Energy Insecurity and Redlined America

A. Justin Kirkpatrick

2021-01-20

This is a report generated by `knitr::spin()`

Introduction

This is the section with the introduction

Details and description

Define energy burden.

Cite severity of problem

Link between energy burden and energy efficiency

Obvious reason: being poor and short-sighted

Conditional on income, problem still persists!

Potential explanations (brief) This section is brief. Full literature review comes later. Or maybe the full lit for why is here?

Causal chain is really long

Potential chain (redlining–> lack of ownership –> why stay in area?)

This paper here...

Explores the role of redlining in explaining energy burden By isolating the energy outcomes that can only be explained by redlining

Plausibly exogenous variation Conditional on similar (but not red-lined) nearby neighborhoods. Observables.

Extracted 1930's data to understand redlining Survey data created by federal HOLC employees in 1936-1939 provides neighborhood-specific data on observable characteristics that can be used to identify the effects of redlining. The designation of red- and yellow-lined areas (as well as green and blue) aggregate away important variation between each grading. Not all redlined areas are identical, nor are all yellow areas. Survey data recorded as part of the redline designation process provides important, but largely unusued, sources of variation. Within-grade variation in housing is common with reported average rents, median income, repair status of housing, share of housing developed, and construction type. Prior to being redlined, areas with high percentages of low-income or minority populations were more likely to have lower rents and lower housing quality. Frequently, the reason for a low-income or minority area's location was associated with the quality of the geography or proximity to natural features - low-lying areas that frequently flooded or areas too steep for conventional building were generally populated by lower-income individuals. These same features also foment low investment in housing stock, and can explain current inefficiencies in housing regardless of the HOLC grade. With HOLC survey data in hand, I can control for these features and separate out the effect of HOLC redlining from the determinants of HOLC grading.

Identification key: there are neighborhoods with identical economics and racial composition where some surveyors designated them red and some designated yellow.

Poor whites vs. poor blacks

Historic data merged to block groups to leverage modern outcomes To assess current energy outcomes, I merge original HOLC neighborhoods to modern census block groups, extracting ACS and census indicators of high energy burden. Census block groups match the granularity of HOLC neighborhoods reasonably well. However, boundaries do not tend to coincide exactly, requiring some aggregation. Once linked, I compare modern energy outcomes with HOLC grading, conditioning on observable characteristics both in the 1930's (selection), and in the present. While an individual household-level analysis would provide the clearest evidence, household-level energy consumption data is limited for privacy reasons, especially at the spatial resolution of HOLC neighborhoods, which can have as few as 100 homes in them.

Data

This is the section with the data. And the section where we process the data

This is the text. $f = \frac{b}{c}$.

Census blockgroups

HOLC grading and survey data are available at the neighborhood level, where the average neighborhood size is approximately 0.72 [mˆ2] square kilometers.

Energy burden

I first examine the incidence of energy burden on minority populations. A model of home selection would clearly predict a relationship between energy burden and income as low-income individuals trade off energy efficient (yet higher cost) housing for lower-cost but energy-inefficient housing. Since a home's energy efficiency is part of a bundle of attributes, households with low income may often trade energy efficiency for other properties, such as larger square footage. Lower efficiency homes may be more expensive to heat to a comfortable standard. However, households with severe budget constraints may select a low-efficiency house and select to spend as little as possible on heating, resulting in very low inside temperatures, lower housing costs, and low energy expenditures.

To show the relationship between home energy efficiency and income, I regress the fraction of households reporting substandard heating technology (coal, wood, fuel oil, or "other"??) in a census block group on measures of income using the following specification:

$$SubstandardHeating_i = \beta_0 + \beta_1 MedInc_i + \beta_2 xxx_i + \epsilon_i$$

	Model 1	Model 2	Model 3
MedIncome2018	-0.00112***	-0.00024*	-0.00024*
	(0.00034)	(0.00013)	(0.00014)
Black	-0.20809*		
	(0.11769)		
White	-0.20479*		
	(0.11938)		
Asian	-0.18858*		
	(0.11078)		
OtherRace	-0.07260		
	(0.06890)		
MedIncome2018 × Black	0.00070**		
	(0.00031)		
MedIncome2018 × White	0.00118***		
	(0.00042)		
Num.Obs.	32403	18573	13170
R2	0.634	0.642	0.650
R2 Adj.	0.632	0.639	0.645
R2 Within	0.038	0.009	0.008
R2 Pseudo			
AIC	-72873.6	-38849.0	-26845.5
BIC	-71020.3	-37283.1	-25408.2
Log.Lik.	36657.787	19624.511	13614.748
FE: STCO	X	X	X
Std. errors	Clustered (STCO)	Clustered (STCO)	Clustered (STCO)

