The impact of weather variation on energy consumption in residential houses

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Abstract

This paper studies the impact of weather variation on energy use by using five-minute interval weather-energy data obtained from two residential houses: house 1 is a conventional house with advanced efficiency features and house 2 is a net-zero solar house with relatively more advanced efficiency features. Our result suggests that energy consumption in house 2 is not as sensitive to changes in weather variables as the conventional house. On average, we find that a one unit increase in heating and cooling degree minutes increases energy use by about 9% and 5% respectively for house 1 and 5% and 4% respectively for house 2. In addition, our findings suggest that non-temperature variables such as solar radiation and humidity affect energy use where the sensitivity rates for house 2 are consistently lower than that of house 1. Furthermore our result suggests that the sensitivity of energy use to weather depends on the season and specific time of the day/night.

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Keywords: energy consumption; solar radiation; solar energy; case study; intraday-variation; Texas climate

1. Introduction

Following the 1970s global oil crisis, the United States (US) put together several energy policies aimed at reducing the country's reliance on fossil fuels and increasing energy efficiency. The Department of Energy (DoE) was created in 1977 with the aim of creating a balanced national energy plan. The Energy Policy and Conservation Act of 1975, which is one of the earliest energy policies targeting energy efficiency, was crafted with the aim of energy efficiency for federal buildings. A few years later, a more comprehensive policy, the National Energy Conservation Policy Act of 1978, set the country's energy policy with the purpose of increasing energy efficiency for the whole country, limiting growth in energy demand, reducing reliance on imported oil, and reducing demand for non-renewables.

Recent policies such as the Energy Policy Act of 2005 emphasized reducing energy consumption and greenhouse gases as well as increasing alternative energy sources. The Energy Policy Act of 2005 also provides tax incentives and subsidies for technologies that reduce greenhouse gases and agents that use alternative energy sources. More recently, the Obama administration has focused on 'building a clean energy economy, tackling climate change and protecting the environment' (www.whitehouse.gov/energy). The proposed plan (Clean Energy Standard Act of 2012) is aimed at doubling the share of electricity generated from clean sources by the year 2035.

According to the US Energy Information Administration (EIA) the residential sector consumes about 21% of total energy delivered to all sectors in the country. The sector is expected to maintain its share of energy consumption until 2040. Even though the sector's share of electricity from renewable sources stood at only 7% in 2011, it has exhibited a fast growth rate (www.eia.gov). For instance, as Figure 1 illustrates the residential sector's solar energy consumption has more than doubled from 2000 to 2011. This is driven by homeowners' preference towards energy efficient and green homes, but also policies which induce energy consumption from solar sources. For instance, a recent study conducted by Shelton Group (2011) shows that 63% of consumers are interested in owning or renting energy efficient home, whereas 43% are interested in green homes. According to the study, about 37% of consumers responded that a green home must have a renewable electric power generation such as from solar, geothermal, or wind.

Thus, if the residential sector continues to consider clean energy sources to light up houses as well as prioritize energy efficiency at their homes, it is important and timely to extensively study how these features perform when the weather fluctuates in the short-run. Furthermore, given the recent incentives and policy focus towards alternative energy sources, it is important to study the impact of weather variation on energy consumption at a residential house which uses an alternative energy source as well as incorporates some efficiency design features. As Hong et al. (2013) points out with a 'better understanding of which technology and energy sources are more sensitive to weather variation, building designers, owners, operators and policy makers can make more informed decisions on energy efficiency implementations'.

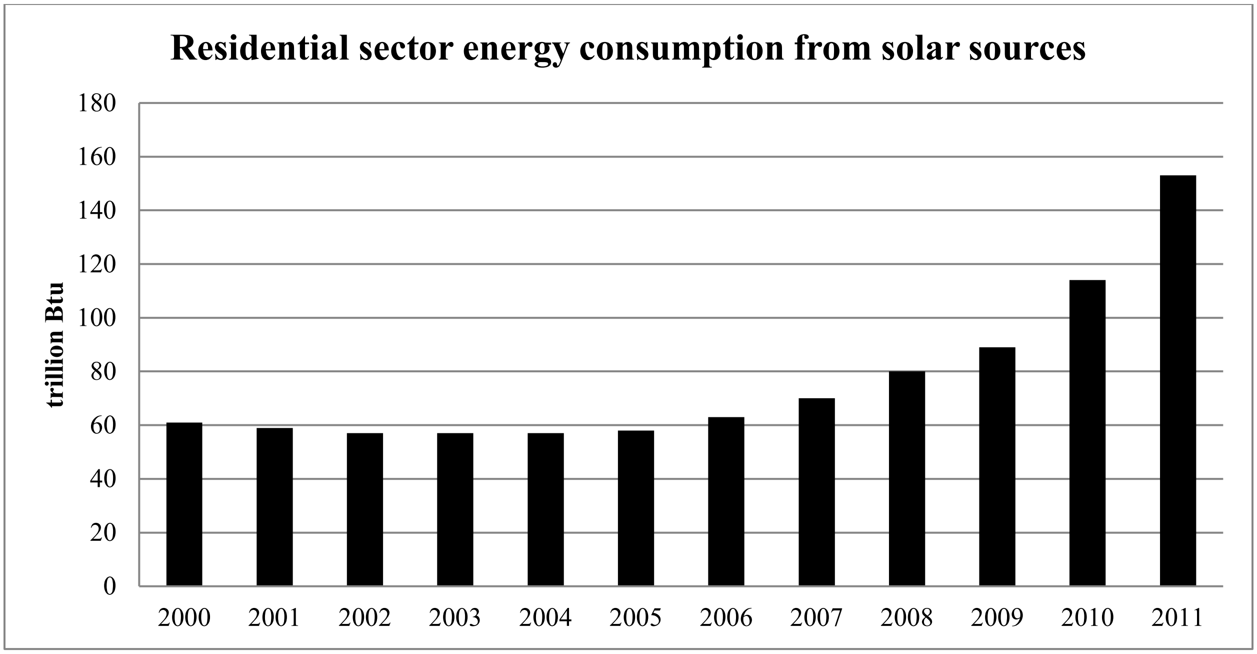


Figure 1: Role of solar energy in residential sector in 2011 (Source: authors' calculation based on EIA data)

This study makes use of a unique detailed dataset obtained from two residential houses. House 1 is a conventional house with advanced efficiency features and house 2 is a net-zero solar house with more advanced efficiency features. We address the following specific research questions: What is the nature of the relationship between weather variables and energy use in residential houses with efficiency designs? How do more advanced energy-efficiency designs improve energy use when the weather changes in the short-run? How sensitive is the energy-temperature relationship to the time of the day/night?

The two houses are located in Tyler, Texas. They are similar in size and location but differ significantly in energy-efficiency design features. We believe Tyler, Texas's experience should be an interesting one for several reasons. First, Texas is one of the leading states in alternative energy sources such as wind power. In addition, the state has recently experienced the fastest growth in renewable electricity production.[1] Furthermore, the state ranks 13th in installing the highest solar electric capacity. The state has installed enough solar energy to light up to 13,000 homes.[2] In 2011, the residential sector in Texas used about 1.4 trillion Btu of solar energy which is about 15.74 kWh per capita.[3]

Second, Texas has several financial incentives for residential renewable energy use as well as efficiency improvements. For instance, there are rebate programs for homeowners who install

[1] Source: retrieved from http://www.eia.gov/todayinenergy/detail.cfm?id=13991&src=Renewable-b1
[2] Source: retrieved from http://www.seia.org/state-solar-policy/texas
[3] Source: authors' calculation based on EIA data.

photovoltaic systems, loan programs to finance residential energy efficiency improvements, exemption of state property tax on the appraised property value that arises from the installation of a solar or wind powered device, etc. Even though the state does not have net metering law, individual cities like Austin and Brenham and retail electricity providers apply net metering procedure for residential photovoltaic systems.[4] Third, results from the analysis may be extended to areas with similar weather conditions such as the hot-humid regions of the country or even other countries with similar weather conditions.

In the following section, we present an overview of findings from previous studies regarding energy-weather relationships; we also establish the contribution of our study relative to past studies. In section 3 we discuss the data source and present the basic empirical methodology employed. In section 4 we present results and discuss findings. Finally, we conclude in section 5 by forwarding some policy recommendations and questions for future study.

2. Literature Review

Although the subject of energy-weather relationship (and long term climate change) is not more than three decades old,[5] there is a growing literature that examines the effect of weather change on energy consumption. The residential sector in the US has one of the highest climate and weather related fluctuations in energy use. Temperature, humidity, wind and precipitation affect how much energy the sector consumes (Earth Gauge Report). The effect of weather change on energy use is usually measured in terms of energy demand for cooling and heating (Isaac and Vuuren, 2008). This is because about 58% of residential energy demand in the US is for heating and cooling (space conditioning) excluding domestic hot water consumption (Earth Gauge Report).

