)	-0.506 (0.520)	1.400 (1.524)	-0.099 (0.665)
Political Ideology (Conservative =1)	-0.712 (0.525)	0.010 (0.458)	0.728 (0.741)	0.557 (0.607)
Conservative White Male	-1.739 (0.881)**	-1.787 (0.722)**	0.620 (1.311)	-1.196 (0.762)
Education: <H.S.	1.204 (1.083)	-1.154 (0.921)	-16.257 (1.474)***	-2.023 (1.101)*
Education: Some College	-1.311 (0.645)**	-0.446 (0.476)	-2.010 (0.928)**	-0.222 (0.533)
Education: >= Bachelor	0.006 (0.588)	-0.077 (0.484)	0.101 (1.237)	-0.219 (0.548)
Income>50k	0.272 (0.475)	-0.046 (0.370)	-0.949 (0.933)	0.411 (0.439)
Unemployment Rate	-0.108 (0.144)	-0.146 (0.106)	-0.356 (0.190)*	-0.096 (0.146)
Corns Soybean Sales	-0.001 (0.007)	-0.007 (0.006)	0.005 (0.009)	-0.009 (0.007)
Fruits & Veges Sales	-0.020 (0.017)	-0.018 (0.013)	-0.001 (0.021)	-0.006 (0.013)
U2	0.467 (0.678)	1.014 (0.635)	-1.273 (1.500)	1.035 (0.877)
U3	0.480 (0.736)	0.542 (0.627)	-0.951 (1.200)	0.965 (0.741)
U4	1.027 (1.267)	1.658 (0.872)*	-14.757 (1.619)***	2.035 (1.023)**
U5	2.010 (0.849)**	1.610 (0.879)*	-13.676 (1.009)***	1.387 (0.795)*
U6	-0.304 (0.977)	0.860 (0.688)	-0.709 (1.400)	0.968 (0.885)
U7	0.465 (0.925)	1.673 (0.671)**	0.017 (1.250)	1.786 (0.787)**
Temperature Deviation	0.025 (0.015)*	0.010 (0.012)	0.010 (0.033)	0.003 (0.016)
Constant	-1.134 (2.223)	1.281 (1.893)	-6.805 (3.649)*	-2.749 (2.305)
Observations	793			
P-Value	0.000			
F	26.696			

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.
++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B5 Results of Multinomial Logit Regression: SGCS

General Adaptation	Strongly Agree	Somewhat Agree	Don't Know/No Answer	Strongly Disagree
Age	0.105 (0.068)	0.110 (0.054)**	0.089 (0.104)	0.192 (0.073)***
Age2	-0.001 (0.001)*	-0.001 (0.000)**	-0.001 (0.001)	-0.002 (0.001)***
Gender (Male=1)	0.884 (0.408)**	0.360 (0.387)	-2.021 (0.972)**	0.365 (0.565)
Race (White=1)	-0.418 (0.516)	0.207 (0.556)	-0.709 (1.123)	0.117 (0.657)
Political Ideology (Conservative =1)	-0.309 (0.463)	-0.435 (0.468)	0.398 (0.815)	-0.672 (0.600)
Conservative White Male	-0.889 (0.707)	-1.053 (0.639)*	0.715 (1.523)	1.066 (0.750)
Education: <H.S.	-0.228 (1.078)	-2.458 (1.128)**	-4.450 (1.738)**	-2.981 (1.467)**
Education: Some College	-1.170 (0.551)**	-0.163 (0.478)	-0.221 (1.001)	-0.570 (0.603)
Education: >= Bachelor	-0.763 (0.537)	-0.084 (0.494)	-0.415 (1.346)	-0.623 (0.624)
Income>50k	-0.692 (0.447)	-1.288 (0.425)***	-2.234 (1.122)**	-0.755 (0.494)
Unemployment Rate	0.078 (0.110)	-0.028 (0.122)	0.195 (0.186)	0.164 (0.135)
Corns Soybean Sales	-0.003 (0.006)	0.008 (0.006)	0.008 (0.010)	-0.008 (0.007)
Fruits & Veges Sales	0.018 (0.014)	0.013 (0.012)	0.019 (0.017)	-0.004 (0.015)
U2	0.169 (0.592)	-0.105 (0.596)	-0.441 (1.096)	1.229 (0.827)
U3	-0.844 (0.760)	-0.513 (0.717)	-2.113 (1.375)	-0.147 (0.870)
U4	0.253 (1.037)	-0.702 (0.833)	-14.558 (1.549)***	-0.150 (1.064)
U5	1.963 (1.002)*	2.093 (0.954)**	1.669 (1.308)	1.822 (1.006)*
U6	-0.508 (0.649)	-2.072 (0.855)**	-0.450 (1.376)	0.172 (0.896)
U7	-0.608 (0.618)	0.300 (0.586)	-1.079 (1.226)	-0.615 (0.837)
Temperature Deviation	0.029 (0.015)**	0.016 (0.013)	0.028 (0.036)	0.018 (0.018)
Constant	-2.061 (2.049)	-0.359 (1.850)	-3.780 (2.226)*	-5.327 (2.561)**
Observations	793			
P-Value	0.000			
F	13.905			

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.
++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B6 Results of Temperature Deviation Model: SGFV

General Adaptation	Strongly Agree	Somewhat Agree	Don't Know/No Answer	Strongly Disagree
Age	0.170 (0.064)***	0.151 (0.049)***	0.409 (0.107)***	0.241 (0.073)***
Age2	-0.002 (0.001)***	-0.002 (0.000)***	-0.004 (0.001)***	-0.002 (0.001)***
Gender (Male=1)	1.020 (0.433)**	0.518 (0.412)	-0.768 (0.723)	0.729 (0.563)
Race (White=1)	-0.504 (0.475)	0.186 (0.524)	-1.006 (0.877)	0.470 (0.688)
Political Ideology (Conservative =1)	-0.046 (0.471)	0.008 (0.457)	-0.375 (0.853)	0.653 (0.619)
Conservative White Male	-1.212 (0.719)*	-1.443 (0.660)**	-1.110 (1.340)	-0.082 (0.826)
Education: <H.S.	-0.845 (0.891)	-2.639 (1.040)**	-3.877 (2.426)	-15.638 (0.908)***
Education: Some College	-1.569 (0.572)***	-0.820 (0.503)	-0.627 (0.856)	-0.582 (0.652)
Education: >= Bachelor	-0.798 (0.554)	-0.453 (0.513)	-1.436 (1.236)	-0.180 (0.682)
Income>50k	-0.563 (0.424)	-1.205 (0.405)***	0.275 (0.889)	-0.123 (0.493)
Unemployment Rate	-0.019 (0.099)	-0.062 (0.102)	0.018 (0.250)	-0.049 (0.118)
Corns Soybean Sales	-0.001 (0.006)	0.010 (0.005)*	0.002 (0.008)	-0.006 (0.007)
Fruits & Veges Sales	0.021 (0.014)	0.006 (0.014)	-0.031 (0.023)	-0.000 (0.015)
U2	-0.626 (0.607)	-0.704 (0.584)	0.906 (1.555)	-0.452 (0.750)
U3	-0.979 (0.751)	-0.608 (0.747)	-1.099 (1.469)	-0.565 (0.860)
U4	-2.010 (1.102)*	-0.897 (0.879)	-14.092 (1.394)***	-0.977 (1.112)
U5	-0.173 (0.867)	-0.310 (0.765)	-1.319 (1.421)	-0.138 (0.848)
U6	-1.381 (0.821)*	-1.947 (0.778)**	1.250 (1.076)	0.120 (0.924)
U7	-0.688 (0.701)	0.031 (0.610)	-0.503 (1.092)	-0.339 (0.795)
Temperature Deviation	0.046 (0.015)***	0.037 (0.014)***	0.031 (0.023)	0.027 (0.018)
Constant	-2.367 (1.902)	-0.720 (1.630)	-9.998 (3.287)**	-5.765 (2.312)**
Observations	793			
P-Value	0.000			
F	39.155			

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B7 Results of Multinomial Logit Regression: NGCS

General Adaptation	Strongly Agree	Somewhat Agree	Don't Know/No Answer	Strongly Disagree
Age	0.188 (0.081)**	0.081 (0.058)	0.148 (0.097)	0.193 (0.065)***
Age2	-0.002 (0.001)***	-0.001 (0.001)*	-0.001 (0.001)	-0.002 (0.001)***
Gender (Male=1)	0.543 (0.495)	0.191 (0.420)	-1.594 (0.867)*	0.052 (0.610)
Race (White=1)	-1.193 (0.674)*	-0.267 (0.628)	-2.111 (1.001)**	-0.315 (0.764)
Political Ideology (Conservative =1)	0.117 (0.521)	-0.357 (0.494)	1.446 (0.749)*	0.317 (0.631)
Conservative White Male	0.026 (0.827)	-0.358 (0.704)	0.370 (1.359)	0.667 (0.767)
Education: <H.S.	1.726 (1.018)*	1.057 (0.987)	-1.001 (1.990)	-12.587 (1.041)***
Education: Some College	-0.685 (0.622)	-0.204 (0.513)	0.033 (1.206)	-0.302 (0.595)
Education: >= Bachelor	-0.161 (0.553)	0.415 (0.486)	0.882 (1.168)	0.333 (0.557)
Income>50k	-1.148 (0.468)**	-1.245 (0.413)**	-1.915 (0.933)**	-0.668 (0.524)
Unemployment Rate	0.177 (0.125)	0.027 (0.115)	-0.080 (0.192)	0.019 (0.139)
Corns Soybean Sales	-0.011 (0.007)	0.001 (0.005)	-0.005 (0.008)	-0.013 (0.006)**
Fruits & Veges Sales	0.012 (0.014)	0.004 (0.012)	0.018 (0.018)	-0.009 (0.013)
U2	0.767 (0.683)	0.402 (0.647)	-0.482 (1.283)	1.772 (0.890)**
U3	-0.208 (0.837)	0.174 (0.784)	-1.889 (1.568)	0.955 (0.839)
U4	0.345 (1.003)	-0.041 (0.907)	-2.246 (1.667)	1.271 (1.064)
U5	-0.221 (0.828)	-0.927 (0.768)	0.154 (1.092)	0.063 (0.793)
U6	-0.695 (0.730)	-1.467 (0.793)*	0.054 (1.524)	1.141 (0.800)
U7	-1.564 (0.750)**	-0.234 (0.565)	-0.714 (1.096)	0.254 (0.662)
Temperature Deviation	0.045 (0.018)**	0.004 (0.015)	0.002 (0.034)	0.006 (0.018)
Constant	-4.293 (2.428)*	0.549 (1.800)	-2.347 (2.418)	-4.037 (2.466)
Observations	793			
P-Value	0.000			
F	39.354			

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B8 Results of Multinomial Logit Regression: NGFV

General Adaptation	Strongly Agree	Somewhat Agree	Don't Know/No Answer	Strongly Disagree
Age	0.240 (0.068)***	0.083 (0.058)	0.538 (0.146)***	0.192 (0.069)***
Age2	-0.002 (0.001)***	-0.001 (0.001)**	-0.004 (0.001)***	-0.002 (0.001)***
Gender (Male=1)	1.162 (0.483)**	0.655 (0.441)	-0.493 (0.744)	0.938 (0.608)
Race (White=1)	-1.263 (0.507)**	-0.309 (0.500)	-2.520 (0.970)***	-0.322 (0.651)
Political Ideology (Conservative =1)	0.106 (0.484)	0.142 (0.441)	0.661 (0.770)	0.671 (0.622)
Conservative White Male	-0.907 (0.832)	-1.332 (0.696)*	-0.132 (1.275)	-0.779 (0.796)
Education: <H.S.	-0.341 (0.977)	-2.456 (1.148)**	-3.675 (2.263)	-14.805 (0.922)***
Education: Some College	-0.249 (0.587)	-0.243 (0.503)	-0.549 (1.209)	0.030 (0.606)
Education: >= Bachelor	-0.085 (0.511)	0.051 (0.450)	-0.631 (1.037)	0.304 (0.575)
Income>50k	-0.797 (0.448)*	-1.073 (0.395)***	0.053 (0.754)	0.001 (0.513)
Unemployment Rate	0.042 (0.121)	0.027 (0.117)	-0.645 (0.286)**	-0.045 (0.146)
Corns Soybean Sales	-0.005 (0.006)	0.002 (0.005)	0.004 (0.011)	-0.007 (0.006)
Fruits & Veges Sales	0.018 (0.012)	0.003 (0.011)	0.075 (0.032)**	-0.003 (0.013)
U2	-0.106 (0.644)	0.375 (0.615)	-5.672 (2.511)**	1.276 (0.913)
U3	-0.714 (0.776)	-0.022 (0.735)	-4.154 (2.225)*	0.228 (0.839)
U4	-0.727 (0.926)	-0.387 (0.819)	-5.369 (2.075)***	0.659 (0.986)
U5	-1.067 (0.871)	-0.481 (0.823)	-0.760 (1.133)	0.006 (0.877)
U6	-0.409 (0.730)	-1.910 (0.857)**	1.707 (1.286)	0.620 (0.857)
U7	-1.260 (0.676)*	-0.297 (0.552)	-0.853 (1.258)	0.196 (0.702)
Temperature Deviation	0.040 (0.017)**	0.012 (0.015)	-0.022 (0.026)	0.016 (0.017)
Constant	-4.616 (2.062)**	0.519 (1.715)	-7.862 (4.440)*	-4.180 (2.221)*
Observations	793			
P-Value	0.000			
F	28.078			

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1.B.4 Results of Temperature Abnormality

Table 1.B9 Results of Usual Identification of Temperature Abnormality

Dep. Variable	G	A	B	C	D	G	A	B	C	D
	Temperature Deviation					Temperature				
Strongly Agree	0.025*	0.029**	0.046***	0.045**	0.040**	0.026*	0.027**	0.041***	0.034**	0.036**
	(0.015)	(0.015)	(0.015)	(0.018)	(0.017)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)
Somewhat Agree	0.010	0.016	0.037***	0.004	0.012	0.019*	0.018	0.036***	0.002	0.015
	(0.012)	(0.013)	(0.014)	(0.015)	(0.015)	(0.011)	(0.012)	(0.013)	(0.013)	(0.013)
DKRA	0.010	0.028	0.031	0.002	-0.022	0.012	0.036	0.020	-0.000	-0.045
	(0.033)	(0.036)	(0.023)	(0.034)	(0.026)	(0.032)	(0.032)	(0.020)	(0.029)	(0.027)
Strongly Disagree	0.003	0.018	0.027	0.006	0.016	0.019	0.029*	0.034**	0.008	0.024
	(0.016)	(0.018)	(0.018)	(0.018)	(0.017)	(0.014)	(0.016)	(0.016)	(0.015)	(0.015)
	Temperature Deviation + Square Term					Temperature + Square Term				
Strongly Agree	0.069*	0.055	0.087***	0.091**	0.051	0.142	0.114	0.106	0.111	0.005
	(0.038)	(0.034)	(0.032)	(0.036)	(0.031)	(0.097)	(0.088)	(0.080)	(0.107)	(0.081)
	-0.002	-0.001	-0.002	-0.002	-0.000	-0.001	-0.001	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Somewhat Agree	0.060**	0.040	0.064**	0.045*	0.036	0.216***	0.139*	0.079	0.184**	0.105
	(0.029)	(0.027)	(0.027)	(0.027)	(0.026)	(0.082)	(0.081)	(0.081)	(0.092)	(0.074)
	-0.002*	-0.001	-0.001	-0.002	-0.001	-0.002**	-0.001	-0.000	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
DKRA	-0.054	-0.057	0.100	-0.034	0.042	-0.216	-0.079	0.033	0.100	0.171
	(0.058)	(0.054)	(0.065)	(0.053)	(0.061)	(0.167)	(0.138)	(0.116)	(0.160)	(0.199)
	0.002	0.003**	-0.003	0.002	-0.003	0.002	0.001	-0.000	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Strongly Disagree	0.008	-0.019	0.015	0.001	-0.009	0.082	0.019	0.007	0.057	-0.060
	(0.029)	(0.032)	(0.035)	(0.032)	(0.032)	(0.080)	(0.093)	(0.093)	(0.093)	(0.082)
	-0.000	0.001	0.000	0.000	0.001	-0.001	0.000	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	7-Day Averaged Temperature Deviation					Standardized Temperature Deviation				
Strongly Agree	0.022	0.029	0.034*	0.043**	0.041**	0.271	0.319**	0.515***	0.503**	0.440**
	(0.018)	(0.020)	(0.017)	(0.020)	(0.018)	(0.168)	(0.162)	(0.165)	(0.200)	(0.190)
Somewhat Agree	0.004	0.014	0.027	0.012	0.026	0.105	0.188	0.415**	0.057	0.142
	(0.015)	(0.018)	(0.017)	(0.019)	(0.018)	(0.133)	(0.139)	(0.150)	(0.163)	(0.164)
DKRA	0.028	0.052	0.038	0.014	-0.067	0.101	0.301	0.331	0.039	-0.212
	(0.031)	(0.038)	(0.031)	(0.040)	(0.047)	(0.383)	(0.403)	(0.262)	(0.371)	(0.286)
Strongly Disagree	0.014	0.031	0.010	0.038	0.047**	0.013	0.185	0.295	0.065	0.163
	(0.022)	(0.023)	(0.021)	(0.023)	(0.021)	(0.174)	(0.194)	(0.202)	(0.194)	(0.193)

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables. DNRA: don't know/refuse to answer.