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

Robust SE clustered by FIPS county

Results Nothing good to report here. High income, as expected, means less likely to have substandard heating (median income; percent in block-group).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
as.factor(GRADE.max)D	-0.01076	-0.01145	-0.01166	-0.00894	-0.00411	-0.00844	-0.00311	0.01271
	(0.00839)	(0.00821)	(0.01069)	(0.00878)	(0.01414)	(0.01122)	(0.00627)	(0.01360)
as.factor(GRADE.max)B	0.01125	0.01178	0.00765	0.01247	0.01596	0.00774	0.02892*	0.01418
	(0.01185)	(0.01254)	(0.01340)	(0.01068)	(0.01261)	(0.01093)	(0.01585)	(0.02818)
as.factor(GRADE.max)A	0.00048	-0.00488	-0.00156	-0.00664	-0.00329	-0.00304	0.01924	0.01460
	(0.02198)	(0.02239)	(0.03052)	(0.02156)	(0.02344)	(0.02857)	(0.04014)	(0.07641)
MedIncome2018	-0.00020	-0.00027	-0.00030	-0.00040*	-0.00042*	-0.00045*	0.00003	0.00039**
	(0.00031)	(0.00034)	(0.00039)	(0.00024)	(0.00025)	(0.00027)	(0.00017)	(0.00019)
MedIncome1936	0.00200***	0.00042	-0.00007	0.00121	0.00106	0.00094	-0.00004	0.01963**
	(0.00060)	(0.00079)	(0.00092)	(0.00088)	(0.00085)	(0.00088)	(0.00320)	(0.00732)
Rent3739_Mean	0.00031	0.00031	0.00032	0.00028	0.00029	0.00027	0.00001	0.00004
	(0.00023)	(0.00023)	(0.00029)	(0.00020)	(0.00021)	(0.00023)	(0.00005)	(0.00011)
MedIncome2018 × MedIncome1936		0.00002*	0.00003*	0.00002**	0.00002**	0.00003*	0.00001	-0.00013***
		(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00003)	(0.00004)
Black				-0.09895	-0.09168	-0.11085	0.00238	-0.00886
				(0.08161)	(0.07787)	(0.08716)	(0.04598)	(0.04463)
White				-0.03628	-0.03582	-0.03633	0.04214	0.03928
				(0.08008)	(0.07972)	(0.08237)	(0.04494)	(0.05079)
Asian				-0.09331	-0.09182	-0.10473	-0.01258	-0.03214
				(0.08697)	(0.08626)	(0.09315)	(0.03652)	(0.03986)
as.factor(GRADE.max)D × Black					-0.01565			
					(0.02191)			
as.factor(GRADE.max)B × Black					-0.01379			
					(0.01512)			
as.factor(GRADE.max)A × Black					-0.01945			
					(0.03411)			
NBlack_YN							0.00222	-0.00317
							(0.01874)	(0.03466)
NBlack_PCT							-0.00025	-0.00033
							(0.00029)	(0.00037)
Num.Obs.	4629	4629	3313	4629	4629	3313	1034	690
R2	0.558	0.559	0.559	0.575	0.575	0.580	0.489	0.451
R2 Adj.	0.553	0.554	0.552	0.569	0.569	0.573	0.462	0.412
R2 Within	0.025	0.027	0.024	0.062	0.062	0.071	0.031	0.049
R2 Pseudo								
AIC	-8361.3	-8366.9	-5718.8	-8530.5	-8527.1	-5874.6	-2071.1	-1301.3
BIC	-7994.2	-7993.4	-5370.7	-8137.7	-8114.9	-5508.2	-1804.3	-1092.6
Log.Lik.	4237.645	4241.444	2916.376	4326.256	4327.547	2997.288	1089.560	696.643
FE: STCO	X	X	X	X	X	X	X	X
Std. errors	Clustered (STCO)	Clustered (STCO)	Clustered (STCO)	Clustered (STCO)	Clustered (STCO)	Clustered (STCO)	Clustered (STCO)	Clustered (STCO)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Robust SE clustered by FIPS county

Results Columns 1, 2, 3, and 5 show results using all blockgroups with greater than 80% of total area contained within one HOLC grade. Columns 4, 6, and 8 set the threshold at 95%. Column 1 allows an additive effect for median income in 2018 and 1936 (reported from HOLC surveys), while 2-6 allow an interaction.

