# Statistical Analysis of Historical State-Level Residential Energy Consumption Trends

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**ABSTRACT**

Obtaining an accurate picture of the major trends in energy consumption in the nation's stock of residential buildings can serve a variety of national and regional program planning and policy needs related to energy use. This paper employs regression analysis and uses a variable degree-day approach with historical data to provide some insight into overall changes in the thermal integrity of the residential building stock by state.

Although national energy use intensity estimates exist in aggregate, these numbers shed little light on what drives building consumption, as opposing influences are hidden within the measurement (e.g., households may contain more appliances that increase energy use while shell improvements reduce it). This study addresses this issue by estimating changes in the reference temperatures that best characterize the existing residential building stock on a state basis. Improvements in building thermal integrity are reflected by declines in the heating reference temperature, holding other factors constant. Heating degree-day estimates to various reference temperatures were computed from monthly average temperature data for approximately 350 climatic divisions in the U.S. A simple cross-sectional analysis is employed to try to explain the differential impacts across states. Among other factors, this analysis considers the impact that the relative growth in the number of residential buildings has had on natural gas consumption in residential buildings. This paper describes the methodology used, presents results, and suggests directions for future research.

## Introduction

Space heating remains the single largest end use of energy in residential buildings. The Energy Information Administration (EIA) estimated that in 1997 residential households used over 5 quadrillion Btu for space heating, approximately 51 percent of total residential energy on a site energy basis (EIA 1999).

Because of ongoing improvements in the efficiency of heating equipment and improved thermal integrity of new homes, the share of total energy attributable to space heating has fallen over the past 20 years. As reported in EIA in 1999, the space heating share of total site energy use was estimated to be 66 percent in 1978 and 54 percent in 1987. These estimates of historical space heating energy consumption shares are based upon the cross-section regression models applied to the various Residential Energy Consumption Surveys by the EIA.

In 2002, the Office of Energy Efficiency and Renewable Energy (EERE), began to develop a system of energy intensity indicators for each of the broad end-use sectors of the U.S. economy (residential, commercial, industrial and transportation). These measures are designed to provide up-to-date annual estimates of energy intensity that can be used to provide insights into the nation's progress in using energy more efficiently.

In the effort to improve the measures of energy intensity for residential buildings--in particular for space heating and cooling--the survey-derived estimates of residential energy use based upon the historical RECS are an invaluable source. However, the RECS–based estimates are available only every three to four years and can suffer from instability due to sampling errors. The work described in this paper stems from an initial effort to use the available supply-side energy consumption data (provided by electric and gas utilities to EIA) as a means to complement the published estimates from the RECS.

The approach followed in this paper is to apply a variable degree-day method to analyze historical monthly natural gas consumption data and published on a state level by EIA in the *Natural Gas Monthly*.[1] This approach has the potential to generate three separate outcomes:

a) Decompose energy used for space conditioning from other end-use consumption;
b) Estimate short-term changes in energy consumption due to weather (weather normalization);
c) Identify long-term trends in the thermal integrity of building stock and occupant behavior.

## General Approach

Energy used in households is the sum of energy for various end uses. For natural gas, the principal use is for space heating, followed by water heating, cooking, clothes drying, and other miscellaneous uses. This leads to the simplest model for residential natural gas use as:

$$E = a + bHDD(T_{rh}) + e \tag{1}$$

where $E$ = Energy consumption
$T_{rh}$ = reference temperature for heating
$a,b$ = parameters to be estimated from regression methods
$e$ = error term

The reference temperature ($T_{rh}$) is defined as the temperature that maximizes the explanatory power of the model above (i.e., minimizes sum of squared residuals). Physically, $T_{rh}$ approximates the outdoor temperature below which the heating system must operate to maintain a constant indoor air temperature (Hirst et al. 1985).

Most energy analysts will recognize that this approach is similar to that used by the PRISM (Princeton Scorekeeping Method) algorithm which first gained popularity in the mid-1980s (Fels 1986). Overall reasonably short time intervals, energy consumption is regressed against heating degree days (and, for electricity, cooling degree days)—a key feature of the PRISM software is its ability to determine the most appropriate reference temperature and provide some level of statistical confidence for that parameter.[2]

The $b$ coefficient indicates the magnitude of the response of the heating system to changes in outside temperature. It embodies both the thermal integrity of the structure (overall

[1] Monthly state-level data for 1989 through August 2003 were downloaded from the EIA website. Monthly data for 1984 through 1988 were from data files supplied by EIA during the 1990s.
[2] A disclaimer is appropriate at this point regarding PRISM. While motivated by the PRISM approach and many of the published studies using the PRISM software, the work in this paper does *not* use that software. PRISM requires daily temperature data; as discussed below, the heating degree-day variables in this work are developed from monthly temperature information.

U-factor and infiltration) as well as the efficiency of the heating system itself (including distribution losses).

Energy consumption for non-space conditioning (often termed base-level consumption) is represented by coefficient *a* in Equation (1). If monthly data is used in (1), then *a* would represent monthly non-space conditioning energy use. As applied to natural gas use, this base level consumption relates primarily to water heating and cooking.

