Temperature Effects are more Complex than Degrees: A Case Study on Residential Energy Consumption

Gi-Eu Lee

Department of Economics, University of Nevada, Reno

gieul@unr.edu

Scott Loveridge

Department of Agricultural, Food, and Resource Economics, Michigan State University

loverid2@msu.edu

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Abstract

An emerging body of research about climate change impacts is exploring temperature effects on human activities. However, most studies use simple identification strategies that only explore one or two attributes relating to temperature or to its abnormalities. These simple strategies limit the understanding of temperature effects, and there is debate about the effectiveness of simple identification strategies. To better understand complex temperature effects on human activities, this study uses residential energy consumption as an example and develops identification strategies to capture the temperature effects resulting from temporal patterns (temperature fluctuation), abnormality (temperature departure from normal), and the interdependence among these attributes.

For comparison, we use the same data set and model specification as in Deschênes and Greenstone (2011) except for specifications to capture complex temperature effects. We construct variables to capture additional temperature attributes and create the interaction terms among these attributes and temperature levels. Our findings verify the existence of complex temperature effects on energy consumption, and our paper may provoke the discussion of different strategies to better capture climate impacts on human activities.

JEL: Q41, Q54

Key Words: *Complex Temperature Effects; Residential Energy Consumption; Climate Change*

1. Introduction

A rapidly emerging body of research about climate change impacts explores temperature effects on human activities, as temperature, especially abnormal temperature, is well-recognized as a key attribute of climate change. Temperature has been found to have effects in diverse areas of human societies, from those with direct or obvious connections, such as public opinions toward climate change (Egan and Mullin, 2012), beverage consumption (Uri, 1986), human health (Deschênes et al., 2009, Deschênes and Greenstone, 2011) or energy consumption (Deschênes and Greenstone, 2011), but also some effects with less intuitive connections, such as civil war (Burke et al., 2009) or stock market returns (Cao and Wei, 2005, Kamstra et al., 2003).

However, in some areas, whether temperature has an effect on the dependent variable of interest is still a matter of debate. For instance, Jacobsen and Marquering (2008, 2009) argue that the strategies used in Kamstra et al. (2003) or Cao and Wei (2005) may misidentify temperature effects on stock market returns. Buhaug (2010) also suggests that temperature has no significant effect on civil wars. In the analyses of temperature effects on public opinions, while Brooks et al. (2014), Hamilton and Stampone (2013), Egan and Mullin (2012), and Scruggs and Benegal (2012) suggest more supportive attitudes when the respondents experience hotter temperature, Brulle et al. (2012), Zaval et al. (2014), and Marquart-Pyatt et al. (2014) find that variables of temperature are not significant in their regression results.

As suggested by Jacobsen and Marquering (2008, 2009), Buhaug (2010), and Lee (2015), such divergent results may come from the identification strategies used to capture weather effects. Jacobsen and Marquering (2008) make an argument that a simple temperature variable used in the analysis cannot distinguish between weather and seasonal effects due to other factors such as a spike consumption near Christmas. While Buhaug (2010) finds no empirical evidence to support the effect of temperature on civil wars, he also mentions that it could be because the yearly measurement of temperature at large scale (country level) eliminates local variations. While Lee et al. (2016) demonstrate a negative effect of warmer temperature on public support toward climate change adaptation policies, Lee (2015) shows that such phenomena cannot be explained by the popularly used identification strategies and the analyses require further refinements in the empirical model.

Most studies of temperature effects include variables of temperature measurements such as degrees (Fahrenheit or Celsius), cooling / heating degree day, days within temperature bins, etc. A few studies, mostly discussing public opinion, further adopt measurements of temperature abnormality, such as temperature deviation from normal level, to explore the effects of climate change. These simpler identification strategies can only explore one or two attributes relating to temperature or to its abnormalities. Such simpler strategies, however, limit the understanding of temperature effects. Lee (2015) found a negative effect of warmer temperature during the second half of a warm spell, a period in which the mean temperature was hotter, is explained by temperature deviation from normal level, short term temperature variation, and the interdependence among the abnormalities. Solely using one of the popular but simple strategies leads to the same conclusion generally found in the existing literature (Lee, 2015), but such findings lose more subtle information meaningful to both scholars and policy makers.

In this article, we explore whether unconventional identification strategies may help explain complex temperature effects in topics other than public opinion. Simple empirical strategies associated with temperature levels, such as Fahrenheit / Celsius, cooling / heating degree day, or temperature bins, are still commonly used in studies focusing on phenomena other than public opinion. To capture the effects due to temperature attributes other than temperature levels, we consider empirical strategies inspired from Lee (2015) to test if other temperature attributes also explain the outcomes of interest.