The literature on residential energy demand uses the concept of cooling and heating degree days to estimate the effect of weather on energy use. A ‘degree day’ is typically defined as the difference between a day’s average temperature and a given threshold temperature, where the threshold is considered to be a normal temperature which does not require heating nor cooling (Earth Gauge Report; Isaac and Vuuren, 2008). Heating degree days are measured for days below the threshold and cooling degree days are days above (Earth Gauge report; Isaac and Vuuren, 2008: Energy Lens online).

Both national and regional studies find a significant effect of weather change on energy use in the residential sector. The general consensus is that very hot temperatures reduce consumption of heating fuel, and increase electricity consumption for cooling. According to Earth Gauge Report, a 1.6 F increase in average temperature decreases demand for residential heating by 6-10% and increases demand for cooling by 5-20%. Using US national data, Mansur et al. (2005), Scott et al. (2005) and Huang (2006) find a 2.8%, 6-10% and 9% reduction in residential space heating

[4] Source: retrieved from http://dsireusa.org/incentives/homeowner.cfm?state=TX&re=0&ee=0
[5] US Climate Change Science Program (2008) reports 20 studies relating climate change to energy consumption in the residential and commercial sector in the USA since 1990.

demand respectively, for every 33.8 F increase in winter temperature. Considine (2000) finds that, for an extra heating degree day, residential energy consumption increased by only 0.49% for the residential sector. Regional studies reveal similar trends, where the reduction in demand for space heating ranges from 2-3% in Maryland (Ruth and Lin, 2006) to 7-33% in Massachusetts (Amato et al., 2005) per 33.8 F increase in winter temperature. For warmer seasons a 33.8 F increase in temperature increases demand for electricity from about 4% (Mansur, 2005) to about 12-20% (Scott, 2005) to as much as 22% (Huang, 2006). Similarly, Amato et al. (2005) finds that a 100 unit increase in cooling degree days results in a 3.8% increase in energy use in Massachusetts.

Even though the general direction of the effect of temperature on energy use is similar for most studies, the relative change in energy demand significantly differs by location, time period and methodology used. For example, Sailor (2001) finds that the response of residential sector energy use to a 33.8 F change in temperature could range from 1.8% in California to -3.9% in Washington. A study by the US Climate Change Science Program (2008) shows that climate warming reduces consumption of heating fuels more than it increases consumption of energy in Northern states, and increases in space cooling dominate in the South. Studies based on data outside the US also show a similar trend where higher summer temperatures lead to higher electricity consumption in hot countries, and cooler spring temperature leads to higher electricity consumption in cooler countries (Cian et al., 2007). Isaac and Vuuren (2008) argue that the net effect of warming on energy use is very small at the global scale; this is because reduction in heating needs is offset by increases in cooling demand.

The contribution of this paper to the literature is two-fold: (1) new local weather data collected with fine temporal rate and five-minute interval energy use, (2) data obtained from two residential houses built with distinct efficiency features (but otherwise similar in size and location) and one powered by solar energy.

Interval meter data, such as five-minute data, has become available only recently. A major problem in generating weather data with fine temporal rate is the substantial cost involved (Bhandari et al., 2012). Even though there is a growing literature that collects and applies energy-weather data with fine temporal rate (Rodriguez-Hidalgo et al., 2008, 2011 a, 2011 b, 2012; Venegas et al., 2011; Coskun et al., 2014; Oktay et al., 2011) only a few use such data to study the relationship between *energy consumption* and weather. For instance, Venegas et al. (2011) uses 10 minute interval data to study the effect of weather on the energy performance (and energy production) of a solar cooling facility. Their result indicates that *energy produced* for cooling is highly influenced by solar radiation, wind speed and direction. Rodriguez-Hidalgo et al. (2011 a, b) uses 10 minute interval data to study the performance of a solar facility in face of changing weather conditions. Their result indicates that wind speed and direction has the highest effect on the efficiency of energy generated. Coskun et al. (2014) and Oktay et al. (2011) generate cooling and heating degree hours based on outdoor temperature collected at an hourly interval.

Studies examining the relationship between energy consumption and weather use monthly, daily or at best hourly data. For instance, Ruth et al. (2006) and Amato et al. (2005) use monthly data; Henley and Peirson (1997) use daily data while Parkpoom and Harrison (2008) and Hernandez et al. (2012) use hourly data. Parkpoom and Harris (2008) use hourly data to examine the relationship between temperature and energy demand in Thailand. Their analysis suggests that the effect of change in temperature on energy use is affected by what time of the day/night it is. Hernandez et al. (2012) use hourly data to study the relationship between weather variables and energy use in Spain. Their study shows that the correlation between weather variables and energy use changes at different times of a day. Henley and Peirson (1997) use daily data to study the non-linear relationship between temperature and residential demand for heating in the UK at different times of a day. Results indicate that the energy-temperature relationship is sensitive to the exact time of the day or night. Kaufman et al. (2013) argue that constructing degree days based on hourly values rather than daily values increases the accuracy of 'temporal downscaling of weather related energy use'.

There are several advantages to using interval metering as compared to an aggregate weekly or monthly data. Besides the fact that it provides accurate data at the exact time, it can reveal the exact times where energy demand is at its peak. In this way, one can examine intra-day variations and how such variations affect the energy use-temperature relationship. It can also help overcome some of the several inherent problems with using the degree day methodology (Energy lens online).

In addition to access to five-minute interval weather data, our local approach, though it may potentially limit any conclusions regarding national levels, has several advantages. For instance, a local weather data (compared to national weather data) can be used to address local problems, to better forecast local energy demand in the region, to improve efficiency of energy in face of changing weather variables, and inform policy making for specific cities in Texas. There are some studies which use data obtained from a smaller region (for example, Hernandez et al., 2012). To satisfy local energy demand and for local energy markets to operate efficiently, we need reliable forecasts of regional demand and this can be achieved through the study of the relationship between weather and energy at a regional level (Henley and Peirson, 1997).

Furthermore, we use weather data obtained from a weather station located very close to the houses. Specifically, weather data is gathered through a weather station located on the roof of one of the houses and not from a "far-away" weather station. As Hong et al. (2013) point out, the use of accurate and localized weather data can affect estimation results of energy-performance of buildings. In addition, Bhandari et al. (2012) finds evidence that there is a significant gap between actual measured weather data and a typical representative weather data of a given location.

3. Data Source and Methodology

3.1. Description of data source

Data used in this study comes from two residential houses with similar size and location in Tyler, Texas. House 1 is a conventional house with advanced efficiency features and house 2 is designed to be a net-zero solar house with relatively more advanced efficiency features. House 2 is tied to grid so when the solar panels overproduce, energy is sent back to the grid and stored until needed during night times.

The houses are built by the Texas Allergy, Indoor Environment, and Energy (TxAIRE) Institute of the University of Texas at Tyler. The houses are each 1500 square foot, three bedroom with attached garages, sloped roofs with attics, low or no-VOC paints and stains, garage ventilation fans, residential fire sprinkler system, energy-recovery ventilation system for fresh outdoor air, security system with remote monitoring and control and water conserving irrigation. A summary of the most distinguishing design features of the houses are presented in Table 1. As Table 1 indicates, house 2 is built with relatively more advanced efficiency features than house 1. In addition, house 2 is powered by a 7.4 kW size photovoltaic panels and designed to be a net-zero energy house and hence it is potentially net-zero.

Currently logged data is available at five-minute interval for approximately 16 months from May 2012 to September 2013. Energy consumption of all major equipment (water heater, heat pump, etc.) is reported in Watt-hours (W-hr) while weather data are available from the weather station installed on the roof of one of the houses.

Tyler, Texas has a typical East Texas climate and is characterized as warm temperate, fully humid and hot summer (Kottek et al., 2006). We compared the weather data collected by the TxAIRE Institute with the National Oceanic and Atmospheric Administration (NOAA) representative data for East Texas and found values to be very consistent. For instance, we calculated monthly averages using TxAIRE data and compared to NOAA monthly weather data for East Texas. The average monthly gap between TxAIRE and NOAA data is only 0.59 F for outside temperature and 0.27 inches for precipitation (authors' calculation using NOAA data).[6] So we can have greater confidence on the accuracy of the TxAIRE weather stations.