To show how the reference temperature depends upon several key factors, we need to consider more carefully the formal physical foundation for the variable degree-day or PRISM approach. On a steady-state basis in a heating situation, the heat required to maintain a constant temperature in a typical residential structure can represented as:

$$q = uA(T_{in} - T_{out}) + I \qquad (\mathrm{T_{in}} > \mathrm{T_{out}}) \tag{2}$$

where $q$ = heat required to maintain constant indoor temperature (Btu/hour), and
$u$ = overall heat transmission coefficient of the building envelope (Btu/hr-ft$^2$-degF)
$A$ = Area of envelope components (ft$^2$)
$T_{in}$ = Indoor temperature
$I$ = Internal gains from people, appliances, and solar gain

The reference temperature, $T_{rh}$, is the outside temperature at which the heating system is not required. At this temperature, $T_{rh} = T_{out}$, and $q = 0$. With these conditions, we can rearrange Equation (2) to solve for $T_{rh}$:

$$T_{rh} = T_{in} - \frac{I}{uA} \tag{3}$$

Equation (3) provides the fundamental explanation of the reference temperature; that is, it is primarily influenced by the indoor temperature but modified by the level of internal gains and the integrity of the building envelope ($u$). $T_{rh}$ becomes the temperature base for the calculation of the heating degree days, $HDD(T_{rh})$; to a first approximation, heating consumption is assumed to be proportional to heating degree days.

## Empirical Implementation

There are several key issues that must be resolved before the variable degree-day approach can be applied to aggregate energy consumption data. These issues are discussed briefly below.

### Matching Reported Consumption and Weather Data

For individual building analysis, the availability of specific utility bills that provide beginning and ending dates, along with daily temperature data, make it possible to construct an appropriate degree-day metric consistent with each billing period. Aggregate data, as that published by EIA, for a calendar month (or year) generally refer to recorded *sales* or billings of energy (electricity or natural gas); sales are recorded in the period in which the bill is processed.

This lag between the actual consumption and the reported consumption must be accounted for in the regression specification. Most empirical studies of monthly electricity and gas consumption for the U.S. have employed a one-half month lag in their regression models. A more general specification is:

$$HDD^*_t\,(T_{rh}) = gHDD(T_{rh})_t + (1-g)HDD(T_{rh})_{t-1} \tag{4}$$

where $g$ represents a weighting fraction between zero and one.[3] Because billing cycles may be less than 30 days for some utilities, a value for $g$ that is greater than 0.5 may provide more explanatory power to the model. Without undertaking a state-by-state examination of this factor, we found that a value of 0.55 provided an overall better statistical fit to the monthly reported consumption.

The geographic matching of the consumption and weather information also must be considered. The weather data for this study are historical monthly mean temperatures by state climatic division defined by the National Climatic Data Center (NCDC).[4] Up to 10 climatic divisions are defined for each state, described by NCDC to be "quasi-homogeneous". The climatic division mean temperature is based upon a simple average of all weather stations that record both temperature and precipitation data. The state-level heating degree-day estimates are based upon weighting the degree days in each climatic division by population weights based upon the 1990 census.

**Degree-Day Estimates to Alternative Reference Temperatures**

To estimate the variable degree-day model, one requires the ability to readily calculate degree days to various reference temperatures. For this study, we take advantage of the fact that NCDC has employed a reasonably straightforward procedure to *estimate* monthly degree days from monthly mean temperatures (developed during the 1950s and 1960s by H.C.S. Thom). The development of this procedure was motivated by the lack of consistent daily mean temperatures for many weather stations. Up until very recently, the "Thom" method and subsequent refinements has been the principal methodology by which the NCDC has used to develop both historical (i.e., degree days based on actual weather data) and normal degree days (average degree days averaged over a number of years, normally 30 years).

The Thom method is based upon the observation that the average temperatures of a particular day through a series of years are normally distributed. The actual implementation of the Thom specification relies upon the construction of the normalized variant $h$, where $h$ is defined as

$$h = \frac{T_{rh} - T_{bar}}{\sqrt{N} \bullet Sigma} \tag{5}$$

[3] The regression specification considers the varying number of days in each month. The weighting in Equation (4) is applied to the calculated heating degrees *per day* for the current and previous month and the resulting variable is adjusted according to the number of days in the current month.

[4] The historical temperature data are described by NCDC as "Time Biased Corrected" state climatic division monthly average temperatures," contained in a downloadable text file "drd964x.tmp." This data can be found on NCDC webpage http://www.ncdc.noaa.gov/oa/climate/onlineprod/drought/ftppage.html.

where

$T_{bar}$ = monthly mean temperature
$N$ = number of days in month
*Sigma* = standard deviation of the monthly mean temperature.

Given the availability of the monthly mean temperatures by climatic division from NCDC, the Thom procedure can be implemented straightforwardly to calculate an estimate of (heating) degree days for each month. The procedure is programmed as a function THOM that maps monthly temperatures to degree days. Thus, Equation (1) and Equation (4) can be combined to yield

$$E = a + b[g(THOM(T_{rh}, T_m, T_{sd})) + (1-g)(THOM(T_{rh}, T_m, T_{sd}))] + e \qquad (6)$$

$T_m$ = monthly mean temperature, $T_{sd}$ = standard deviation of the monthly mean temperature, and $g$ is the weighting factor for the billing lag. As above, *a, b*, and $T_{rh}$ are estimated parameters.

Because this specification is nonlinear, the nonlinear regression program CurveFit, available as an application in the GAUSS programming language, is employed. Unfortunately, when applied to Equation (6), a standard statistical fitting program will often fail to generate estimates of the standard errors. Because degree days are zero in months for which the average temperature is sufficiently greater than $T_{rh}$, the THOM function is not continuous throughout its range.

This problem of how to generate the appropriate standard errors for a specification using degree days was a major contribution of Miriam Goldberg's 1984 Ph.D. thesis (Goldberg 1984). That work focused upon the statistical problem inherent in the nondifferentiable function that maps daily temperatures to degree days. Her solution was to take advantage of the linearity of the function between successive integer values of the reference temperature.