This study uses residential energy consumption to develop example identification strategies capturing temperature effects resulting from temporal patterns (short term temperature fluctuation), abnormality (temperature departure from normal), and the interdependence among these attributes. We use residential energy consumption for the example outcome of interest for two reasons. First, residential energy consumption is likely also associated with other temperature attributes such as short term temperature change (fluctuation), since human thermal sensation is not linear with objective ambient temperature (Li, 2005), and sudden ambient temperature changes may lead to larger magnitude of thermal sensation (de Dear et al., 1993, Arens et al., 2006). Second, to verify whether these additional attributes help to explain the outcome of interest, further analysis of a published study can avoid improvements due to different measurements, syntaxes, etc. Among the published studies, we found Deschênes and Greenstone's (2011) work (hereafter, D&G) fits the purpose of our analysis.

We adopt D&G's data set and empirical work about residential energy consumption as the baseline for comparison and discuss if the strategies capturing other features of temperature can help explain the outcome of interest. Our findings suggest the existence of complex temperature effects on energy consumption, and our paper may provoke the discussion of different strategies to better capture climate impacts on human activities. While most areas discussing temperature effects, mostly use simpler strategies, our findings suggest the need to further develop identification strategies for better capturing the temperature effects.

2. Identification Strategies in the Energy Consumption Literature

For decades, identification strategies used in energy consumption studies relied on variables measuring temperature per se (degree Fahrenheit / Celsius), temperature deviation from comfort level (cooling / heating degree days, hereafter, CHDD), or a simple transformation of these measurements. The use of these two main measurements is because of intuitive and observable phenomena: humans prefer a specific level of temperature and air conditioning is turned on when ambient temperature deviates from this level. Thus, CHDD is measured with a chosen set point, such as 65^{o} F, and represents the deviation from preferred temperature.

Quayle and Diaz (1980), in one of the earliest studies, used heating degree days to analyze the temperature effect on residential electricity consumption. Similarly, Eskeland and Mideksa (2010) include CHDD variables in their empirical model to estimate electricity demand in European countries. Savić et al. (2014) also use CHDD to capture the influence of air temperature. Based on the purposes of analysis, there are other measurements similar to the CHDD used in aforementioned empirical studies. To capture the sensitivity of temperature variation on energy consumption, Kaufmann et al. (2013) measure cooling / heating degree by hour, and Fikru and Gautier (2015) measure cooling / heating degree by minute. Kaufmann et al. (2013) also find that cooling / heating degree calculated by set points other than 65^{o} F may better explain energy consumption. Instead of regular CHDD, Considine (2000) calculates the deviation of CHDD from 30-year-averaged level to identify the influence of abnormal weather on energy consumption in the USA. This study finds both warm and cool temperature has statistically significant influences, but the coefficients of the former are generally larger than the latter.

However, using CHDD may not be an ideal strategy to capture temperature effects on energy consumption. The calculation of CHDD is criticized for the arbitrary choice of set point (Mansur et al., 2008). Although it is found that that the Americans, on average, favor 65^{o} F (Albouy et al., 2013), other studies suggest the preference can depend on socio-economic factors and scatter across a certain range (Wang et al., 2015, Kaufmann et al., 2013). In addition, as indicated by Mansur et al. (2008), "it is not clear that *i* degrees for *j* days is equivalent to *j* degrees for *i* days." In fact, while CHDD are calculated by a single set point, using such variables to capture the temperature effect on energy consumption implicitly assumes that the use of air conditioning is the optimal choice to respond the departure of ambient temperature from one's preferred level.However, within a range of departure, alternative measures to adapt to temperature change without energy consumption, such as wearing lighter clothing, could be preferred options. If this is the case, the partial derivative of temperature with respect to indirect utility is zero conditional on the temperature range.

The other main empirical strategy to capture temperature effects is using variables that represent temperature level or its simple transformation such as temperature bins. Since temperature varies across time, the temperature level of a certain window is often represented by mean value of temperature. For example, De Cian et al. (2013) use seasonal mean temperature to capture the temperature effect on energy demand. However, averaged temperature of a longer time period could mask short term variations of temperature during the window and cause the analyses to be less accurate (Kaufmann et al., 2013, Lee, 2015, Buhaug, 2010).

A commonly used alternative measurement is sorting temperature into a set of bins and counting the number of days falling into each of the bins. For instance, temperature bins may be set by equidistant cutoffs (e.g., 10^{o} F - 20^{o} F as one bin) or by equal percentile of temperature distributions (Auffhammer and Aroonruengsawat, 2011). Then, the number of days with daily temperature falling into each bin within the time period of measurement is counted. Say, the number is 25 for bin 10^{o} F - 20^{o} F if there are 25 days with daily temperature falling into the bin during the year. Through this strategy, the information about temperature levels is kept even in a longer time period of measurement. This strategy also allows the non-linearity of temperature effect on the outcome of interest. Deschênes and Greenstone (2011), Auffhammer and Aroonruengsawat (2011), and De Cian and Sue Wing (2016) all use this strategy in their energy studies. In addition to the above articles, several technical reports studying energy consumption use CHDD or days in temperature bins to capture temperature effects (Mideksa and Kallbekken, 2010).