As expected, current median blockgroup income predicts a lower share of homes with substandard heating fuel across all models. Median income in 1936 predicts **higher** prevalance of substandard heating in higher 1936 median income areas. Can I explain this?

Columns 4-7 include controls for current racial composition. These results consistently find that higher percentages of Blacks are associated with lower likelihood of substandard heating fuel. **EXPLAIN!!**

The coefficient on HOLC Grade D is positive and significant across all specifications, indicating that, conditional on a rich set of controls including 1936 characteristics to control for selection, areas that were graded "D" by the HOLC are more likely to have substandard heating fuels in 2018 relative to those graded "C".

Results using Zip Code Tabulation Area (ZCTA)

Zipcode Tabulation Areas are coarser than census blockgroups. Due to this, there are fewer ZCTAs that fall predominantly in one HOLC grade, resulting in a smaller sample size. Of the 2,842 zip codes that touch on one or more HOLC neighborhoods, 45 zip codes have greater than 80% within one HOLC grade. Of these, 19 are Grade D (red). Of these, only 2 zip code(s) have HOLC survey data including median income, presence of minorities, and rent data for 1936-38. This precludes the use of zip code aggregations to estimate HOLC grading on current substandard heating fuel.

Household-level energy

Aggregation can mask important heterogeneity in household energy consumption. We use household-level monthly consumption data geolocated to the zip-code level to identify HOLC-zone specific energy consumption responses to cooling and heating events.

Household energy consumption data is retrieved from the California Residential Appliance Saturation Survey (RASS) for 2009 and (hopefully) 2019. The RASS is commissioned by the California Public Utilities Commission and implemented by DNV GL Energy Insights. The survey contains information on household energy consumption including home age, primary heating fuel source, and thermostat setpoint. The survey also includes the household's zip code, household characteristics including income and number of children, and merges two years of billing information obtained direclty from the gas and electric utilities serving the household. The survey sample consists of 25721 households sampled from all over California.

We are interested in household's energy consumption response to increases in heating degree days. We focus on households that rely primarily on electric heating. For each household, we estimate a consumption response function that summarizes the household's change in electricity consumption per change in monthly heating degree days. This measure will be larger if a household consumes more energy when temperatures are lower, and smaller if a household consumes less energy when temperatures drop. I allow this response to vary bsed on the HOLC grade that covers the plurality of the zip code in which the household lies. I use only those zip codes in which greater than 80% of the zip code is within one specific HOLC grade.

A priori, it is not clear whether the interaction of heating degree days and HOLC-designated redlining should be positive or negative. If a household prefers to remain warm and comfortable on a cold night, then expenditures will be higher when temperatures are lower. Similarly, if a household in a redlined area maintains the same indoor temperature setpoint but has a home with lower energy ratings or is otherwise less efficient, then energy expenditures will be greater as well. If expenditures are not greater, then it may be that the household trades off comfort by lowering the indoor temperature in order to keep expenditures low, or it may be that the home is very efficient, and more energy is not needed to maintain a constant temperature. This ambiguity confounds interpretation of estimates.

Table (below) reports the results from a regression of the form:

$$hdd_h^e = \beta_0 + \sum 1(grade_h = g)\beta_g + \beta_{inc} avgincome_h + cdd_h^e + \gamma^{CZ} + \varepsilon$$

Where hdd^e is the electricity consumption response to one additional heating degree day for household h located in HOLC grade g. cdd^e is the household's electricity consumption response to an additional cooling degree day. Table (below that) shows results for hdd^g. γ^{CZ} are climate-zone fixed effects.