++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B10 Influence of Heat Wave and Temperature Fluctuation

Dep. Variable	G	A	B	C	D	G	A	B	C	D
	Experiencing Heat Wave: 10 F above for 7 Days					If Temperature 10 F above Normal on the Day				
Strongly Agree	-0.082	-0.341	-0.167	-0.633	0.141	0.682	1.019**	1.063***	1.480***	0.915**
	(0.417)	(0.424)	(0.416)	(0.485)	(0.423)	(0.435)	(0.397)	(0.387)	(0.451)	(0.432)
Somewhat Agree	0.479	0.059	0.455	-0.092	0.613*	0.100	0.511	0.760**	0.307	0.271
	(0.354)	(0.375)	(0.373)	(0.411)	(0.369)	(0.336)	(0.340)	(0.341)	(0.370)	(0.384)
DKRA	-0.990	-0.133	-0.044	-1.223*	-1.162	0.385	1.389	0.239	0.799	-1.504
	(0.834)	(0.694)	(0.641)	(0.660)	(0.924)	(0.705)	(0.874)	(0.636)	(0.774)	(0.999)
Strongly Disagree	1.007**	0.575	0.592	0.363	1.293***	-0.152	0.591	0.279	0.526	0.259
	(0.437)	(0.470)	(0.495)	(0.461)	(0.452)	(0.425)	(0.458)	(0.480)	(0.443)	(0.452)
	Experiencing Heat Wave: 95% above Normal (1.645 Z)					If Standardized Temperature above 1.645 Z on the Day				
Strongly Agree	-0.131	-0.256	-0.155	-0.664	-0.008	1.199***	1.027**	1.243***	1.427***	1.123**
	(0.431)	(0.434)	(0.420)	(0.503)	(0.448)	(0.429)	(0.405)	(0.406)	(0.474)	(0.445)
Somewhat Agree	0.484	0.085	0.342	-0.191	0.480	0.521	0.251	0.596*	0.205	0.276
	(0.368)	(0.382)	(0.376)	(0.421)	(0.386)	(0.351)	(0.349)	(0.360)	(0.401)	(0.403)
DKRA	-0.875	-0.970	0.170	-0.962	-1.210	1.029	1.766**	0.747	0.932	-0.756
	(0.879)	(0.730)	(0.695)	(0.727)	(0.948)	(0.727)	(0.847)	(0.615)	(0.853)	(0.847)
Strongly Disagree	1.074**	0.680	0.563	0.442	1.269***	0.179	0.675	0.560	0.514	0.512
	(0.448)	(0.481)	(0.503)	(0.470)	(0.461)	(0.466)	(0.476)	(0.511)	(0.477)	(0.469)
	Temperature Deviation Fluctuation					Temperature Fluctuation in % Change				
Strongly Agree	-0.006	-0.001	0.030	0.026	0.016	-0.335	0.112	1.540	1.437	0.816
	(0.020)	(0.020)	(0.022)	(0.020)	(0.020)	(1.040)	(0.993)	(1.092)	(0.963)	(0.980)
Somewhat Agree	-0.015	0.009	0.014	-0.015	-0.008	-0.765	0.562	0.887	-0.358	-0.169
	(0.017)	(0.016)	(0.018)	(0.018)	(0.018)	(0.834)	(0.836)	(0.966)	(0.907)	(0.936)
DKRA	-0.033	-0.049	-0.015	-0.053	0.002	-1.459	-2.413	-0.044	-2.036	0.220
	(0.025)	(0.031)	(0.030)	(0.036)	(0.023)	(1.334)	(1.633)	(1.540)	(1.923)	(1.155)
Strongly Disagree	-0.021	-0.020	0.020	-0.031	-0.011	-0.981	-0.992	0.688	-1.137	-0.451
	(0.020)	(0.020)	(0.021)	(0.023)	(0.023)	(0.919)	(0.993)	(1.108)	(1.105)	(1.109)
	Absolute Temperature Deviation Fluctuation					Absolute Temperature Fluctuation in % Change				
Strongly Agree	-0.010	0.031	0.009	-0.001	0.006	-0.666	0.826	-0.155	-0.438	-0.331
	(0.028)	(0.027)	(0.025)	(0.025)	(0.028)	(1.412)	(1.172)	(1.057)	(1.173)	(1.255)
Somewhat Agree	-0.004	-0.003	-0.030	-0.023	-0.003	-0.658	-0.644	-1.749	-1.511	-0.800
	(0.023)	(0.025)	(0.024)	(0.023)	(0.026)	(1.132)	(1.170)	(1.122)	(1.100)	(1.175)
DKRA	-0.040	-0.004	-0.033	0.012	-0.131*	-2.711	-1.162	-3.321	0.029	-6.337*
	(0.046)	(0.059)	(0.036)	(0.047)	(0.079)	(2.412)	(3.037)	(2.346)	(2.102)	(3.274)
Strongly Disagree	-0.014	-0.014	-0.056*	-0.018	-0.022	-1.217	-2.131	-3.196**	-1.815	-2.095
	(0.025)	(0.030)	(0.031)	(0.028)	(0.031)	(1.221)	(1.416)	(1.445)	(1.340)	(1.423)

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables. DNRA: don't know/refuse to answer.
Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B11 Test of Lagged Effect with Warm Spell Dummy Variables: 3 Day Lagged

	G	A	B	C	D
Strongly Agree					
1st Half of WS	0.153	1.260**	1.205**	1.175*	1.003
	(0.543)	(0.551)	(0.555)	(0.667)	(0.676)
2nd Half of WS	0.167	0.482	0.695	0.640	1.158**
	(0.550)	(0.527)	(0.540)	(0.601)	(0.550)
After WS	-0.562	-0.744	-0.467	-1.483*	-0.406
	(0.759)	(0.727)	(0.668)	(0.798)	(0.620)
Somewhat Agree					
1st Half of WS	-0.173	0.979*	1.075*	0.402	0.382
	(0.432)	(0.539)	(0.572)	(0.594)	(0.619)
2nd Half of WS	0.403	0.304	0.827	0.402	1.153**
	(0.463)	(0.491)	(0.515)	(0.548)	(0.521)
After WS	0.702	0.299	0.606	-0.283	0.289
	(0.528)	(0.518)	(0.490)	(0.546)	(0.490)
DKRA					
1st Half of WS	0.472	2.875**	-0.703	1.274	-1.236
	(0.925)	(1.203)	(0.904)	(1.097)	(0.976)
2nd Half of WS	0.046	-0.942	0.845	-1.059	-1.634
	(0.986)	(1.140)	(0.807)	(1.443)	(1.739)
After WS	-15.261***	0.289	-1.357	-0.786	-1.271
	(0.797)	(0.819)	(0.998)	(0.729)	(0.920)
Strongly Disagree					
1st Half of WS	-0.278	1.650**	1.235	0.131	0.279
	(0.628)	(0.703)	(0.763)	(0.744)	(0.734)
2nd Half of WS	0.797	0.726	0.305	0.915	1.683**
	(0.638)	(0.681)	(0.631)	(0.625)	(0.611)
After WS	1.421***	1.176*	1.447**	-0.197	0.809
	(0.544)	(0.608)	(0.659)	(0.626)	(0.631)
N	793	793	793	793	793
p	0.000	0.000	0.000	0.000	0.000
F	32.693	6.592	39.457	42.305	21.660

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables. DNRA: don't know/refuse to answer.

++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B12 Test of Lagged Effect with Warm Spell Dummy Variables: 7 Day Lagged

	G	A	B	C	D
Strongly Agree					
1st Half of WS	-0.333	-0.633	-0.592	-0.319	0.687
	(0.638)	(0.604)	(0.577)	(0.648)	(0.559)
2nd Half of WS	-0.117	-0.135	-0.097	0.321	-0.050
	(0.504)	(0.547)	(0.518)	(0.645)	(0.560)
After WS	0.217	-0.381	-0.079	-1.807**	-0.123
	(0.744)	(0.712)	(0.697)	(0.833)	(0.688)
Somewhat Agree					
1st Half of WS	-0.176	-0.196	0.682	-0.272	0.889*
	(0.493)	(0.490)	(0.522)	(0.591)	(0.515)
2nd Half of WS	0.353	-0.000	-0.109	0.809	0.481
	(0.425)	(0.491)	(0.475)	(0.538)	(0.470)
After WS	1.247**	0.327	0.776	-0.566	0.574
	(0.620)	(0.588)	(0.584)	(0.585)	(0.564)
DKRA					
1st Half of WS	-0.343	0.344	0.912	-2.616**	-2.491
	(0.961)	(0.991)	(0.854)	(1.318)	(1.690)
2nd Half of WS	-1.189	-0.797	-1.136	-0.667	-0.674
	(1.223)	(0.927)	(0.917)	(1.230)	(1.230)
After WS	-14.098***	-0.173	-1.979*	-1.266*	-1.307
	(0.767)	(0.855)	(1.122)	(0.736)	(1.049)
Strongly Disagree					
1st Half of WS	0.855	0.723	0.316	0.830	2.099***
	(0.647)	(0.656)	(0.601)	(0.631)	(0.593)
2nd Half of WS	0.264	0.060	0.078	1.010	0.745
	(0.600)	(0.651)	(0.691)	(0.658)	(0.606)
After WS	1.832***	0.843	1.345*	-0.594	1.011
	(0.662)	(0.708)	(0.770)	(0.684)	(0.732)
N	793	793	793	793	793
p	0.000	0.000	0.000	0.000	0.000
F	27.720	13.447	32.815	33.254	22.415

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables. DNRA: don't know/refuse to answer.

++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B13 Estimates of 3 Day Dummy Variable

	Strongly Agree				
	G	A	B	C	D
Feb. 19-21	1.094	1.347	0.283	1.473	0.199
	(1.103)	(1.082)	(0.981)	(1.168)	(1.164)
Feb. 22-24	0.585	1.664	0.436	0.361	-0.107
	(1.081)	(1.115)	(1.085)	(1.224)	(1.215)
Feb. 25-27	1.380	1.661	0.873	2.191^{*}	2.026
	(1.222)	(1.053)	(0.977)	(1.120)	(1.331)
Feb. 28-Mar 1	1.724	2.310^{**}	1.099	1.182	0.534
	(1.200)	(1.016)	(0.917)	(1.147)	(1.108)
Mar 2-4	2.324^{**}	2.682^{***}	1.480	2.837^{***}	1.254
	(1.137)	(0.986)	(0.933)	(1.040)	(1.075)
Mar 5-7	1.155	1.830^{*}	0.697	1.658^{*}	0.407
	(1.232)	(0.970)	(0.889)	(0.986)	(1.026)
Mar 8-10	4.073^{***}	2.559^{**}	0.895	2.258^{**}	1.255
	(1.101)	(0.995)	(0.912)	(1.041)	(1.060)
Mar 11-13	2.579^{**}	3.852^{***}	3.158^{***}	4.063^{***}	2.131^{*}
	(1.164)	(1.084)	(1.029)	(1.094)	(1.089)
Mar 14-16	1.852	3.727^{***}	2.349^{**}	3.260^{***}	1.621
	(1.125)	(1.106)	(0.970)	(1.157)	(1.178)
Mar 17-19	2.200^{*}	1.177	0.483	1.979^{*}	1.637
	(1.179)	(1.182)	(1.038)	(1.058)	(1.180)
Mar 20-22	1.284	1.604	1.143	1.905	3.242^{***}
	(1.236)	(1.206)	(1.190)	(1.285)	(1.218)
Mar 23-25	2.775^{**}	2.208^{**}	1.701^{*}	3.308^{***}	1.793
	(1.253)	(1.041)	(0.962)	(1.082)	(1.099)
Mar 26-28	1.041	2.944^{***}	1.478	2.493^{**}	1.484
	(1.173)	(1.112)	(1.008)	(1.217)	(1.205)
Mar 29-31	-0.642	-1.681	-1.991	-0.047	-2.052
	(1.695)	(1.753)	(1.370)	(1.547)	(1.492)
Apr 1-3	0.841	3.187^{**}	5.426^{***}	2.551^{*}	1.440
	(1.648)	(1.427)	(1.553)	(1.427)	(1.410)
Apr 4-6	1.831	0.462	2.108	-2.903^{*}	2.571
	(1.424)	(1.373)	(1.474)	(1.587)	(1.587)
Apr 7-9	2.580^{*}	1.882	1.120	1.389	0.314
	(1.403)	(1.457)	(1.290)	(1.443)	(1.487)
Apr 10-12	1.937	3.348^{**}	0.893	1.574	2.162
	(1.368)	(1.515)	(1.250)	(1.520)	(1.473)
Apr 13-15	-15.145^{***}	2.015	1.375	-0.646	0.851
	(1.371)	(1.848)	(1.890)	(1.803)	(1.816)

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables.
++ Shaded area approximates the warm spell as it was from Mar. 10 to 25.
+++ Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B13 (Cont'd)

	Somewhat Agree				
	G	A	B	C	D
Feb. 19-21	-1.518	1.300	-0.446	0.466	0.282
	(0.943)	(1.199)	(1.009)	(1.190)	(1.165)
Feb. 22-24	-0.432	1.480	-0.815	0.183	-0.126
	(0.993)	(1.035)	(0.910)	(0.896)	(1.040)
Feb. 25-27	0.230	0.663	-1.254	0.087	0.501
	(1.055)	(0.965)	(0.875)	(0.912)	(1.187)
Feb. 28-Mar 1	0.720	1.507	-0.429	0.222	0.301
	(1.055)	(0.929)	(0.810)	(0.833)	(0.963)
Mar 2-4	0.828	1.072	-0.773	0.543	0.165
	(1.064)	(0.990)	(0.944)	(0.948)	(1.016)
Mar 5-7	-0.600	1.387	-0.338	-0.109	-0.441
	(0.992)	(0.924)	(0.778)	(0.844)	(0.955)
Mar 8-10	1.912*	1.483	-0.100	0.873	0.320
	(1.049)	(0.926)	(0.818)	(0.873)	(0.966)
Mar 11-13	1.139	2.698***	1.460	1.550	1.000
	(1.034)	(1.006)	(0.958)	(0.941)	(1.026)
Mar 14-16	0.088	2.423**	0.262	0.392	0.012
	(0.996)	(1.079)	(0.898)	(0.942)	(1.026)
Mar 17-19	-0.066	1.138	-0.329	0.173	0.867
	(1.011)	(1.019)	(0.920)	(0.891)	(1.087)
Mar 20-22	0.077	0.993	2.033*	-0.085	2.187*
	(1.061)	(1.008)	(1.063)	(1.206)	(1.164)
Mar 23-25	0.735	1.561	-0.029	0.988	0.974
	(1.142)	(0.981)	(0.886)	(0.930)	(1.004)
Mar 26-28	0.879	1.701	-0.229	1.198	0.986
	(0.966)	(1.040)	(0.888)	(0.995)	(1.071)
Mar 29-31	-0.596	0.535	-1.341	0.562	-1.026
	(1.081)	(1.103)	(1.045)	(1.001)	(1.163)
Apr 1-3	3.211**	3.008**	4.772***	1.717	1.316
	(1.376)	(1.252)	(1.394)	(1.143)	(1.188)
Apr 4-6	0.883	1.150	2.582*	-0.839	2.201*
	(1.362)	(1.243)	(1.345)	(1.238)	(1.323)
Apr 7-9	1.238	1.865*	0.369	0.178	0.059
	(1.083)	(1.103)	(1.031)	(0.971)	(1.064)
Apr 10-12	-0.723	1.154	-1.426	-0.015	1.405
	(1.281)	(1.580)	(1.228)	(1.250)	(1.428)
Apr 13-15	1.920	2.575	1.897	-1.411	1.010
	(1.632)	(1.608)	(1.882)	(1.302)	(1.539)

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables.
++ Shaded area approximates the warm spell as it was from Mar. 10 to 25.
++ Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B13 (Cont'd)

	Don't Know/Refuse to Answer				
	G	A	B	C	D
Feb. 19-21	-2.389	2.076	-20.148***	-1.241	-18.421***
	(2.327)	(2.954)	(1.574)	(1.777)	(1.759)
Feb. 22-24	17.047***	1.661	-5.747**	-2.547	-5.449***
	(1.515)	(2.603)	(2.309)	(1.847)	(1.578)
Feb. 25-27	18.196***	6.119**	-2.071	2.119	-0.677
	(1.461)	(2.759)	(1.428)	(1.660)	(1.538)
Feb. 28-Mar 1	15.109***	2.875	-19.981***	0.228	-17.760***
	(1.770)	(2.576)	(1.532)	(1.660)	(1.148)
Mar 2-4	18.536***	5.303*	-3.502*	1.518	-3.304**
	(1.949)	(2.711)	(2.114)	(1.742)	(1.411)
Mar 5-7	14.697***	1.406	-5.932*	-0.424	-5.637***
	(1.598)	(2.530)	(3.212)	(1.515)	(1.774)
Mar 8-10	2.085	5.848*	-1.727	1.745	-2.478*
	(1.653)	(3.326)	(1.555)	(2.288)	(1.283)
Mar 11-13	1.166	-9.441***	-17.942***	-12.307***	-16.904***
	(1.441)	(2.663)	(1.507)	(1.466)	(1.317)
Mar 14-16	17.358***	7.103***	-2.857*	2.271	-3.534**
	(1.483)	(2.674)	(1.700)	(1.828)	(1.437)
Mar 17-19	1.226	6.654**	-19.908***	-13.472***	-17.356***
	(1.848)	(2.711)	(1.838)	(1.603)	(1.629)
Mar 20-22	17.104***	-11.568***	-18.347***	-13.467***	-15.901***
	(1.702)	(2.070)	(2.156)	(1.371)	(1.637)
Mar 23-25	16.325***	-11.383***	-1.386	-1.150	-4.470**
	(1.690)	(2.575)	(1.486)	(2.278)	(2.003)
Mar 26-28	15.961***	4.624*	-5.858***	1.003	-3.111
	(1.616)	(2.541)	(1.836)	(1.639)	(2.425)
Mar 29-31	0.856	3.092	-3.318*	0.044	-2.988*
	(1.102)	(2.192)	(1.736)	(1.819)	(1.700)
Apr 1-3	1.835	3.300	-0.879	-0.611	-4.786**
	(1.602)	(2.748)	(2.316)	(1.896)	(2.246)
Apr 4-6	1.051	-13.010***	-17.607***	-16.011***	-16.892***
	(1.721)	(2.670)	(1.940)	(1.942)	(2.452)
Apr 7-9	1.618	-12.510***	-19.301***	-15.703***	-3.923**
	(1.670)	(2.436)	(1.613)	(1.520)	(1.703)
Apr 10-12	-0.642	8.283***	-4.675**	3.112*	-2.895
	(1.373)	(2.582)	(2.186)	(1.665)	(1.846)
Apr 13-15	2.122	-10.587***	-17.720***	-15.808***	-16.776***
	(1.878)	(2.410)	(2.139)	(1.781)	(2.275)