Although the strategy of temperature bins avoids some disadvantages that CHDD strategy has, it has some drawbacks. While numbers of days are counted, this strategy ignores the dynamic and path-dependent nature of temperature variation. For instance, within a year, if there are 25 days with daily temperature in the bin of 40^{o} F - 50^{o} F, the record is 25, regardless of whether they occur consecutively or spread across several months. Also, the measure is the same irrespective of season. Thus, temporal patterns of temperature variations cannot be analyzed though this strategy. This strategy, therefore, implicitly assumes human thermal sensation and the consequent energy consumption do not depend on short term temperature change. As we discussed above, this implicit assumption is not valid if the sensation-temperature stimulus relationship is non-linear.

In addition, while studies using this temperature bins strategy simply count the days of temperature for each bin (e.g., Deschênes and Greenstone, 2011, Auffhammer and Aroonruengsawat, 2011, De Cian and Sue Wing, 2016), the abnormality of temperature is not fully captured. For the same instance of 25 days with daily temperature in the bin of 40^{o} F - 50^{o} F, in northeastern states, such temperature would be abnormal in summer and winter but quite normal in spring or fall. To explore the effect of abnormal temperature in the context of climate change, Deschênes and Greenstone (2011), for instance, adopt simulation results of future temperature based on the scenario of climate change with rising temperature. This method, however, estimates the potential impact of future climate change instead of the impact from the historical changing climate (Lee and Loveridge, 2016). The CHDD strategy also suffers from these two disadvantages if it is adopted without proper improvement. To our knowledge, in the energy consumption literature, we find that only Considine (2000) uses CHDD deviation to capture temperature abnormality.

In short, while both CHDD and temperature bins strategies are commonly found in the literature, these two mainstream strategies do not identify the effects resulting from temporal patterns or other attributes relating to temperature that may also influence energy consumption. The effect of temperature abnormality is also rarely identified in the energy consumption literature. Thus, in addition to CHDD and temperature bins, our study will adopt identification strategies for short term temperature variation and temperature abnormality to discuss the potential contribution of these strategies in the analysis of energy consumption.

3. Method and Data

To explore potential complex temperature effects and to avoid that improvement of our empirical work is due to other causes, such as better data collection, empirical models, or software syntaxes, we use D&G's published work on residential energy consumption as the baseline for comparison. We use the same panel data set and model specification as in D&G except for the set of temperature variables for capturing complex temperature effects. Many studies do not provide necessary details to replicate their empirical work due to length limits of the papers. D&G's work is an exception, and their data set and Stata modeling codes are accessible on the website of *American Economic Journal: Applied Economics*. We construct different temperature variables that represent the temperature attributes of interest through their temperature data set using Stata 13 in the Unix system. D&G's accessible Stata codes also allow us to use exactly the same syntaxes for our regressions. Thus, except for the temperature variables, the rest of our empirical model are controlled and the same as D&G's work.

The empirical model used in D&G for residential energy consumption analysis is the following:

$$\ln(C_{st}) = \sum_{j} \theta_j^{TMEAN}\, TMEAN_{stj} + \sum_{l} \delta_l^{PREC}\, PREC_{stl} + \boldsymbol{X}_{st}\boldsymbol{\beta} + \alpha_s + \gamma_{dt} + \varepsilon_{st}$$

In the equation, C_{st} is annual residential energy consumption for year t and state s. $TMEAN_{stj}$ denotes the number of days with daily temperature in *j*th temperature bin, state s, and year t. $PREC_{stl}$ is a similar variable for the *l*th precipitation bin. The vector $\boldsymbol{X}_{st}$ includes population, GDP, and their squared terms at the state level. In the model, α_s captures state fixed effects and γ_{dt} captures census division-by-year fixed effects (Deschênes and Greenstone, 2011). D&G also use CHDD as an alternative strategy. In the empirical model using CHDD, variables of temperature bins are replaced by variables of cooling and heating degree days. Because the temperature bins approach produces a better statistical fit, we refer it as the baseline model for comparing to other temperature specifications.

Based on the above baseline model, we used different specifications for capturing temperature effects. While the days within temperature bins captures the distribution of absolute temperature level within a year, we construct variables representing alternative temperature attributes, such as temperature fluctuation and temperature departure, for capturing the rapid change of temperature in a temporal pattern and abnormality of temperature, respectively. We also construct the interaction terms between these alternative attributes and days in temperature bins.

Thus, there are three types of model specifications. In the first type of model specification, we replace the temperature variables used in D&G's empirical model by each of the temperature variables we construct. Since the outcome variable is measured annually, these temperature variables are generated from daily data aggregated into yearly level. The construction of temperature variables are shown in Table 1. This allows us to compare the conventional strategy of using days in temperature bins with other identification strategies.