Rainfall is reported in inches, outside temperature in degree Fahrenheit (F), solar radiation in watt-hours per square meter (W/m^2), wind speed in miles per hour (mph), relative humidity in percentage and barometric pressure in inches of mercury (inHg). There are no residents living in the houses during the time data were collected; and there are no appliances running. Because of this there will be no need to control for the effect of socio-economic parameters such as prices, income and number of residents on energy demand. In addition, energy usage is largely dependent

[6] Source: retrieved http://www.ncdc.noaa.gov/cag/time-series/us

upon fluctuation in weather variables.[7] Under usual conditions the air conditioner is automatically set to 70 F during heating seasons and 76 F during cooling seasons. The water heaters have been turned off, so the air conditioner seems to be the main source of energy usage. All the equipment including the heating and cooling equipment are new and not defective.

Table 1: Summary of key features

Features	**House 1**	**House 2**
Design	Conventional house with advanced efficiency features	Net-zero solar house with more advanced efficiency features
Location	Lat. +32.314590 Long. -95.259257	Lat. +32.314593 Long. -95.259005
Roofing	Conventional architectural shingles	Shingle with higher solar reflectance to provide cooler roof during summer
Energy efficiency	Energy-efficient (HERS 65) and air-tight (0.18 ACH)	More energy-efficient (HERS 52) and air-tight (0.08 ACH)
Heat Pump	– Ducted single-split heat pump in attic (18.2 SEER, 9.7 HSPF) and ductless multi-split heat pump in house (14.5 SEER, 8.5 HSPF) – Heat pump water heaters (2.35 EF) in house and attic	– Ducted single-split system in attic (19.0 SEER, 9.0 HSPF) – Heat pump water heater in house
Wall framing	Conventional wall framing with blown-fiberglass insulation	Advanced wall framing with open-cell foam insulation resulting in 13% less wood used and 50% more wall insulation.
Exterior wall	Conventional wood backing	Sheetrock clip used to reduce lumber use and improves insulation
Attic	Vented attic with blown-fiberglass ceiling insulation and three roof vent options	Unvented attic with open-cell foam, insulated roof deck which improved performance of equipment and ductwork in attic
Windows	Aluminum-frame windows with double-pane glass (U=0.55, SHGF=0.36)	Vinyl-frame windows with double-pane, low-E glass (U=0.33, SHGF=0.23)
Lighting	High-efficiency compact fluorescent lighting	High-efficiency and longer-life LED lighting

[7] It should be noted, however, that the houses and data collected were not intended to solely study the weather-energy use relationship. So there is a possibility for the energy data to capture changes in unknown factors which may be related to research projects or tours taking place at the houses.

Source: http://www.uttyler.edu/txaire/houses/specs.php

3.2. Empirical strategy

Several studies have established that the relationship between temperature and energy demand is at best non-linear (Henley and Peirson, 1997; Amato et al., 2005). Amato et al. (2005)'s theoretical framework shows a V-shaped relationship between temperature and energy use and this has been applied by studies like Deschenes and Greenston (2011) and Aroonruengsswat and Auffhammer (2011). In fact, the use of the heating and cooling degree days correctly capture the non-linear relationship between temperature and energy use. Hors et al. (2005) finds that using heating and cooling degree days proves superior than using actual temperature values.

Since we use a five-minute interval data, we calculate heating and cooling degree minutes as follows:

$$\begin{aligned} &HDM_t = 70 - T_t \ \text{ if } \ T_t < 70 \quad \text{and} \quad HDM_t = 0 \text{ otherwise} \\ &CDM_t = T_t - 76 \ \text{ if } \ T_t > 76 \quad \text{and} \quad CDM_t = 0 \text{ otherwise} \end{aligned} \qquad [1]$$

where *HDM* is heating degree minutes and *CDM* is cooling degree minutes. T_t is the actual temperature recorded every 5 minutes in degrees F. The threshold temperatures (70 F for heating and 76 F for cooling) are obtained from what the houses are automatically set to. In a similar fashion, Coskun et al. (2014) introduced heating and cooling degree hours based on outdoor temperature distribution. The heating and cooling degree minutes measure random weather surprise (Considine, 2000).

Past studies agree that temperature is the most important variable that affects energy demand (Hor et al., 2005; Parkpoom and Harrison, 2008) while the effect of other variables like humidity, wind speed and precipitation are relatively less important (Deschenes and Greenstone, 2011; Sailor, 2001; Hernandez et al., 2012; Griffin, 2008; Mansur et al., 2005). Even though the most significant variation in energy use comes from changes in temperature, it is very important to control for other non-temperature variables. Coskun et al. (2014) argue that, in addition to outdoor temperature, solar radiation, humidity, and wind speed can affect a building's heating and cooling loads. Furthermore, temperature can directly affect non-temperature variables and vice versa. For instance, temperature can directly affect relative humidity (Time Space and People, 2011) and precipitation can directly affect solar radiation and temperature (Richardson, 1981). Pitt (2000) argues that solar radiation may have an implication for the possibility of precipitation and precipitation may affect relative humidity. Thus, none of the weather variables are independent. Even though we do not claim to model the complex relationship between different weather variables, we develop a methodology that accounts for some of these complexities instead of relying on a simple relationship between energy use and temperature.

There are some studies that explicitly control for some of the non-temperature variables. For instance, Hor et al. (2005) shows that models used to predict energy demand improve with the addition of more weather variables and in particular, the authors find that solar radiation, wind speed and precipitation matter for electricity demand. Hernandez et al. (2012) find a moderate positive correlation between humidity and energy consumption, a moderate negative correlation between solar radiation and energy consumption, but a weak effect of rain, wind speed, wind direction, and pressure on energy use. Likewise, Amato et al. (2005) find a significant negative effect of solar radiation on monthly electricity use in the residential sector. This may be because solar radiation is correlated with temperature and could affect energy use for lighting needs. Wind speed may decrease the demand for cooling in hot days and increase the demand for heating in cold days by cooling the exterior walls of a building especially if the walls are wet due to rainfall (Hor et al., 2005). Following this argument, we control for the effect of five non-temperature weather variables on energy use: humidity, precipitation, solar radiation, wind speed and barometric pressure. In addition, following Considine (2000) we add dummy variables for each month to control for fixed seasonal effects.

Furthermore, we examine lagged effect of weather on energy use. Since our data is reported at a five minute interval, we expect change in weather in the previous minutes to affect current energy use. Pitt (2000) showed that there is a lagged effect of precipitation on energy use, and this is because rain can result in wetness for longer hours especially if there is cloud cover. Pitt (2000) also showed that wind speed in previous hours may slightly affect energy use.

We fit the following baseline regression for each house:

$$E_t = a_0 + a_1 HDM_t + a_2 CDM_t + \sum_{z=0}^{n} \sum_{j=1}^{5} a_{z,j} X_{t-z,j} + \sum_{k=1}^{11} b_k M_k + \sum_{l=1}^{3} c_l D_l + \sum_{z=1}^{m} \delta_z E_{t-z} + \theta_1 \tau + \theta_2 \tau^2 + e_t \tag{2}$$

E_t is energy consumption in logarithms at time t

a_o is non-weather sensitive energy consumption

HDM and CDM are heating and cooling degree minutes respectively

$X_{t-z,1}$ is solar radiation at time $t-z$

$X_{t-z,2}$ is humidity at time $t-z$

$X_{t-z,3}$ is precipitation at time $t-z$

$X_{t-z,4}$ is wind speed at time $t-z$

$X_{t-z,5}$ is barometric pressure at time $t-z$

M_k represents 11 dummy variables for months February to December where $k = 1$ to 11

D_l where $l=1,2,3$ is an intraday dummy variable for early morning (12 am to 6 am), morning (6.05 am to 12 pm) and afternoon (12.05 pm to 6 pm) respectively

τ is a time trend and e_t denotes the error term.

Lagged values of the dependent variable (E_{t-z}) are included to correct for auto correlation. Intraday dummy variables are included to study how sensitive the energy-weather relationship is to the specific time of the day or night, after controlling for seasonal effects. Since there are no residents living in the houses, no appliances running, water heaters are off and the air conditioner seems to be the main source of energy usage, we expect a_o to be close to zero. In relation to Amato et al.'s (2005) theory, this implies that the non-weather sensitive energy component would be very close to zero.

In addition to the baseline model given in Equation [2] we control for the possibility of non-linear relationship between energy and non-temperature variables by including second order polynomials of the X_j variables. Mansur et al. (2005) controls for a non-linear relationship between precipitation and energy use.