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables.
++ Shaded area approximates the warm spell as it was from Mar. 10 to 25.
++ Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 1.B13 (Cont'd)

	Strongly Disagree				
	G	A	B	C	D
Feb. 19-21	-1.295	1.132	-0.874	0.512	-0.096
	(1.279)	(1.537)	(1.633)	(1.354)	(1.476)
Feb. 22-24	0.743	2.343	0.330	1.465	0.830
	(1.160)	(1.688)	(1.631)	(1.359)	(1.476)
Feb. 25-27	1.256	1.561	0.115	2.376^{**}	2.568^{*}
	(1.096)	(1.332)	(1.360)	(1.100)	(1.382)
Feb. 28-Mar 1	0.255	-0.239	-1.832	-0.363	-0.512
	(1.201)	(1.714)	(1.661)	(1.301)	(1.398)
Mar 2-4	1.423	2.862^{**}	0.904	2.835^{**}	1.809
	(1.254)	(1.457)	(1.524)	(1.175)	(1.327)
Mar 5-7	0.073	2.074	-0.394	0.995	0.458
	(1.073)	(1.410)	(1.457)	(1.142)	(1.269)
Mar 8-10	1.878	2.625^{*}	0.481	1.739	0.811
	(1.185)	(1.399)	(1.564)	(1.281)	(1.377)
Mar 11-13	-0.540	3.075^{**}	1.559	2.682^{**}	1.674
	(1.077)	(1.427)	(1.555)	(1.174)	(1.264)
Mar 14-16	0.552	4.205^{***}	1.549	1.004	-0.076
	(1.231)	(1.549)	(1.544)	(1.347)	(1.457)
Mar 17-19	0.670	0.584	-0.557	0.374	1.789
	(1.117)	(1.493)	(1.566)	(1.298)	(1.402)
Mar 20-22	0.720	2.646^{*}	2.313	2.037^{*}	4.169^{***}
	(1.193)	(1.517)	(1.554)	(1.236)	(1.292)
Mar 23-25	2.294^{*}	3.623^{**}	-0.128	3.759^{***}	2.979^{**}
	(1.351)	(1.478)	(1.439)	(1.190)	(1.356)
Mar 26-28	0.304	2.153	-0.177	1.899	1.314
	(1.185)	(1.493)	(1.584)	(1.270)	(1.402)
Mar 29-31	1.500	3.275^{**}	1.441	2.854^{*}	1.790
	(1.336)	(1.465)	(1.677)	(1.480)	(1.517)
Apr 1-3	2.538^{*}	3.516^{**}	5.223^{***}	2.030	1.492
	(1.388)	(1.602)	(1.803)	(1.423)	(1.473)
Apr 4-6	2.463^{*}	3.581^{**}	4.679^{***}	1.851	4.686^{***}
	(1.458)	(1.711)	(1.801)	(1.475)	(1.608)
Apr 7-9	2.699^{**}	2.639	0.899	1.091	0.723
	(1.325)	(1.607)	(1.703)	(1.390)	(1.497)
Apr 10-12	0.886	3.164^{*}	-1.324	1.334	0.983
	(1.274)	(1.667)	(1.896)	(1.402)	(1.911)
Apr 13-15	3.477^{**}	5.904^{***}	5.513^{**}	0.072	4.339^{**}
	(1.705)	(1.858)	(2.243)	(1.644)	(1.902)

+ G: general adaptation; A: the adaptation regarding state level and corn/soybeans; B: the adaptation regarding state level and fruits/vegetables; C: the adaptation regarding national level and corn/soybeans; D: the adaptation regarding national level and fruits/vegetables.

++ Shaded area approximates the warm spell as it was from Mar. 10 to 25.

+++ Standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 1.B14 Results of Interaction Model: General Adaptation

	Strongly Agree		Somewhat. Agree		DNRA		Strongly Disagree	
Age	0.043	(0.063)	0.011	(0.049)	0.297	(0.115)***	0.093	(0.057)
Age2	-0.000	(0.001)	0.000	(0.000)	-0.002	(0.001)**	-0.001	(0.001)
Gender (Male=1)	1.382	(0.472)***	1.311	(0.397)***	-1.710	(1.062)	1.461	(0.519)***
Race (White=1)	-0.714	(0.507)	-0.646	(0.456)	0.173	(1.297)	-0.574	(0.685)
Political Ideology (Conservative =1)	-1.084	(0.514)**	-0.241	(0.425)	0.361	(0.894)	0.626	(0.508)
Conservative White Male	-1.546	(0.853)*	-1.652	(0.669)**	0.424	(1.468)	-1.254	(0.715)*
Education: <H.S.	1.031	(0.885)	-0.889	(0.873)	-12.771	(0.963)***	-1.438	(1.114)
Education: Some College	-2.024	(0.608)***	-0.811	(0.462)*	-1.516	(0.910)*	-0.431	(0.552)
Education: >= Bachelor	-0.092	(0.549)	-0.254	(0.487)	-0.452	(1.227)	-0.366	(0.565)
Income>50k	0.555	(0.456)	0.244	(0.368)	-0.926	(0.674)	0.909	(0.433)**
Unemployment Rate	-0.022	(0.138)	-0.088	(0.101)	-0.483	(0.233)**	-0.018	(0.118)
Corns Soybean Sales	-0.007	(0.007)	-0.010	(0.006)*	0.004	(0.010)	-0.011	(0.006)
Fruits & Veges Sales	-0.001	(0.014)	-0.012	(0.012)	0.003	(0.021)	0.006	(0.012)
U2	0.672	(0.702)	1.049	(0.609)*	-2.081	(1.558)	0.903	(0.646)
U3	0.801	(0.741)	0.685	(0.654)	-0.856	(1.401)	0.960	(0.788)
U4	1.651	(1.199)	2.150	(0.997)**	-14.060	(2.494)***	2.095	(1.103)*
U5	2.746	(0.915)***	2.258	(0.839)***	-13.848	(1.977)***	1.987	(0.896)**
U6	-0.373	(0.951)	0.916	(0.695)	-0.995	(1.957)	0.563	(0.942)
U7	0.170	(1.052)	1.624	(0.692)**	-1.224	(1.802)	1.572	(0.849)*
WS1	0.517	(1.792)	0.957	(1.516)	-3.246	(2.358)	-8.022	(2.874)***
WS2	1.738	(1.844)	1.097	(1.556)	-11.475	(7.105)	1.616	(1.725)
WS3	-0.126	(0.745)	0.329	(0.579)	-2.367	(1.111)**	1.306	(0.607)**
TDTF	0.042	(0.111)	0.072	(0.089)	0.062	(0.202)	0.136	(0.095)
WS1*TD*TF	-1.725	(0.650)***	-1.205	(0.475)**	-3.617	(1.474)**	-0.329	(0.721)
WS2*TD*TF	-0.239	(0.894)	-0.158	(0.678)	-0.585	(1.083)	-1.408	(0.869)
WS3*TD*TF	0.554	(0.433)	0.504	(0.418)	-0.394	(1.083)	0.095	(0.435)
TF	-4.894	(1.820)***	-3.966	(1.372)***	3.297	(3.260)	-3.912	(1.721)**
WS1*TF	43.728	(15.613)***	31.593	(13.198)**	43.911	(21.519)**	-9.351	(23.646)
WS2*TF	18.907	(20.377)	9.305	(15.699)	-18.548	(28.502)	27.029	(17.591)
WS3*TF	5.194	(3.078)*	1.197	(2.309)	-8.691	(5.567)	7.434	(2.886)**
TD	0.082	(0.034)**	0.073	(0.028)***	-0.222	(0.095)**	0.037	(0.033)
WS1*TD	-0.022	(0.073)	-0.051	(0.064)	0.342	(0.132)***	0.266	(0.107)**
WS2*TD	-0.117	(0.069)*	-0.093	(0.057)	0.549	(0.256)**	-0.060	(0.067)
WS3*TD	-0.008	(0.077)	0.153	(0.070)**	0.327	(0.121)***	0.020	(0.086)
Constant	-1.661	(2.316)	0.010	(1.800)	-4.823	(3.718)	-4.376	(2.135)**
Observations	793							
p	0.000							
F	8.711							

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ WS1~3:1st half, 2nd half and after Warm Spell; TD: Temperature Deviation; TF: Temperature Fluctuation

+++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B15 Results of Interaction Model: SGCS

	Strongly Agree		Somewhat. Agree		DNRA		Strongly Disagree	
Age	0.118	(0.061)*	0.138	(0.049)***	0.108	(0.101)	0.200	(0.068)***
Age2	-0.001	(0.001)**	-0.001	(0.000)***	-0.001	(0.001)	-0.002	(0.001)***
Gender (Male=1)	0.766	(0.404)*	0.264	(0.380)	-2.030	(0.916)**	0.450	(0.526)
Race (White=1)	-0.108	(0.519)	0.602	(0.525)	0.118	(1.044)	0.472	(0.628)
Political Ideology (Conservative =1)	-0.405	(0.459)	-0.606	(0.448)	0.274	(0.731)	-0.614	(0.554)
Conservative White Male	-0.931	(0.645)	-0.977	(0.627)	0.806	(1.530)	1.070	(0.715)
Education: <H.S.	0.650	(0.974)	-1.914	(1.062)*	-3.982	(1.929)**	-2.746	(1.628)*
Education: Some College	-1.272	(0.525)**	-0.372	(0.466)	0.101	(0.995)	-0.742	(0.585)
Education: >= Bachelor	-0.793	(0.504)	-0.198	(0.504)	-0.332	(1.330)	-0.589	(0.596)
Income>50k	-0.848	(0.487)*	-1.399	(0.456)***	-2.405	(1.076)**	-0.784	(0.500)
Unemployment Rate	0.041	(0.116)	-0.028	(0.120)	0.163	(0.206)	0.221	(0.129)*
Corns Soybean Sales	-0.003	(0.006)	0.008	(0.006)	0.006	(0.009)	-0.008	(0.007)
Fruits & Veges Sales	0.017	(0.013)	0.006	(0.011)	0.018	(0.017)	-0.006	(0.015)
U2	-0.076	(0.636)	-0.028	(0.612)	-0.631	(1.112)	1.385	(0.752)*
U3	-0.982	(0.737)	-0.479	(0.678)	-1.784	(1.458)	-0.041	(0.788)
U4	0.478	(1.001)	-0.334	(0.901)	-15.340	(2.400)***	0.172	(1.165)
U5	2.034	(1.096)*	2.052	(1.092)*	1.993	(1.700)	2.215	(1.152)*
U6	-0.231	(0.691)	-1.373	(0.812)*	0.721	(1.343)	0.626	(0.869)
U7	-0.593	(0.619)	0.431	(0.608)	-0.561	(1.222)	-0.705	(0.848)
WS1	3.712	(1.905)*	5.233	(1.913)***	2.308	(2.274)	3.031	(2.221)
WS2	0.043	(2.047)	0.686	(1.747)	2.103	(1.911)	0.697	(1.938)
WS3	-0.311	(0.749)	0.198	(0.587)	-0.965	(1.074)	0.835	(0.660)
TDTF	-0.037	(0.090)	-0.115	(0.089)	-0.348	(0.219)	-0.284	(0.171)*
WS1*TD*TF	0.576	(0.420)	1.053	(0.411)**	-0.074	(1.327)	1.057	(0.516)**
WS2*TD*TF	1.636	(0.995)	1.304	(0.883)	-0.182	(0.932)	1.441	(1.074)
WS3*TD*TF	-0.279	(0.442)	-0.069	(0.357)	0.741	(0.518)	0.434	(0.357)
TF	0.457	(1.361)	2.731	(1.365)**	0.703	(2.813)	0.164	(1.900)
WS1*TF	-9.481	(7.837)	-22.680	(8.233)***	-6.362	(14.264)	-17.432	(11.090)
WS2*TF	-36.197	(23.796)	-31.126	(21.933)	12.896	(21.437)	-32.308	(23.927)
WS3*TF	-7.172	(3.184)**	-6.151	(2.869)**	-4.938	(4.134)	-0.374	(2.886)
TD	0.019	(0.028)	-0.006	(0.026)	-0.029	(0.112)	-0.015	(0.037)
WS1*TD	-0.102	(0.076)	-0.156	(0.076)**	0.005	(0.140)	-0.053	(0.089)
WS2*TD	-0.028	(0.070)	-0.023	(0.060)	-0.023	(0.143)	0.013	(0.068)
WS3*TD	0.141	(0.088)	0.094	(0.062)	-0.059	(0.145)	-0.032	(0.077)
Constant	-1.945	(2.011)	-1.018	(1.818)	-4.293	(3.180)	-6.671	(2.517)***
Observations	793							
p	0.000							
F	2.801							

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ WS1~3:1st half, 2nd half and after Warm Spell; TD: Temperature Deviation; TF: Temperature Fluctuation

+++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B16 Results of Interaction Model: SGFV

	Strongly Agree		Somewhat. Agree		DNRA		Strongly Disagree	
Age	0.205	(0.059)***	0.177	(0.049)***	0.471	(0.145)***	0.244	(0.066)***
Age2	-0.002	(0.001)***	-0.002	(0.000)***	-0.004	(0.001)***	-0.002	(0.001)***
Gender (Male=1)	1.048	(0.437)**	0.542	(0.406)	-0.434	(0.634)	0.940	(0.645)
Race (White=1)	-0.298	(0.467)	0.550	(0.465)	-0.856	(0.875)	0.676	(0.723)
Political Ideology (Conservative =1)	-0.054	(0.492)	-0.160	(0.457)	0.063	(0.744)	0.665	(0.623)
Conservative White Male	-1.461	(0.692)**	-1.302	(0.647)**	-1.641	(1.758)	-0.019	(0.833)
Education: <H.S.	-0.693	(0.798)	-2.400	(0.968)**	-3.243	(3.097)	-16.460	(1.065)***
Education: Some College	-1.606	(0.557)***	-0.949	(0.497)*	-1.110	(0.859)	-0.647	(0.646)
Education: >= Bachelor	-0.785	(0.518)	-0.548	(0.522)	-1.569	(1.048)	-0.132	(0.667)
Income>50k	-0.756	(0.472)	-1.317	(0.436)***	-0.278	(0.741)	-0.094	(0.538)
Unemployment Rate	-0.080	(0.105)	-0.069	(0.100)	-0.448	(0.292)	0.023	(0.113)
Corns Soybean Sales	0.000	(0.006)	0.010	(0.006)*	0.001	(0.010)	-0.004	(0.007)
Fruits & Veges Sales	0.020	(0.013)	-0.002	(0.012)	0.001	(0.028)	-0.005	(0.016)
U2	-0.965	(0.648)	-0.795	(0.600)	-2.034	(1.770)	-0.364	(0.757)
U3	-1.271	(0.788)	-0.795	(0.716)	-3.510	(2.060)*	-0.636	(0.849)
U4	-1.826	(1.121)	-0.619	(0.937)	-15.057	(1.609)***	-0.615	(1.144)
U5	-0.287	(0.908)	-0.379	(0.778)	-8.173	(5.814)	0.436	(0.886)
U6	-0.836	(0.778)	-1.400	(0.714)*	2.131	(1.147)*	0.521	(0.872)
U7	-0.678	(0.715)	0.097	(0.671)	-1.360	(1.733)	-0.367	(0.827)
WS1	4.604	(1.956)**	5.905	(1.866)***	-0.348	(3.315)	3.099	(2.418)
WS2	1.412	(1.428)	-1.692	(1.544)	9.146	(4.505)**	-3.599	(1.861)*
WS3	-0.215	(0.703)	0.498	(0.627)	-1.760	(1.083)	1.158	(0.798)
TDTF	-0.142	(0.083)*	-0.119	(0.079)	-0.809	(0.230)***	-0.295	(0.159)*
WS1*TD*TF	1.050	(0.428)**	1.036	(0.395)***	0.598	(0.703)	1.502	(0.527)***
WS2*TD*TF	-0.919	(0.737)	0.132	(0.709)	-9.280	(4.401)**	1.059	(0.876)
WS3*TD*TF	0.016	(0.655)	-0.036	(0.611)	-0.190	(0.766)	0.431	(0.600)
TF	2.167	(1.255)*	2.064	(1.227)*	4.456	(3.060)	0.016	(1.820)
WS1*TF	-15.500	(8.138)*	-24.594	(8.219)***	9.454	(15.153)	-26.080	(11.436)**
WS2*TF	23.350	(15.843)	-3.230	(14.928)	212.668	(92.481)**	-17.995	(18.009)
WS3*TF	-5.756	(2.857)**	-2.836	(2.520)	-6.315	(4.511)	3.995	(3.211)
TD	0.022	(0.029)	0.020	(0.028)	-0.008	(0.051)	0.015	(0.036)
WS1*TD	-0.153	(0.081)*	-0.203	(0.074)***	-0.033	(0.123)	-0.100	(0.094)
WS2*TD	-0.056	(0.055)	0.069	(0.056)	-0.383	(0.239)	0.115	(0.068)*
WS3*TD	0.094	(0.100)	0.062	(0.090)	-0.044	(0.099)	-0.056	(0.117)
Constant	-2.516	(1.811)	-1.320	(1.600)	-5.525	(4.594)	-7.155	(2.198)***
Observations	793							
p	0.000							
F	36.210							