In Table 1, we define temperature fluctuation as the temperature change from one day prior. Temperature departure, as commonly suggested in the literature, is defined by the difference between observed temperature and normal temperature, which is usually represented by a long term average value. We define normal temperature asthe mean value of temperature from 1968 to 2002, which is the period in D&G's data set. Since this definition of temperature departure does not take the normal variation of temperature into consideration (Lee, 2015), we further construct a variable of extreme temperature departure by measuring the deviation values above 1.645 standard deviation so that the variation within a 95% confidence interval is omitted and only the extreme values are counted. We also construct two variables to denote the days of extreme hot and cold temperature within a year.

In the second type of model specification, we add each of the variables we construct to the baseline model. Instead of replacing the variables of days in temperature bins, adding the variables to the baseline model allows us to explore if capturing additional temperature attributes improves the explanatory power of the baseline model. In the third type of model specification, we further include interaction terms the empirical model. Lee's (2015) public opinion study finds that short term temperature variation and temperature abnormality depend on each other as well as on the time period of a warm spell. Thus, through adding interaction terms, we further explore the potential complexity of temperature effects on residential energy consumption.

Table 1 Temperature Variables Measuring Different Attributes

Specification Number	Identification Strategies
N/A	Baseline specification: days in temperature bins $\sum_j \theta_j^{TMEAN}\, TMEAN_j, j = 1\sim10$ Bin_1 < 10º F ≤ Bin_2 < 20º F ≤ …< 80º F ≤ Bin_9 < 90º F ≤ Bin_10
1	Sum of daily mean temperature $T\_Mean = \sum_{i=1}^{365} Temp_i$
2	Temperature fluctuation $Flc = \sum_{i=2}^{365} Temp_i - Temp_{i-1}$ $Temp_i$is the daily temperature of day *i*.
3	Absolute temperature fluctuation $Flc\_Abs = \sum_{i=2}^{365} abs(Temp_i - Temp_{i-1})$
4	Temperature fluctuation: measured by percentage change $Flc\_Pct = \sum_{i=2}^{365}(Temp_i - Temp_{i-1})/abs(Temp_{i-1})$
5	Temperature fluctuation: absolute percentage change $Flc\_Pct\_Abs = \sum_{i=2}^{365} abs\{(Temp_i - Temp_{i-1})/abs(Temp_{i-1})\}$
6	Temperature departure $Dep = \sum_{i=1}^{365} Temp_i - Normal\, Temp_i$ $Normal\, Temp_i$ denotes normal temperature of day *I* represented by mean value of 1968-2002 records of day *i*.
7	Absolute temperature departure $Dep\_Abs = \sum_{i=1}^{365} abs(Temp_i - Normal\, Temp_i)$
8	Extreme temperature departure $Dep\_Std = \sum_{i=1}^{365}(T\_Dep\_Hot_i + T\_Dep\_Cold_i)$

	$T\_Dep\_Hot_i = a\{(Temp_i - Normal\ Temp_i) - 1.645 Standard\ Deviation_i\}$ $a\{.\}$ reports temperature departure above 1.645 standard deviation from normal level and 0 if temperature departure smaller than 1.645 standard deviation $T\_Dep\_Cold_i = \{(Temp_i - Normal\ Temp_i) + 1.645 Standard\ Deviation_i\}$ $b\{.\}$ reports temperature departure below -1.645 standard deviation from normal level and 0 if temperature departure larger than -1.645 standard deviation
9	Days of extreme temperature (this specification contains two variables) $Day\_Extreme = \binom{T\_Dep\_Hot\_Days}{T\_Dep\_Cold\_Days}$ $T\_Dep\_Hot\_Days = \sum_{i=1}^{365} d\{(Temp_i - Normal\ Temp_i) - 1.645 Standard\ Deviation_i\}$ $d\{.\}$ Is a dummy function which returns 1 if temperature departure is larger than 1.645 standard deviation from normal level $T\_Dep\_Cold\_Days = \sum_{i=1}^{365} d\{(Temp_i - Normal\ Temp_i) + 1.645 Standard\ Deviation_i\}$ $d\{.\}$ Is a dummy function which returns 1 if temperature departure is less than -1.645 standard deviation from normal level

4. Baseline Results from Deschênes and Greenstone (2011)

We consider results reported in D&G's Table 4, Panel A, as the baseline for comparison. Their results show that all the coefficients for temperature bins and CHDD are positive. These estimates are significant at the 5% level, except for the bin of 60° – 70° F and the bin of 70° – 80° F.[1] The estimates of temperature bins suggest a U-shaped temperature effect while, in the range of 50° – 80° F, there seems no influence on residential energy consumption as the coefficients are not

[1] In their model, bin of 50° – 60° F is set as the base (Deschênes and Greenstone, 2011).

significant. This result also implies that CHDD might lead to certain bias for capturing temperature effects, since CHDD suggests that minor deviation from the set point temperature has the influence.