Motivated by Goldberg's general approach, we apply a two-stage procedure to ensure that some measure of the standard errors of parameter estimates can be generated. In the first stage, the CurveFit determines the optimal $T_{rh}$* on the basis of a least squares fit. We then calculate degree days for reference temperatures $T_{rh}^-$ and $T_{rh}^+$ at 0.5 degrees below and above $T_{rh}$*, respectively. Degree days between $T_{rh}^-$ and $T_{rh}^+$ are assumed to vary linearly between these values: $T_{rh} = s\, T_{rh}^+ + (1 - s)\, T_{rh}^-$. Because this new function (of variable *s*) is now continuous in this local area, the program is able to generate standard errors of the parameters.

**Seasonality of base-level consumption.** If the PRISM-type procedure is being used to decompose total energy use into space-conditioning (heating) and non-space conditioning (or base-level) energy use, then an important empirical issue is how constant is the non-space conditioning use over the course of a year, and how its variability affects the model parameters

The problem is easily illustrated in this case of natural gas used for space and water heating. Given a positive relationship between monthly consumption for water heating and heating degree-days, the estimated reference temperature for space heating will be biased as it will incorporate both a space heating and water heating response.

In order to account for seasonal fluctuations in gas consumption for water heating we developed a simple model based, in part, upon estimates of the inlet water temperature and the ambient temperature in the space occupied by the water heater. The inlet water temperature was based primarily upon a weighted average of monthly air temperatures from the current and previous months. The weights were based upon a regression of monthly ground temperatures for selected locations derived from files used for the DOE-2 building simulation model.[5] Water heaters were assumed to be primarily located in semi-conditioned spaces--the ambient temperature was assumed to be a weighted average of the monthly air temperature, the calculated ground temperature and the temperature of the conditioned space (70 degrees F).[6] The average setpoint of the water heater was assumed to be 130 degrees F.

The estimation of water heating energy consumption was based on a single equation specification from the Water Heater Analysis Model (WHAM) (DOE 2000). WHAM calculates average daily energy input as follows:

$$Q_{in} = a_1(T_{tank} - T_{in}) \bullet (1 - a_2(T_{tank} - T_{amb})) + a_3(T_{tank} - T_{amb}) \qquad (7)$$

where $Q_{in}$ = daily energy input
$a_1$ = function of volume of hot water supplied, water density, specific heat of water and recovery efficiency
$a_2$ = function of standby heat loss coefficient and rated input power
$a_3$ = function of hours of operation and standby heat loss coefficient

Water heating *usage* is also assumed to show a seasonal pattern, with higher consumption in the winter as compared to the summer. Based upon the model developed by the National Renewable Energy Laboratory, monthly consumption factors were applied to the estimates derived from the WHAM model.[7]

The estimated seasonal pattern for water heating from Equation (7) was then incorporated as part of the variable degree-day model. Based loosely upon RECS national end-use gas consumption estimates, the monthly estimates for water heating were combined with an assumed constant monthly consumption for other non-heating end uses (primarily cooking). Thus, the

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[5] The ground temperatures were derived from DOE-2 files from the www.doe2.com website. Based upon a sample of selected locations, the regressions indicated that a geometric decay pattern of the weights appears to satisfactorily fit the ground temperature values. A single value of the decay rate (0.75) was used to generate the ground temperatures for each climate division. This formulation leads to the following weights for the current and first three lagged months [m(t)]: m(0), 0.268; m(-1), 0.194; m(-2), 0.145; m(-3), 0.109. The sum of the weights was normalized to 1.0, so that the mean annual ground temperature is equal to the mean annual air temperature. The inlet temperatures was assumed to be a weighted average of the calculated ground temperature (weight = 0.9) and the current month's average air temperature (> 32 deg. F). As examples, the seasonal variation (max – min) of the estimated inlet temperatures, based upon long-term statewide air temperatures, varied from 25 degrees in Illinois to 11 degrees in Florida. Parker (2002) reports that tap water temperatures in central Florida range by a little over 14 degrees between February and September.

[6] The weights were based upon an assumption that 30% of water heaters in garages and 70% in basements. In each location, the ambient temperature was assumed to be an average of 70 degrees and either the air temperature (garage) or ground temperature (basement).

[7] The NREL spreadsheet model was downloaded from NREL's Building America website. The estimated monthly profile of *hot water* consumption for each state was estimated on the basis of one or more selected cities from each state. In addition, a separate monthly profile was incorporated multiplicatively; this factor varied hot water usage by roughly an additional two percent during winter and summer from the annual mean (used, in part, to better calibrate the model to available metered data). The resulting monthly use factors were then used to adjust parameter *a*, in Equation (7) above. The calculated seasonal difference from the annual average of estimated *energy* consumption across states generally ranged from about 10 percent (Oregon, California) to 19 % (Minnesota). The Oregon and Washington state results are reasonably close to the seasonal variation in electricity consumption for water heating from a large metered study conducted by the Bonneville Power Administration in the mid 1980s.

constant term in Equation (1) [or Equation (6)] was replaced by a variable that approximates the seasonal pattern of non-heating consumption:

$$E = aNH + bHDD(T_{rh}) + e \tag{8}$$

where NH = estimated monthly profile of non-heating gas use relative to the annual mean.