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ WS1~3:1st half, 2nd half and after Warm Spell; TD: Temperature Deviation; TF: Temperature Fluctuation

+++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B17 Results of Interaction Model: NGCS

	Strongly Agree		Somewhat. Agree		DNRA		Strongly Disagree	
Age	0.203	(0.065)***	0.101	(0.052)*	0.130	(0.110)	0.184	(0.063)***
Age2	-0.002	(0.001)***	-0.001	(0.000)**	-0.001	(0.001)	-0.002	(0.001)***
Gender (Male=1)	0.419	(0.487)	0.133	(0.412)	-1.821	(0.866)**	0.227	(0.538)
Race (White=1)	-0.964	(0.539)*	0.105	(0.511)	-1.657	(0.900)*	0.144	(0.691)
Political Ideology (Conservative =1)	0.044	(0.562)	-0.434	(0.512)	1.573	(0.766)**	0.501	(0.566)
Conservative White Male	-0.250	(0.805)	-0.479	(0.678)	0.011	(1.333)	0.359	(0.754)
Education: <H.S.	2.057	(1.198)*	1.094	(1.168)	2.251	(1.976)	-12.547	(1.207)***
Education: Some College	-0.734	(0.606)	-0.222	(0.510)	0.360	(1.102)	-0.229	(0.584)
Education: >= Bachelor	0.008	(0.545)	0.496	(0.518)	0.957	(1.219)	0.521	(0.563)
Income>50k	-1.509	(0.534)***	-1.576	(0.466)***	-1.950	(0.835)**	-1.002	(0.523)*
Unemployment Rate	0.100	(0.121)	-0.023	(0.107)	-0.329	(0.209)	-0.018	(0.112)
Corns Soybean Sales	-0.011	(0.007)*	0.001	(0.006)	-0.004	(0.009)	-0.014	(0.006)**
Fruits & Veges Sales	0.010	(0.015)	-0.001	(0.012)	0.022	(0.018)	-0.008	(0.013)
U2	0.711	(0.681)	0.519	(0.621)	-0.954	(1.266)	1.930	(0.745)***
U3	-0.303	(0.881)	0.019	(0.770)	-1.786	(1.545)	0.743	(0.852)
U4	0.458	(1.014)	-0.111	(0.910)	-3.290	(1.830)*	1.181	(1.176)
U5	-0.578	(0.895)	-1.314	(0.799)	-0.350	(1.161)	-0.251	(0.847)
U6	-0.237	(0.794)	-0.801	(0.777)	1.487	(1.520)	1.504	(0.908)*
U7	-1.264	(0.723)*	0.100	(0.628)	-0.102	(1.190)	0.466	(0.726)
WS1	8.360	(3.812)**	9.140	(3.662)**	5.755	(3.979)	7.205	(3.954)*
WS2	4.028	(2.130)*	3.473	(1.995)*	20.033	(6.216)***	4.738	(2.151)**
WS3	-0.970	(0.843)	-0.095	(0.583)	-2.482	(1.027)**	-0.002	(0.631)
TDTF	-0.089	(0.094)	-0.208	(0.091)**	-0.327	(0.163)**	-0.188	(0.121)
WS1*TD*TF	1.194	(0.607)**	1.562	(0.580)***	1.108	(0.776)	1.413	(0.574)**
WS2*TD*TF	-1.896	(0.842)**	-1.266	(0.856)	-8.039	(2.039)***	-1.404	(1.025)
WS3*TD*TF	-0.407	(0.373)	-0.056	(0.250)	0.600	(0.521)	0.180	(0.251)
TF	1.895	(1.534)	2.022	(1.338)	4.369	(2.820)	1.234	(1.597)
WS1*TF	-23.232	(13.572)*	-34.021	(13.248)**	-26.901	(14.455)*	-33.643	(13.768)**
WS2*TF	42.466	(19.158)**	30.818	(18.563)*	183.855	(42.951)***	32.882	(21.402)
WS3*TF	-6.823	(3.436)**	-6.222	(2.374)***	-13.340	(4.447)***	-2.564	(2.489)
TD	0.007	(0.037)	0.029	(0.027)	0.002	(0.085)	0.008	(0.035)
WS1*TD	-0.257	(0.138)*	-0.345	(0.129)***	-0.177	(0.164)	-0.262	(0.143)*
WS2*TD	-0.100	(0.073)	-0.136	(0.065)**	-1.016	(0.298)***	-0.126	(0.069)*
WS3*TD	0.165	(0.102)	0.012	(0.058)	-0.066	(0.114)	-0.098	(0.077)
Constant	-3.376	(2.127)	0.771	(1.752)	0.715	(3.386)	-3.614	(2.304)
Observations	793							
p	0.000							
F	31.499							

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ WS1~3:1st half, 2nd half and after Warm Spell; TD: Temperature Deviation; TF: Temperature Fluctuation

+++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.B18 Results of Interaction Model: NGFV

	Strongly Agree		Somewhat. Agree		DNRA		Strongly Disagree	
Age	0.242	(0.066)***	0.092	(0.052)*	0.449	(0.150)***	0.168	(0.066)**
Age2	-0.002	(0.001)***	-0.001	(0.000)**	-0.004	(0.001)***	-0.002	(0.001)***
Gender (Male=1)	1.085	(0.477)**	0.547	(0.443)	-0.815	(0.856)	1.165	(0.574)**
Race (White=1)	-1.060	(0.519)**	0.156	(0.504)	-2.303	(0.863)***	0.140	(0.649)
Political Ideology (Conservative =1)	-0.002	(0.501)	-0.002	(0.449)	0.376	(0.869)	0.656	(0.571)
Conservative White Male	-1.053	(0.787)	-1.294	(0.669)*	0.515	(1.220)	-0.771	(0.782)
Education: <H.S.	-0.132	(0.916)	-2.395	(0.993)**	-1.092	(2.123)	-15.478	(1.007)***
Education: Some College	-0.217	(0.586)	-0.223	(0.491)	-1.523	(1.181)	0.099	(0.602)
Education: >= Bachelor	0.029	(0.517)	0.149	(0.482)	-1.599	(1.108)	0.457	(0.591)
Income>50k	-1.064	(0.498)**	-1.407	(0.449)***	-0.518	(0.826)	-0.195	(0.512)
Unemployment Rate	-0.026	(0.123)	-0.009	(0.107)	-1.147	(0.315)***	-0.027	(0.120)
Corns Soybean Sales	-0.004	(0.006)	0.003	(0.005)	0.020	(0.011)*	-0.006	(0.006)
Fruits & Veges Sales	0.022	(0.014)	0.003	(0.012)	0.108	(0.052)**	0.001	(0.014)
U2	-0.568	(0.680)	0.129	(0.632)	-10.314	(3.474)***	1.115	(0.792)
U3	-1.219	(0.810)	-0.447	(0.709)	-7.582	(3.372)**	-0.319	(0.852)
U4	-1.066	(0.957)	-0.498	(0.843)	-8.840	(2.813)***	0.495	(1.090)
U5	-1.392	(0.920)	-0.873	(0.842)	-3.101	(1.664)*	-0.117	(0.884)
U6	-0.326	(0.694)	-1.330	(0.754)*	2.180	(1.205)*	0.710	(0.940)
U7	-1.317	(0.674)*	-0.239	(0.622)	-2.793	(1.701)	-0.034	(0.743)
WS1	2.867	(1.987)	4.446	(1.815)**	-8.197	(7.279)	2.176	(2.243)
WS2	-0.898	(1.959)	-0.831	(1.930)	29.242	(8.691)***	-0.880	(2.155)
WS3	-0.334	(0.696)	-0.114	(0.593)	-2.779	(1.084)**	0.402	(0.665)
TDTF	-0.082	(0.090)	-0.238	(0.101)**	-1.170	(0.253)***	-0.203	(0.136)
WS1*TD*TF	0.832	(0.424)*	1.284	(0.418)***	1.521	(0.952)	1.115	(0.409)***
WS2*TD*TF	-0.565	(0.784)	0.942	(0.710)	-11.008	(2.947)***	0.767	(0.980)
WS3*TD*TF	-0.061	(0.516)	0.297	(0.403)	-0.091	(0.653)	0.347	(0.386)
TF	0.923	(1.472)	2.785	(1.509)*	11.780	(3.578)***	1.530	(1.774)
WS1*TF	-9.408	(7.964)	-21.310	(7.579)***	4.955	(24.206)	-22.385	(8.870)**
WS2*TF	14.075	(18.742)	-17.385	(15.535)	262.695	(66.288)***	-14.903	(20.189)
WS3*TF	-5.230	(2.979)*	-7.813	(2.399)***	-22.112	(5.289)***	-1.028	(2.831)
TD	0.014	(0.031)	0.011	(0.026)	-0.040	(0.041)	-0.015	(0.035)
WS1*TD	-0.102	(0.083)	-0.189	(0.076)**	0.167	(0.259)	-0.092	(0.092)
WS2*TD	0.073	(0.075)	0.050	(0.075)	-1.462	(0.405)***	0.110	(0.075)
WS3*TD	0.101	(0.087)	0.058	(0.066)	-0.049	(0.079)	-0.029	(0.085)
Constant	-3.705	(2.189)*	0.811	(1.644)	1.624	(4.461)	-4.032	(2.141)*
Observations	793							
p	0.000							
F	31.093							

+ U2~U7: Urbanization level from 2 (250K ≤ Metro < 1M), 3 (Metro < 250K), 4(Urban ≥ 20K, adj Metro), 5 (Urban ≥20K, not adj Metro), 6 (Urban < 20K, adj Metro), 7 (Urban < 20K, not adj Metro); number in parentheses denotes population.

++ WS1~3:1st half, 2nd half and after Warm Spell; TD: Temperature Deviation; TF: Temperature Fluctuation

+++ Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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ESSAY 2: LOCAL ACCEPTANCE AND HETEROGENEOUS EXTERNALITIES OF BIOREFINERIES

2.1 Introduction

Biofuel production has grown rapidly in the U.S. since 2007 (Renewable Fuels Association, 2015; US EIA, 2015) in response to biofuel mandates under various laws including the Energy Security and Independence Act of 2007 which mandates the use of 36 billion gallons (137 Gigaliters) of biofuels by 2022.[20] For the bioenergy industry, site selection is an important component of the success of a project, especially because transportation costs (for both inputs and outputs) constitute a significant portion to the cost of production. However, acceptance by the local community also plays a key role in the success of a biofuel refinery project, as a more accepting community may offer incentives that offset costs, while a less accepting community may create delays in permitting or increase project and other costs. Some studies show that opposition from the local community also decreases the probability of siting a bioenergy plant (Fortenbery et al., 2013; Haddad et al., 2009; Tigges and Noble, 2012). These studies view the opposition mainly as a not-in-my-back-yard (NIMBY) effect, when the reasons may be more nuanced.

We posit that local acceptance is a function of local welfare changes due to the proposed biorefinery project. While a biorefinery project may impose both positive and negative externalities on local communities, so long as perceived benefits exceed perceived costs, such a project is likely to be welcomed by the local community. A biofuel facility might bring benefits such as job opportunities, purchases of locally produced inputs, tax revenues, funding sources for local infrastructure, to the local community (Fletcher, 2014; Futch, 2014). To reap these benefits,

[20] This essay is co-authored with members of my dissertation committee, Dr. Scott Loveridge and Dr. Satish Joshi.

local governments may offer property tax relief and other financial support to the biorefinery investors (Blackwell, 2014; Abuelsamid, 2010; Hoppe et al., 2011). On the other hand, there are also instances of communities resisting planned investments in biofuel facilities (Selfa, 2010; Stephen et al., 2010; Lambert, 2009; CTV Kitchener, 2012). Local opposition might reduce profitability (Panoutsou et al., 2013) due to project delays, lawsuits or protests from local groups, or in more extreme cases, vandalism. The opposing groups also incur costs (primarily time, but potentially out-of-pocket expenses for media campaigns or lawsuits), further reducing welfare.

Developing systematic information on community attitudes towards biofuel facilities and degree of acceptability can aid regional planners and biorefinery developers in making informed decisions and avoid potential waste of money and time for both proponents and opponents. However, there is little systematic analysis of local acceptability with regard to biofuel production (Chin et al., 2014). A straightforward approach might be to poll the residents, but a simple poll may produce information on the proportion of local residents who are supportive or against the biorefinery without indicating the strength of welfare gains/losses associated with a new facility. For example, projects that have widespread but individually small welfare losses, along with highly concentrated benefits to a minority, are likely to indicate lack of support in polls, but in reality such opposition may not produce protests and lawsuits. In contrast, substantial welfare losses to a minority may bring about vocal opposition and lawsuits.

This study aims to identify the factors that might influence local acceptability of a biorefinery by estimating the willingness to pay (WTP) either to support or oppose a biorefinery. We use WTP estimates as a measure of local acceptance since WTP originally developed as a measure of welfare changes. We assume that local acceptance is a function of welfare change.

We conduct a statewide survey including a scenario in which a proposed biorefinery would be sited in the community where the respondent lives. We adopt a two-step framework to stratify the supporters and opponents and estimate the WTPs conditional on the attitudes towards the biorefinery. The Heckman process is used to correct potential sample selection bias. The determinants of the attitudes or WTPs are informative for decision making. Finally we provide spatial analysis to show how the results can be used to map potential areas of local acceptance or opposition. While the current study specifically analyzes community acceptance of biorefineries, the methods are broadly applicable to acceptance of any kind of facility, including other energy production facilities, that may involve heterogeneous welfare changes among community members.

2.2 Literature Review

Studies on local acceptance of renewable energy facilities began appearing in the literature in the late 1990s (Roos et al. 1999). The early literature focused more on the opposition part of local acceptance, i.e. NIMBYism, but then shifted to more generic ideas about public attitudes toward such facilities, suggesting that NIMBYism is not the only factor influencing public attitudes toward proposed projects, and labeling opposition as NIMBYism may oversimplify its causes (Chin et al., 2014; Devine-Wright, 2005; Wolsink, 2007a). For instance, local opposition to wind power facilities was found to be independent of the distance between the respondent and the facilities (Wolsink, 2007b, 2000).

The terms used to describe the public attitudes of the local community towards a certain project include community acceptance (Wüstenhagen et al., 2007), local social acceptance (Breukers and Wolsink, 2007), local acceptance (Soland et al., 2013), among others. We use “local acceptance” to refer to public attitudes of the local community and “social acceptance” when the scope includes the broader society.

The acceptance of bio-energy plants from the general public, locally or not, is important (Breukers and Wolsink, 2007; McCormick, 2010), but understanding of the factors contributing to local acceptance of biorefineries or bio-energy plants is limited. Many articles discuss the acceptance of renewable energy facilities such as wind farms and solar farms, but only few analyze acceptance of biofuel production facilities. Chin et al. (2014) discuss social acceptance of biofuel development, but no quantitative analysis was conducted. Sacchelli (2014) use a Fuzzy Cognitive Map technique to identify the factors influencing social acceptance of biomass plants from the view of bio-energy experts rather than local community. To understand local attitudes towards the biofuel facilities, Amigun et al. (2011) conducted a survey and interviews to explore the local acceptance of biodiesel production in South Africa and found the main concerns were pollution and health risks.

Similarly, among dozens of site selection articles which discuss biofuel facilities, only a few studies have taken local acceptance into consideration. For example, Tigges & Nobel (2012) qualitatively assess factors influencing biofuel facility location decisions, while Haddad et al. (2009) find an association between population density and biofuel location decisions. Fortenbery et al. (2013) used population and education to capture local acceptance in their study of biorefinery location decisions. They found that population has a positive effect on biorefinery siting while higher education level is associated with more opposition of such facilities.

Very few studies quantitatively analyze factors influencing local acceptance of biofuel facilities from the perspective of local residents. The exception is the study by Soland et al.

(2013), which quantitatively explored the local acceptance of a biogas plant using a multiple choice question.