Table 2: Correlation matrix

Five minute interval data	HDM	CDM	Solar radiation	Humidity	Pressure	Rain	Wind speed
HDM	1.00						
CDM	-0.38	1.00					
Solar radiation	-0.23	0.44	1.00				
Humidity	0.12	-0.51	-0.45	1.00			
Pressure	0.55	-0.27	0.01	-0.09	1.00		
Rain	-0.00	-0.03	-0.02	0.06	-0.03	1.00	
Wind speed	0.01	0.03	0.39	-0.17	-0.11	0.03	1.00
Daily interval data	HDD	CDD	Solar radiation	Humidity	Pressure	Rain	Wind speed
HDD	1.00						
CDD	-0.48	1.00					
Solar radiation	-0.46	0.47	1.00				
Humidity	-0.10	-0.25	-0.56	1.00			
Pressure	0.58	-0.31	-0.14	-0.19	1.00		
Rain	-0.01	-0.17	-0.39	0.35	-0.10	1.00	
Wind speed	0.14	-0.11	-0.18	0.04	-0.19	0.05	1.00

Solar radiation is measured in logarithm.

Table 2 presents the Pearson correlation coefficient among different weather variables and the coefficients suggest some degree of correlation. For example, CDM is highly correlated with solar radiation, solar radiation with humidity and HDM with pressure. Further inspection of the data suggests that correlation coefficients among weather variables are even higher if calculated for each season separately. For example, the correlation coefficient between humidity and CDM during summer is -0.98. This high correlation among weather variables not only raises the issue of how to best isolate the effects of temperature on energy consumption, but also, it illustrates the complex interaction among weather variables. We address this issue by employing a difference-in-difference estimation method. The idea is that although the levels might be correlated, first-differenced series may not, thereby reducing issues of mutlicollinearity. Additionally, difference-in-difference estimations correct for potential unobserved house-specific effects or unobserved heterogeneity before and after the change in the weather.

4. Results and Discussion

In section 4.1 we present evidence for intraday variation in energy use and the different weather variables. In section 4.2 we present regression results based on the model specified in equation [2]. We address the question of what the nature of the relationship is between energy use and the different weather variables. Furthermore, we compare the sensitivity of energy use to changes in the different weather variables for house 1 and house 2. In section 4.3 we illustrate how the sensitivity of energy use to weather variables depends on the specific time of the day/night.

4.1. Intraday variation of energy use and weather

Average daily energy consumption in house 1 is greater than that of house 2 for all seasons and for the entire sample. This is not a big surprise since house 2 has relatively more advanced energy efficiency design features. Moreover, Table 3 indicates large differences in energy consumption between the two houses during winter and fall. For both houses the highest energy consumption is recorded during winter while the lowest energy is recorded during fall and spring. The high energy consumption during winter may be attributed to a combination of low temperatures, low solar radiation and high wind speed.

Figures 2A and 2B show intraday variations in energy consumption for house 1 and house 2 respectively based on averages calculated for a given season at a given time of the day/night. During winter there is high intraday variation of energy use for both houses, with large spikes during the early hours of the day (around 6:30 am) followed by a modest rise in the evening. During summer there is a modest rise in energy consumption in the afternoon and evening. In contrast, spring and fall reflect relatively less clear, abrupt spikes and variations.

Even though energy consumption is on average lower in house 2 than house 1 for each season (please see Table 3) this may not always be true for all time periods of the day/night. Figure 2C shows the difference in energy use between house 1 and house 2 at all time periods and is used to identify the specific hours in which the difference between house 1 and house 2 in energy consumption is more apparent. As can be seen from Figure 2C during fall and summer seasons energy use in house 2 is on average relatively lower than house 1 for all hours of the day/night. During summer, the difference in energy use between house 1 and house 2 is the highest in the afternoon hours.

Table 3: Seasonal five-minute daily averages

Season	Energy use (W-hr)			Non-temperature weather variables				
	House 1	House 2	Temp. (F)	Solar radiation (W/m^2)	Humidity (%)	Rain (inch)	Pressure (inHg)	Wind speed (mph)
Summer	937.7	746.15	81	261.6	68.8	.0003	29.54	1.85
Fall	911.7	588.8	61	146.4	73.5	.0003	29.97	2.43
Winter	1558.3	1347.7	50	137.7	70.7	.0004	29.66	3.31
Spring	761.97	720.7	70	250.5	73.7	.0005	29.86	2.75
Average	1042.4	850.8	65	199.1	71.7	.0004	29.76	2.59

Figure 2C also indicates that in spring there are some abrupt times with no particular pattern in which energy consumption in house 2 is slightly relatively higher than house 1. This may be just a random outlier or due to tours needing to heat the house for spring visitors. In winter, house 2 uses relatively less energy in early morning hours between 3:50 am and 6:05 am, however immediately followed by a relatively higher energy use compared to house 1. Between 6:15 am and 7 am house 2 uses higher energy than house 1. Even though we are not able to give a clear cut justification, this inefficiency may be attributed to different factors such as late sunrises in winter. In the dark hours (late evening and early morning), the house may be using stored energy to heat and maintain the house temperature at 70 F. The study by Kabir et al. (2014) suggests that during winter, power consumption of a photovoltaic powered house with battery storage system remains more or less constant from midnight to 5 am and from 5 am onwards sharply rises (from 6 am onwards the solar panel will start generating power). Similarly, in our case during winter mornings the solar panel starts its energy production when the sun starts to rise which is usually after 7 am in Tyler. Thus, right before sunrise there may be a higher energy demand from stored sources.

Figure 2A: Intraday variation of energy consumption in house 1 (average values for a given season and given time)

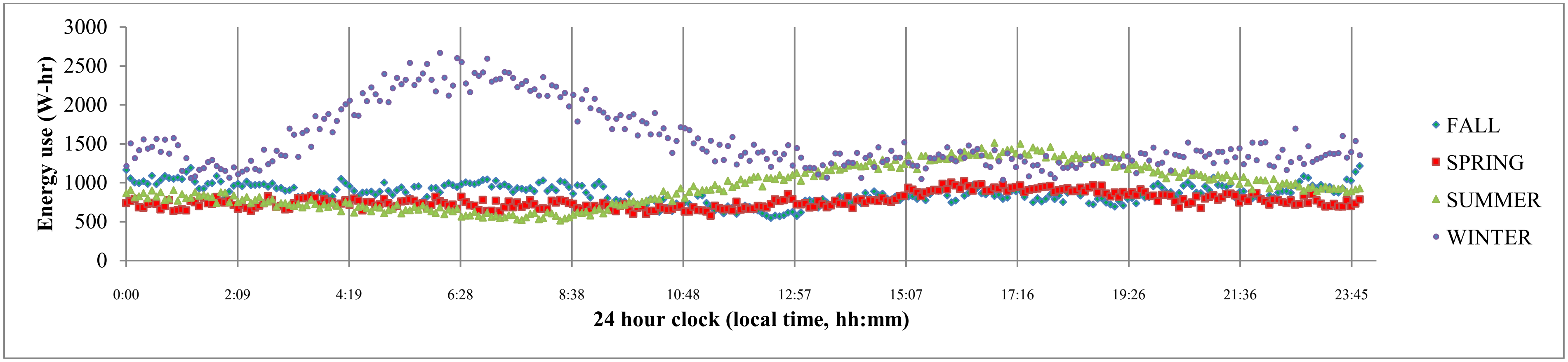


Figure 2B: Intraday variation of energy consumption in house 2 (average values for a given season and given time)

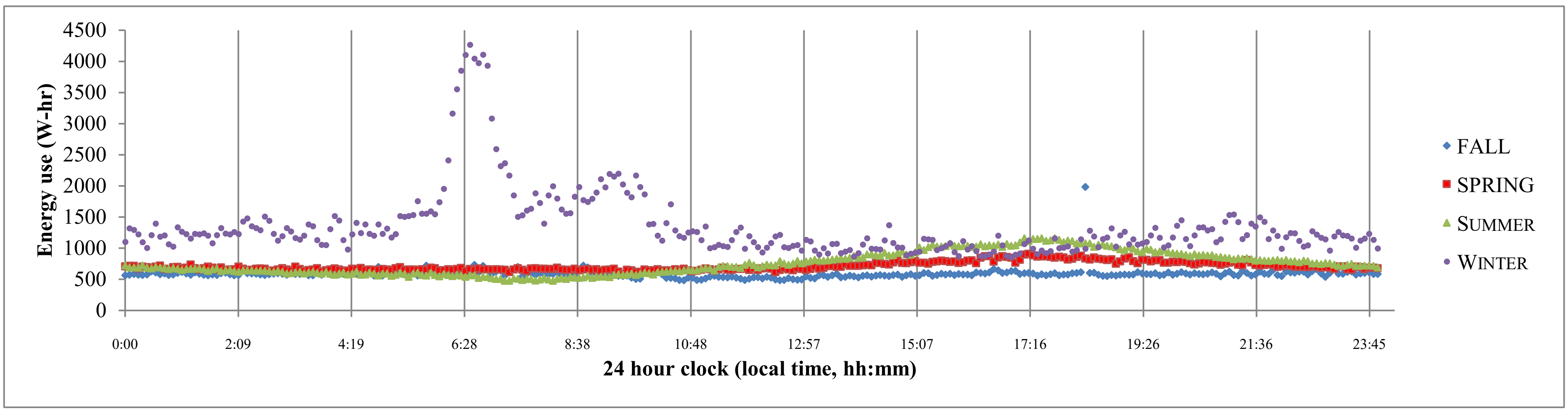


Figure 2C: Average difference in energy consumption (house 1 minus house 2)