	Model 1	Model 2
as.factor(GRADE.max)D	0.290***	-0.057
	(0.049)	(0.042)
as.factor(GRADE.max)X	0.227***	0.240***
	(0.029)	(0.040)
avginc	0.000	0.000
	(0.000)	(0.000)
cdd.e		0.002
		(0.003)
Num.Obs.	14822	9220
R2	0.107	0.109
R2 Adj.	0.107	0.108
R2 Within	0.004	0.007
R2 Pseudo		
AIC	13135.9	7592.6
BIC	13227.2	7685.3
Log.Lik.	-6555.968	-3783.290
FE: CZT24	X	X
Std. errors	Clustered (CZT24)	Clustered (CZT24)

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

	Model 1	Model 2
as.factor(GRADE.max)D	-4.591***	-3.988***
	(1.194)	(0.740)
avginc	0.000	0.000
	(0.000)	(0.000)
cdd.e		0.720***
		(0.176)
Num.Obs.	988	988
R2	0.206	0.268
R2 Adj.	0.198	0.260
R2 Within	0.068	0.141
R2 Pseudo		
AIC	7034.5	6956.2
BIC	7088.3	7015.0
Log.Lik.	-3506.238	-3466.109
FE: CZT24	X	X
Std. errors	Clustered (CZT24)	Clustered (CZT24)

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

Coefficient results in Model (1) indicate that households located inside the HOLC red (D) areas have significantly higher gas responses, but significantly lower electricity responses. In each case, only households that report primary heating fuel of gas (first table) and electricity (second table) are included. The ambiguity in effect is clear in examining Table 2, which shows a significantly *lower* effect within the HOLC red (D) areas.

To address this confounding, I leverage the household's response to the question on thermostat setpoint. Conditioning on a specific overnight or daytime thermostat setting forecloses the possibility that households adjust thermostat setting since the adjustment is answered in the question. Household consumption response functions for those that save on heating by setting the thermostat setpoint very low are identified by variation conditional on their setpoint. By allowing each setpoint bin (<55, 55-60, 60-65, 65-70, 70-75, 75+) to have a separate estimate of response to heating degree days, I capture the effect of heating degree days separate from thermostat setpoint adjustments. Once properly conditioned, the difference between HOLC red and HOLC yellow housing can be estimated.

$$usage_h^g = \beta_0 + \beta_1 hdd_h + \beta_2 hdd_h * (grade_h = D) + \beta_3 averageincome_h * hdd_h + \beta_4 cdd_h^e * hdd_h + \sum_{s=1}^{S} hdd_h * \theta^s + \kappa_h + \varepsilon$$

Where $usage_h^g$ is the monthly observed gas usage, hdd_h is the household's monthly heating degree days, $s \in S$ are the temperature setpoint bins, and κ_h is a vector of household fixed effects.

```
# What if we pool all of the monthly bill observations? Turns out, there are very few (if any) NG-using
all09.use.pooled = all09.use %>% unnest(edata) %>% dplyr::filter(share.max > .90 & cdd<=0 & (PHTELCRH==
  dplyr::mutate(NITESET = relevel(NITESET, ref = '>75'),
                DAYSET = relevel(DAYSET, ref = '>75'),
                ethnicity = relevel(ethnicity, ref = 'White'),
                avginc1000 = avginc/1000)

modelsummary(list(
  feols(u ~ hdd + hdd:GRADE.max + hdd:avginc | IDENT, weights=~d, data = all09.use.pooled, warn = F), #
  feols(u ~ hdd + hdd:GRADE.max + hdd:avginc + hdd:cdd.e | IDENT, weights=~d, data = all09.use.pooled, w
  feols(u ~ hdd + hdd:NITESET + hdd:GRADE.max + hdd:avginc + hdd:cdd.e | IDENT, weights=~d, data = all09
  feols(u ~ hdd + hdd:DAYSET + hdd:GRADE.max + hdd:avginc + hdd:cdd.e | IDENT, weights=~d, data = all09
  stars = T)
```