Polls or similar methods may not adequately assess the degree of support or opposition since a biofuel facility would bring various kinds of positive and negative impacts, which affect different sections of the community in different ways. As a result, the degree of opposition/support can vary significantly across members of a community, which may not be captured with a “yes/no” format, or even with a Likert scale type questions. The WTP method is an alternative to polls not only to explore the public opinions on certain policies but also to elicit the strength of such opinions (Hall et al., 2004; Joewono, 2009; Jones-Lee, 1993; Nagin et al., 2006; Walton et al., 2004). Since a WTP question involves the respondents’ welfare change, Nagin et al. (2006) further argue that it is a more accurate tool than traditional polls. The WTP approach also allows decision makers to anchor the possible benefits or costs due to the biorefinery which a poll cannot. To our knowledge, no prior study has estimated public WTP for a biorefinery. Our study addresses this gap in the literature, and also offers a method that might be used for siting decisions of other types of facilities where opinions about the desirability of the facility may differ among members of potential host communities.

2.3 Method

Conventionally, contingent valuation methods estimating WTP assume that WTP is non-negative (Clinch and Murphy, 2001) due to the probability distributions commonly used in the likelihood functions. The simple reason for such an assumption is public goods can be ignored if they are not desired (Bohara et al., 2001; Haab and McConnell, 1998, 1997). However, public goods result in both winners (positive utility) and losers (negative utility) (Haab and McConnell, 1998; Kriström, 1997) to some degree. In the case of biorefineries, the potential for negative externalities might be higher compared to other public goods (such as a library or an emergency response system), so it is important to treat the negative side of the distribution with care in the case at hand. Further, exclusion of negative WTP in the estimation would result in biased estimates in the cases with both positive and negative externalities (Hanley et al., 2009). To deal with the negative WTP, Kriström (1997) suggested that the spike model designed for non-negative WTP can be extended using a mixture likelihood function which incorporates positive, zero, and negative utility changes into one function; Hanemann & Kanninen (1999) illustrate this idea in a more comprehensive way. Bohara et al. (2001) evaluated the performance of the mixture model by Monte Carlo simulation and found that it does not outperform the standard models if the negative WTP proportion is more than 30%. Nahuelhual-Muñoz et al. (2004) used empirical data to test if there is a difference between the estimates from the spike model and the extended spike model. They found the estimate from the extended spike model is lower than that from general (non-negative) spike model.

Alternatively, Macmillan et al. (2001) dealt with the negative WTP issue by including willingness to accept (WTA) questions to the opponents and incorporating the WTA as negative WTP bids within one regression function by either dropping the non-negative assumption or introducing two variables to represent zero and negative WTP (Macmillan et al., 2001). However, the use of a WTA framework often leads to the concern of unrealistically high numbers in the question (Arrow et al., 1993). Moreover, significant disparity between WTP and WTA estimates for the same good have been reported, especially in the case of non-market goods (Horowitz and McConnell, 2002; Zhao and Kling, 2001). This disparity could lead to biased estimates of the strength of support and the strength of opposition to a biorefinery.

One way to handle this winners and losers issue within a WTP frame work is to separate the respondents into supporters and opponents. Keith et al. (1996), in their valuation of wilderness designation, separately estimate supporters' WTP and opponents' WTP. Clinch & Murphy (2001) stratify the respondents according to their attitudes towards a forest plantation project while estimating the WTPs. They first ask the respondents' opinions regarding the effect of the forest project on the environment; then depending on their responses, the respondents are classified into two groups, welfare gainers and losers (Clinch and Murphy, 2001). Loureiro et al. (2004) also used a censoring framework in their survey design when they conducted a valuation of forest clearing burn program in Florida. Nahuelhual-Muñoz et al. (2004) used a similar framework in their questionnaire design, but they employed the extended spike model proposed by Kriström (1997). McCartney (2006) and Hanley et al. (2009) also adopted the extended spike model in their studies after they stratified the respondents according to their attitudes.

Hanley et al. (2009) argued that the scenario framework of negative WTP should take the format of reducing the good rather than preventing the increase of the good as suggested by Clinch & Murphy (2001) since, with the same amount of marginal change, the two formats elicit different measurements of welfare change. In the case of the biorefinery, however, it is not practical to design scenarios implying a reduction of the good if the question is one of build/not build. To enable an apples-to-apples comparison, we measure the strength of support (WTP to support installing a biorefinery) of the project vs. the strength of opposition (WTP to oppose installing a biorefinery).

Our study adopts a format similar to Clinch & Murphy (2001). This method supports the non-negative assumption by separating the respondents into supporters and opponents. This allows us to identify the heterogeneity in either the supporters' or the opponents' group.

Furthermore, the first stage result can be analyzed as a simple poll, and that approach facilitates exploration of potential differences in conclusions based simply on percent support vis a vis conclusions based on the WTP based assessments of relative strength of support/opposition.

A single bounded dichotomous choice question is used to elicit the respondent's valuation of the biorefinery. The supporters' WTP and opponents' WTP are estimated separately using different sub-samples, and the Heckman process is used to test and correct the potential sample selection bias due to the use of sub-samples. Robust cluster variance estimator is used to correct for the potential correlation clustered at county level due to demographic factors.

2.4 Survey Design and Data

We implemented the WTP scenario and questions via a stratified random telephone survey of Michigan adults.[21] A total of 1,013 residents were interviewed using a standard protocol and questionnaire between January 14, 2013, and March 4, 2013. Respondent gender, race, and locality, etc. were weighted to represent the population distribution of Michigan. To capture community-level effects, we merged the survey data with county level data from USDA

[21] For details of the basic survey design or to access the data, access http://ippsr.msu.edu/soss/. Refer to SOSS 64. We implemented some post-survey data treatment, as follows. Since the number of opponents was fewer than expected, we added the pretest observations into the dataset and imputed the missing data in dependent variables. Since the WTP eliciting format in pretest was open ended, to add them to the major data set, we randomly stratified the pretest observations to one of the five bid value groups in the same proportion as in the main survey. Monte Carlo simulation confirms that the significant level of the coefficient of the bid value variable, which in theory should be significant, is within 10% according to the results of a 1,000 time simulation. Some respondents did not reveal their attitudes towards the biorefinery. These were randomly assigned to either supporter group or opponent group and then were asked the second stage WTP question. Although it is possible that the respondents might have positive attitude but were assigned to the opposite group, the pretest result of open ended question shows no such situation. If they did not reveal their attitudes towards the biorefinery, these respondents just have zero value or answered "Don't Know" or "Refuse to Answer". The respondents who did not reveal their valuation of the biorefinery are treated as "No" response using the same logic as Caudill and Groothuis (2005) and Groothuis and Whitehead (2002). We test the potential bias resulting from the random assignment of the respondents who did not reveal attitudes. The results show that except for race, there is no support to reject the hypothesis that the mean values of the characteristics are the same between the two sub groups.

2012 Agriculture Census, American Community Survey (5-Year Estimates), U.S. Geological Survey, National Climatic Data Center and National Oceanic and Atmospheric Administration.

At the beginning of the survey, we use the cheap talk method to alleviate the potential issues, such as hypothetical bias and consequentiality, associated with stated preference methods (Kling et al., 2012). During the telephone survey, the respondents were first asked if they support or oppose a possible biorefinery given the following scenario:

Consider the following scenario. A company is considering opening a biofuel plant in your community. They plan to buy corn and grass from nearby farmers and process it into biofuel that can be used instead of gasoline in cars. Building the plant will take one hundred million dollars, and it will employ thirty people with an average salary of sixty-five thousand dollars plus health insurance when complete.

The question specified the investment and job creation numbers based on information about typical facility size supplied by industry experts. The information was provided to control for possible variations in WTP due to variations in respondent's assumptions on these parameters. The question framing mirrors the situation that the general public would face at an early stage of biorefinery siting: limited information about the proposed plan.

After the respondents stated whether they would support or oppose the biorefinery, we employed a single-bounded dichotomous choice question for eliciting the WTP conditional on the respondent's attitude. Based on pretest results, we selected a set of five bid values[22] for each

[22] Simulations by Alberini (1995) indicate that, for a 960 sample size survey using single bounded dichotomous choice question, 6 to 12 sub-groups/bid-values have better powers than other numbers of sub-groups.

group. The proportion of sample size for each stratum of the bid values was determined by the method which minimizes MSE of the estimated WTP given a total sample size (Cooper, 1993).

The supporters were asked the following WTP question where t_s is one of \$1, \$5, \$10, \$30, or \$100 bid values:

What if your local government were considering a proposal to help the company with its start-up costs as a way to attract the plant? Would you be willing to vote for a program that would cost you t_s dollar(s) in one-time taxes to help the plant get started?

The opponents were asked the following symmetric question to avoid bias due to asymmetric description. Here, t_s is assigned a value of \$1, \$3, \$5, \$10, or \$30.

What if your local government were considering methods to prevent companies like this from coming to your area? Would you be willing to vote for a program that would cost you t_s dollars in one-time taxes to prevent biofuel plants from being built in your community?

2.5 Estimation

The conceptual model is similar to the conventional WTP estimation models except that the model is conditional on attitude toward the biorefinery:

$$Prob_s(Y = 1|Z, t_s) = 1 - G(\boldsymbol{Z\beta}, \theta t_{\boldsymbol{s}})$$

The variable Y is a dummy representing the WTP response and t_s is a bid value as defined above. We index support/opposition towards the biorefinery with S. The set of individual characteristics and socio-economic variables are represented with $\boldsymbol{Z}$. We include race, political ideology and their interaction term with gender because these factors are likely to influence the attitudes towards issues of climate change (McCright and Dunlap, 2011).

The county level variables include urbanization level as represented by USDA's 2013 Rural-Urban Continuum Codes; dummies for counties with more than $20M increase or decrease in oil and natural gas production in 2000 - 2011; poverty rate; unemployment rate; and a set of agricultural variables. Several variables characterized the nature of the county's agriculture: median farm size, as well as the value of corn, milk, nursery and vegetable sales. We include a temperature variable because in Essay 1 we found local acceptance can be influenced by temperature spikes and variations. The model also includes a dummy variable representing if the respondents have a computer at home (a proxy for access to information); and it is then employed as the exclusion restriction which ensures that the Heckman process is credible (Wooldridge, 2010).

Our estimation procedure assumes that the respondent follows a two-step decision process, i.e. in the first stage they decide on whether they would oppose or support the biorefinery, and in the next step they would decide whether they would be willing to pay the bid amount presented (in the questionnaire) in support of their selected position. Since the bid amount is conditional on their initial decision as to oppose or support of the biofuel facility, we use a Probit model[23] with sample selection (Wooldridge, 2010). We estimate the initial selection and the WTP estimation models together using a maximum likelihood procedure, which prevents the worse potential bias in a non-linear regression when the selection model were to be estimated separately (Freedman and Sekhon, 2010).

Since the WTPs condition on the attitudes toward the biorefinery, we carry out two separate set of estimations. The first set estimates the selection model where supporters are

[23] We employ the 'heckprobit' command in Stata 14.

coded as 1 and the subsample of supporters is used in estimating the WTP equation. In the second set opponents are coded as 1 and the subsample of opponents is used in estimating the WTP equation.

2.6 Results

The first stage question, whether the respondents support or oppose the facility, can be analyzed as a simple poll. About two thirds of respondents (65%[24]) said they support the biorefinery while 27% of them were against it. The remainder, about 8%, chose "don't know" or refused to answer the question. If we only take the respondents who revealed their attitudes into consideration, 70.4% support the project. The survey summary statistics are reported in Table 2.A1 in Appendix 2.

Table 2.1 reports the key advantages or drawbacks selected by respondents, in support of their position, from a list developed via an open-ended pretest question. While the supporters tended to select jobs benefits, opponents appear to focus on the possible negative "social" externalities such as environmental pollution, and economic infeasibility, and not so much on the personal negative impacts most typically associated with NIMBYism (e.g., smell/noise, congestion).

Table 2.2 shows the distribution of "yes" responses to the WTP question for supporters and opponents under various bid amounts for WTP in support of their position. One would expect as bid values increase, the percent of respondents willing to pay the bid value would decline. The distribution of supporters' "Yes" response to the presented WTP question in general[25] follows this non-increasing assumption while the opponents' "yes" distribution is

[24] If not specified, the results reported are from weighted data.
[25] Without imputation, the supporters' "yes" distribution is strictly non-increasing.

ambivalent. However, it is not rare to have an empirical distribution somewhat violating the assumption in choice experiments.[26]

Table 2.1 Reasons for Supporting or Opposing the Biofuel Production Facility (% of Respondents Choosing)

Supporters (N=660)	Biggest Advantage	Smallest Advantage
Job Creation	45.2	7.58
Increased Sales for Area Farmers	11.1	15.8
Environmental Benefits	10.3	18.3
The Plant would Pay Local Taxes	8.6	20.5
Reducing Dependence on Foreign Oil	22.3	28.9
Opponents (N=353)	Biggest Drawback	Smallest Drawback
Daily Smells or Noises	7.4	15.0
Long-term Environmental Effects	26.4	6.2
More Trucks on the Road	5.1	28.9
Risk of Industrial Accidents	2.8	11.1
Biofuels Not Economically Viable	33.1	9.9
Biofuels Increase Food Prices	13.3	12.5

Table 2.2 Summary of WTP Responses

	Supporter				
Bid offer ($)	1	5	10	30	100
Yes Response (%)	83.7	91.4	79.7	68.7	62.2
N	13	29	96	325	197
	Opponent				
Bid offer ($)	1	3	5	10	30
Yes Response (%)	58.8	24.2	41.6	42.1	26.7
N	13	27	59	159	95

* The percentage and number of observation are not weighted.

The selection model regression results are shown in Table 2.3. The ρ statistics (*athrho*) reported in the last row support the maintained hypothesis of sample selection bias in conditional estimation of the WTPs and validate the use of the Heckman process. Overall, most respondent

[26] For example Haab & McConnell (2002) document empirical studies violating the non-increasing assumption.

demographic variables are not significant except for race in the opponent selection model. The statistically significant coefficients on the county level variables suggest that the decision to support or oppose the biorefinery is more likely to be influenced by the community characteristics rather than individual heterogeneity.[27] For instance, the dummy variable which indicates if the county had a significant increase (at least 20 million) of oil and natural gas production in the first decade of 21st century, is significant at 5% level. The significant (at 5% level) negative coefficients on urbanization variables also imply that, less urbanized areas (relative to metropolitan area with >1 million population) are more likely to oppose the biorefinery. This result is somewhat different from Haddad et al. (2009)'s finding that, from the perspective of existence of bio-ethanol plants, a higher density of population has a negative association with the plants' location choice. However, our finding is consistent with Fortenbery et al.(2013). It is not surprising that, from local resident's view, a less urbanized community may be more concerned with higher levels of environmental amenities which could be endangered by a biorefinery.

The county poverty rate influences the attitudes toward the biorefinery with the expected signs (significant at the 5% level). Higher poverty rate results in higher probability to support and lower probability to oppose such a program. Median farm size as well as nursery sales[28] also have effects on the attitudes (significant at 10% and 5% level, respectively). The larger the

[27] Consistent with emerging literature we control for ambient temperature conditions the day of the survey. According to AIC, models with temperature deviation from average perform better than those using temperature per se. Both the *temperature* and *temperature deviation* are negative in supporters' WTP but not significant for opponents' WTP (Table 2.A2 in Appendix 2). We define the comfortable temperature zone as 60°F - 65°F and construct a dummy variable to index it. The *temperature* and *temperature deviation* are interacted with the dummy variable to identify the influence temperature within or outside the comfortable zone. The non-interaction terms are negative while the interaction terms are positive but insignificant (Table 2.A3 in Appendix 2).

[28] We transform the sales variables except for corn sales through inverse hyperbolic sine function to reduce the multicollinearity among these variables.

median farm size in the respondent's county, the less likely the respondent would oppose the biorefinery. On the contrary, sales nursery has the negative effect on the support of the program.

Table 2.4 shows the estimation result of WTP conditional on the decision to oppose or support the biofuel facility. Similar to the selection model, individual characteristics are mostly not significant except for *conservative* in supporter's WTP and the interaction variable *Conservative *White*Male* in opponent's WTP. The significant county level variables in the WTP estimations are different from those in the selection model. For instance, the urbanization level is not significant in supporter's WTP. However in the case of opponents, coefficients of urbanization levels are negative and significant (at 5-10%) implying that the opponents from less urbanized counties are less willing to pay for preventing the biorefinery.

The coefficient of the dummy variable for the considerable increase of oil and natural gas production in the supporters' WTP is positive, which may seem counterintuitive because people may assume bio-energy production is a substitute for conventional energy. The possible alternative explanations are: (a) supporters from those counties are already familiar with externalities associated with energy production and hence more supportive of bioenergy, (b) they or their friends have skills sets that might be employed in such a facility, and/or (c) they think that bioenergy can reduce the adverse impacts of conventional energy sources. Both increase and decrease of oil and natural gas production have positive coefficients in the opponents' WTP.

Poverty rate is positive in both supporter and opponent WTP estimates. This result may appear contradictory. However, conditional on the attitudes, the supporters from poorer counties may believe the biorefinery will lead to the increase of their welfare due to jobs, while the opponents from poorer counties may believe the plant would bring negative impact to their welfare due to pollution and sites closer to poor neighborhoods.

The coefficients of agriculture variables imply that the strength of local acceptance might depend on agriculture commodities. While we cannot reject the hypothesis that *corn sales* has no influence on supporters' WTP, its positive coefficient on opponents' WTP, significant at 5% level, indicates that residents, conditional on the attitude, from counties with more sales of corn are more likely to perceive welfare loss from the biorefinery.