For comparison, we report the relative qualities of the two baseline models from D&G in Table 2, as these are not shown in their article. Given these measures, the model using temperature bins explains residential energy consumption better than the model using CHDD. Three measures, adjusted R^2, Akaike information criterion (AIC) and Bayesian information criterion (BIC) are developed for comparing model's explanatory power, but there is no consensus about which criteria is best for model selection (Lindsey and Sheather, 2010). Although the criteria are designed to produce penalties for more predictors, there still could be overfitting issues (Lindsey and Sheather, 2010). Therefore, when comparing models with different numbers of predictors, we should be conservative in using these criteria for model selection.

Table 2 Relative Qualities of Baseline Models

Model	Temperature Bins	CHDD
Adjusted R^2	0.99735	0.99735
AIC	-5651.3679	-5641.3060
BIC	-5389.9038	-5379.8419

5. Results

5.1 Models Replacing Temperature Bins with Other Temperature Features

By replacing the variables of days in each temperature bin in the baseline model with alternative measures of temperature attributes, we have nine specifications different from the baseline model (Table 1). The regression results of the first type model specifications show that, overall, the non-temperature control variables have estimates of coefficients with same direction and significance level as to the corresponding estimates in the baseline model. For brevity, we report the estimates of the temperature variables only in Table 3.

Among the nine alternative specifications of temperature, temperature fluctuation and extreme temperature departure are both significant (Table 3). The positive coefficient on temperature fluctuation implies that a rapid increase of temperature within two days leads to more energy consumption, which is consistent with the non-linear thermal sensation we discussed above. The negative sign on extreme temperature requires careful discussion. While it suggests less energy consumption when temperature deviates to an extreme heat level, it makes sense when the absolute temperature is cold but it is not reasonable when absolute temperature level is hot. The results of the last model in Table 3 suggest that the negative sign of extreme temperature could be due to the dominant effect of temperature deviation in cold days. In model 9, more days of extreme cold temperature results in more energy consumption while the coefficient of more days of extremely hot temperature is not significant.

However, replacing temperature bins by those temperature variables does not provide better fit according to adjusted R^2, AIC, or BIC. Since there could be an overfitting issue in the baseline model because it includes 8 additional predictors from 9 temperature bin variables, we calculate the temperature fluctuation, temperature departure, and extreme temperature departure for each of the ten temperature bins. The construction of these variables are the same as described in Table 1 except that the calculation includes the observations with daily temperature in the bin to which it belongs. For instance, the calculation of temperature fluctuation for each bin is:

$$Flc\_Bin\_j = \sum_{i=2}^{365} Flc_i \;\; \forall \, Temp_i \; \in Bin\_j, j = 1 \sim 10$$

We use these sets of variables constructed by temperature bins instead of the corresponding single variables and the regression results are reported in Table 4. Still, after adjusting the numbers of predictors to be equal in each model, the baseline model has the best performance according to adjusted R^2, AIC and BIC. More significant coefficients of temperature departure (*Dep* and *Dep_Std*) in colder temperature bins also support our guess about the negative sign of *Dep* and *Dep_Std* in Table 3. These negative coefficients suggest that, when absolute temperature is low but relatively warmer than usual, residential energy consumption could be less than the prediction solely considering temperature level, as households may be used to colder temperature and require less heat.

Overall, these results suggest that, among the strategies in the first type of model specifications that capture only one feature of temperature, number of days in temperature bins explains the overall temperature effect better. However, temperature fluctuation and temperature departure could be associated with residential energy consumption as several of their coefficients are statistically significant (Table 3 and Table 4). Therefore, in the second type of model specification, we add one of the two temperature attributes to the baseline model to explore if capturing more temperature attributes improve the explanation of temperature effects.

Table 3 Estimates of Different Temperature Measures

Model Temperature Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
T_MEAN	-0.0000 (0.0000)								
FLC		0.0003*** (0.0001)							
FLC_ABS			0.0000 (0.0000)						
FLC_PCT				-0.0000 (0.0000)					
FLC_PCT_ABS					0.0000 (0.0000)				
Dep						-0.0000 (0.0000)			
Dep_ABS							0.0000 (0.0000)		
Dep_Std								-0.0002*** (0.0001)	
Dep_Plus_Days									0.0004 (0.0004)
Dep_Minus_Days									0.0005* (0.0003)
Adjusted R^2	0.99724	0.99723	0.99723	0.99723	0.99723	0.99724	0.99724	0.99725	0.99724
AIC	-5571.9824	-5566.7054	-5563.9187	-5565.4775	-5565.3728	-5571.9824	-5567.9255	-5574.6582	-5568.7488
BIC	-5310.5183	-5305.2414	-5302.4546	-5304.0134	-5303.9087	-5310.5184	-5306.4614	-5307.7470	-5307.2847