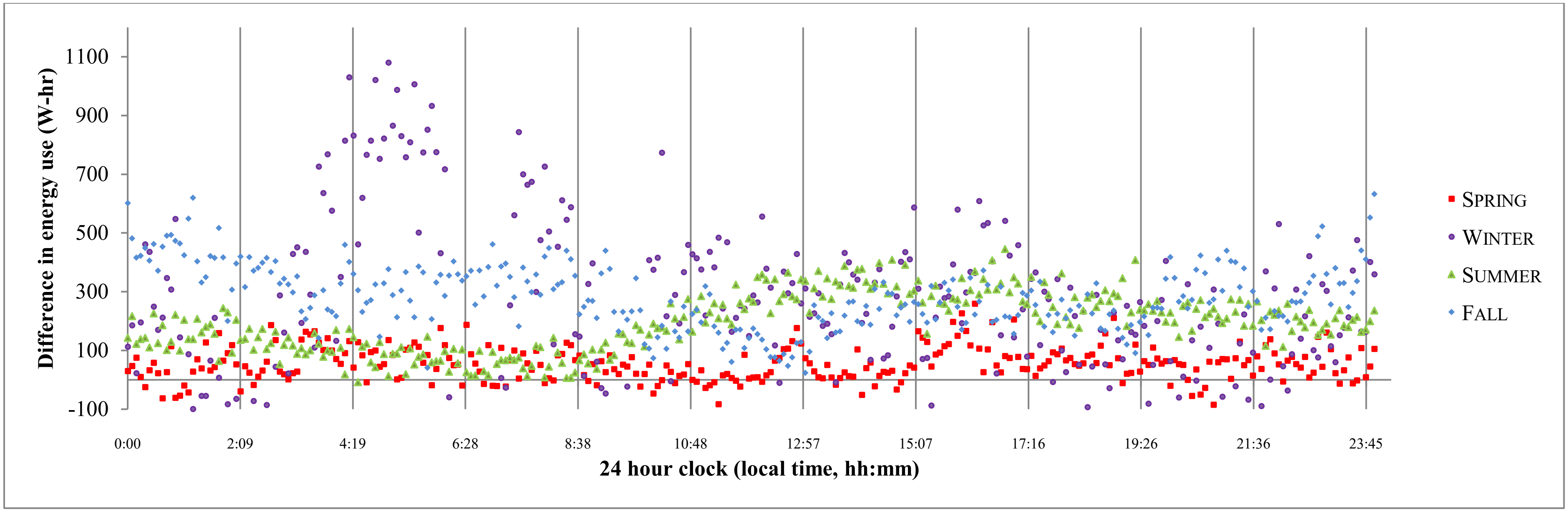


Figure 2D: Intraday variation in selected weather variables

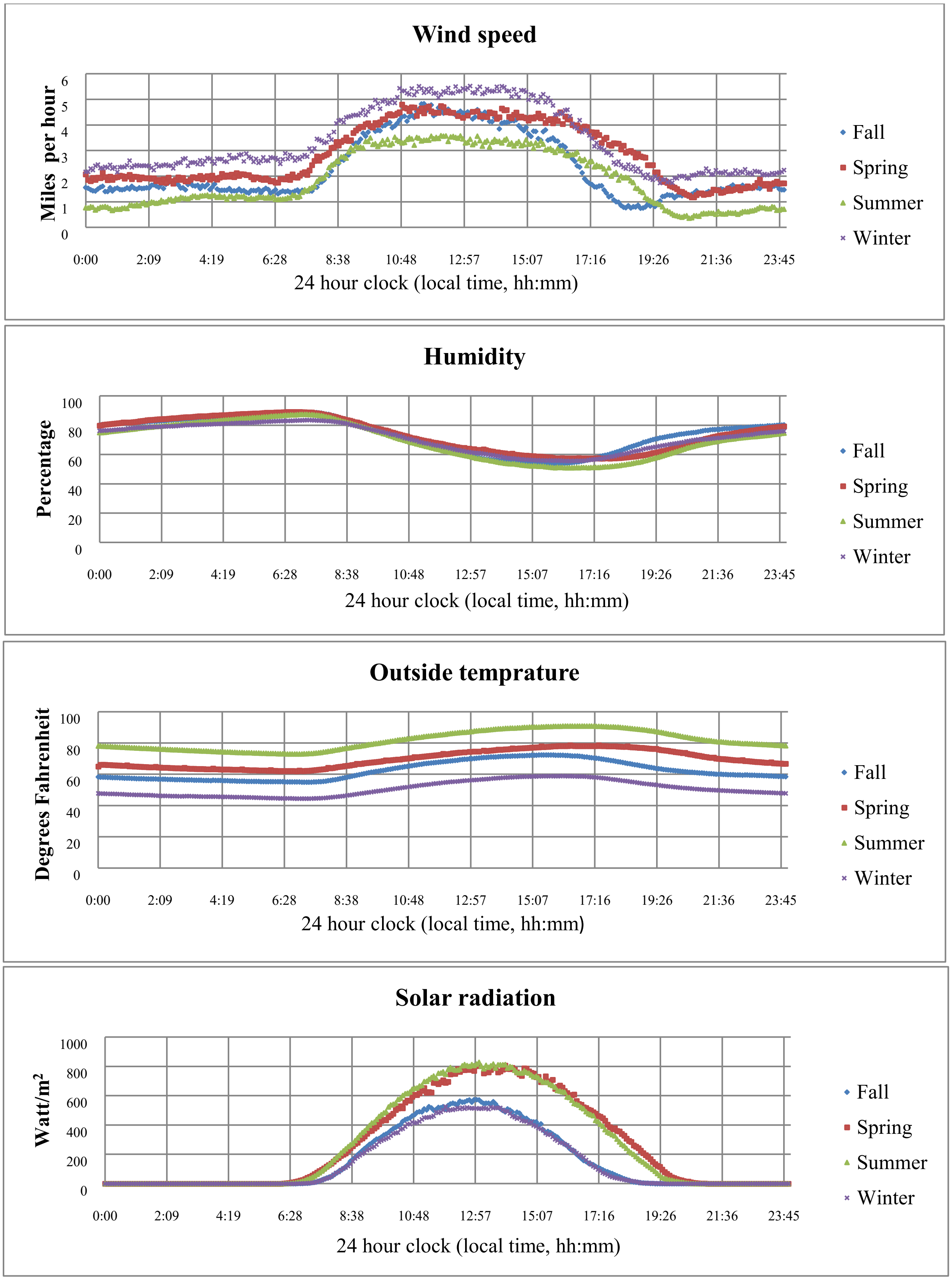


Figure 2D presents intraday variation in selected weather variables. The figure illustrates how weather variables can significantly change within a day and this intraday variation in weather is expected to create variation in energy use throughout a given day. For instance, similar to Coskun et al. (2011) solar radiation is at its highest around 1 pm for all seasons; similarly outside temperature is at its highest in the afternoon throughout the year. Humidity has its highest value just before sunrise in the early morning after which it declines with the rise in solar radiation and outside temperature. It appears from Figure 2D that for all seasons wind speed starts to rise in the morning hours, reaches a maximum around midday and then fades out. Priedite (2014) and Jennings (2012) report a similar trend in wind speed where wind speed picks up around midday and fades out thereafter. Likewise, Torres et al. (2005) argue that the evolution of the wind speed during the day may shows a cyclic behavior.

4.2. Sensitivity of energy use to weather variables

Regression results using five-minute interval data from house 1 and house 2 are presented through a selected number of regression outputs in Table 4. All regressions include 11 month dummy variables and lagged variables of the dependent variable (results from these variables are not reported for brevity). The dependent variable is energy use measured in logarithms. Residuals were modelled as an autoregressive process of order one, AR(1), or higher order when required. Moreover, all series were subjected to Augmented Dickey–Fuller unit root tests, which indicate that these are stationary and therefore do not exhibit a unit root. We use the Durbin-Watson statistic to test for issues of first-order autocorrelation in the error terms. The Durbin-Watson statistic is equal to or very close to 2 in all cases suggesting that autocorrelation is not a major issue; inspection of the correlogram of residuals also indicates no issues of serial correlation of higher orders. Models 1.a to 1.d and 2.a to 2.d present coefficients of the independent variables using difference-in-difference regression for house 1 and 2 respectively. Additional robustness check results are attached in the appendix for further reference.