**Treatment of time-varying parameters.** The variable degree-day method is designed for use over time intervals sufficiently short such that the parameters can be assumed to be constant. This clearly will not be the case for aggregate data that extends more than a few years. Unfortunately, annual (12-month) periods typically lead to considerable year-to-year variation in the parameter estimates. Accordingly, this study followed the smoothing procedure used in the 1986 study by Fels and Goldberg--a series of overlapping four-year intervals were used to better identify trends in the underlying parameters. Following the convention of treating heating seasons as distinct observational periods, the first four-year period covers the period July 1984 through June 1988. Calendar year 1986 is centered in this interval and, in the results reported in the next section, the estimated parameters are assumed to best represent this calendar year.

The regression analysis in this study is performed on the aggregate data itself rather than on a normalized per customer basis (as in Fels and Goldberg 1986). First, Fels and Goldberg had access to New Jersey utility data for the number of customers using gas for heating, rather than gas customers in general. Second, with the exception of a few states, the level of aggregate gas consumption has remained relatively constant during the 1990s, the growth in customers being largely offset by the increased efficiency of gas furnaces and the improved thermal integrity of the building stock. Thus, from a statistical point of view, we believed the parameters of Equation (8) were likely to be more stable over four-year periods using total consumption rather than consumption per customer.

The standard regression model assumes that the variance of the disturbance term ($e$) in Equation (8) is constant. Because the level of gas consumption varies considerably over the year, this assumption is particularly suspect in the application here. Preliminary examination of the regression residuals confirms significantly greater errors in the winter months. Accordingly, a two-stage procedure was adopted. The standard deviation of the residuals for each month was calculated on the basis of all 16 sliding four-year regression data sets. The reciprocals of standard deviations were then used to weight all of the observations in a second stage. Overall, the use of the weighted least squares reduces the fluctuations in the reference temperatures from one (four-year) period to the next.

## Results

Figures 1 and Figure 2 illustrate the empirical results for two northern states, Michigan and Vermont. The estimated reference temperature for Michigan remained nearly constant over the span of the 16 overlapping four heating-year intervals. The dotted lines bracket the confidence interval to one standard error. The standard errors fell generally in the range of 0.8 to 1.1.

The bottom portion of Figure 1 shows the estimate for the slope coefficient [$b$ in Equation (8)]. As the regression was performed on the aggregate consumption data, the slope coefficient incorporates any effect due to the growth in the number of gas customers. As a crude means of normalizing for this effect, the lower line shows the slope coefficient divided by an index of gas customers (where the index is set to 1.0 in 1986). This normalization suggests that, on balance, the average responsiveness of the housing stock to changes in temperature has changed little over the period.

The results for Vermont are somewhat different. The penetration of natural gas for heating in New England has grown rapidly in the past decade or so. Customer growth in Vermont has averaged nearly 5 percent per year over the 1985-2002 period. Figure 2 shows a significant decline in the reference temperature of about 3 degrees F. By itself, this reduction in the reference temperature suggests a decline in the heating requirements of about 12 percent (roughly HDD(57) ~ 5850, HDD(54) ~ 5150 for Vermont). The normalized slope coefficient also shows a more recognizable decline in the heating slope as compared to Michigan.

Table 1 shows the reference temperatures and other key metrics for each state. Column 3 shows the average reference temperature over the first four estimation periods. As labeled in the table, this period essentially covers the full calendar years 1985 through 1990. The next column shows the average standard error for this same period. Column 5 shows the average reference temperature for the last four estimation periods, with the next column displaying the average standard error for these same periods. Column 7 displays the change in the reference temperature over this approximately 12-year period.

We can summarize the key results as follows:

1) Reference temperatures for the residential sector in all states are lower than the 65 degrees, the reference temperature typically used in the published heating degree days reported by the National Climatic Data Center.
2) Reference temperatures are generally higher in the south, reflecting both somewhat higher thermostat settings (see below) and lower insulation levels of the building stock.
3) Reference temperatures have declined in about three quarters of the states over the past decade. The greatest declines have generally been in the southern states. Using state population weights based upon the 2000 census, the national average reference temperature fell from 58.5 degrees to 57.7 degrees over the two periods.

Equation (2) indicates that the key influences on the reference temperature are the indoor thermostat setting, the level of internal gains, and the overall thermal integrity of the building stock. Let us consider each of these factors in light of the estimated results in Table 1.[8]

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[8] One additional factor affecting this aggregate analysis is the geographic shift of population *within* a state that results in higher or lower heating requirements for the state average residential stock. Based upon a comparison of population weights for climatic divisions between the 1990 and 2000 census, the change in the long-term *population-weighted* temperature was estimated for each state. The most significant change is in Nevada, where the extraordinary growth in the Las Vegas area has effectively increased the statewide average temperature by 1.8 degrees F. (A caveat: the weights are based on population by climatic division, not gas customers) Given this population shift, the estimated decline in the reference temperature in Nevada (-3.4 degrees) is overstated by approximately 1.8 degrees. Other states that showed significant weighted temperature changes from such shifts (temperature change in parentheses) were: Arizona (+0.3), Georgia (-0.2), Idaho (+0.4), Maine (+0.6), New York (-0.3), Utah (-0.5), and Washington (+0.3).