Standard errors in parentheses

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

Table 4 Estimates of Different Temperature Measures by Bins

	(1) Flc	(2) Dep	(3) Dep_Std
BIN_1	-0.0000	-0.0001**	-0.0005***
	(0.0002)	(0.0000)	(0.0001)
BIN_2	0.0003**	-0.0001*	-0.0003**
	(0.0002)	(0.0000)	(0.0001)
BIN_3	0.0003**	-0.0001	-0.0006**
	(0.0001)	(0.0001)	(0.0002)
BIN_4	0.0003***	-0.0000	-0.0002
	(0.0001)	(0.0000)	(0.0002)
BIN_5	0.0002***	-0.0001**	0.0003
	(0.0001)	(0.0000)	(0.0004)
BIN_7	-0.0000	0.0000	0.0001
	(0.0001)	(0.0000)	(0.0002)
BIN_8	-0.0000	0.0001*	0.0002
	(0.0001)	(0.0000)	(0.0002)
BIN_9	0.0001	0.0001***	0.0010***
	(0.0003)	(0.0000)	(0.0002)
BIN_10	0.0037**	0.0002	0.0003
	(0.0019)	(0.0002)	(0.0010)
Adjusted R^2	0.99727	0.99732	0.99729
AIC	-5599.0296	-5629.6531	-5608.9510
BIC	-5332.1183	-5362.7419	-5342.0397

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

5.2 Models Including Additional Temperature Features

The results show that adding temperature attribute variables to the baseline model improves adjusted R^2, AIC and BIC (Table 5), while estimates of temperature bins are similar to those in baseline model. Among the variables added to the baseline model, only temperature fluctuation has a significant coefficient (Table 5). Temperature departure, regardless whether it is measured with extreme abnormality or not, is not significant, although the AICs and BICs of the two models including either one of the two measurements of temperature abnormality are better than those in the baseline model. While the joint test of temperature bins and each of the added variables rejects the null hypothesis that the coefficients are jointly zero, variance inflation factors (VIFs) suggest the potential issue of multicollinearity among temperature bins and the added temperature variable. These results suggest the improvement by capturing more features of temperature, even though the potential collinearity issue could influence the estimates. The results also imply that rapid change of temperature could be one feature of temperature which is not well modeled with temperature bins. We also add variables of these temperature features calculated by each temperature bin. The results of temperature fluctuation are in general similar to Table 4, while most of the estimates for temperature departure or extreme departure are not significant.

Table 5 Adding Temperature Attributes to Baseline Model

Model Coefficient	(1)	(2)	(3)
Flc	0.0002**		
	(0.0001)		
Dep		-0.0001	
		(0.0001)	
Dep_Std			-0.0001
			(0.0001)
Adjusted R^2	0.99735	0.99736	0.99735
AIC	-5652.9014	-5658.6828	-5653.0557
BIC	-5391.4373	-5397.2187	-5391.5916

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

5.3 Interdependence Models

We further explore the potential interdependence among the temperature attributes through a third type of model. We report the results of interaction models in Table 6. The days of temperature bins used in baseline model represent the distribution of daily temperature, and interacting temperature fluctuation in each temperature bin with the corresponding number of days in that bin implies the conditional effect of temperature fluctuation or the temperature bin.

In Table 6, we can see that some coefficients for *Days_Bin_j* in bin 1 and 2 are no longer significant despite their significance in the baseline regression. This could be due to multicollinearity as well. All joint tests of temperature variables reject the hypotheses that the coefficients are jointly zero. For temperature fluctuation, its coefficients in bin 2 to bin 5 are significant and positive, while interaction terms of temperature fluctuation and the corresponding bins are both negative. The coefficients of interaction terms are significant for bin 2 and bin 5, suggesting the existence of interdependence. Therefore, in cooler days (< 50^{o} F), while a rapid increase of temperature within two days leads to more residential energy consumption, more days in the corresponding temperature bin hamper the fluctuation effect slightly. In other words, when humans' non-linear thermal sensation leads to more energy consumption, more days of similar temperature, restricted within the 10^{o} F bin, decreases the fluctuation effect, as it implies a relatively more stable temperature within a year. The positive coefficients of temperature fluctuation in bins with lower temperature seem to be counterintuitive, as it suggests that rapid increase of temperature in colder days actually results in more residential energy consumption. While the D&G's data set has no information about what the uses of the energy, we cannot verify if this positive effect is due to cooling demand as people have *heat illusion*[2] or they experience the illusion as unbearable cold and take defensive action by using heat. We should keep in mind that in this model, the marginal effect of temperature fluctuation is not constant and depends on days of the corresponding bin. When the number of days is larger than 38 days, the marginal effect of rapid temperature increase is positive. Therefore, when the small range of temperature occurs more frequently, a rapid increase of temperature in such a relatively stable weather still results in increased energy use.