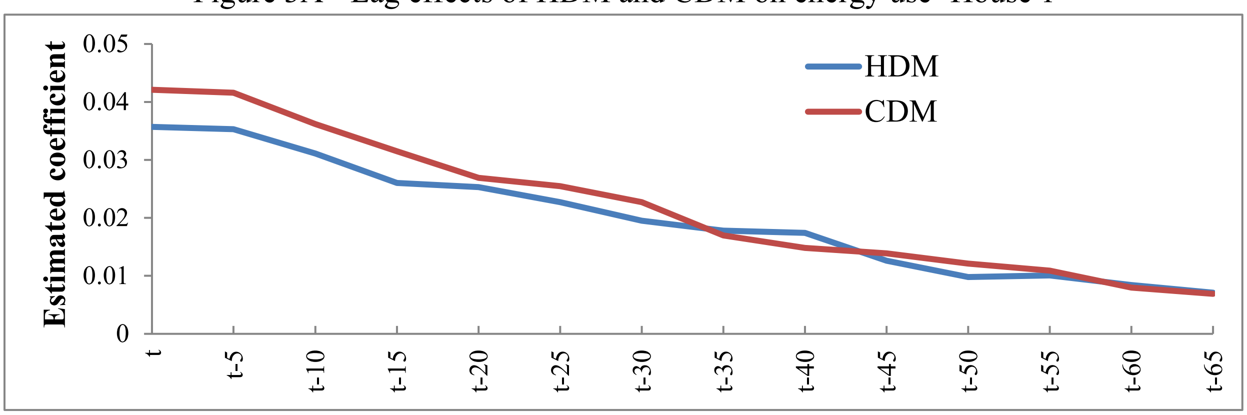
While controlling for seasonal effects, residual autocorrelation and intraday effects, estimations under various model specifications yield consistent results especially for HDM and CDM. A one unit increase in HDM leads to 8.2%-10.5% (average of 9%) increase in energy use in house 1 and 4.6%-5.3% (average of 5%) increase in house 2. Similarly we find that a one unit increase in CDM leads to 4.4%-6.2% (average of 5%) increase in energy use in house 1 and 3.5%-4.5% (average of 4%) increase in house 2. Even though these values are within the range of findings of past studies, the lower estimated coefficients for house 2 suggest that adding more advanced efficiency features provides the advantage of making house 2 not as sensitive to changes in temperature as in house 1. This is especially evident for colder times because HDM induces larger changes in energy consumption compared to CDM. This result may be partially due to the location of the houses in the south where high temperatures are common; and the efficiency additions to house 2 may be targeting heat conservation (for instance, house 2 has more wall insulation than house 1).

The fact that the sensitivity of energy use needed for heating declines from 9% in house 1 to 5% in house 2 as compared to energy demand for cooling from 5% in house 1 to 4% in house 2 suggests that savings from house 2 is more evident during colder times, which is when peak demand is registered as shown in Figures 2A and 2B.

Due to the high frequency nature of the dataset we except high correlation between temperature at a given time and past values where correlations are expected to diminish with higher lag order. For instance, Pearson's correlation coefficient between HDM at time *t* and time *t-2* is 0.634, HDM at time *t* and *t-10* is 0.391, and HDM at time *t* and time *t-20* is 0.264. Similarly, we find that Pearson's correlation coefficient between CDM at time *t* and CDM at *t-10* is 0.243, whereas that between CDM at *t* and CDM at *t-20* is 0.178.

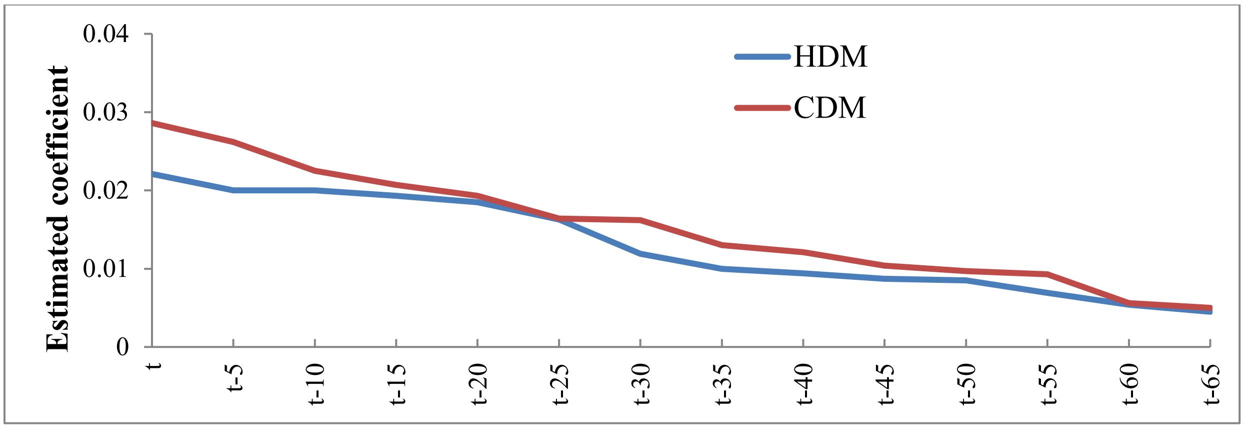
Thus, the estimated coefficient of HDM at time *t* (i.e., $\partial E_t/\partial HDM_t$) may already be capturing the effects of past lags. To control for potential issues of multicolinearity and isolate the lagged effects of temperature on energy use, we estimate the effects of HDM and CDM, separately, at various time lags on energy use in each house. For instance, for house 1 we estimate the coefficient of HDM at time *t-5* (i.e., $\partial E_t/\partial HDM_{t-5}$), and on a separate regression the coefficient of CDM at *t-5* (i.e., $\partial E_t/\partial CDM_{t-5}$), while controlling for seasonal and intraday variations. Figures 3A and 3B present a summary of the slope coefficients for HDM and CDM at various time lags for house 1 and 2 respectively. The figure suggests that the effect of lagged values of temperature on energy use diminishes as the lag order increases and becomes very small at *t-65*, the equivalent of about 5 hours.

Figure 3A - Lag effects of HDM and CDM on energy use- House 1



We used the following simplified specification to obtain the estimated coefficients: $E_t = c + DM_{t-k}$ + *monthly dummies* + *intraday dummies* + *AR(p)*, where DM_{t-k} denotes either CDM or HDM at lag *k*. Residuals are modeled as an autoregressive process of order *p*. Including both CDM and HDM in the same regression does not affect the qualitative results.

Figure 3B - Lag effects of HDM and CDM on energy use- House 2



We used the following simplified specification to obtain the estimated coefficients: $E_t = c + DM_{t-k} +$ *monthly dummies + intraday dummies + AR(p)*, where DM_{t-k} denotes either CDM or HDM at lag k. Residuals are modeling as an autoregressive process of order p. Including both CDM and HDM in the same regression does not affect the qualitative results.

In both houses, solar radiation and its squared term are statistically significant determinants of energy use (see Table 4) thus suggesting that the relationship between solar radiation and energy use is non-linear (Coskun et al., 2011).[8] Figure 4 also suggests a nonlinear relationship; the figure shows this result by taking average values of solar radiation and energy use at each time during the day for the summer season. At lower levels of solar radiation (before 6:30 am) energy use shows a downward trend, but as solar radiation starts to rise during the morning hours energy use rises accordingly. Between 9.30 am and 2 pm an increase in solar radiation is associated with increases in energy use. However, starting from 2 pm to around 5:30 pm a decrease in solar radiation is associated with rise in energy use (which may indicate a lag effect), while beyond 5:30 pm further declines in solar radiation is associated with decline in energy use. Thus, the relationship between solar radiation and energy use oscillates throughout the day, thereby indicating a non-linear relationship.

Given the evidence of a non-linear relationship between the two variables in Table 4 and Figure 4, one implication is that the effect of an increase in solar radiation on energy use depends on the level of solar radiation. The lower impact of solar radiation in house 2 may be due to the high solar

[8] The present study focuses on the effects of heating and cooling degree minutes on energy use while accounting for solar radiation, among other factors. We therefore feel that the study of nonlinearities in weather variables, including solar radiation, as it pertains to energy use is beyond the scope of this paper. Thus, we simply point out that the analysis shows evidence of nonlinearities but refrain from drawing further conclusions.

reflectance shingles installed in house 2 and more energy efficient insulation features, among other features such as the duct work. For example, in summer, when the cool air is passing through the duct work, a lower overall attic temperature means less hot air is getting into the ducts, which leads to potentially less energy consumed.