	Model 1	Model 2	Model 3	Model 4
hdd	1.083***	1.068***	2.700***	2.644***
	(0.264)	(0.278)	(0.205)	(0.201)
hdd × GRADE.maxD	3.729***	3.821***	2.917***	3.445***
	(0.407)	(0.407)	(0.728)	(0.614)
hdd × avginc	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
hdd × cdd.e		-0.049	-0.058*	-0.078*
		(0.036)	(0.031)	(0.044)
hdd × NITESETOff			-1.348***	
			(0.454)	
hdd × NITESET55-60			-1.418*	
			(0.769)	
hdd × NITESET60-65			-2.664***	
			(0.693)	
hdd × NITESET65-70			-0.604	
			(0.536)	
hdd × NITESET70-75			-1.793***	
			(0.539)	
hdd × NITESETUnk			-1.921***	
			(0.163)	
hdd × DAYSETOff				-1.038**
				(0.508)
hdd × DAYSET55-60				-2.035***
				(0.404)
hdd × DAYSET60-65				-2.614***
				(0.891)
hdd × DAYSET65-70				-1.333**
				(0.573)
hdd × DAYSET70-75				-1.421**
				(0.599)
hdd × DAYSETUnk				-1.978***
				(0.204)
Num.Obs.	1150	476	476	476
R2	0.846	0.902	0.907	0.906
R2 Adj.	0.824	0.877	0.881	0.880
R2 Within	0.089	0.250	0.285	0.280
R2 Pseudo				
AIC	15451.3	6323.9	6312.9	6316.5
BIC	16163.0	6732.1	6746.1	6749.7
Log.Lik.	-7584.656	-3063.967	-3052.463	-3054.233
FE: IDENT	X	X	X	X
Std. errors	Clustered (IDENT)	Clustered (IDENT)	Clustered (IDENT)	Clustered (IDENT)

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

Results have the expected sign - an increase in the heating degree days leads to an increase in gas consumption across each of the specifications. Households located inside a HOLC red (D) area show around two to three times the consumption per hdd relative to the omitteed category, Grade C. Unfortunately, too few households lie in HOLC areas with reported covariates necessary to control for unobservables that may have effected the treatment (assignment to HOLC red) and the current outcome (home efficiency / gas consumption per hdd). Column (3) and (4) control for the reported nighttime and daytime temperature setpoints. In both 3 and 4, the main effect remains (and increases in magnitude) - conditional on a target setpoint, an increase in *hdd* leads to an increase in usage. Although insignificant, the interaction for the two lowest bins, 55-60 and 60-65, is negative, indicating that an increase in *hdd* for households with very low overnight setpoints leads to smaller increases in gas consumption relative to the omitted category, which is "off/other". As expected, households with very high overnight setpoints (>75) have very high consumption responses to *hdd*.

Notably, households within the HOLC red (D) area continue to exhibit two to three times the consumption response relative to households in the omitted category, even accounting for potentially heterogeneous preferences for overnight temperature setpoints. This indicates that households in HOLC red areas are not simply consuming more energy or exhibiting greater preference for overnight comfort, but rather face higher expenditures simply to maintain one constant temperature. #### Household level energy by ethnicity This section examines the coefficient of response across ethnicity, as well as HOLC grade and thermostat set points.

	Model 1	Model 2	Model 3	Mode
hdd	1.601***	1.188***	1.585***	1.478
	(0.402)	(0.309)	(0.347)	(0.46
hdd × GRADE.maxD	1.764**	1.120	1.770**	1.35
	(0.733)	(1.016)	(0.807)	(1.74
hdd × ethnicityAsian and Pacific Islander	-0.674*	-0.467	-0.948*	-0.78
	(0.370)	(0.311)	(0.491)	(0.76
hdd × ethnicityBlack	-0.869**	-0.460*	-0.982**	-0.70
	(0.405)	(0.270)	(0.387)	(0.47
hdd × ethnicityHispanic	-0.093	0.211	-0.392	-0.43
	(0.546)	(0.511)	(0.583)	(0.94
hdd × ethnicityOther	2.066***	1.905***	1.755**	1.89
	(0.697)	(0.719)	(0.862)	(1.61
hdd × ethnicityMixed	2.119***	2.666***	1.848***	2.97
	(0.383)	(0.662)	(0.566)	(2.16
hdd × avginc1000	-0.002	-0.001	-0.001	-0.00
	(0.003)	(0.003)	(0.003)	(0.00
hdd × NITESETOff		0.563		4.544
		(0.465)		(1.73
hdd × NITESET55-60		0.256		1.25
		(0.757)		(1.70
hdd × NITESET60-65		-0.978		1.79
		(0.742)		(1.72
hdd × NITESET65-70		1.182**		2.47
		(0.587)		(1.91
hdd × NITESET70-75		-0.160		2.68
		(0.497)		(2.41
hdd × DAYSETOff			0.722	-2.29
			(0.533)	(1.53
hdd × DAYSET55-60			-0.697	-2.65
			(0.524)	(2.39
hdd × DAYSET60-65			-1.239	-4.875
			(1.044)	(1.80
hdd × DAYSET65-70			0.199	-2.31
			(0.675)	(1.48
hdd × DAYSET70-75			0.248	-3.26
			(0.575)	(2.61
Num.Obs.	1086	1086	1086	108
R2	0.846	0.848	0.848	0.83
R2 Adj.	0.824	0.825	0.825	0.81
R2 Within	0.095	0.104	0.107	0.04
R2 Pseudo				
AIC	14625.9	14624.4	14621.6	1470
BIC	15314.6	15338.0	15335.2	1544
Log.Lik.	-7174.967	-7169.180	-7167.811	-7205.
FE: IDENT	X	X	X	X
Std. errors	Clustered (IDENT)	Clustered (IDENT)	Clustered (IDENT)	Clustered (

