Housing Market Institutions Drive Race and Ethnicity Differences in Energy Consumption

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March 27, 2015

Abstract

When socio-demographic factors are considered in any kind of analysis of household electric and gas utility data, it is common to observe differences in energy use between households with different self-reported race and ethnicity compositions. These differences persist controlling for structure type, e.g., single family dwelling, age and size of housing units, and, other common control variables. Without the information necessary to better explain these differences, they are commonly summarized simply as cultural differences. This paper demonstrates that these differences can be partially explained by differential sorting by structure and ownership, i.e., endogenizing housing choice and rental decisions. We will show that these differences in energy consumption may be because of housing market institutions and restrictions.

1 Introduction

*******Observed differences evident between different households can at least be partially explained by race and ethnicity composition. That is, there
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- Differences in energy use by race and ethnicity is frequently reported in the literature
- Much of the difference has to do with differences in income levels and education but not frequently modeled correctly.
- Even with proper race and ethnicity controls with income, some patterns persist.
- We assert that these differences are caused, at least in part, by housing discrimination, forcing people into housing types different than what they would prefer without discrimination; and renting rather than buying.

- We show this with a model that endogenizes structure type and tenure decision.
- emphasize that this is early work.

1.1 Race and Ethnicity in Conditional Demand

1.2 How Race and Ethnicity are Interpreted

2 RECS

RECS data set is the 2009 publication. 12083 observations are included in the data, of which 11395 are included in the struture-tenure model.

- Description on RECS data size number of observations sampling method etc.
- Scope of data
- Weighting to account for stratified sampling
- We need more tables and graphics here.

	Mobile	SFDetached	SFAttached	SmApartment	LgApartment
FALSEWt	371	5694	544	430	951
FALSEAfAm	24	754	121	174	382
FALSEAsian	1	231	48	52	113
FALSEMulti	6	87	14	12	27
FALSENativeAm	7	35	9	7	15
FALSEOther	2	59	8	13	29
FALSEPacific	1	22	1	2	10
TRUEAfAm	3	8	10	5	8
TRUEAsian	0	5	0	0	1
TRUEMulti	1	10	2	4	4
TRUENativeAm	2	17	3	6	9
TRUEOther	6	41	12	16	24
TRUEPacific	0	2	1	1	0
TRUEWt	97	730	105	184	332

Table 1: Count of Observations by Race and Structure Type

2.1 Race and Ethnicity Differences in Equipment and Structure

- differences in structure type x
- difference in tenure x

Figure 1: Annual kWh by Rent/Own and Race

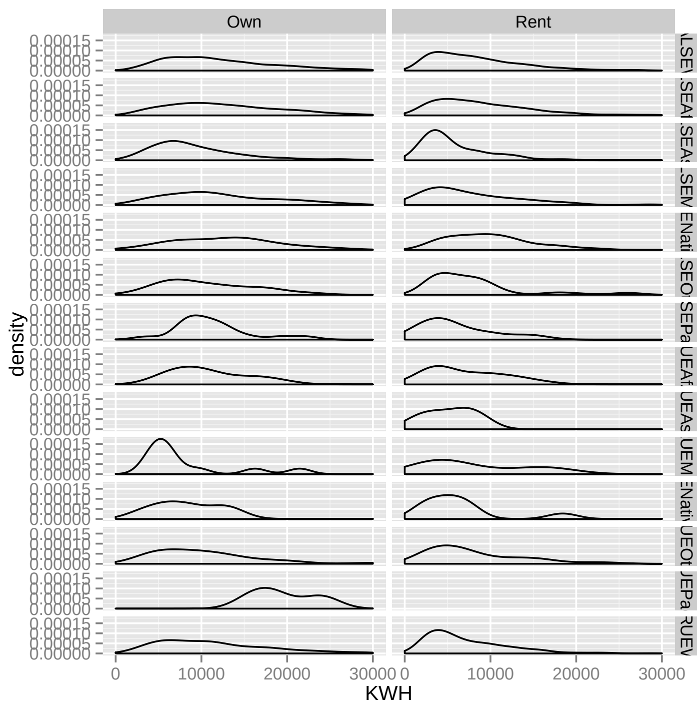
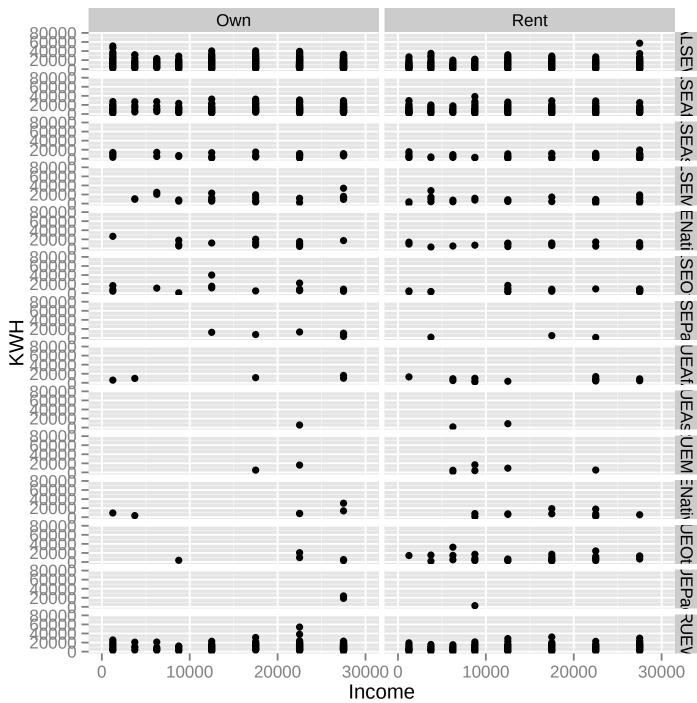
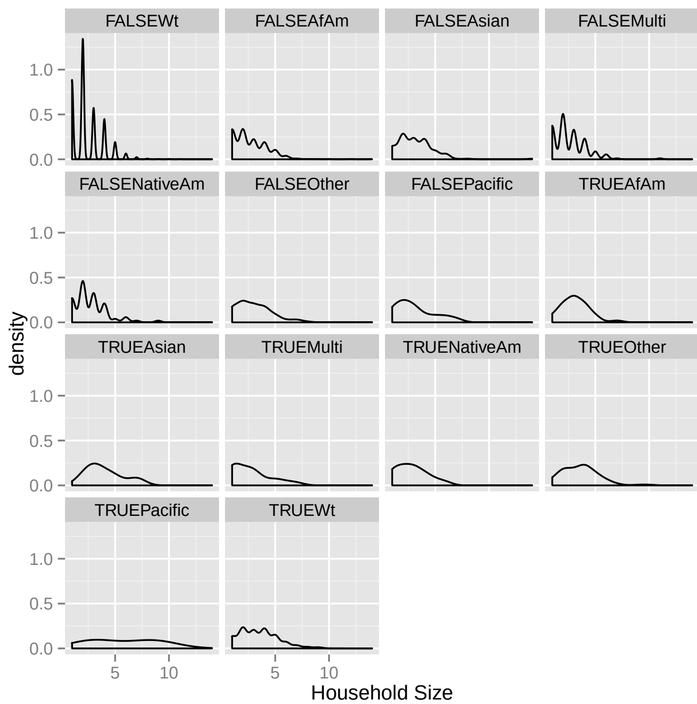