Figure 4: Non-linear relationship between energy use and solar radiation (summer)

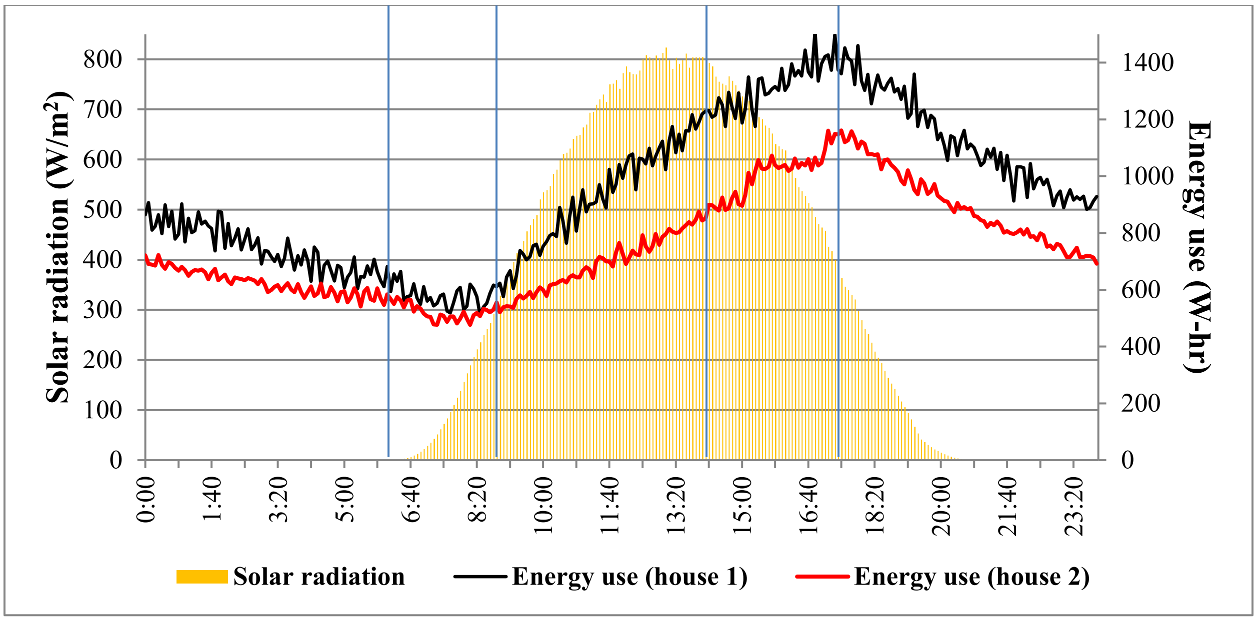
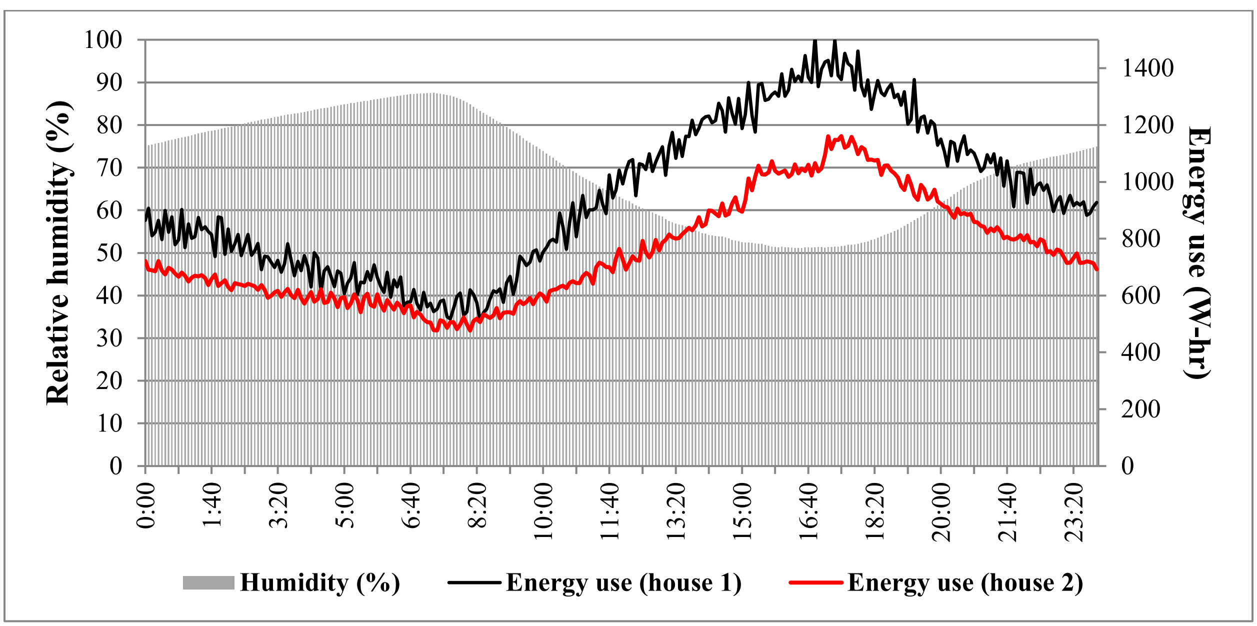


Figure 5: Humidity and energy use (summer)



The regression results in Table 4 also suggest that relative humidity is a statistically significant determinant of energy use in house 1 but not house 2, keeping other factors constant. This suggests that one of the advantages of the efficiency improvements of house 2 is to make the house less responsive to changes in the humidity level, so that when humidity declines in the afternoons, the house is able to maintain its energy use without increasing it. Consistent with our regression coefficient on humidity, Figure 5 shows that when humidity is declining (from 8:00 am to around 5: 30 pm) energy use is increasing; and when humidity is increasing (after 6 pm) energy use is declining. Even though Figure 5 suggests a pattern between humidity level and energy use in house 2, the regression results indicate that this relationship is not statistically significant.[9]

Table 4: Selected representative regression estimates

Coefficients of:	House 1				House 2			
	1.a	1.b	1.c	1.d	2.a	2.b	2.c	2.d
Constant	-0.010	-0.011	-0.010	-0.072	-0.003	-0.011[a]	-0.012[a]	-0.011[a]
HDM	0.082[a]	0.091[a]	0.093[a]	0.105[a]	0.053[a]	0.046[a]	0.049[a]	0.050[a]
CDM	0.062[a]	0.055[a]	0.056[a]	0.044[a]	0.036[a]	0.045[a]	0.039[a]	0.035[a]
X_1		-0.027[a]	-0.026[a]	-0.027[a]	-0.018[a]	-0.018[a]	-0.018[a]	
X_2		-0.006[a]	-0.007[a]	-0.006[a]	0.001	0.000	0.000	
X_3		-0.189	-0.260	-0.016	0.400	0.556	0.517	
X_4		-0.001	0.001	-0.001	0.001	0.002[a]	0.001	
X_5		-0.515	-0.460	-0.153	-0.015	-0.099	-0.136	
$X_{t-1,1}$			-0.002			-0.013[a]		
$X_{t-1,2}$			-0.003			-0.000		
$X_{t-1,3}$			-0.500			0.39		
$X_{t-1,4}$			0.003			0.003[a]		
$X_{t-1,5}$			-0.490			-0.27		
X_1^2				0.001[a]	0.0003[a]			
X_2^2				0.000	0.000			
X_5^2				0.000	-0.000			
X_3^2				-2.67	1.20			
X_4^2				0.000	0.000			
D_1	0.004	0.005	0.004	0.007	0.008[a]	0.007[a]	0.007[a]	0.006[a]
D_2	0.011[a]	0.013[a]	0.011[a]	-0.006	0.010[a]	0.016[a]	0.016[a]	0.013[a]
D_3	0.021[a]	0.020[a]	0.018[a]	-0.006	0.015[a]	0.022[a]	0.023[a]	0.023[a]
R^2	0.44	0.44	0.44	0.44	0.48	0.48	0.48	0.48
Adjusted R^2	0.44	0.44	0.44	0.44	0.48	0.48	0.48	0.48
Durbin-Watson	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Obs.	126,602	126,602	126,602	126,602	135,183	135,183	135,183	135,183

Solar radiation is measured in logarithms; [a] represents significance at 1% (numbers are rounded off to the nearest decimal). All regressions include 8 lagged variables of the dependent variable. All variables are in first-differences except for squared terms and dummy variables.