The interaction model of extreme temperature departure and days in bins tells a slightly different story, which consistently demonstrates the complex effects of temperature. Similar to the

[2] A similar example is that, when skin temperature is quite low, flushing skin with water of a bit higher temperature than the skin often leads to a strong but mistaken sensation that the water is hot. This illusion may cause some people to take action to warm up.

results in Table 4, most of the temperature departure and extreme departure coefficients in the lower temperature bins are negative. These coefficients are not significant, possibly due to multicollinearity. The interaction terms of temperature departure or extreme temperature departure with number of days have a similar explanation. We thus focus on results of extreme departure as it captures abnormality without counting normal variation of temperature.

The coefficients of the interaction terms are negative in colder bins (i.e., bin 1 and bin 3), which suggests that, conditional on same number of days in the temperature bin, a warmer departure from long term trend contributes to less residential energy consumption in cold days and a colder departure further increases the consumption in addition to the absolute temperature level. Similarly, the positive coefficient (0.0001) in of the interaction term in bin 10 suggests that, when the absolute temperature level is above 90^{o} F, extreme temperature departure leads to further consumption of residential energy.

The negative coefficient of extreme departure in bin 10 (-0.004) seems counterintuitive at first glance. Yet, as the coefficient of its interaction term with days of that bin is significant, it suggests the interdependence. The marginal effect of this extreme departure of hot days can lead to either more or less energy consumption, because of inverse sign of the coefficient for that interaction term. Therefore, when temperature is high but total hot days in bin 10 ($> 90^{o}$ F) in a year is less than 35, heatt abnormality leads to less residential energy consumption. But if hot days within bin 10 occur more frequently, heat departure from long term trend results in additional residential energy consumption. Together, these results suggest that, when temperature is hotter than its long term trend, households' adaptation activities are conditional on how frequently the hot days occur, regardless whether it is usual or not.

Table 6 Adding Interaction Terms to Baseline Model

	(1) Fluctuation	(2) Departure	(3) Extreme Departure
Days_Bin_1	0.003214***	0.000487	0.001825
	(0.0006)	(0.0023)	(0.0015)
Days_Bin_2	0.001479	0.002404	0.002411**
	(0.0011)	(0.0022)	(0.0010)
Days_Bin_3	0.001989***	0.002409*	0.001848***
	(0.0006)	(0.0014)	(0.0006)
Days_Bin_4	0.001037**	0.001694*	0.001398**
	(0.0005)	(0.0010)	(0.0006)
Days_Bin_5	0.000763**	0.001091***	0.000840**
	(0.0004)	(0.0004)	(0.0004)
Days_Bin_7	-0.000076	0.000266	-0.000029
	(0.0004)	(0.0006)	(0.0004)
Days_Bin_8	0.000382	0.000009	-0.000046
	(0.0005)	(0.0008)	(0.0005)
Days_Bin_9	0.001534**	0.001498	0.001205*
	(0.0006)	(0.0012)	(0.0007)
Days_Bin_10	0.003348***	0.004269*	0.003233***
	(0.0011)	(0.0023)	(0.0012)
Var_Bin_1+	-0.000086	-0.000186**	-0.000098
	(0.0003)	(0.0001)	(0.0002)
Var_Bin_2	0.000612***	-0.000036	-0.000114
	(0.0002)	(0.0001)	(0.0003)
Var_Bin_3	0.000393**	-0.000056	0.000674
	(0.0002)	(0.0001)	(0.0005)
Var_Bin_4	0.000353*	0.000156	-0.000079
	(0.0002)	(0.0001)	(0.0005)
Var_Bin_5	0.000561**	0.000022	0.001622
	(0.0003)	(0.0001)	(0.0010)
Var_Bin_7	-0.000239	0.000185*	0.000186
	(0.0004)	(0.0001)	(0.0010)
Var_Bin_8	0.000489	-0.000107	-0.000043
	(0.0003)	(0.0001)	(0.0005)
Var_Bin_9	-0.000145	-0.000114	0.000646
	(0.0006)	(0.0001)	(0.0006)
Var_Bin_10	-0.001196	-0.000576**	-0.003968***
	(0.0023)	(0.0003)	(0.0013)
Var_x_Days_Bin_1+	0.000006	0.000000	-0.000009*
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_2	-0.000016**	-0.000000	0.000007
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_3	-0.000007	0.000001	-0.000034*
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_4	-0.000003	-0.000002	0.000007
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_5	-0.000007*	-0.000000	-0.000019
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_7	0.000004	-0.000002*	0.000000
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_8	-0.000006	0.000002*	0.000003
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_9	0.000002	0.000001	-0.000007
	(0.0000)	(0.0000)	(0.0000)
Var_x_Days_Bin_10	0.000039	0.000010**	0.000112*
	(0.0000)	(0.0000)	(0.0001)
Adjusted R^2	0.99736	0.99737	0.99737
AIC	-5680.4808	-5688.7458	-5689.1631
BIC	-5419.0167	-5427.2817	-5427.6990