Figure 2: Annual kWh by Income




FALSEWt
FALSEAfAm
FALSEAsian
FALSEMulti
FALSENativeAm
FALSEOther
FALSEPacific
TRUEAfAm
TRUEAsian
TRUEMulti
TRUENativeAm
TRUEOther
TRUEPacific
TRUEWt
density
1.0
0.5
0.0
5
10
Household Size

	Mobile	SFDetached	SFAttached	SmApartment	LgApartment
NE	47	1173	218	326	470
MidWest	92	2080	162	145	323
South	245	2685	257	226	603
West	137	1757	241	209	509

Table 2: Count of Observations by Region and Structure Type

- differences in energy star controlling for own rent
- general differences in own vs rent.
- explain with split incentives story
- difference in age of structure x
- differences in hot water fuel x
- difference in heating fuel x
- difference in climate/location x

	FALSE	TRUE
FALSEWt	7606	384
FALSEAfAm	1367	88
FALSEAsian	424	21
FALSEMulti	133	13
FALSENativeAm	68	5
FALSEOther	102	9
FALSEPacific	30	6
TRUEAfAm	31	3
TRUEAsian	4	2
TRUEMulti	19	2
TRUENativeAm	36	1
TRUEOther	88	11
TRUEPacific	4	0
TRUEWt	1330	118

Table 3: EnergyStar Wall AC by Race and Ethnicity

2.2 Differences in Reported Behavior

- Differences in thermostat settings
- difference in cooking behavior x
- difference in reported AC use

Figure 3: Age of Structure by Rent/Own and Race/Ethnicity

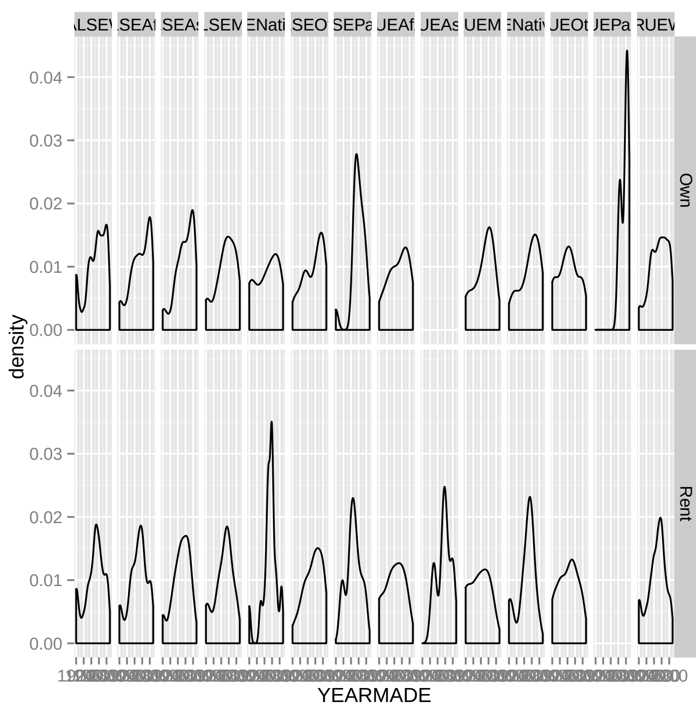


Figure 4: Daytime Temp and Race/Ethnicity (Winter)

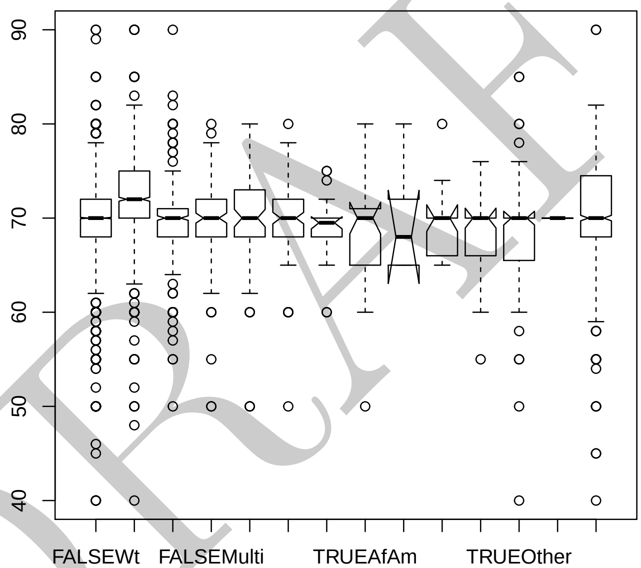


Figure 5: Daytime Temp When Away and Race/Ethnicity (Winter)