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

Results surprisingly show that Black households with natural gas as a primary heating fuel have lower responses to increases in heating degree days relative to White households. A similar effect holds for Hispanic households, though in no specifications are the results statistically significant for Hispanic households.

Conditioning on separate effects for nighttime and daytime thermostat setpoints reduces the magnitude of the coefficient of response for households in HOLC grade red (D), but the point estimate is still positive.

	Model 1	Model 2	Model 3	Mode
hdd	0.326***	0.307***	0.331***	0.308
	(0.082)	(0.088)	(0.090)	(0.08
hdd × GRADE.maxX	-0.093	-0.110	-0.122*	-0.11
	(0.072)	(0.073)	(0.071)	(0.07
hdd × ethnicityNative American	-0.037	-0.077	-0.024	-0.05
	(0.053)	(0.074)	(0.054)	(0.06
hdd × ethnicityAsian and Pacific Islander	-0.077***	-0.066***	-0.061**	-0.054
	(0.029)	(0.025)	(0.027)	(0.02
hdd × ethnicityBlack	-0.069*	-0.056	-0.054	-0.03
	(0.038)	(0.034)	(0.033)	(0.03
hdd × ethnicityHispanic	-0.080***	-0.063***	-0.057**	-0.050
	(0.028)	(0.022)	(0.026)	(0.02
hdd × ethnicityOther	0.073	0.069	0.052	0.04
	(0.056)	(0.048)	(0.063)	(0.05
hdd × ethnicityMixed	-0.083**	-0.086*	-0.061*	-0.05
	(0.039)	(0.052)	(0.033)	(0.03
hdd × avginc1000	0.000	0.000	0.000	0.00
	(0.000)	(0.000)	(0.000)	(0.00
hdd × NITESETOff		0.021		0.04
		(0.035)		(0.04
hdd × NITESET<55		0.007		0.06
		(0.053)		(0.07
hdd × NITESET55-60		0.112		0.14
		(0.090)		(0.11
hdd × NITESET60-65		0.043		0.05
		(0.037)		(0.05
hdd × NITESET65-70		0.052		0.04
		(0.039)		(0.04
hdd × NITESET70-75		0.028		0.03
		(0.039)		(0.05
hdd × NITESETUnk		-0.023		-0.02
		(0.047)		(0.05
hdd × DAYSETOff			-0.014	-0.03
			(0.039)	(0.04
hdd × DAYSET<55			-0.063	-0.13
			(0.061)	(0.07
hdd × DAYSET55-60			0.013	-0.06
			(0.045)	(0.07
hdd × DAYSET60-65			0.017	-0.03
			(0.039)	(0.05
hdd × DAYSET65-70			0.069	0.03
			(0.055)	(0.05
hdd × DAYSET70-75			0.050	0.02
			(0.041)	(0.04
hdd × DAYSETUnk			-0.046	
			(0.051)	
Num.Obs.	3564	3564	3564	356
R2	0.954	0.954	0.954	0.95
R2 Adj.	0.944	0.944	0.944	0.94
R2 Within	0.143	0.146	0.147	0.15
R2 Pseudo				
AIC	38783.9	38786.0	38781.6	38782
BIC	42806.2	42851.6	42847.2	4288
Log.Lik.	-18740.952	-18735.022	-18732.813	-18727
FE: IDENT	X	X	X	X
Std. errors	Clustered (IDENT)	Clustered (IDENT)	Clustered (IDENT)	Clustered (

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

Here, an insufficient number of gas households in HOLC grade D (red) areas precludes us from seeing the effect of HOLC red on response to heating degree days. Results focused on ethnicity show that Hispanic households are less responsive to heating degree days conditional on daytime and nighttime thermostat setpoints. A similar result for Black households is not significant. Table blah blah blah # End

```
##################
##################
##################
```