+ Var in column 1, 2, and 3, is temperature fluctuation, temperature departure, and extreme temperature departure, respectively. For instance, in column 1, Var_Bin_1 is the temperature fluctuation that occurs below 10º F, and Var_x_Days_Bin_1 is the interaction term of temperature fluctuation and number of days in this temperature bin.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Discussion and Conclusion

Using D&G's data set and empirical model, but adding strategies for capturing alternative and additional temperature attributes, our work discuss potentially ignored features of temperature and the complexity of temperature effects on energy consumption. Our results show that, in models capturing a single temperature attribute, popularly used temperature bin strategy provides better explanatory power according to the adjusted R^2, AIC and BIC. However, the significance of the alternative temperature variables other than temperature bins suggests omitted temperature attributes when empirical models include variables such as temperature bins which capture only absolute temperature level. By adding a variable capturing additional temperature attribute to the baseline model using temperature bins, we further explore if these additional attributes contribute to the analysis of temperature effects. The results suggest an improvement in explanatory power in comparison to the baseline model. In particular, variables measuring rapid temperature change may capture the influence of temperature not identified by temperature bins. While the positive coefficient of temperature fluctuation implies additional residential energy consumption from absolute temperature level, omitting non-linear human sensation of short term temperature change may produce models that suffer from biased estimates and prediction.

We further explore the potential complexity of temperature effects through interaction terms between distribution of absolute temperature level and the alternative temperature attributes. The results suggest that, for some ranges of temperature levels, the effect of temperature fluctuation or extreme temperature departure do depends on the days in the corresponding bins. Yet, the results and implication of the two types of attributes are different. If the temperature is less than 50^o F, the rapid temperature increase results in more residential energy consumption. While nonlinear thermal sensation suggests a stronger hot feeling from such temperature change, due to data limitations, we cannot further verify the increase in energy consumption is for cooling due to heat illusion or for heating. But more days with similar temperature hampers the fluctuation effect, which could be due to that fact that humans adjust to the stimulus of rapid temperature change if similar temperatures occur often, such that people perceive the weather as stable. Similarly, the more dramatic the rapid increase, the smaller marginal effect of colder temperature bins could be on increasing energy consumption, which is consistent with non-linear thermal sensation.

The results of the interaction model including extreme temperature departure, days of temperature bins, and their interaction terms, demonstrate more complicated temperature effects in hot days, which are somewhat counterintuitive, while the effect of temperature abnormality is straightforward in cold days. When temperature level is low (e.g., bin 1), warmer abnormality results in less residential energy consumption, as households are used to normally even lower temperature in the long term. The coefficients of abnormality in hot temperature (i.e., bin 10, > 90^{o} F) are negative. It indicates less energy consumption when temperature should be cooler than usual but is actually hotter. Taking the interaction term into consideration, the marginal effect of temperature abnormality in hot days depends on the frequency of temperature in bin 10. Our results suggest that, households have different responses to adapt hot abnormality conditional on the frequency of hot days. If a year has more than 35 hot days (> 90^{o} F), households appear to respond to extreme hot abnormality through alternative actions not associated with residential energy consumption. But if such hot days are more frequent in the year, then households' adaptation to heat abnormality results in more residential energy consumption. While heat abnormality represents the departure of temperature from long term trend, households may not invest in air conditioning if normal temperature is not that hot and in the abnormal year hot days are infrequent.

Our findings also have policy implications. In the context of climate change and global warming, our findings suggest that abnormal weather may not always lead to more energy consumption, which is somewhat different than the findings in received literature. Abnormally hot weather in the cold days reduces energy consumption, and its effect in the hot days could either decrease or increase residential energy consumption, depending on the frequency of hot days of the year. In the long term, climate change may not necessarily lead to more residential air conditioning energy demand, if climate change is associated with larger variation in temperature. Residential energy policies aiming to respond climate change need to be reviewed if they adopt the assumptions based on non-conditional relationships between temperature abnormality and energy consumption.

Through the discussion of three types of model specification, our study provides a more complete understanding of complex temperature effects on residential energy consumption and suggests ways to improve the effectiveness of related research methods. Our analysis of interdependence and abnormality further demonstrates the existence of complex temperature effects on energy consumption. These findings may also contribute to energy supply management and power plant construction policies in the context of climate change in which there could be more variations in temperature in addition to warmer annual temperature, or even simply to better forecast power needs in the short term. According to our findings, empirical models discussing temperature effects on energy consumption may consider including temperature variables in addition to the conventional CHDD or temperature bins. The inclusion of interdependence among temperature attributes may also help to explain the influences of abnormal temperature instead of the comparison of historical temperature data and forecasted temperature data. While our analysis provides some insights into the relationship between temperature and market outcomes, the analysis of complex temperature effects requires further efforts to better deal with potential multicollinearity and to understand the positive correlation between temperature fluctuation and low temperature.

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