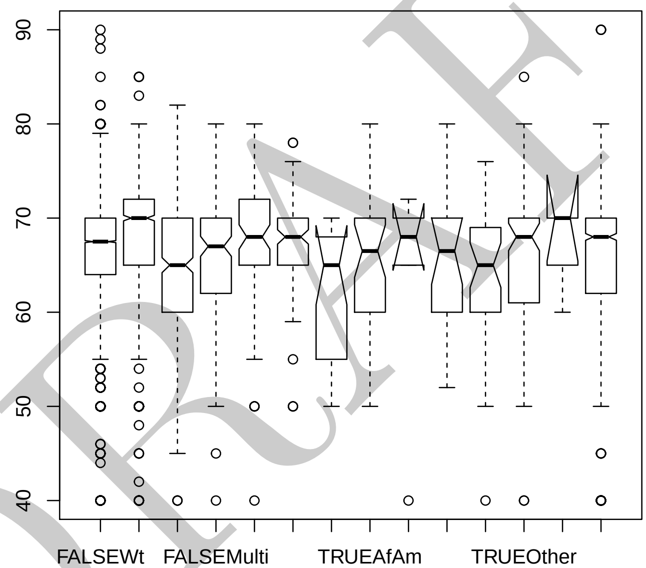


Figure 6: Nighttime Temp and Race/Ethnicity (Winter)

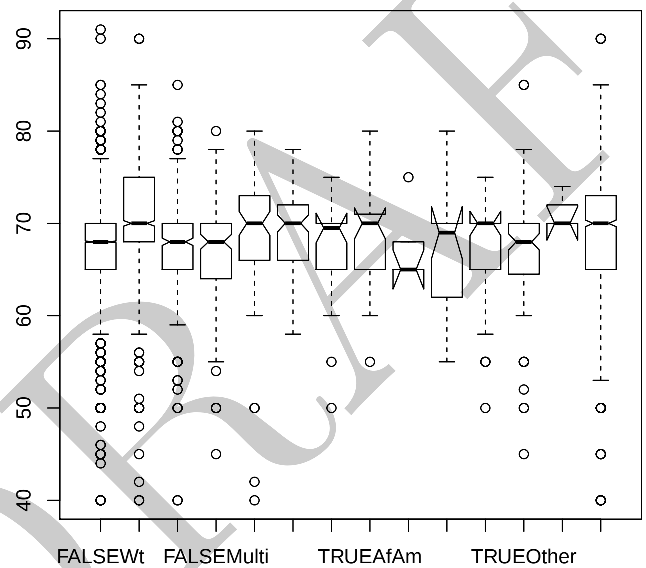


Figure 7: Daytime Temp Home by Race/Ethnicity (Summer)

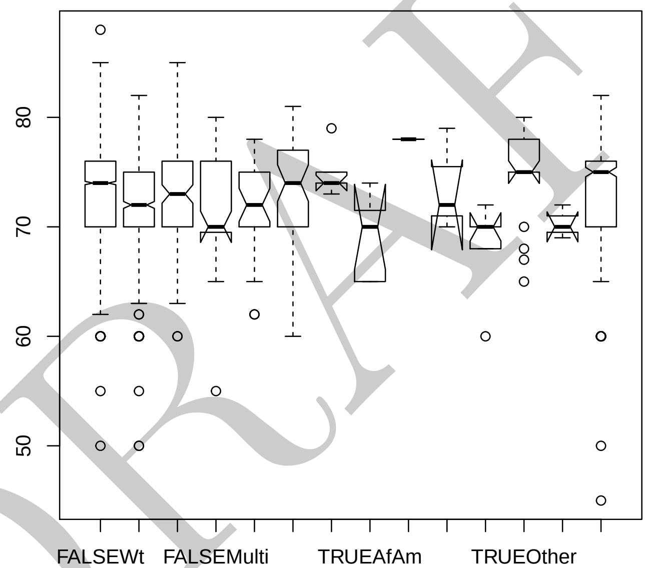


Figure 8: Day Temp Away by Race/Ethnicity (Summer)

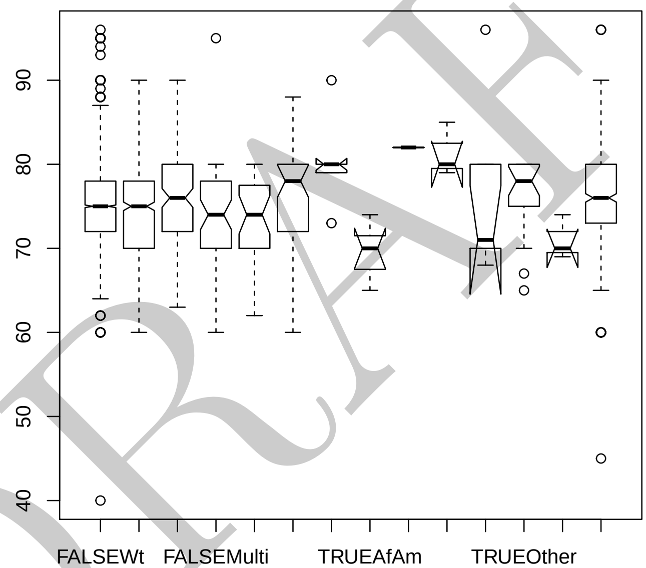
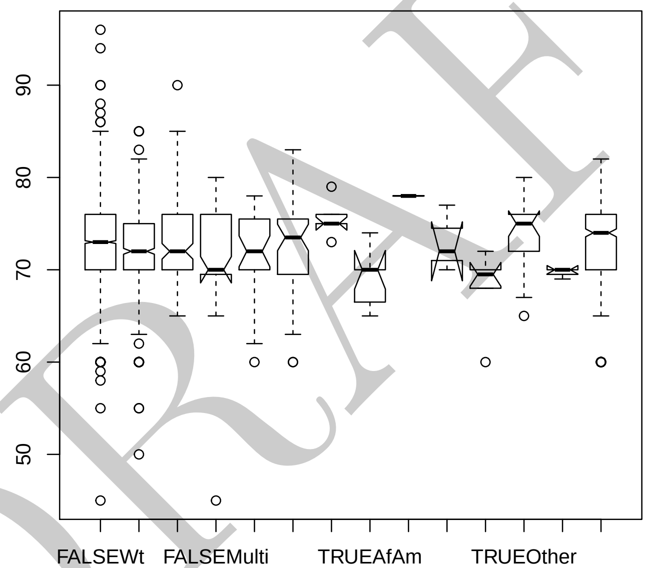