[9] As in the case of solar radiation, further analysis of nonlinearities in humidity are needed to make additional observations.

4.3. Sensitivity of energy use to time of the day/night

Overall, our results indicate that the relationship between energy use and weather is sensitive to what time of the day/night it is as gauged by the significance of the intraday dummies in most of the regression outputs presented in Table 4. For both houses the morning and afternoon dummy variables, D_2 and D_3, are statistically significant with a positive coefficient for models 1.a to 1.c and 2.a to 2.d. This suggests that, after controlling for seasonal effects, higher energy consumption is more evident in the morning (6:05 am to 12 pm) and afternoon periods (12:05 pm to 6 pm) than other time periods. Though it is of a smaller value, the early morning dummy variable, D_1, is statistically significant with a positive coefficient only for house 2. This may be reflecting the higher energy use in early morning hours of winter in house 2.

Interestingly, once we include squared terms of weather variables in model 1.d, the coefficients on D_2 and D_3 are no longer statistically significant in house 1. However, to further examine the effect of intraday dummy variables on energy use in both houses we perform additional exercises.

The effect of the specific time of the day/night on energy use is not a unique value; it differs for different months and seasons. For instance, the effect of early morning hours on energy use is not the same in winter and summer. Figures 2A and 2B illustrate that at a given time of a day/night the trend in energy use really depends on what season is being considered.

Because of this we included interaction terms between intraday dummy variables, month dummy variables and HDM/CDM in our basic model presented in Equation [2], that is we add $HDM \times M_k \times D_l$ or $CDM \times M_k \times D_l$ as additional independent variables. The addition of these interaction terms implies that the effect of intraday dummy variables on energy use is different for different months and seasons (heating or cooling season).

We examine the following marginal effects:

$$\frac{dE_t}{dHDM_t} = a_1 + a_{1,k,l} M_k \times D_l \text{ and } \frac{dE_t}{dCDM_t} = a_2 + a_{2,k,l} M_k \times D_l \qquad [3]$$

where a_1 and a_2 are the unique effects of HDM and CDM on energy use only when $D_l = 0$. $a_{1,k,l}$ indicates how different the slopes (sensitivity of energy use to temperature) are for different time periods of the day/night and different months.

For example, to ascertain whether the increase in energy consumption due to CDM is increased in the afternoon hours of July we look at whether the coefficient on the interaction term *CDM*D_3*July* is statistically significant from zero. If we find a statistically significant positive coefficient, the implication is that the sensitivity of energy use to a change in CDM is significantly higher than a_2 during afternoon hours of July. If a coefficient on a given interaction term is not statistically significant, the implication is that only the unique effects, a_1 and a_2, matter. Table 5 summarizes results from estimations which include such interaction terms. We find that on average for house 1 a_1 is 5.4% and a_2 is 9%. For house 2, on average a_1 is 4% and a_2 is 5%. These coefficients are very close to the regression results achieved in Table 4.

Table 5: Coefficients from regressions including interaction terms

Intraday dummy variables	House 1		House 2	
	CDM	HDM	CDM	HDM
	$a_1 + a_{1,k,l}$	$a_2 + a_{2,k,l}$	$a_1 + a_{1,k,l}$	$a_2 + a_{2,k,l}$
$D_1=1$	36.68% (July)	52.66% (June)		16.19% (Feb.)
$D_2=1$	13.39% (Aug.) 13.74% (Sept.)	21.02% (Jan.) 22.27% (Dec.)	9.71% (Sept.)	17.59% (Jan.) 12.06% (Feb.) 10.33% (Nov.)
$D_3=1$	-7.64% (May)		0.62% (June)	-2.34% (Nov.)

We present only those regressions that yield a significant coefficient on an interaction term. Significance level is taken at 5% or less. Each regression includes one interaction term only. Presented values are sums of two components, $a_1 + a_{1,k,l}$ or $a_2 + a_{2,k,l}$, for a month which yields a statistically significant coefficient on the interaction term.

For house 1, there is higher sensitivity of energy use to HDM (higher than the 9% average) during early morning hours of June and morning hours of December and January. Similarly, for house 1, early morning in July and morning hours of August and September represent a significantly higher sensitivity of energy use for cooling (higher than the 5% average). However, during May afternoons, the demand for cooling actually declines by 7.64% for each increase in cooling degree minutes in house 1.

For house 2, there is higher sensitivity of energy use to HDM (higher than the 5% average) during early mornings of February, and morning hours of January, February and November. However, during November afternoons, the demand for heating declines by 2.34% for each increase in heating degree minutes in house 2.

The sensitivity of energy use to cooling remains around the 4% average in house 2 in early morning hours for all months. This suggests that a significant portion of energy used in the early morning in house 2 may be due to heating not cooling. The sensitivity of energy use to changes in cooling degree minutes is about 9.71% for September mornings (higher than the 4% average) but only 0.62% higher for June afternoons (much lower than the 4% average).

Overall our result in Table 5 indicates that the sensitivity of energy use to HDM and CDM remain lower for house 2 than house 1. Furthermore, these results imply that the sensitivity of energy use to changes in temperature depends highly on what specific months and specific time period is under consideration. Hence, having a high frequency dataset would have several advantages in terms of identifying specific time periods in which energy efficiency is achieved or not.

5. Conclusion and Policy Implications

The residential sector in the US seems to be moving towards cleaner energy sources and improved efficiency features. This may be attributed to changes in consumer preferences as well as policy incentives towards greener and efficient houses. In terms of policy incentives, Texas has put forward several incentives in order to encourage the residential sector to invest in improving home efficiency and also consider alternative energy sources. In spite of the growing demand for green and/or efficient houses, there are not many studies that examine the performance of green and efficient homes in face of weather variation.

This paper studies the impact of weather variation on energy use by using five-minute interval weather-energy data obtained from two residential houses: house 1 is a conventional house with advanced efficiency features and house 2 is a potentially net-zero solar house with relatively more advanced efficiency features. Our result suggests that energy consumption in house 2 is not as sensitive to changes in weather variables as the conventional house. On average, we find that a one unit increase in heating and cooling degree minutes increases energy use by about 9% and 5% respectively for house 1 and 5% and 4% respectively for house 2. In addition, our finding suggests that non-temperature variables such as solar radiation and humidity affect energy use where the sensitivity rates for house 2 are consistently lower than that of house 1. The implication of this finding is that adding more advanced efficiency improvements to residential houses may have the benefit of reducing the need to increase energy consumption during unfavorable weather conditions. However, whether these benefits warranty the costs of home improvement should be studied in depth.

Furthermore our result suggests that the sensitivity of energy use to weather changes is highly dependent not only on what season or month is considered, but also on the specific time of the day/night. The availability of fine temporal data may help accurate modeling and understating of the energy-weather relationship in the residential sector. However, we need future research to determine whether such benefits of interval metering are cost-effective or not to the general public.

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Appendix

In order to minimize potential issues arising from the complex relationship among weather variables (i.e., run into specification bias issues) we perform a robustness check by adopting a Two-Stage-Least Square regression (2SLS) approach. In the first-stage HDM and CDM are estimated using non-temperature weather variables and seasonal effects; and in the second-stage regression we use the predicted values of HDM and CDM to estimate their impact on energy consumption. The first two columns of table A.1 present regression results from 2SLS.

To determine the rate at which energy consumption returns to its long-run equilibrium we estimate an error correction model. The last two columns of Table A.1 show regression results using an error correction model specification. The coefficient on the error correction term (Residual (t-1)) measures the speed at which prior deviation of energy use from equilibrium is adjusted in the next 5 minutes. Energy use will start falling to its long-run equilibrium value at a rate of 58% and 54% in house 1 and 2 respectively. One of the reasons why there is a slightly faster adjustment rate in house 1 is because it uses on average relatively more energy, and the size of deviation of actual energy use from its estimated value in the short-run is relatively larger.

Table A.1. Robustness check

	2SLS regression		Speed of long-run adjustment in energy use	
Coefficients of:	House 1	House 2	House 1	House 2
Constant	-0.000	-0.000[a]	-0.0004	0.0000
HDM	0.038[a]	0.023[a]	0.02[b]	0.02[a]
CDM	0.041[a]	0.029[a]	0.02[a]	0.02[a]
R^2	0.43	0.48	0.41	0.42
Adjusted R^2	0.43	0.48	0.41	0.42
Durbin-Watson	2.01	1.99	2.02	2.06
Residual (t-1)			-0.58[a]	-0.54[a]
Obs.	126,259	134,852	126,658	135,225

[a] represents significance at 1%, [b] represents significance level at 5% (numbers are rounded off of the nearest decimal).