The supporter's average WTP is \$59.2 and the opponent's average WTP is \$95.7 per person. This confirms our suspicion that even though there are more residents who support the biorefinery, a simple poll may not properly reveal the strength of local acceptance/opposition. We can calculate the weighted proportion of supporters and opponents through the raw survey data. Taking the proportion mentioned at the beginning of this section (70.4% for supporter and 29.6% for opponent), we further weight the WTPs to calculate the total residents' WTPs in Michigan. The total supporters' WTP versus the total opponents' WTP at Michigan is 1.47:1. Although the net support for the biorefinery is still positive, the results suggest that opposition may be much stronger and financially better supported than what a simple poll might suggest.

Table 2.3 Regression Results: Selection Model

	Supporter		Opponent	
Temperature Deviation (Daily Max)	-0.000	(0.004)	0.000	(0.004)
Age	-0.004	(0.019)	0.010	(0.018)
AgeSQ	-0.000	(0.000)	0.000	(0.000)
Income > 50 K	-0.041	(0.114)	-0.037	(0.112)
Less than H.S.	0.200	(0.331)	-0.310	(0.348)
Some College	-0.063	(0.178)	0.017	(0.180)
More than College	0.077	(0.112)	-0.143	(0.116)
Male	0.215	(0.164)	-0.195	(0.160)
White	0.127	(0.117)	-0.203*	(0.119)
Conservative	-0.124	(0.193)	0.179	(0.187)
Conservative White Male	-0.138	(0.190)	0.133	(0.175)
Oil & Natural Gas Production Decrease	0.393	(0.334)	-0.291	(0.321)
Oil & Natural Gas Production Increase	0.745**	(0.318)	-0.685**	(0.338)
Urbanization Level				
2 (250K ≤ Metro < 1M)	0.121	(0.208)	-0.085	(0.170)
3 (Metro < 250K)	-0.506**	(0.200)	0.557**	(0.196)
4 (Urban ≥ 20K, adj to Metro)	-0.487	(0.343)	0.437	(0.273)
5 (Urban ≥20K, not adj to Metro)	-0.860**	(0.356)	0.993**	(0.361)
6 (Urban < 20K, adj to Metro)	-0.761**	(0.365)	0.814**	(0.305)
7 (Urban < 20K, not adj Metro)	-0.429	(0.348)	0.610*	(0.321)
Poverty Rate	0.024**	(0.009)	-0.023**	(0.009)
Unemployment Rate	-0.065	(0.086)	0.095	(0.079)
Home Computer	0.110	(0.152)	0.172*	(0.104)
Median Size of Farm Land (acres)	0.007	(0.004)	-0.008*	(0.004)
Milk Sale IHT	0.027	(0.053)	-0.025	(0.052)
Nursery Sale IHT	-0.151**	(0.047)	0.156**	(0.056)
Vegetable Sale IHT	0.048	(0.060)	-0.069	(0.055)
Corn Sale ($1M)	-0.000	(0.003)	0.002	(0.003)
Constant	0.384	(0.640)	-0.651	(0.572)
athrho	2.340***	(0.461)	-12.428***	(0.219)
N	907		907	

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.001

Table 2.4 Regression Results: WTP Estimation

	Supporter		Opponent	
WTP Bids	-0.004***	(0.001)		
WTP Bids			-0.010**	(0.004)
Temperature Deviation (Daily Max)	-0.011**	(0.005)	-0.000	(0.006)
Age	-0.000	(0.019)	-0.012	(0.019)
AgeSQ	-0.000	(0.000)	0.000	(0.000)
Income > 50 K	0.098	(0.141)	0.072	(0.160)
Less than H.S.	0.200	(0.355)	-0.072	(0.390)
Some College	0.018	(0.191)	-0.207	(0.169)
More than College	0.101	(0.118)	-0.165	(0.184)
Male	0.099	(0.143)	0.309	(0.202)
White	0.190	(0.173)	0.153	(0.181)
Conservative	-0.364**	(0.160)	0.153	(0.239)
Conservative White Male	0.136	(0.205)	-0.429**	(0.203)
Oil & Natural Gas Production Decrease	-0.269	(0.319)	0.652*	(0.371)
Oil & Natural Gas Production Increase	0.672***	(0.150)	0.603*	(0.334)
Urbanization Level				
2 (250K ≤ Metro < 1M)	0.258	(0.220)	-0.095	(0.230)
3 (Metro < 250K)	-0.362	(0.282)	-0.653**	(0.287)
4 (Urban ≥ 20K, adj to Metro)	-0.058	(0.377)	-1.058**	(0.431)
5 (Urban ≥20K, not adj to Metro)	-0.136	(0.395)	-0.758*	(0.431)
6 (Urban < 20K, adj to Metro)	-0.067	(0.450)	-0.997**	(0.367)
7 (Urban < 20K, not adj Metro)	-0.178	(0.414)	-0.347	(0.431)
Poverty Rate	0.019**	(0.009)	0.030**	(0.012)
Unemployment Rate	-0.111	(0.092)	-0.130	(0.108)
Median Size of Farm Land (acres)	0.002	(0.004)	0.006	(0.007)
Milk Sale IHT	-0.051	(0.052)	0.047	(0.074)
Nursery Sale IHT	-0.133**	(0.044)	-0.147*	(0.083)
Vegetable Sale IHT	-0.020	(0.052)	-0.030	(0.072)
Corn Sale ($1M)	0.004	(0.003)	0.007**	(0.003)
Constant	0.167	(0.551)	0.901	(0.549)
N	601		306	

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.001

2.7 Spatial Analysis

Since attitudes and the valuations of the biorefinery appear to be strongly determined by several county level variables, we offer a spatial analysis using county level averages. Figure 2.1 shows the proportion of the respondents who support the biofuel facility in each county calculated from the result of first stage question.[29] For the whole State of Michigan, as we reported in section 6, the total supporters' proportion is about 70%. For some counties, however, their supporters' proportions are much lower than 50%. We can also find extremely high or low proportions in Figure 2.1. The supporters' proportions at county level are somewhat misleading because of the small sub-sample sizes. Although the survey has about 1,000 observations and weights the data to represent the actual population distribution across Michigan, some counties have few observations[30] and hence the attitudes towards the biorefinery might be mis-estimated at the county level. Due to this limitation, a survey designed at the scope of a State can hardly be used to explore local acceptance at county level without such concern of bias. At the early stage of searching a location for biorefinery investment from counties statewide, if the decision maker uses a statewide poll to explore the local acceptance, to prevent the possible bias at small scope, the poll would need more than 1,000 observations, which would result in high cost.

Figure 2.2 shows the ratio of supporters' WTP over total WTP, which is the summation of supporters' and opponents' WTP.[31] We find that, when the welfare change is taken into consideration, some counties have stronger tendency to support a biorefinery. Meanwhile, the

[29] We test the spatial correlations of the attitudes and WTP responses using Moran's I and Geary's C. The results suggest that there is no global spatial correlation.
[30] One county has no observation, 10 counties have 1 observation, 58 counties have less than 10 observations.
[31] Both the supporters' and opponents' WTP are weighted by the corresponding proportions. The supporters' proportion is predicted from the results of Table 2.3. We use Romney's 2012 U.S. presidential election result in each county in Michigan to approximate the mean value of conservative political ideology.

ratios in Figure 2.2 are not as extreme as the proportions in Figure 2.1, which implies the WTP ratio may be a better index of local acceptance.

We further compare the supporters' proportion[32] to the supporters' WTP ratio, and find that, in some counties, the proportion is larger than 50% while the ratio is less than 50% (Figure 2.3). This implies that, although the majority supports the biorefinery, total welfare gain is less than the total welfare loss. In these counties, while a poll could show that opponents are a minority, the opposing actions might be more severe than expected. This result validates our concern about the use of polls to measure local acceptance. The investment of a biorefinery may face higher risk due to local opposition.

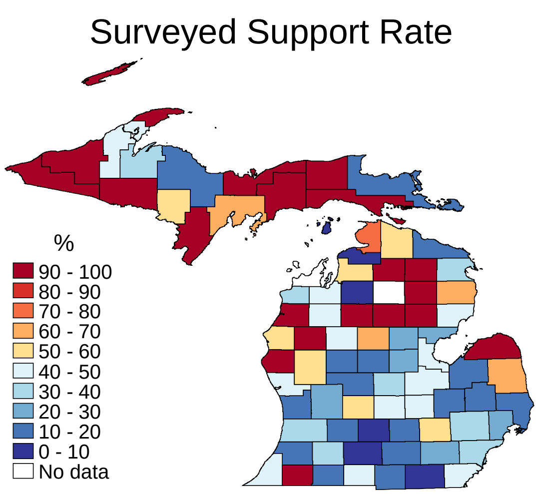

Figure 2.1 Proportion of Supporters from Weighted Survey Data

[32] The supporters' proportion is predicted by the results of Table 2.3 since, as Figure 2.1 shows, the proportions calculated directly from survey data can be misleading. Even if we use the surveyed proportions instead of the predicted proportions, we can still find counties with a majority of supporters and negative welfare change (Figure 2.A1 in Appendix 2).

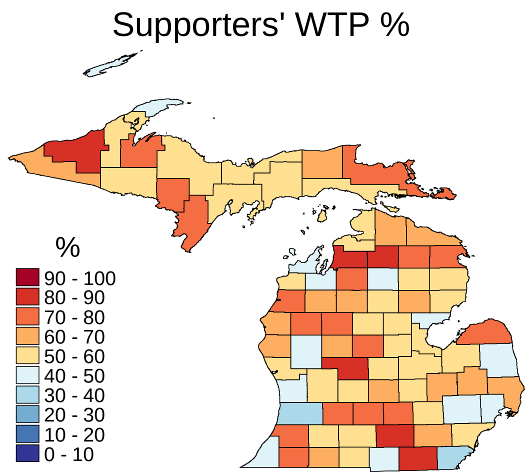

Figure 2.2 Supporters' WTP among Total WTP

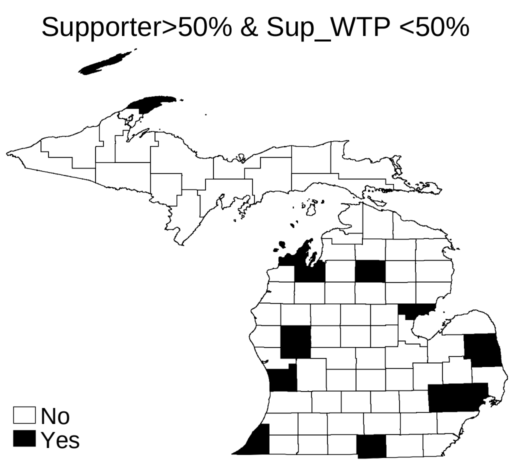

Figure 2.3 Counties where a Majority Supports the Biorefinery, but the Opponents' WTP Outweighs Supporters' WTP

2.8 Discussion and Conclusion

While a biofuel facility would have various kinds of positive and negative impacts on the community where it is located, local acceptance is more complex than a yes/no question about the facility. Our study proposed a WTP protocol to access not only the attitudes but also the strength of local acceptance through the welfare change of local residents. We used a two stage method to estimate the WTPs conditional on the residents' attitudes toward a proposed biorefinery since such a facility can have both positive and negative externalities, which renders the conventional non-negative assumption for WTP estimation invalid.

Our first stage question was a poll of attitudes regarding a proposed biorefinery located in the respondent's community. More than two thirds of Michigan respondents were in favor of such a project going to their community and the key reasons were the potential economic benefits that the project may bring to the local community. The opponents were concerned about the environmental effects, but not so much the highly localized issues typically associated with NIMBYism.

The estimates of mean WTPs further show the strength of the supporters' and opponents' welfare changes due to the biorefinery, which provides an approximation of local acceptance. The supporter's personal mean WTP is around $36 less than the opponent's WTP, confirming our suggestion that yes/no polls cannot reveal the welfare, thereby misjudging the level of local support/opposition. The relative strength of supporters and opponents of the biorefinery is estimated at 1.47:1 for the whole State of Michigan, which indicates the overall support, after taking the welfare gain and loss into consideration, is positive but weaker than what a simple poll might indicate. Our analysis also shows that, at county level, this problem can be worse and some counties may suffer net welfare loss while a poll may find they have a majority of support.

The techniques employed in our analysis can help investors and policy makers choose the location for a biorefinery or other energy facility. Because most significant variables are county level variables, investors or decision makers could potentially adopt the calibrated model instead of conducting a survey with larger sample size for their search of sites at the early stage in which they are choosing candidate sites. Potential sites can be signaled by the WTP ratio while investors might want to be more cautious in counties or places where the ratio is smaller than 1.

APPENDIX

APPENDIX 2 Supplementary Information and Results for Essay 2

Table 2.A1 Variable Description

Variable	Mean	Standard Errors
Daily Max Temperature Deviates from 30 Year Normal (^{o} F)	1.0	(0.633)
Age	46.2	(0.777)
Income > 50 K (%)	55.4	(0.023)
Education Level Less than H.S. (%)	3.3	(0.007)
Education Level With Some College (%)	33.7	(0.022)
Education Level More than College (%)	41.9	(0.022)
Gender (Male=1) (%)	49.2	(0.023)
Race (White=1) (%)	78.3	(0.020)
Political Ideology is Conservative (%)	36.1	(0.021)
Conservative White Male (%)	16.5	(0.015)
Oil & Natural Gas Production Decrease (>$20 M in 2000 ~ 2011 = 1) (%)	3.1	(0.007)
Oil & Natural Gas Production Increase (>$20 M in 2000 ~ 2011 =1) (%)	2.9	(0.009)
Urbanization Level (%)		
2 (250K ≤Metropolis Population < 1M)	28.6	(0.020)
3 (Metropolis Population < 250K)	13.4	(0.015)
4 (Urban Population≥ 20K, adjacent to Metropolis)	4	(0.009)
5 (Urban Population≥20K, not adjacent to Metropolis)	3.5	(0.007)
6 (Urban Population < 20K, adjacent to Metropolis)	4.1	(0.008)
7 (Urban Population< 20K, not adjacent Metropolis)	6.2	(0.008)
Poverty Rate (%)	17.1	(0.257)
Monthly Unemployment Rate Deviated from 5 Year Average (%)	-1.7	(0.029)
Home Computer (%)	87.8	(0.014)
Median Size of Farm Land (acres)	43.2	(0.916)
Milk Sales ($1M)	14.9	(0.874)
Nursery Sales ($1M)	22.8	(1.292)
Vegetable Sales ($1M)	5.6	(0.384)
Corn Sales ($1M)	25.5	(1.058)
Observations	907	

+ Mean of county level variable is sample average

Table 2.A2 Test of Non-linearity of Temperature on Supporters' WTP

Model	S1	S2
Temperature	-0.011**	-0.052
	(0.005)	(0.046)
Temperature SQ		0.001
		(0.001)
Model	S3	S4
Temperature Deviation	-0.011**	-0.022**
	(0.005)	(0.010)
Temperature Deviation SQ		0.001
		(0.001)

+ Temperature or temperature deviation and their square terms (in model O1 ~ O4) are in general not significant for opponents' WTP.
++ The control variables are all the same as the regressions in the main text except for the vegetable sales is not transformed due to non-convergence caused by the transformed variable in one opponent's regression.
+++ Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.001

Table 2.A3 Temperature Interaction with Comfortable Zone Dummy

	Supporter WTP	Opponent WTP
Model	S5	O5
Temperature	-0.014**	-0.007
	(0.004)	(0.008)
Temp.* Comfortable Zone	0.007	0.033**
	(0.010)	(0.010)
Model	S6	O6
Temperature Deviation	-0.016***	-0.007
	(0.005)	(0.007)
Temperature Deviation * Comfortable Zone	0.013	0.068**
	(0.022)	(0.021)

+ The control variables are all the same as the regressions in the main text except for the vegetable sales is not transformed due to non-convergence caused by the transformed variable in one opponent's regression.
++ Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.001

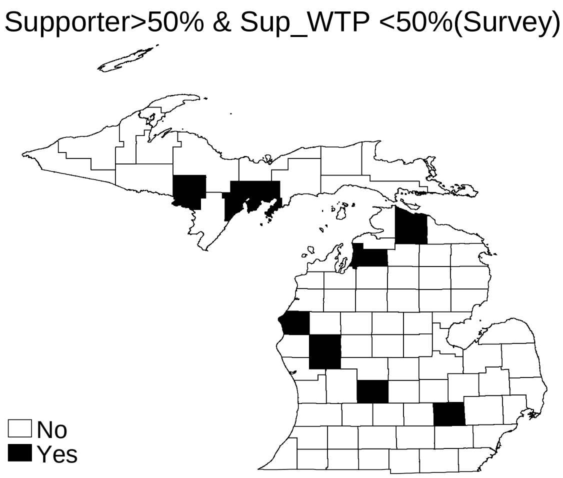

Figure 2.A1 Counties where a Majority Supports the Biorefinery, but the Opponents' WTP Outweighs Supporters' WTP: Supporters' Proportion Calculated Directly from First Stage Question (Poll)

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ESSAY 3: MODELLING LOCAL FOOD POLICY AND GREENHOUSE GAS EMISSION DUE TO TRANSPORTATION

3.1 Introduction

Food advocates have been increasing the public's interest in purchasing locally produced foods (Low et al., 2015; Martinez et al., 2010), emphasizing potential benefits such as food safety, freshness, environment, or regional economic growth (Feenstra, 1997; Weatherell et al., 2003; Roininen et al., 2006; Feagan, 2007; Martinez et al., 2010; Zepeda and Leviten-Reid, 2004; Darby et al., 2008; Kemp et al., 2010).[33] National and regional surveys have found that a high proportion of Americans either purchased foods directly from growers or are interested in purchasing local food products (Pirog, 2003; Zepeda and Li, 2006; Bond et al., 2009). As farmers' markets in the U.S. increased from 1,775 in 1994 to 8,268 in 2014 (USDA-AMS, 2014), groups and governments have launched many programs to support local foods (Martinez et al., 2010).