Figure 9: Nighttime Temp and Race/Ethnicity (Summer)



	Rural	Urban
FALSEWt	1937	6053
FALSEAfAm	192	1263
FALSEAsian	14	431
FALSEMulti	28	118
FALSENativeAm	25	48
FALSEOther	12	99
FALSEPacific	4	32
TRUEAfAm	6	28
TRUEAsian	0	6
TRUEMulti	1	20
TRUENativeAm	3	34
TRUEOther	5	94
TRUEPacific	2	2
TRUEWt	137	1311

Table 4: Race by Urban/Rural

2.3 HUD Complaints as a Measure of Discrimination

- trouble finding a good statewide index of housing discrimination
- the HUD complaint measure
- may be endogenous and be indicative of reduced discrimination

3 Conditional Demand Estimation

3.1 Orthodox Results

- Emphasize that we are making better use of race and ethnicity as a control with income than is common.
- We are not using the same estimation method as in RECS estimates of end use. Our model is much simpler and does not use engineering estimates or significant non-linearity.
- Major end-uses are included but relatively unsophisticated.
- discuss the orthodox results.

Modern conditional demand models of the kind commonly created as part of the process of data collection of large residential appliance and use surveys such as RECS, include a mix of engineering estimates, survey responses and analyst best estimates to produce energy end-use estimates. For example, survey respondents will give an age range on the furnace they have installed, the square footage of the residence, and some indication of heating set points. The

	NG	LPG	Oil	Kerosene	Elec	Wood	Solar	Other
FALSEWt	4077	315	361	3	3190	11	12	7
FALSEAfAm	755	17	35	0	640	0	2	0
FALSEAsian	312	7	12	0	109	0	0	2
FALSEMulti	85	5	3	0	53	0	0	0
FALSENativeAm	34	2	1	0	36	0	0	0
FALSEOther	57	3	6	0	44	0	0	0
FALSEPacific	15	0	2	0	17	0	2	0
TRUEAfAm	20	0	1	0	13	0	0	0
TRUEAsian	5	0	0	0	1	0	0	0
TRUEMulti	12	0	1	0	8	0	0	0
TRUENativeAm	29	0	0	0	8	0	0	0
TRUEOther	62	1	5	0	30	0	0	0
TRUEPacific	1	1	0	0	2	0	0	0
TRUEWt	830	33	26	0	552	0	1	0

Table 5: Water Service by Race and Ethnicity

analyst will assign a likely efficiency for the furnace based on the average of the age ranges and then estimate hours used based on set points, weather, and the reported thermostat settings. This produces estimates that are closer to a Statistically Adjusted Engineering (SAE) model than what is normally regarded as a conditional demand model outside of the energy community.

Our model is based more on the traditional conditional demand models, and includes terms for electricity use contingent on: the age of the home, which is a proxy for building code requirements and insulation; the weather, in the form of Heating and Cooling degree days with a base temperature of 65F; Meals cooked at home, to indicate energy use related to food preparation; the number and age of refrigerators, a major end-use; the number of and types of TVs and computers, as a proxy for major plug loads; the existence of a well pump; weather the residence has electric hot water service; the existence of pools and hot tubs as well as if they are electrically heated; the kind of windows installed, as another indication of shell quality; the number of people in the home; and finally the income, race and ethnicity of the residents.

The parameter estimates of the full model can be found in appendix , partial results are shown in table .

	Estimate	Std. Error	t value	Pr(>|t|)
Income	0.01	0.00	5.37	0.00
Income:EthRaceFALSEAfAm	0.00	0.00	1.14	0.25
Income:EthRaceFALSEAsian	-0.02	0.00	-7.16	0.00
Income:EthRaceFALSEMulti	-0.02	0.01	-2.43	0.02
Income:EthRaceFALSENativeAm	0.01	0.01	0.95	0.34
Income:EthRaceFALSEOther	-0.02	0.01	-2.99	0.00
Income:EthRaceFALSEPacific	-0.02	0.01	-1.18	0.24
Income:EthRaceTRUEAfAm	-0.01	0.02	-0.73	0.47