**Figure 1. Reference Temperatures and Slope Coefficients for Michigan**

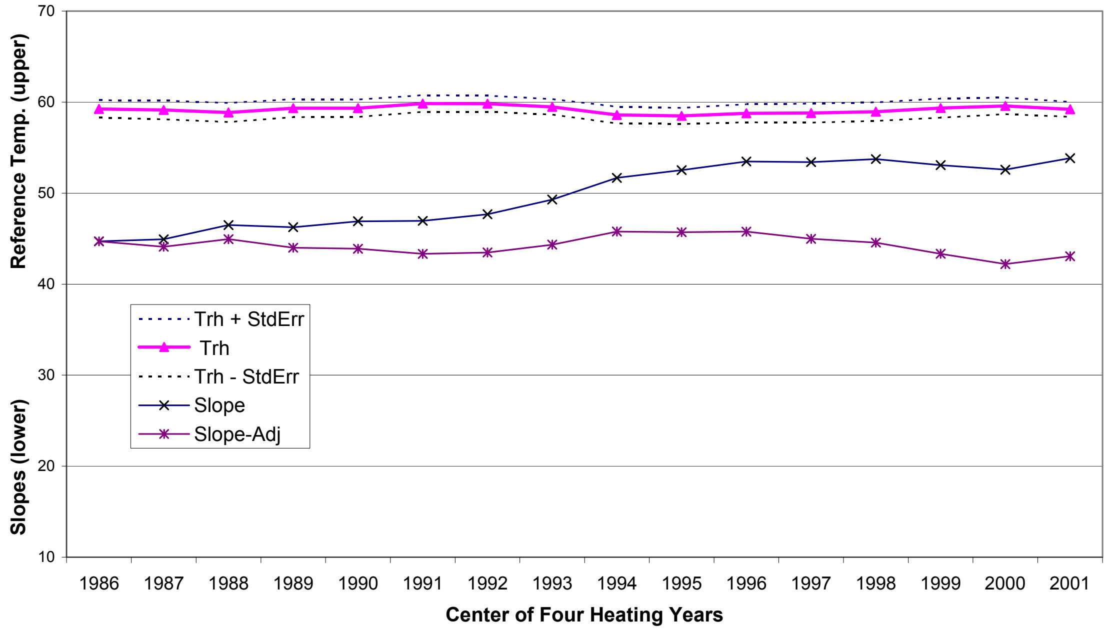
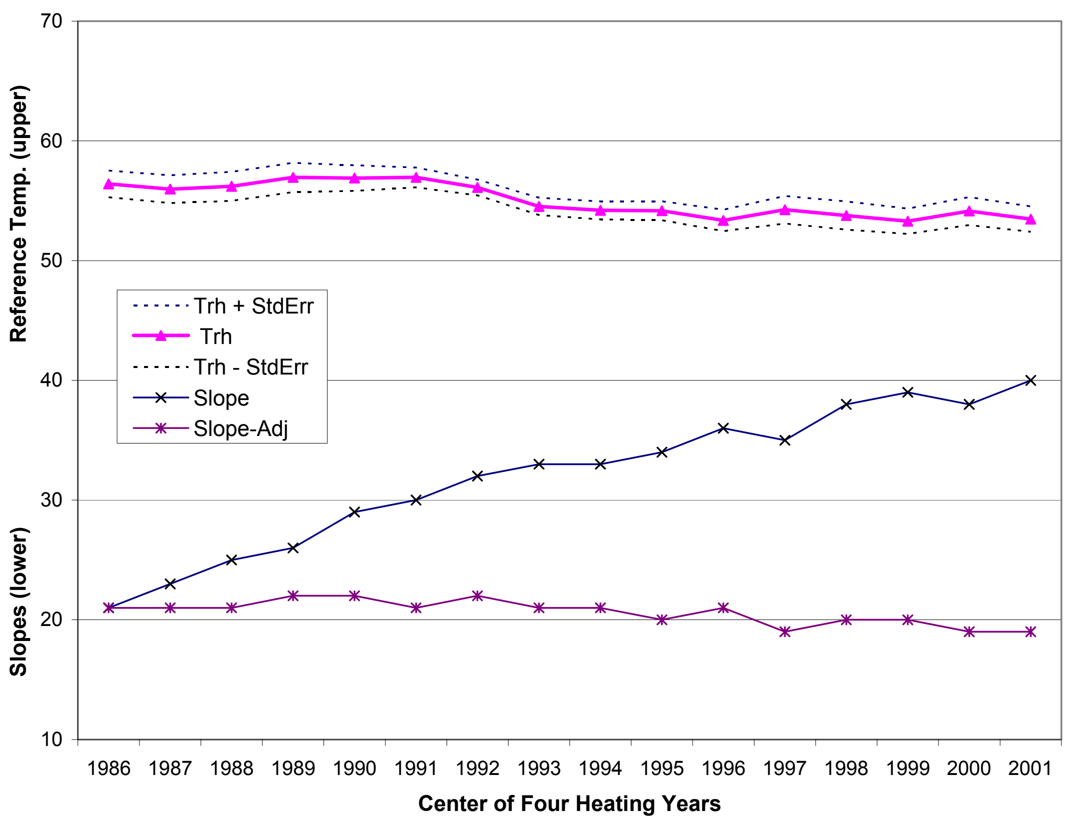