While several researchers, advocates and policymakers have proposed definitions of what constitutes local food, no clear consensus exist on what makes up local food (Hand and Martinez 2010, Martinez et al. 2010). Regardless of what definition of local food is used, it always involves the idea of closer geographic connections between producers and consumers. In the local food context, local foods compete and substitute for foods imported from outside the local area, and therefore afford shorter food miles from producer to consumer (Pirog et al. 2001). As local food advocates attest, locally-sourced foods travel fewer miles and therefore generate less greenhouse gas (GHG) in transit (Coley et al., 2009; Edwards-Jones et al., 2008; Weber and Matthews, 2008). Various studies have generated a range of food miles for conventional food,

[33] This essay is co-authored with members of my dissertation committee, Dr. Steven Miller and Dr. Scott Loveridge.

indicating that typical food miles can range from one to two thousand miles, depending on methods used in estimation and food commodities measured (Hendrickson, 1996; Pirog et al., 2001; Weber and Matthews, 2008). These estimates of conventional food miles are often the basis for measuring GHG savings from local food systems' transportation GHG emissions (Coley et al., 2009; Edwards-Jones et al., 2008; Meisterling et al., 2009; Weber and Matthews, 2008).

Common approaches estimate food miles and the corresponding transportation GHG emissions can fall into one of two categories; 1) bottom-up, or 2) top-down. We posit that current methods in the literature may lead to biased estimates, depending on the approach.

Bottom-up approaches usually follow select stages of the supply chain and add up all the GHG emissions along the measured stages. For instance, the transportation costs may be used to proxy for transportation distances of all inputs and processes from raw materials to final consumption as the basis for GHG generation (Sundkvist et al., 2001). Bottom-up approaches can be comprehensive, but accounting for all inputs may be challenging even for studies that focus on single commodities. Because tracing all the inputs into all food-sector products is largely infeasible, bottom-up approaches are usually limited to a sub-section of the agri-food system and are limited to first-order transactions (do not include indirect transaction). That is, data limitations often restrict the completeness of the analysis.

Top-down approaches, by which a class of models called extended input-output lifecycle analysis (EIO-LCA) belong, use secondary measures of aggregate flows to estimate transportation movement of inputs through to final goods (Hendrickson et al., 1998; Joshi, 1999; Lave, 1995). Generally this approach uses a representative input-output table of the region, which is a social accounting construct that traces inter-industry transactions in the production of final goods and services for final consumption. The top-down method, by representing the comprehensive set of transactions within an economy, can better represent the full range of transportation miles for primary and secondary inputs that go into the production of final goods. In the EIO-LCA literature, the researchers assume that conventional food systems generate food miles, while local food systems create no food miles (Weber and Matthews, 2008).

With the emphasis on the GHG emissions resulting from the change in distances that foods are transported due to a local food policy, this study shows how existing EIO-LCA studies of transportation GHG emissions of local food systems may lead to biased estimates, and develop a modified EIO-LCA model that corrects this problem. Particularly, to explore the transportation GHG emissions driven by local food production, the model is modified to incorporate the imported inputs used to produce local food. We exemplify the approach using IMPLAN Pro. 3.1 software for Michigan. We also show to what extent the results might be biased if these issues are not corrected.

3.2 Literature Review

Studies assessing GHG emissions with regard to local food policies often use food-miles as a basis for GHG generation, as the distance food travels is a primary descriptor of how advocates define local food systems, and transportation is a key determinant of relative GHG emissions along the food supply chain (Edwards-Jones et al., 2008; Sim et al., 2007). The existing literature highlights the dominant approaches to measuring food-miles and GHG emissions of food systems, including bottom-up and top-down approaches.

Bottom-up approaches trace the transportation of key inputs along the value chain. It is limited in that not all of the inputs required can be calculated due to the lack of data and the limitations of research resources. For similar reasons, materials required for producing the inputs are not comprehensively identified. That is, analysis is generally limited to direct effects. Alternatively, top-down approaches, based on EIO-LCA models, are more comprehensive in the inclusion of relevant inputs but may be less precise in the actual transportation miles generated. The EIO-LCA method starts with a conventional input-output model, extending it by linking the economy impacts estimated by the input-output model with the pollutant coefficients. In the application of the GHG emissions of local foods, the ton-mile coefficients[34] of commodities and the CO_2 emission coefficients are linked to the input-output model through transportation expenditures.

Most local food studies measuring environmental impacts use a bottom-up approach. Of these, Sundkvist et al. (2001) estimated the potential reduction of environmental impacts in local production of bread by calculating the GHG emissions for the transportation of final goods, soft bread, as well as for the transportation of the key inputs of the bread. In their study, transportation costs and GHG emissions are limited to key inputs, such as grain, flour, salt, margarine, syrup, sugar, and yeast, but fail to trace other direct inputs, such as packaging, and secondary inputs, like fertilizer for cultivating the grain, etc. In their study of GHG of local and imported apples, Blanke and Burdick (2005) used distance traveled and temperature-controlled storage to estimate relative energy consumption of locally grown apples, but did not include the transportation use for inputs to cultivating the apples locally versus imported. Thus, only the transportation for final goods from farm gate to the consumers is estimated. Pirog et al. (2001) estimated the CO_2 emissions due to conventional, regional, and local food systems using food-miles in the key stages of the supply chain. Sim et al. (2007) estimated the GHG emissions in the

[34] Ton-mile coefficient is the distance (ton-miles) per unit value of the commodity travelled. This coefficient may vary according to the region, transportation mode, etc.

supply chain of fresh agriculture products from the viewpoint of a food retailer by identifying the production system and the supply chain. Coley et al. (2009) estimated the energy use for consumers' trips to purchase local foods by the average trip distance and the number of trips per year. These bottom-up studies are limited by the number of GHG sources that can be traced along the value chain.

Moreover, studies applying the bottom-up method usually do not trace GHG emissions from transportation through secondary transactions. Secondary transactions are the inputs for producing the commodities directly used in the local foods production. For instance, fertilizers and pesticides are indirect inputs from the retailer's perspective of apple sales and are overlooked by the retailer seeking to minimize his or her environmental footprint. In effect, the bottom-up method can hardly identify all the upstream inputs, and the related transportation is not calculated. This omission results in underestimation of baseline and impacted GHG emissions.

Top-down approaches, based on input-output tables, include all the production and distribution information among the industries in the region and can account for all the intermediate purchases that go into final goods. Meisterling et al. (2009) combine a top-down assessment with elements of bottom-up assessments in estimating the GHG emissions of organic as well as conventional wheat. In their study, the bottom-up approach was used as the principal driver of direct GHG emissions, while a top-down approach was used to measure GHG emissions of secondary processes in the production of inputs such as pesticides. Weber & Mathews (2008) used a top-down approach to estimate the GHG emissions due to foods systems, where an EIO-LCA model provided the fundamental framework for capturing both direct and indirect GHG generation in the production of goods. A shortcoming of the study recognized by the authors is that they implicitly assume that local foods do not generate transportation miles and hence, GHG emissions. This omission results in an overestimate of the GHG reduction potential of local food systems.

EIO-LCA models are more comprehensive in the inclusion of relevant inputs. As these models are based on standard input-output analysis, the transactions traced are upstream, accounting for all the primary and secondary transactions that go into the raw material production, processing, transportation and marketing of final goods for consumption. It affords a more comprehensive view of the underlying inputs. However, without careful application of the top-down approach, estimated GHG emission savings of local food systems may be overstated.

3.3 The EIO-LCA and its Potential Bias in Estimating Transportation GHG

To illustrate the EIO-LCA model, we first introduce the input-output model, and then we show how it is extended for GHG emission calculation. Consider an open industry-by-industry input-output model comprised of *n* different commodities made by each one of the associated *n* industry sectors. Let *i* and *j* denote the producing (row) and buying (column) industries, respectively. Then, Z_{ij} represents the value of the commodity produced by industry *i* and used as the intermediate inputs by industry *j*; F_i is the final demands for sector *i*, and Q_i is total sector output for sector *i*. A simple input-output model can be illustrated as the following (Miller and Blair, 2009). It is assumed the input-output table is balanced and total input of an industry equals the total output of that industry, $Q_i = Q_j$ for all $i=j$.

$$\begin{cases} Z_{11} + Z_{12} + \cdots + Z_{1n} + F_1 = Q_1 \\ Z_{21} + Z_{22} + \cdots + Z_{2n} + F_2 = Q_2 \\ \qquad\qquad\vdots \\ Z_{n1} + Z_{n2} + \cdots + Z_{nn} + F_n = Q_n \end{cases}$$

By definition, $a_{ij} = \frac{Z_{ij}}{Q_{j=i}}$, solving for Z_{ij} and replacing $Z_{ij} = a_{ij} \cdot Q_j$ gives:

$$\begin{cases} a_{11}Q_1 + a_{12}Q_2 + \cdots + a_{1n}Q_n + F_1 = Q_1 \\ a_{21}Q_1 + a_{22}Q_2 + \cdots + a_{2n}Q_n + F_2 = Q_2 \\ \vdots \\ a_{n1}Q_1 + a_{n2}Q_2 + \cdots + a_{nn}Q_n + F_n = Q_n \end{cases}$$

$$\begin{bmatrix} a_{11}a_{12} \cdots a_{1n} \\ a_{21}a_{22} \cdots a_{2n} \\ \vdots \\ a_{n1}a_{n2} \cdots a_{nn} \end{bmatrix} \begin{bmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_n \end{bmatrix} + \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_n \end{bmatrix} = \begin{bmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_n \end{bmatrix}$$

In matrix form, this can be stated as:

$$AQ + F = Q$$

Solving for Q:

$$(I - A)^{-1}F = Q \qquad (3.1)$$

In the equation (3.1), Q is the n-vector of total output, I is an identity matrix of dimension n, A is the matrix of technical coefficients, F is a n-vector of final demand and $(I - A)^{-1}$ is the Leontief inverse matrix. The above equation is the basic input-output model that relates total industry output, Q, to a given level of exogenous demands, F.

This simple model can be extended into an environmental input-output model following Weber and Mathews (2008), in their specification of the EIO-LCA model. We simplify Weber & Mathews (2008)'s model without degrading its applicability as:

$$FoodMiles = D(I - A)^{-1}F,$$

$$GHG\ Emission = g \cdot D(I - A)^{-1}F \qquad (3.2)$$

where, D is the diagonal matrix of the food-miles coefficients, where each entry is the food-miles per dollar output of the associated sector. Post multiplying D by the Leontief inverse allocates sector average transportation miles throughout all secondary transactions. In equation (3.2), g is a scalar coefficient that translates miles of travel to CO_2 emission equivalence (CO_2 equivalent per mile). This model allows for the development of baseline values of GHG generation from local food purchases based on a given level of final demands. In difference form and holding constant g, D and the Leontief inverse, equation (3.2) provides an estimate of the change in GHG emissions from a given change in final demands.

There are different modes used to transport commodities and each transportation mode has its associated food-miles coefficients and CO_2 emissions coefficient. That is, food-mile coefficient matrix and the g scalar can be subscripted as: D_t and g_t where *t = (truck, rail, water, air, pipeline)*. For illustration purposes, the transportation type subscript is dropped but reintroduced in calculations undertaken in section 6.

In omitting local food transportation, the existing literature uses the above model for calculating the GHG emissions associated with non-local foods only (Weber and Matthews 2008), resulting in an overstatement of the true GHG savings from local food systems. There should exist a method within the standard EIO-LCA model to reintroduce GHG generation from local food systems.

Figure 3.1 shows the components of a more comprehensive input-output table. Above, we show the model, which captures the elements of first row in Figure 3.1, which breaks out industry imports from aggregated imports, allowing specific treatment of each imported sector in isolation. This figure emphasizes the imported inputs used in local production. Conventional applications of the EIO-LCA model usually omit the imported inputs in estimation because of their research scopes. As local food production also generates energy use and corresponding GHG emissions to transport imported inputs, the omission leads to underestimation. In section 4, we modify the EIO-LCA model to incorporate the GHG emissions resulting from transporting the imported inputs. Figure 3.1 will be the basis for recognizing differences in GHG emissions of locally produced goods from those imported. That is, it accounts for exogenous substitution of local foods for imported foods.

Z: outputs used as intermediate inputs	+	*F*: outputs consumed by institutional sectors (final demand)	=	*Q*: total outputs (locally produced)
+				
Im: imports used as intermediate inputs	+	*FIm*: imports used for consumption	=	*M*: total imports
+				
Value added				
=				
Q: total inputs = Z+Im+Value Added				

Figure 3.1 Components of Input-Output Table

3.4 A Non-Biased EIO-LCA for Local Food Transportation GHG

This section illustrates an unbiased EIO-LCA model for estimating the potential GHG emissions reduction of a local food system. The existing EIO-LCA model is augmented with a second system that accounts for change in imports and the simultaneous GHG generation between local and conventional food systems. The net transportation GHG reduction, due to local food promotion, is the transportation-related reduction in GHG emissions from reduced imported foods minus the transportation-related GHG emissions from increased local foods production. Each of the two sets of GHG emissions (local or imported foods) is calculated by the conventional EIO-LCA model as well as the second system which captures the transportation of imported inputs. The change of imports used by institutional sectors is exogenously determined by the local food policy studied. Consider the following system representation of Figure 3.1:

$$\begin{array}{cccc}
Z_{11} & Z_{12} & \dots & Z_{1n} \\
Z_{21} & Z_{22} & \dots & Z_{2n} \\
\dots & \dots & \dots & \dots \\
Z_{n1} & Z_{n2} & \dots & Z_{nn} \\
Im_{11} & Im_{12} & \dots & Im_{1n} \\
Im_{21} & Im_{22} & \dots & Im_{2n} \\
\dots & \dots & \dots & \dots \\
Im_{n1} & Im_{n2} & \dots & Im_{nn} \\
Int_1 & Int_2 & \dots & Int_n \\
= & = & \dots & = \\
Q_1 & Q_2 & \dots & Q_n
\end{array}
+
\begin{array}{c}
F_1 \\ F_2 \\ \dots \\ F_n \\ FIm_1 \\ FIm_2 \\ \dots \\ FIm_n \\ 0
\end{array}
=
\begin{array}{c}
Q_1 \\ Q_2 \\ \dots \\ Q_n \\ M_1 \\ M_2 \\ \dots \\ M_n \\ INT
\end{array}$$

The above input-output table[35] is the one that includes the use of imported commodities as the intermediate input, Im_{ij} and value added component, Int_j. FIm_i is the value of imported commodity i consumed by the institutional sector. M_i is the row sum of imported commodity i. Since the consumption of imports is assumed to be exogenously determined by the local food policy, the vector of FIm_i can be separated from the table without influencing the model. That is, a GHG calculation through institutional consumption of imported goods is analyzed separately without affecting the analysis. Note that, once we take the FIm_i out of the input-output table, M_i is the row sum of imported commodity i without FIm_i ($M_i = \sum_j Im_{ij}$).

[35] For simplification, we assume no transaction occurs between institutional sectors. This assumption is used for illustration and will not affect the results we analyze.

Therefore, substitute Z_{ij} with a_{ij}, as illustrated above, we have:

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} Q_1 \\ Q_2 \\ \dots \\ Q_n \end{bmatrix} + \begin{bmatrix} F_1 \\ F_2 \\ \dots \\ F_n \end{bmatrix} = \begin{bmatrix} Q_1 \\ Q_2 \\ \dots \\ Q_n \end{bmatrix}$$

Using a similar idea, we define $m_{ij} = \frac{Im_{ij}}{Q_{j=i}}$ and we have:

$$\begin{bmatrix} m_{11} & m_{12} & \dots & m_{1n} \\ m_{21} & m_{22} & \dots & m_{2n} \\ \dots & \dots & \dots & \dots \\ m_{n1} & m_{n2} & \dots & m_{nn} \end{bmatrix} \begin{bmatrix} Q_1 \\ Q_2 \\ \dots \\ Q_n \end{bmatrix} = \begin{bmatrix} M_1 \\ M_2 \\ \dots \\ M_n \end{bmatrix}$$

Thus, we have two systems, $aQ+F=Q$ and $mQ=M$ that together describe the transaction in the economy and the transportation contribution to GHG emissions more comprehensively.

This two-system approach accounts for both the final demands and changes in imports when calculating GHG emissions. It also indicates the importance of M values of imported inputs for producing the outputs. For producing Q, local inputs aQ and imported inputs mQ are required[36] and transported to the factory or farm in the study area. The F values of commodities are final commodities consumed by the institutional sectors and they are transported from the factory or farm gate to consumers. The transactions of both aQ and mQ give rise to transportation expense and therefore to subsequent calculations of GHG emissions, where GHG associated with mQ is the savings from reducing imports, while those associated with aQ are associated with increases from local production.

For local goods that are both produced and consumed locally, there are three sources of transportation emissions: 1) among producers and processors within the region: 2) between

[36] Excluding value added components such as payments to labor, capital, and indirect business taxes.

producers and suppliers outside the region; and 3) direct sales from farms to households. The imported goods have three parallel components of GHG emissions. The associated vectors of ton-mile coefficients are different among the three sources of transportation. The ton-mile coefficients for local commodities between factories are not the same as those for the imported commodities used as inputs since the latter travels a longer distance. Rates and miles vary by commodity and by region, and regionalized input-output tables account for the different modes of transportation. Depending on the region and on the commodity, the ton-mile coefficients should vary. Similarly, the ton-mile coefficients within the studied region can be quite different due to the geographic, inter-industry linkages and transportation modes selected.