Income:EthRaceTRUEAsian	-0.04	0.05	-0.80	0.42
Income:EthRaceTRUEMulti	-0.03	0.02	-1.37	0.17
Income:EthRaceTRUENativeAm	-0.02	0.01	-1.26	0.21
Income:EthRaceTRUEOther	-0.03	0.01	-2.63	0.01
Income:EthRaceTRUEPacific	-0.01	0.04	-0.32	0.75
Income:EthRaceTRUEWt	-0.02	0.00	-6.29	0.00
StrTenureOwnSFDetached:TOTSQFT_EN:HDD65	0.00	0.00	4.10	0.00
StrTenureOwnLgApartment:TOTSQFT_EN:HDD65	-0.00	0.00	-0.96	0.34
StrTenureOwnMobile:TOTSQFT_EN:HDD65	0.00	0.00	5.98	0.00
StrTenureOwnSFAttached:TOTSQFT_EN:HDD65	-0.00	0.00	-0.55	0.58
StrTenureOwnSmApartment:TOTSQFT_EN:HDD65	0.00	0.00	0.54	0.59
StrTenureRentLgApartment:TOTSQFT_EN:HDD65	-0.00	0.00	-4.00	0.00
StrTenureRentMobile:TOTSQFT_EN:HDD65	0.00	0.00	1.76	0.08
StrTenureRentSFAttached:TOTSQFT_EN:HDD65	0.00	0.00	0.60	0.55
StrTenureRentSFDetached:TOTSQFT_EN:HDD65	0.00	0.00	0.55	0.58
StrTenureRentSmApartment:TOTSQFT_EN:HDD65	-0.00	0.00	-1.86	0.06
StrTenureOwnSFDetached:TOTSQFT_EN:CDD65	0.00	0.00	19.21	0.00
StrTenureOwnLgApartment:TOTSQFT_EN:CDD65	-0.00	0.00	-0.82	0.41
StrTenureOwnMobile:TOTSQFT_EN:CDD65	0.00	0.00	7.32	0.00
StrTenureOwnSFAttached:TOTSQFT_EN:CDD65	0.00	0.00	5.01	0.00
StrTenureOwnSmApartment:TOTSQFT_EN:CDD65	0.00	0.00	0.40	0.69
StrTenureRentLgApartment:TOTSQFT_EN:CDD65	0.00	0.00	0.39	0.69
StrTenureRentMobile:TOTSQFT_EN:CDD65	0.00	0.00	6.32	0.00
StrTenureRentSFAttached:TOTSQFT_EN:CDD65	0.00	0.00	4.02	0.00
StrTenureRentSFDetached:TOTSQFT_EN:CDD65	0.00	0.00	9.27	0.00
StrTenureRentSmApartment:TOTSQFT_EN:CDD65	0.00	0.00	2.84	0.00

Table 10: Orthodox kWh Model

The top parameter, Income, shows the estimate for annual kWh per dollar of income for a household headed by a non-Hispanic Caucasian. The remaining income related variables show the deviations from this case for Hispanic headed households, labeled TRUE in the table, and by the other self reported races. Note that in all cases, with the exception of non-Hispanic Native Americans, the parameter estimates show less electricity used than non-Hispanic Caucasian households. Only a few of these differences are statistically significant, non-Hispanic Asian and multi-ethnic households, as well as Hispanic Caucasian households and households that reported some other race.

The remaining items shown in the table show the electricity use per square foot for each of the structure types, e.g., Single Family Detached, and tenure, i.e., Rent or Own, per annual heating and cooling degree days. Aside from the negative and significant estimate for the heating load in large Rented apartments, the results are unremarkable.

	NG	LPG	Oil	Kerosene	Elec	Wood	Solar	District	Other
FALSEWt	3987	400	642	40	2515	245	1	11	19
FALSEAfAm	674	29	60	6	640	10	0	5	0
FALSEAsian	249	1	21	0	122	1	0	2	0
FALSEMulti	80	6	7	0	41	7	0	0	1
FALSENativeAm	34	3	1	0	33	2	0	0	0
FALSEOther	59	1	9	0	36	3	0	0	0
FALSEPacific	16	0	2	0	5	1	0	0	0
TRUEAfAm	21	0	1	1	9	0	0	0	0
TRUEAsian	4	0	0	0	1	0	0	0	0
TRUEMulti	11	0	4	0	4	1	0	0	0
TRUENativeAm	26	1	2	0	7	0	0	0	0
TRUEOther	53	0	8	1	32	0	0	2	0
TRUEPacific	1	0	0	0	2	0	0	0	0
TRUEWt	604	25	51	2	540	18	0	3	1

Table 6: Heating Fuel by Race and Ethnicity

3.2 Endogenizing Structure and Other Variables

Treating structure type and square footage as endogenous is our first step in estimating conditional demand for many end uses treating the choice of things like, EnergyStar appliances, refrigerator size and design. The current standard, treating these as exogenous drivers of energy use biases or estimates of energy use in unknown ways.

Focusing on tenure, i.e., the decision to own or rent, structure and square footage decisions allows us to see if other housing market institutions are driving energy use differently depending on ethnicity. At this early stage of research we are focusing only on these major drivers but we can expand the analysis to other choices including clothes washing, hot water service and other large energy drivers.

As stated in section 2.3, using HUD complaints as a measure of housing market discrimination based on race and ethnicity is less than optimal measure, but at this early stage is an adequate measure to determine the scale of the effect.

Table shows only the discrimination related results for our model of square footage. Full results can be seen in appendix . Note that the square footage model includes structure type and tenure as an exogenous variable. This model of square footage will be included later as part of a system estimation of electricity use.

The key discrimination variable, reporttot, is the count of complaints received by HUD per 100,000 people in the state where the household is located. We interacted this variable with race and ethnicity to allow for different effects groups but we do not allow the discrimination to vary by state. Note that the effects of HUD reports on square footage are rarely significant, only strongly significant for Hispanic Caucasian households. In this case incidences of HUD

	VColdCold	HotDryMixedDry	HotHumid	MixedHumid	Marine
FALSEWt	3118	850	1216	2382	424
FALSEAfAm	299	131	383	611	31
FALSEAsian	95	128	60	77	85
FALSEMulti	51	27	13	40	15
FALSENativeAm	23	10	7	28	5
FALSEOther	29	16	24	37	5
FALSEPacific	4	6	13	4	9
TRUEAfAm	16	5	4	9	0
TRUEAsian	2	2	1	0	1
TRUEMulti	12	6	1	0	2
TRUENativeAm	9	14	1	8	5
TRUEOther	35	19	10	28	7
TRUEPacific	2	0	2	0	0
TRUEWt	237	481	406	237	87

Table 7: Climate by Race and Ethnicity

complaints per 100,000 of state population results in a reduction in the square footage for Caucasian Hispanics by 22.73 square feet.

While the impact of housing market discrimination has some effect on the size of residences, the effects on the ownership and structure type decision is expected to be more dramatic. Housing market discrimination can be expected to push some people away from owned property and into the rental market, which is rife with split incentives for conservation and energy efficiency investments.

Discrimination can also be a force pushing some households into structure types, where even when owned, that have significant split incentives for energy efficiency investments. Take, for example, small and large apartment buildings. While the householder may have control over some appliances, the building shell and some of the heating and cooling equipment decisions are made by others.