**Figure 2. Reference Temperatures and Slope Coefficients for Vermont**

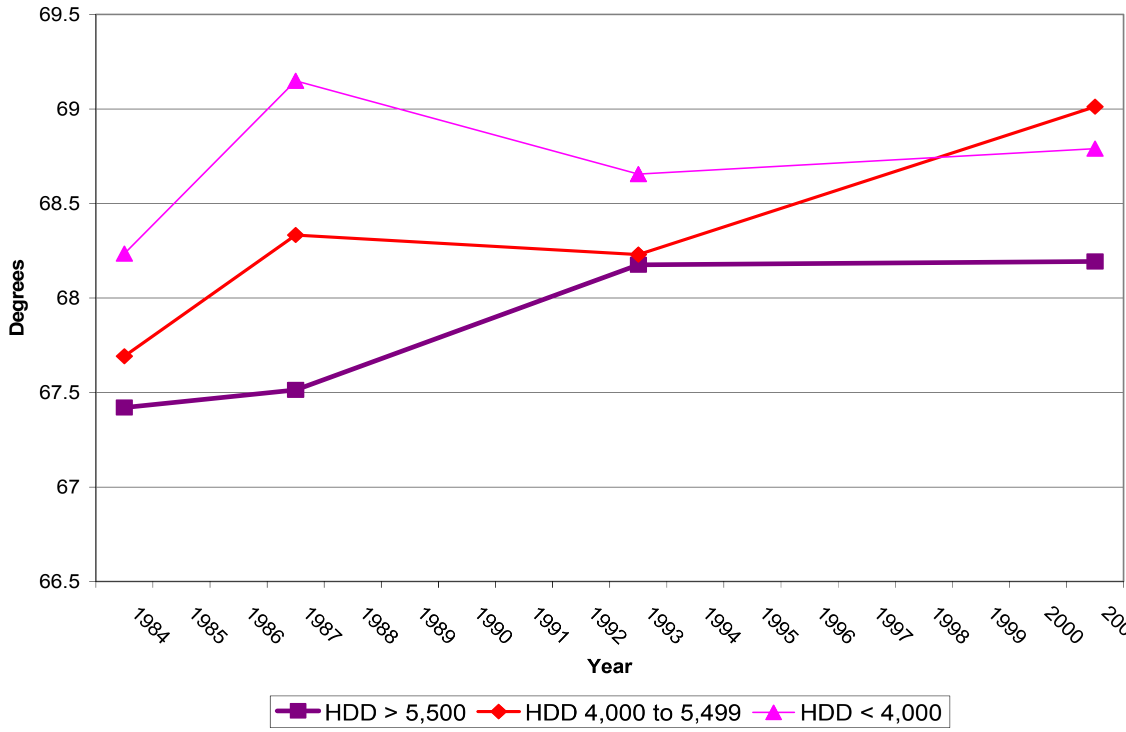


## Table 1. Estimated Reference Temperatures and Other Key Metrics by State

| | Annual Growth Rates, 1985-2002 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Heating Use per Customer | Number of Customers | Reference Temp. 1985-1990 | Std. Error | Reference Temp. 1997-2002 | Std. Error | Change in Reference Temp. | Predicted Change |
| Alabama | -0.6 | 1.4 | 61.8 | 1.2 | 57.1 | 1.1 | -4.8 | -1.9 |
| Arizona | 0.2 | 3.1 | 58.8 | 1.1 | 59.2 | 1.2 | 0.4 | -1.5 |
| Arkansas | -0.7 | 1.1 | 59.1 | 0.9 | 59.9 | 1.1 | 0.8 | -0.9 |
| California | 1.0 | 1.4 | 54.9 | 1.0 | 54.9 | 1.2 | 0.0 | 0.3 |
| Colorado | 0.8 | 2.6 | 53.1 | 1.2 | 52.1 | 1.2 | -1.0 | 0.4 |
| Connecticutt | 0.1 | 0.8 | 57.2 | 0.7 | 56.3 | 1.1 | -0.9 | -0.2 |
| Delaware | -2.1 | 3.0 | 60.9 | 1.2 | 59.5 | 1.1 | -1.3 | -2.1 |
| Florida | -0.4 | 2.0 | 65.4 | 0.9 | 61.8 | 1.4 | -3.7 | -3.2 |
| Georgia | 1.1 | 2.5 | 62.8 | 1.0 | 59.3 | 1.9 | -3.6 | -2.5 |
| Idaho | -0.4 | 6.3 | 55.7 | 1.3 | 56.1 | 0.9 | 0.4 | -1.6 |
| Illinois | -0.8 | 1.1 | 58.9 | 1.3 | 58.8 | 1.9 | -0.1 | -0.8 |
| Indiana | -0.7 | 1.9 | 58.4 | 1.1 | 58.9 | 1.0 | 0.5 | -0.9 |
| Iowa | -0.2 | 1.2 | 57.6 | 0.8 | 56.2 | 1.3 | -1.4 | -0.5 |
| Kansas | -1.0 | 1.1 | 58.6 | 1.6 | 56.9 | 1.0 | -1.7 | -0.7 |
| Kentucky | 0.0 | 1.7 | 58.6 | 0.9 | 58.1 | 1.8 | -0.5 | -0.9 |
| Louisiana | 3.0 | 0.1 | 60.4 | 0.7 | 59.4 | 1.0 | -1.1 | -1.0 |
| Maine | 0.5 | 2.6 | 60.2 | 1.6 | 58.2 | 2.0 | -2.0 | -1.7 |
| Maryland | 0.0 | 1.7 | 58.1 | 0.7 | 57.1 | 1.0 | -1.0 | -0.8 |
| Massachusetts | -0.2 | 1.2 | 57.7 | 0.9 | 56.8 | 1.3 | -0.9 | -0.5 |
| Michigan | -0.5 | 1.6 | 59.1 | 1.0 | 59.3 | 1.0 | 0.1 | -1.1 |
| Minnesota | 2.3 | 2.6 | 53.9 | 0.9 | 55.6 | 1.7 | 1.7 | 0.2 |
| Mississippi | -0.4 | 1.2 | 59.6 | 1.4 | 57.5 | 1.1 | -2.1 | -1.1 |
| Missouri | -0.2 | 0.9 | 56.4 | 0.7 | 56.8 | 0.8 | 0.4 | 0.0 |
| Montana | -0.6 | 2.2 | 55.6 | 1.3 | 54.9 | 1.1 | -0.6 | -0.2 |
| Nebraska | 0.1 | 1.4 | 55.3 | 0.9 | 56.3 | 1.4 | 1.0 | 0.2 |
| Nevada | -0.3 | 6.9 | 55.0 | 1.9 | 51.7 | 1.2 | -3.3 | -1.5 |
| New Hampshire | 0.9 | 2.7 | 56.1 | 1.3 | 54.4 | 0.7 | -1.7 | -0.5 |
| New Jersey | 1.1 | 1.8 | 58.7 | 0.7 | 57.7 | 0.7 | -0.9 | -1.0 |
| New Mexico | 0.8 | 2.4 | 57.3 | 1.2 | 56.1 | 2.1 | -1.2 | -0.8 |
| New York | -0.3 | 0.6 | 58.6 | 0.6 | 57.6 | 0.8 | -1.0 | -0.6 |
| North Carolina | -0.5 | 4.9 | 61.6 | 0.8 | 60.1 | 0.9 | -1.6 | -3.0 |
| North Dakota | -1.0 | 1.8 | 56.0 | 1.2 | 56.5 | 1.6 | 0.6 | -0.1 |
| Ohio | -0.2 | 1.3 | 58.9 | 1.3 | 58.3 | 1.0 | -0.6 | -0.9 |
| Oklahoma | 0.7 | 0.5 | 60.1 | 0.9 | 58.4 | 1.0 | -1.6 | -1.0 |
| Oregon | -0.4 | 4.7 | 55.3 | 0.9 | 54.8 | 0.6 | -0.5 | -0.9 |
| Pennsylvania | 0.0 | 0.9 | 58.3 | 0.5 | 57.1 | 0.9 | -1.2 | -0.6 |
| Rhode Island | -0.6 | 1.3 | 58.5 | 0.7 | 56.9 | 0.9 | -1.6 | -0.8 |
| South Carolina | -0.7 | 3.6 | 61.9 | 0.8 | 60.4 | 1.0 | -1.5 | -2.6 |
| South Dakota | -0.4 | 2.6 | 57.1 | 1.0 | 56.5 | 1.0 | -0.6 | -0.8 |
| Tennessee | 0.7 | 4.5 | 59.1 | 0.8 | 56.3 | 0.8 | -2.8 | -2.0 |
| Texas | -0.7 | 1.2 | 59.0 | 1.0 | 60.7 | 1.2 | 1.7 | -0.9 |
| Utah | -1.7 | 3.1 | 57.1 | 1.8 | 53.4 | 2.2 | -3.8 | -0.9 |
| Vermont | -0.3 | 4.9 | 56.4 | 1.2 | 53.7 | 1.1 | -2.7 | -1.3 |
| Virginia | 0.4 | 3.8 | 57.7 | 0.6 | 56.7 | 0.8 | -1.0 | -1.4 |
| Washington | -0.2 | 5.5 | 58.1 | 1.0 | 56.1 | 1.0 | -2.0 | -2.1 |