After decomposing the whole transaction in the economy, the total transportation of the foods imported to Michigan from the other states include the transportation for three parts (F, AQ, and MQ) while the conventional adaptation of EIO-LCA only takes two parts into consideration. To include all the transportation miles into the calculation, instead of using the conventional EIO-LCA model, we treat each of the decomposed parts. This decomposing method can also reflect the different ton-miles for each of the three parts in the whole economy.

3.4.1 Calculating the Potential GHG Savings through Reduced Imports

To calculate the potential GHG savings through local food systems, we use the national input-output table to represent the conventional transactions used for foods produced outside the research area to estimate the secondary transaction. By decomposing the transaction into the final demand and secondary transactions, we can calculate the two associated transportation activities with the associated ton-mile coefficients and estimate transportation miles more accurately. The potential of GHG reduction due to the imports substituted (GHG_{Import}) can be calculated as:

(3.3) $GHG_{Import} = gD_{UStoMI}S + gD_{US}[A_{US}(I - A_{US})^{-1}S]$

In equation (3.3), S is the vector of the values of the imported foods substituted by local foods, D_{UStoMI} is the diagonal matrix of the per dollar ton-miles vector of the commodities imported from rest of the contiguous U.S. area[37] to Michigan and D_{US} is the diagonal matrix of per dollar ton-miles vector of commodities transported in the U.S. The first part of the right hand side of the equation calculates the emission saved due to the transportation of the substituted foods from the factories or farms to Michigan retailers and consumers. The second part in the right hand side of the equation calculates the saved GHG emission due to the production process of the imported foods. A_{US} is the technical coefficient matrix calculated from the U.S. national input-output table to represent the average technology used to produce the imported foods.

3.4.2 Calculating the GHG Emissions due to Local Foods Production

We use the same decomposing method to calculate the GHG emissions that might be generated due to the production of local foods which substitute for the imported foods. Recalling the model demonstrated in section 3, the emission caused by local production is constituted by three parts. One is the local transportation for local inputs, another is the transportation for imported inputs, and the other is the transportation of final products from factory or farm gate to retailers and consumers. Even locally produced goods have elements of imports. For instance, the salsa made in Michigan is considered as a Michigan product in the input-output model, but it may be made with Michigan tomatoes and Indiana peppers. Thus, the production of local goods often entails some imported components.

[37] Hawaii is not included.

GHG generation of local food production (GHG_{LF}) can be estimated in the three parts as:

(3.4) $GHG_{LF} \; = gD_{MItoMI}F + gD_{MItoMI}[A_{MI}(I - A_{MI})^{-1}F] + gD_{UStoMI}[M_{MI}(I - A_{MI})^{-1}F]$

This equation is parallel but somewhat different from equation (3.3). In equation (3.4), D_{MItoMI} is the diagonal matrix of the per dollar ton-miles vector of the commodities transported within Michigan, A_{MI} and M_{MI} are the technical coefficient matrix of Michigan's local commodities and the technical coefficient matrix of commodities imported to Michigan, respectively. The ton-miles matrixes used are different to reflect the different distance that local foods and imported foods are moved. The technical coefficient matrices should also reflect the inputs required in local production. Further, the last part of equation (3.4) calculates the GHG emissions resulting from moving imported inputs for the local production to satisfy the increased demand of local foods.[38] F is the increase of locally produced foods. The first part of the right hand side equation calculates the GHG emission for transporting local foods from factory or farm gates to local retailers and consumers. The second part calculates the GHG emission due to the transportation of local inputs. The third part calculates the emission due to transportation of imported inputs. We use the same vector of ton-miles coefficients for calculating the transportation of commodities for final consumption and intermediate use due to data limitation. Thus, equation (3.4) can be simplified as:

$$GHG_{LF} \; = gD_{MItoMI}[(I - A_{MI})^{-1}F] + gD_{UStoMI}[M_{MI}(I - A_{MI})^{-1}F]$$

[38] The last part of equation (3.4) has no parallel one in quotation (3.3) due to lack of data. But, if all data required are available, there should be a parallel part in equations (3.3).

The last part of the right hand side equation is usually not calculated in the environmental input-output model. When estimating the transportation and the associated GHG emissions due to the local food policies, it should be included or the estimates are biased.

3.5 Methods

We use a hypothetical assumption that the State of Michigan will implement a program that results in a $10 million increase of local food sales in place of $10 million in imported foods. Many local food policies employed to date aim to increase the purchase of local foods by local consumers and reduce the use of foods produced outside the local area. With this scenario, the local food policy will have two effects on GHG emission through transportation; 1) reduction of GHG emissions from reduced food miles of imported food, and 2) increase in GHG emissions due to increased transportation of locally-sourced food and the associated inputs.

The U.S. transactions table for calculating the regional and national Leontief inverses and the related import matrix are obtained from the IMPLAN Pro 3.0 1990 database for Michigan. The model is aggregated to IMPLAN's internal 2-digit NAICS. The model used is closed to a Type I multiplier construct (Miller and Blair 2009). The transaction data of imported commodities used in Michigan is also retrieved from IMPLAN. Commodity imports are matched with the industries in the transactions table by matching importing industries and import proportions by industry, allowing the comparison of transportation miles between local and imported intermediate and food goods.

The data required for calculating the transportation ton-miles by industry was obtained from the 2012 Commodity Flow Survey (CFS), which reports both ton-miles and commodity values by origin and destination and aggregated to their respective industries. Thus, we can calculate the ton-miles coefficients for the commodities transported from the U.S. territory to Michigan,[39] from Michigan to Michigan, or within the U.S. territory. The CFS commodity classification is mapped into the 2- digit NAICS scheme, as shown in Appendix 3.A.

The CFS data distinguishes transportation mode into five categories (truck, rail, water, air, and pipeline) and includes transportation hauls made up of multiple modes. Since the CO_2 coefficients are based on single transaction modes, ton-miles data of multiple transportation modes must be allocated into the corresponding single transportation modes. We assume for each multiple transportation mode, the usage of the corresponding single modes is the same as the relative proportion between the single modes.

We assume only goods give rise to transportation miles, though transportation costs of services trade may be captured in the transactions table. Hence, for some commodity i, where i is the subset of non-goods industries, $d_i = 0$ due to no physical transportation. We also assume that, when estimating the GHG emissions due to local food production, the ton-miles coefficients for the travel between factories and farms are the same as those for the travel from factory and farm gate to consumers due to the lack of data.

The CO_2 coefficients by mode are obtained from Weber and Matthews (2008). There are five modes of CO_2 coefficients in their study, each with its own GHG emission coefficient g. For illustration, in next section we only show the model that calculates the GHG emission in one transportation mode. To calculate the GHG emissions in different transportation modes, we match the food miles vector and the related GHG coefficient. The GHG emissions calculated in the results section sum up the estimates of five simultaneous transportation modes.

[39] The data on ton-miles and values transported from the U.S. to Michigan include those from Michigan to Michigan since Michigan is part of the U.S. territory. We deducted the latter from the former.

3.6 Results

Using the State of Michigan as the example, we calculate the both the GHG reductions from savings of imported foods and the GHG emissions due to increased demand of local foods related to the local food policy in the scenario. The results are shown in Table 3.1.[40]

We find that, if the policy exogenously reduces demand of the imported foods by $10 million, the GHG emissions related to transport of the decreased demand of imported foods is 1,063 tons of CO_2 equivalent. As a point of comparison, 1,000 tons of CO2 equivalent would be produced by about 102 thousand gallons of gasoline burned by automobiles, and it requires 744 acres of U.S. forests in one year to sequester the carbon within the emission (US EPA, 2015). Among the 1,063 tons of CO_2 equivalent, 735 tons is due to transporting the final goods and 328 tons is due to transporting the U.S. produced inputs for producing those final goods. Due to data limitations, we cannot estimate the food-miles and the related GHG emissions of the non U.S. produced inputs. The potential to save the GHG emission due to the policy is thus underestimated in the calculation.

The food-miles and the related GHG emissions due to producing local foods are relatively small, but local foods production for increased demand still generates a certain amount of GHG emissions due to transportation. In total, there are 333 tons of CO_2 equivalent due to producing more local foods to substitute the imported foods. Thus local transport costs offset about 30% of the potential of GHG reduction. Of course, the proportion should be smaller once we take the GHG reduction of the non U.S. produced inputs into consideration. But this result shows to what extent the estimation may be biased without deducting the GHG emissions due to producing the local foods.

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[40] The total output change due to the local food policy can be found in Appendix 3.B.

From Table 3.1, we can also find that the imported inputs from places outside Michigan lead to significant amount of food-miles and CO_2 equivalent. This confirms our concern that if the environmental input-output model is not carefully adjusted, one may omit the GHG emissions due to the imported inputs and thus lead to biased estimates.

While the GHG reduction potential is underestimated due to data limitations, the net saving of the GHG emissions implies the lower bound of the possible reduction of the local food policy which substitutes the imported foods for local consumers by local foods.

Table 3.1 Food-miles and Related CO2 Emission from Scenario

		Food-miles*	CO_2 Equivalent**
Savings (from Imported Foods)	Final Consumption	2.538	735.2
	US Inputs	2.826	328.3
	Non-US Inputs	NA	NA
	Sub Total	5.364	1063.4
Generation (due to Local Foods Production)	Final Consumption	0.135	39.1
	MI Inputs	0.063	9.9
	Non-MI Inputs	2.930	283.6
	Sub Total	3.128	332.6
Net Saving		2.236	730.8

**Unit: Million ton-miles*
*** Unit: Ton*

3.7 Discussion and Conclusion

Our study provides an adjusted model for estimating the potential change of the GHG emissions due to the transportation caused by a local food policy. We show that the results from existing studies for calculating GHG emissions can be biased whether the study uses a top-down method or a bottom-up method. While the top-down method can trace the upstream inputs thoroughly and hence the resulted GHG emissions due to the required transportation, we modified the existing top-down method to correct the potential biases when calculating the GHG emissions. We also use the State of Michigan as an example and demonstrate how a regional level local food policy can be modeled.

Our calculation shows the GHG emissions due to transport associated with producing increased demand of local foods are relatively small comparing to the possible savings from the emissions resulted from the transport associated with decreased demand of imported foods, but it might be not small enough to be ignored as it is treated in existing literature.

Further, the GHG emissions due to transport of imported inputs take a significant portion and they are even larger than the emissions caused by transporting final consumption. Existing literature using conventional EIO-LCA framework omits this part of transaction and the associated travel as well as GHG emissions. The bias due to the omission of transport of imported inputs should not be omitted from policy analysis. In fact, future studies of local foods GHG emissions should pay more attention to imported inputs.

Data limitations restrain estimating transportation miles of foreign-imported goods. Hence, we are unable to estimate the emissions due to transporting the commodities from other countries to the U.S. The GHG reductions resulting from the savings of imported foods are underestimated to this extent. If we can find the information on the transportation as well as the technology used for the imported goods from other countries, we can estimate the GHG emission through this expression: $gD_{World\ to\ US}[(I - A_{World})^{-1}S]$.

As mentioned in Weber and Mathews (2008), the GHG emissions can be saved due to a local food policy is relatively smaller than the amounts that might be associated with other CO_2 mitigation policies, and it is also the case in our calculation. However, we should note that the savings of transport GHG emissions are just one part of the benefits resulting from local food policy. It is not even comprehensive for estimating the total GHG reductions that the policy might have. The calculation only analyzes the GHG emissions associated with transport, and the GHG emissions due to local food also include the emissions due to production process which is not included in our study scope. Unlike the transport-related GHG emissions, the net savings of GHG emissions might not be positive if the technology used to produce local foods is less energy efficient than that used to produce imported foods. Future study may further address the energy use and the resulted GHG emissions in production process as well as food growing using similar framework we showed.

In short, our calculation is the lower bound of GHG transport-related emissions that may be reduced by a policy which has $10 million of imported foods substituted by the same values of local foods. Our method corrects the potential biases in existing top-down method and enables the policy maker to be informed with more accurate estimates.

In the context of policy comparison, we should also keep in mind that the cost for certain activities should also be taken into consideration. Policies such as eating less meat may require more promotional cost and economic impact although it has greater potential to reduce GHG emissions than a local food policy can achieve. We may thus not draw the same conclusion through the comparison of GHG emission per unit cost. The estimates of GHG reduction may also be transferred into dollar units so that this benefit can be added up with other benefits, such as the increased growth of the local economy resulting from a local food policy. Also, it should be noted that if all localities implement a local foods policy, then areas exporting substantial amounts of food may face demand reductions in their economies. On the positive side, local foods may decrease the likelihood of national (intended or unintended) food poisoning, or impacts of localized disasters on overall food supply.

APPENDICES

Appendix 3.A Mapping the Sectors in the Commodity Flow Survey

Table 3.A1 Mapping NAICS 2 Digit Code to SCTG

Sector	NAICS 2-digit Description	Standard Classification of Transported Goods (SCTG)
11	Agriculture, Forestry, Fishing and Hunting	01 Animals and Fish (live) 03 Agricultural Products (excludes Animal Feed, Cereal Grains, and Forage Products) 05 Meat, Poultry, Fish, Seafood, and Their Preparations 25 Logs and Other Wood in the Rough
21	Mining, Quarrying, and Oil and Gas Extraction	10 Monumental or Building Stone 11 Natural Sands 12 Gravel and Crushed Stone (excludes Dolomite and Slate) 13 Other Non-Metallic Minerals not elsewhere classified 14 Metallic Ores and Concentrates 15 Coal 16 Crude Petroleum
22	Utilities	
23	Construction	
31-33	Manufacturing	02 Cereal Grains (includes seed) 04 Animal Feed, Eggs, Honey, and Other Products of Animal Origin 06 Milled Grain Products and Preparations, and Bakery Products 07 Other Prepared Foodstuffs, Fats and Oils 08 Alcoholic Beverages and Denatured Alcohol 09 Tobacco Products 17 Gasoline, Aviation Turbine Fuel, and Ethanol (includes Kerosene, and Fuel Alcohols) 18 Fuel Oils (includes Diesel, Bunker C, and Biodiesel) 19 Other Coal and Petroleum Products, not elsewhere classified 20 Basic Chemicals 21 Pharmaceutical Products 22 Fertilizers 23 Other Chemical Products and Preparations 24 Plastics and Rubber 26 Wood Products 27 Pulp, Newsprint, Paper, and Paperboard 28 Paper or Paperboard Articles 29 Printed Products 30 Textiles, Leather, and Articles of Textiles or Leather 31 Non-Metallic Mineral Products 32 Base Metal in Primary or Semi-Finished Forms and in Finished Basic Shapes 33 Articles of Base Metal 34 Machinery 35 Electronic and Other Electrical Equipment and Components, and Office Equipment 36 Motorized and Other Vehicles (includes parts) 37 Transportation Equipment, not elsewhere classified 38 Precision Instruments and Apparatus 39 Furniture, Mattresses and Mattress Supports, Lamps, Lighting Fittings, and Illuminated Signs 40 Miscellaneous Manufactured Products 41 Waste and Scrap 43 Mixed Freight

Source: Global Insight (2007)

Table 3.A2 Transformation of Multiple Transportation Modes to Single Transportation Modes

CFS Code	Single Mode	Multiple Mode	
		14	Parcel, U.S.P.S. or courier
		15	Truck and rail
		16	Truck and water
3	Truck	18	Other multiple modes
		14	Parcel, U.S.P.S. or courier
		15	Truck and rail
		17	Rail and water
6	Rail	18	Other multiple modes
		14	Parcel, U.S.P.S. or courier
		16	Truck and water
		17	Rail and water
7	Water	18	Other multiple modes
	Air (include truck	14	Parcel, U.S.P.S. or courier
11	and air)	18	Other multiple modes
12	Pipeline	18	Other multiple modes

+ Some numbers in the CFS are withheld because the estimates do not meet publication standards. We assume they are zero since they are quite small in general.

++ If there is no value in any of the five basic single modes for a commodity, the multiple transportation mode is not distributed.

Appendix 3.B Results of Economic Impact Simulation Using IMPLAN

Table 3.B1 Economic Impacts of the Local Food Policy

Unit: $Million

Sector	Increase of MI Outputs	Decrease of Imported Inputs
11 Ag, Forestry, Fish & Hunting	10.6189	12.2249
21 Mining	0.0126	0.2152
22 Utilities	0.1841	0.2956
23 Construction	0.0343	0.0801
31-33 Manufacturing	0.8352	3.3718
42 Wholesale Trade	0.3804	0.6677
44-45 Retail trade	0.0126	0.0249
48-49 Transportation & Warehousing	0.2177	0.4417
51 Information	0.0446	0.1749
52 Finance & insurance	0.3737	0.6533
53 Real estate & rental	0.7704	1.0449
54 Professional- scientific & tech services	0.1723	0.3823
55 Management of companies	0.0405	0.1526
56 Administrative & waste services	0.0737	0.1574
61 Educational services	0.0215	0.0336
62 Health & social services	0.0000	0.0001
71 Arts- entertainment & recreation	0.0083	0.0180
72 Accommodation & food services	0.0228	0.0540
81 Other services	0.0326	0.0722
92 Government & non NAICs	0.0705	0.1499
Sub Total	13.9266	20.2151

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