Our model of structure type and tenure includes categories for both owned and rented: Large Apartments, Small Apartments, Mobile Homes, Single Family Detached, and Single Family Attached. We explain the joint tenure and structure type with: the square footage of the structure, if the household receives rental assistance, Income, number of people in the household, education level of the head of household, the HUD reports per 100,000 in that state and whether the household is in a rural or urban location. As in the square footage model, HUD reports are interacted with the race and ethnicity variables to allow for separate discrimination effects for each.

All parameter estimates for the models are statistically significant at the 1% level and are displayed in appendix

Since all the parameters are statistically significant it is easier to show the effects of our measure of housing market discrimination on the probability of each structure and tenure choice for the race and ethnicity combinations. The HUD reports run from 1.81249 complaints per 100,000 to 20.496 complaints

	Never	ThreeDay	TwoDay	OneDay	FewWeek	OneWeek	LessWeek
FALSEWt	67	452	1814	3303	1825	254	275
FALSEAfAm	11	156	351	341	448	80	68
FALSEAsian	4	63	111	148	91	13	15
FALSEMulti	2	14	45	40	36	7	2
FALSENativeAm	0	7	22	27	11	3	3
FALSEOther	2	10	25	21	43	3	7
FALSEPacific	0	3	9	10	11	0	3
TRUEAfAm	1	4	7	13	9	0	0
TRUEAsian	0	0	1	3	2	0	0
TRUEMulti	0	2	1	11	5	2	0
TRUENativeAm	0	3	12	15	4	2	1
TRUEOther	0	20	28	31	14	3	3
TRUEPacific	0	3	0	1	0	0	0
TRUEWt	22	208	453	435	226	42	62

Table 8: Weekly Meals Cooked by Race and Ethnicity

per 100,000. Figure shows the reaction to HUD complaints over the 1 to 21 complaint range.

Lots of explanation goes here

3.3 System Estimation

The single equation results discussed in section 3.2 show strong promise for endogenizing some of the decisions made about structure and equipment within the conditional demand model as well as the potential importance of housing market discrimination in structure choice. In this section we treat square footage, tenure and structure type as endogenous and estimate estimate the electricity, structure/tenure, and square footage model as a system.

It is unclear how this can be accomplished in a full information, so we chose a two-state least squares technique estimating first the square footage model, then using forecasted values to estimate tenure and structure type model. Forecasts from that model were used to resestimate and produce a new round of forecasts for the square footage model. Both the forecasts of the structure tenure model and square footage model were then used to estimate the conditional demand model.

This should produce consistent results but the variance of the parameter estimates are biased. It is unclear how to make the usual corrections to the variance of the parameter estimates given that the structure and tenure model is estimated as a multinomial logit. The best alternative is to bootstrap the system. There are a few caveats.

First, the bootstrap sampling is stratified so that all parameter estimates in all models can be estimated. This is particularly important in the structure and tenure model. We had to ensure enough observations of the rare cells, rented mobile homes being the most restricted. This was accomplished by simple rejection sampling rather than assigning different probabilities of selection to each of the cells.

Second, we did not censor non-positive square footage forecasts. The square footage model is weaker than expected and it was quite possible to have negative forecasts. Alternative models, such as Tobit, would not be effective, but we are considering transformations of square footage as we move forward.

Finally, only 400 bootstrap replicates were evaluated. This is usually enough to produce adequate estimates of the standard deviations of the parameter estimates in the electricity model but insufficient for BCa, percentile, or even basic bootstrap confidence intervals.

NEED TEXT TO EXPLAIN HERE

4 Summary and Conclusions

5 Orthodox Results

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2181.1197	1792.3947	1.22	0.2237
ElecMealsThreeDay	1338.6588	297.7217	4.50	0.0000
ElecMealsTwoDay	1644.3185	185.0764	8.88	0.0000
ElecMealsOneDay	1685.3404	159.1570	10.59	0.0000
ElecMealsFewWeek	1451.1356	183.7584	7.90	0.0000
ElecMealsOneWeek	1726.8842	406.3322	4.25	0.0000
ElecMealsLessWeek	992.8116	424.8594	2.34	0.0195
NUMFRIG	1574.9574	120.8432	13.03	0.0000
AgeFridge2to4Years	49.6457	195.1174	0.25	0.7992
AgeFridge5to9Years	312.9075	183.1243	1.71	0.0875
AgeFridge20PlusYears	282.4503	328.6753	0.86	0.3902
AgeFridge10to14Years	392.2705	207.4396	1.89	0.0587
AgeFridge15to19Years	3.4299	283.6629	0.01	0.9904
NUMPC	345.0370	64.3126	5.37	0.0000
TIMEON1OneTo3Hrs	-142.2026	160.6198	-0.89	0.3760
TIMEON1ThreeTo6Hrs	-5.9463	186.4186	-0.03	0.9746
TIMEON1SixTo10Hrs	224.2810	239.0840	0.94	0.3482
TIMEON1Gr10	823.2281	214.7291	3.83	0.0001
WELLPUMPTRUE	1501.4018	183.5027	8.18	0.0000
ElecWaterSmall	4421.9192	256.3522	17.25	0.0000
ElecWaterMed	4658.3555	163.9114	28.42	0.0000
ElecWaterLrg	5809.5827	189.7584	30.62	0.0000
ElecWaterTankless	3251.7517	755.3718	4.30	0.0000
SWIMPOOLTRUE	3228.7285	222.3292	14.52	0.0000
ElecPoolTRUE	4604.1557	837.0574	5.50	0.0000
RECBATHTRUE	1013.4653	426.3413	2.38	0.0175