| West Virginia | -0.9 | 0.2 | 59.2 | 0.7 | 59.5 | 1.0 | 0.2 | -0.7 |
| Wisconsin | -0.5 | 2.5 | 57.3 | 1.1 | 56.5 | 2.1 | -0.8 | -0.8 |
| Wyoming | -0.5 | 1.6 | 55.9 | 1.5 | 57.0 | 1.6 | 1.1 | -0.1 |

**Thermostat settings.** To examine potential impact of trends in residential thermostat temperature settings, we looked at the average thermostat settings during the past 20 years as reflected in the US DOE's Residential Energy Consumption Survey (RECS).[9] As this survey is only completed every few years, we calculated the average winter thermostat settings by climate zone for 1984, 1987, 1993, and 2001. The data show that the thermostat setting is somewhat higher in the south and thus is a factor in explaining the higher reference temperatures in the southern states. Figure 3 does suggest that in general, from 1984 to 2001, the thermostat settings trend upward slightly. Thus, it is unlikely that changes in the thermostat settings could be primarily responsible for overall downward trend in reference temperatures.

**Figure 3. Average Thermostat Settings by Climate Zone**




**Internal gains.** Electricity consumption per household has grown rapidly in the past decade and presumably a portion of heat generated from increased appliance use would reduce the use of gas for heating. What is surprising from Table 1 are the results for states such as Michigan, Indiana, and West Virginia that show virtually no change in the reference temperature over the two periods.[10] At this point, we leave as future research the question as to what contribution the change in internal gains may have made in the overall reduction in the reference temperatures. For the analysis here, we assume that changes in internal gains are likely to have roughly similar impacts in each state.

[9] The RECS collects information on winter thermostat setting in three different situations: 1) when someone is at home during the day, 2) when no one is at home during the day, and 3) night time. The thermostat settings are based upon a weighted average of these three regimes.

[10] While the quality of the regression results vary by state, the standard errors of the reference temperature in these three states are relatively small.

If we discount impacts of the thermostat settings and internal gains (at least in a relative sense), then the observed changes in the reference temperature stem primarily from improved thermal integrity of the building stock. Moreover, this view suggests that changes in reference temperatures would be related to the growth in the number of residential customers. Higher insulation levels, better windows, and lower infiltration levels in new homes should result in a falling average reference temperature for the entire stock. To test that hypothesis, we estimated the following linear regression equation for the cross section of 48 states (t-statistics in parentheses):

$$\Delta T_{rh} = 17.8 \; - \underset{(3.0)}{0.333} \text{ Growth} - \underset{(4.1)}{0.310} \text{ Reftemp80} \qquad R^2 = 0.33 \tag{9}$$

Growth is the average annual growth rate in the number of gas customers over the 1985 to 2002 period and Reftemp80 is the average reference temperature in the late 1980s. The values for these variables are shown in Columns (2) and (3) in Table 1. The last column in Table 1 shows the predicted changes from this simple model. The actual changes that are less than the predicted change are shaded in Column (7) of the table.