ElecTubTRUE	1218.8041	486.6005	2.50	0.0123
NHSLDMEM	952.0720	42.5506	22.38	0.0000
Income	0.0086	0.0016	5.37	0.0000
TVONWD1LessHour:TVTYPE1Standard	-3266.1101	1800.2730	-1.81	0.0697
TVONWD1OneTo3Hrs:TVTYPE1Standard	-3010.1255	1775.5111	-1.70	0.0900
TVONWD1ThreeTo6Hrs:TVTYPE1Standard	-2516.9211	1772.6818	-1.42	0.1557
TVONWD1SixTo10Hrs:TVTYPE1Standard	-1794.7156	1778.9345	-1.01	0.3131
TVONWD1Gr10:TVTYPE1Standard	-1290.6207	1784.9518	-0.72	0.4697
TVONWD1LessHour:TVTYPE1LCD	-2896.8097	1807.2466	-1.60	0.1090
TVONWD1OneTo3Hrs:TVTYPE1LCD	-2313.1891	1773.9814	-1.30	0.1923
TVONWD1ThreeTo6Hrs:TVTYPE1LCD	-1955.8036	1770.9445	-1.10	0.2695
TVONWD1SixTo10Hrs:TVTYPE1LCD	-1593.9919	1777.1898	-0.90	0.3698
TVONWD1Gr10:TVTYPE1LCD	-485.7205	1785.6404	-0.27	0.7856
TVONWD1LessHour:TVTYPE1Plasma	-1497.7500	1988.0024	-0.75	0.4512
TVONWD1OneTo3Hrs:TVTYPE1Plasma	-1664.7504	1800.8346	-0.92	0.3553
TVONWD1ThreeTo6Hrs:TVTYPE1Plasma	-2001.8306	1788.6852	-1.12	0.2631
TVONWD1SixTo10Hrs:TVTYPE1Plasma	-940.8541	1815.7684	-0.52	0.6044
TVONWD1Gr10:TVTYPE1Plasma	418.9083	1846.1024	0.23	0.8205
TVONWD1LessHour:TVTYPE1Projection	-2094.9059	2146.9297	-0.98	0.3292
TVONWD1OneTo3Hrs:TVTYPE1Projection	-1639.6049	1851.1064	-0.89	0.3758
TVONWD1ThreeTo6Hrs:TVTYPE1Projection	-2152.3377	1812.9470	-1.19	0.2352
TVONWD1SixTo10Hrs:TVTYPE1Projection	-925.1902	1837.7040	-0.50	0.6147
TVONWD1Gr10:TVTYPE1Projection	1530.2305	1911.2140	0.80	0.4234
TVONWD1LessHour:TVTYPE1LED	-4513.1128	2901.1001	-1.56	0.1198
TVONWD1OneTo3Hrs:TVTYPE1LED	-1678.7884	2013.2805	-0.83	0.4044
TVONWD1ThreeTo6Hrs:TVTYPE1LED	-2106.7446	1923.5912	-1.10	0.2735
TVONWD1SixTo10Hrs:TVTYPE1LED	-3418.0720	2390.7609	-1.43	0.1528
TOTSQFT_EN:TYPEGLASSSinglePane	-0.1921	0.1586	-1.21	0.2259
TOTSQFT_EN:TYPEGLASSDoublePane	-0.0336	0.1540	-0.22	0.8271
TOTSQFT_EN:TYPEGLASSTriplePane	0.0093	0.2093	0.04	0.9644
Income:EthRaceFALSEAfAm	0.0031	0.0027	1.14	0.2548
Income:EthRaceFALSEAsian	-0.0243	0.0034	-7.16	0.0000
Income:EthRaceFALSEMulti	-0.0168	0.0069	-2.43	0.0153
Income:EthRaceFALSENativeAm	0.0117	0.0123	0.95	0.3425
Income:EthRaceFALSEOther	-0.0249	0.0083	-2.99	0.0028
Income:EthRaceFALSEPacific	-0.0163	0.0138	-1.18	0.2378
Income:EthRaceTRUEAfAm	-0.0120	0.0165	-0.73	0.4672
Income:EthRaceTRUEAsian	-0.0365	0.0454	-0.80	0.4219
Income:EthRaceTRUEMulti	-0.0291	0.0212	-1.37	0.1693
Income:EthRaceTRUENativeAm	-0.0187	0.0148	-1.26	0.2077
Income:EthRaceTRUEOther	-0.0262	0.0099	-2.63	0.0085
Income:EthRaceTRUEPacific	-0.0122	0.0380	-0.32	0.7474
Income:EthRaceTRUEWt	-0.0192	0.0031	-6.29	0.0000
StrTenureOwnSFDetached:TOTSQFT_EN:HDD65	0.0001	0.0000	4.10	0.0000
StrTenureOwnLgApartment:TOTSQFT_EN:HDD65	-0.0001	0.0001	-0.96	0.3381
StrTenureOwnMobile:TOTSQFT_EN:HDD65	0.0004	0.0001	5.98	0.0000

StrTenureOwnSFAttached:TOTSQFT_EN:HDD65	-0.0000	0.0000	-0.55	0.5812
StrTenureOwnSmApartment:TOTSQFT_EN:HDD65	0.0000	0.0001	0.54	0.5866
StrTenureRentLgApartment:TOTSQFT_EN:HDD65	-0.0002	0.0001	-4.00	0.0001
StrTenureRentMobile:TOTSQFT_EN:HDD65	0.0004	0.0002	1.76	0.0779
StrTenureRentSFAttached:TOTSQFT_EN:HDD65	0.0000	0.0001	0.60	0.5479
StrTenureRentSFDetached:TOTSQFT_EN:HDD65	0.0000	0.0000	0.55	0.5813
StrTenureRentSmApartment:TOTSQFT_EN:HDD65	-0.0001	0.0001	-1.86	0.0632
StrTenureOwnSFDetached:TOTSQFT_EN:CDD65	0.0008	0.0000	19.21	0.0000
StrTenureOwnLgApartment:TOTSQFT_EN:CDD65	-0.0002	0.0002	-0.82	0.4140
StrTenureOwnMobile:TOTSQFT_EN:CDD65	0.0009	0.0001	7.32	0.0000
StrTenureOwnSFAttached:TOTSQFT_EN:CDD65	0.0006	0.0001	5.01	0.0000
StrTenureOwnSmApartment:TOTSQFT_EN:CDD65	0.0001	0.0003	0.40	0.6875
StrTenureRentLgApartment:TOTSQFT_EN:CDD65	0.0000	0.0001	0.39	0.6946
StrTenureRentMobile:TOTSQFT_EN:CDD65	0.0024	0.0004	6.32	0.0000
StrTenureRentSFAttached:TOTSQFT_EN:CDD65	0.0007	0.0002	4.02	0.0001
StrTenureRentSFDetached:TOTSQFT_EN:CDD65	0.0008	0.0001	9.27	0.0000
StrTenureRentSmApartment:TOTSQFT_EN:CDD65	0.0005	0.0002	2.84	0.0046