The analysis clearly shows that the differential growth rates among the states are a key explanatory factor in the degree to which the reference temperatures have changed across the states.[11] The statistical significance of the initial level of the reference temperature is more difficult to explain. Clearly, the reference temperatures have declined to greater degree in those states that had higher reference temperatures in the late 1980s. Whether retrofit activity or the difference between the new construction and the existing stock is higher in these states requires more study.

To follow up on this last point, we are perplexed by the relatively large reductions in the reference temperature in nearly all southern states. For fast growing states such as North Carolina, South Carolina, Tennessee and Georgia, this result has more plausibility. However, consider, for example, Mississippi—a state where growth has been modest. The average reference temperature declines from 59.6 to 57.5 degrees, a difference considerably greater than what could be explained by the thermal integrity of new gas-heated homes. A likely contributing factor to this result is the rapid penetration of heat pumps in the south and the potential for switching from gas as the primary heating source to a secondary heating source in existing homes.[12] An examination of data from the 1987 and 2001 RECS suggest this possibility. In the south census region in 1987, RECS reports that of all houses consuming natural gas, 89.4 % used gas as a primary heating fuel. By 2001, that percentage had fallen to 84.0%. The share of homes in the south using heat pumps as a primary heating source increased from 9.7% in 1987 to 20.3% in 2001. Over the same time, the percentage of homes reporting natural gas as a secondary heating fuel grew from 3.9% to 6.7%.

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[11] More precisely, this effect is a function of both the relative growth and the relative thermal integrity of new homes as compared to the existing stock in the state. An outlier state in this regard is Oregon—relatively precise estimates of the reference temperatures indicate little change over the period. Oregon has long maintained an active program of building codes and the low values of the reference temperature are suggestive of stringent thermal standards. The lack of change may result from new homes not being dramatically different from the existing stock of gas-heated homes. The number of gas customers in Oregon more than doubled between 1982 and 2002, implying more than half of the existing stock is less than 20 years old.

[12] Acknowledgment is made to one of the reviewers of the draft version of this paper for suggesting this factor.

At this point, we believe we should mention that cautions have been expressed by previous users of a variable degree-day approach. Several of the published studies using the PRISM methodology discuss the considerable covariance among the estimated parameters of the basic model in Equation (1). In her introduction to the PRISM methodology, Fels (1986) argues for the use of the complete *set* of estimated parameters in Equation (1) as a means of developing reliable measures of weather-adjusted consumption that can be compared between periods. In essence, caution is urged regarding quantitative interpretation of the individual parameters ($a$, $b$ and $T_{rh}$), but the hope is expressed that with aggregate data sets “the individual parameters … can offer valuable insight into the nature of conservation activities.” (Goldberg and Fels 1986). Even with this caveat, we continue to believe that observed reductions in the reference temperatures from the analysis here are primarily an indicator of improved thermal integrity of the residential housing stock, primarily achieved from a growing share of more energy-efficient new homes. However, additional analysis is required to better rationalize the observed magnitude of changes in the reference temperatures in individual states.

**Estimates of Weather-adjusted Heating Consumption per Customer**

The eventual goal of the overall project that motivated this study is to develop measures of energy intensity for various aspects of the residential building sector. The availability of the monthly data as well as the estimated reference temperatures provided a means of developing preliminary estimates of *annual* weather-adjusted space heating consumption per gas customer in each state. Column (1) of Table 1 shows the annual average change in this intensity, based upon a trend regression over the 1985-2002 period.

At this point, this metric appears to be unsuitable as a robust measure of heating intensity. No explicit accounting for housing unit size has been developed at either the state or national levels. Thus, as illustrated in Column (1) increases in annual heating consumption per customer at the state level appears to follow no definite pattern. New single-family homes are considerably larger than the existing homes, but have improved thermal integrity. Which of these factors predominates will bear upon the trends in the intensity for the overall stock. No correlation was found between the observed state-by-state growth rates in the heating intensity and growth in customers, as was found for the change in the reference temperature.

## Future Directions

The results of this study provide further evidence that the appropriate reference temperature for the residential building is considerably less than 65 degrees F. and that, over the past decade and a half, an indication that the thermal integrity of the building stock has influenced this parameter. However, the study also shows that over long periods of time and widely different climate regimes, considerable attention must be paid to model specification and statistical techniques, and interpretation of the estimated parameters is not straightforward. While a number of expected patterns emerged from this study, the results for a number of states do not offer a ready explanation. Additional research in several directions may prove useful in complementing this type of analysis.

1) While convenient, the use of the monthly mean temperature data--with the Thom method to estimate degree days--may not provide as precise a characterization of weather impacts as would daily data. One extension of the current study would be to choose several states

with relatively homogenous climates and employ daily data in the computation of degree days.

2) The impact of internal gains needs to be more explicitly identified. The magnitude to which internal gains can be expected to influence the heating requirements may require simulation analysis with prototypical residential structures.

3) Gas utilities continually develop models of gas demand that incorporate weather variables. For states in which the characteristics of gas demand are changing rapidly, an effort to learn from these models would likely suggest improvements in the approach used in this study.

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