Table 11: Orthodox kWh Model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1944.2850	75.4800	25.76	0.0000
RENTHELPTRUE	182.1575	82.5453	2.21	0.0274
StrTenureOwnLgApartment	-1374.2383	67.6666	-20.31	0.0000
StrTenureOwnMobile	-1095.7710	47.1356	-23.25	0.0000
StrTenureOwnSFAttached	-493.4629	52.5900	-9.38	0.0000
StrTenureOwnSmApartment	-776.3654	87.1475	-8.91	0.0000
StrTenureRentLgApartment	-1393.2440	30.1078	-46.28	0.0000
StrTenureRentMobile	-1202.7143	95.8133	-12.55	0.0000
StrTenureRentSFAttached	-807.0103	62.9410	-12.82	0.0000
StrTenureRentSFDetached	-561.3334	38.9760	-14.40	0.0000
StrTenureRentSmApartment	-1142.2015	41.4263	-27.57	0.0000
Income	0.0079	0.0003	30.04	0.0000
reporttot	11.6455	2.0454	5.69	0.0000
EDUCATIONNoHS	45.4843	77.6015	0.59	0.5578
EDUCATIONHS	77.1327	73.4168	1.05	0.2935
EDUCATIONSomeCol	131.9180	74.1386	1.78	0.0752
EDUCATIONAA	123.6675	77.9407	1.59	0.1126
EDUCATIONBA	330.4375	75.4797	4.38	0.0000
EDUCATIONMA	334.8239	80.7072	4.15	0.0000
EDUCATIONProf	585.2435	104.0935	5.62	0.0000
EDUCATIONPHD	436.0771	115.7913	3.77	0.0002
URUrban	-232.6741	24.4942	-9.50	0.0000
reporttot:EthRaceFALSEAfAm	-6.9645	4.4105	-1.58	0.1143
reporttot:EthRaceFALSEAsian	-6.5949	8.0953	-0.81	0.4153

reporttot:EthRaceFALSEMulti	-18.6324	10.3186	-1.81	0.0710
reporttot:EthRaceFALSENativeAm	-11.9507	11.6925	-1.02	0.3068
reporttot:EthRaceFALSEOther	0.1925	14.9557	0.01	0.9897
reporttot:EthRaceFALSEPacific	-34.7044	19.0077	-1.83	0.0679
reporttot:EthRaceTRUEAfAm	-18.4892	31.5771	-0.59	0.5582
reporttot:EthRaceTRUEAsian	-24.6105	43.8328	-0.56	0.5745
reporttot:EthRaceTRUEMulti	4.1417	17.6508	0.23	0.8145
reporttot:EthRaceTRUENativeAm	-19.0098	37.4768	-0.51	0.6120
reporttot:EthRaceTRUEOther	5.9743	13.0668	0.46	0.6475
reporttot:EthRaceTRUEPacific	-19.2825	57.2286	-0.34	0.7362
reporttot:EthRaceTRUEWt	-22.7295	5.5102	-4.12	0.0000

Table 12: Orthodox Square Foot Model

	State	Population	Reports (per 100,000)
1	Alabama	4,677,464	7.50
2	Alaska	688,125	13.01
3	Arizona	6,499,377	3.68
4	Arkansas	2,867,764	9.26
5	California	36,580,371	3.03
6	Colorado	4,935,213	1.97
7	Connecticut	3,502,932	20.50
8	Delaware	876,211	14.00
9	District of Columbia	590,074	14.00
10	Florida	18,423,878	3.93
11	Georgia	9,697,838	2.06
12	Hawaii	1,287,481	13.01
13	Idaho	1,527,506	9.94
14	Illinois	12,842,954	2.88
15	Indiana	6,388,309	9.14
16	Iowa	2,993,987	19.92
17	Kansas	2,797,375	10.31
18	Kentucky	4,287,931	7.50
19	Louisiana	4,451,513	9.26
20	Maine	1,319,691	20.50
21	Maryland	5,658,655	14.00
22	Massachusetts	6,543,595	4.51
23	Michigan	10,002,486	4.97
24	Minnesota	5,230,567	19.92
25	Mississippi	2,940,212	7.50
26	Missouri	5,956,335	4.99
27	Montana	968,035	9.94
28	Nebraska	1,781,949	10.31
29	Nevada	2,615,772	5.08
30	New Hampshire	1,321,872	20.50
31	New Jersey	8,663,398	2.34
32	New Mexico	1,986,763	5.08
33	New York	19,467,789	4.60
34	North Carolina	9,247,134	4.22
35	North Dakota	641,421	19.92
36	Ohio	11,528,072	9.14
37	Oklahoma	3,644,025	9.26
38	Oregon	3,782,991	13.01
39	Pennsylvania	12,566,368	1.87
40	Rhode Island	1,053,502	20.50
41	South Carolina	4,503,280	4.22
42	South Dakota	804,532	19.92
43	Tennessee	6,240,456	2.61
44	Texas	24,304,290	4.18
45	Utah	2,727,343	9.94
46	Vermont	621,049	20.50
47	Virginia	7,795,424	2.03
48	Washington	6,566,073	13.01
49	West Virginia	1,814,873	14.00
50	Wisconsin	5,627,610	1.81
51	Wyoming	532,981	9.94

Table 9: HUD Complaints per 100,000 Population