EIA's Experience with End-Use Estimation

For

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By

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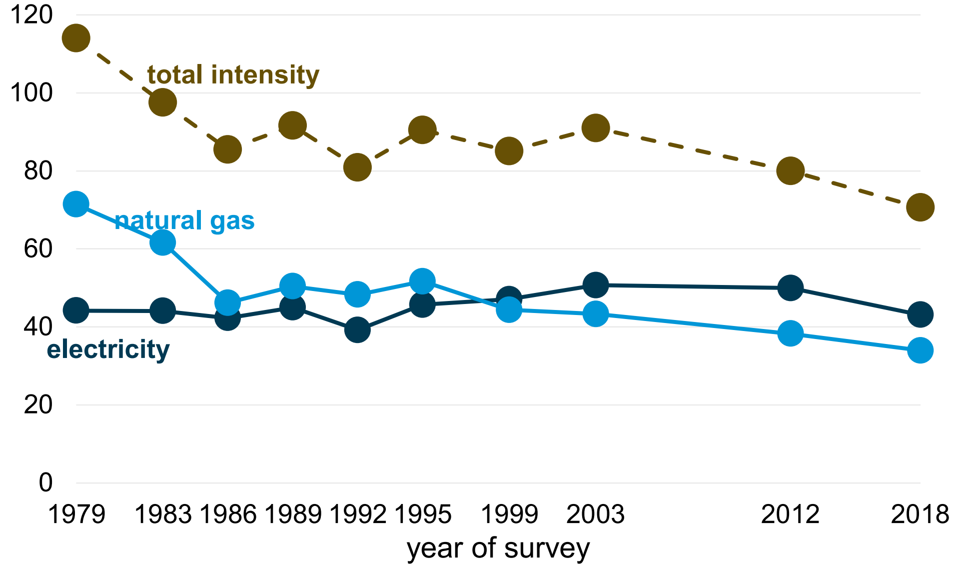
Plan of talk

- Importance
- Data needs
- Approaches
- Illustrative example
- Conclusions

Recent headline: Energy intensity decreases in U.S. commercial buildings

Energy intensity by select fuels, 1979–2018
thousand British thermal units per square foot



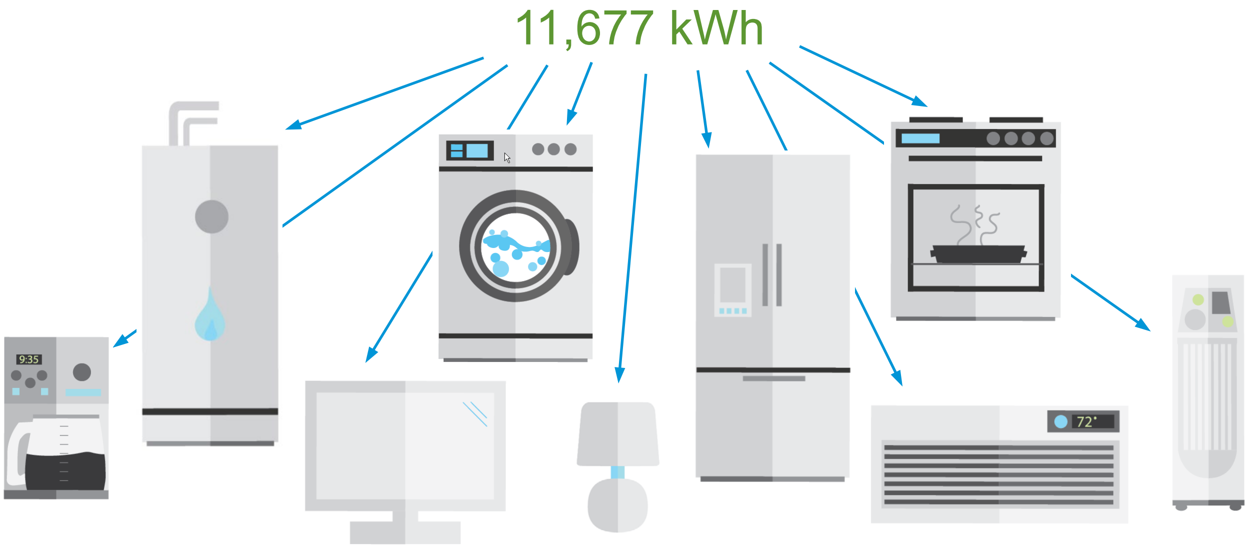
Source: U.S. Energy Information Administration, *Commercial Buildings Energy Consumption Survey*
Note: Btu = British thermal units

- Total floorspace in commercial buildings increased while energy consumption did not, meaning consumption per square foot (energy intensity) decreased.
- The average total energy used per square foot in commercial buildings decreased by 12% since the 2012 CBECS, from 80.0 thousand Btu per square foot to 70.6 thousand Btu per square foot.
- In addition, electricity intensity decreased by 14%, and natural gas intensity decreased by 11% from 2012 to 2018.

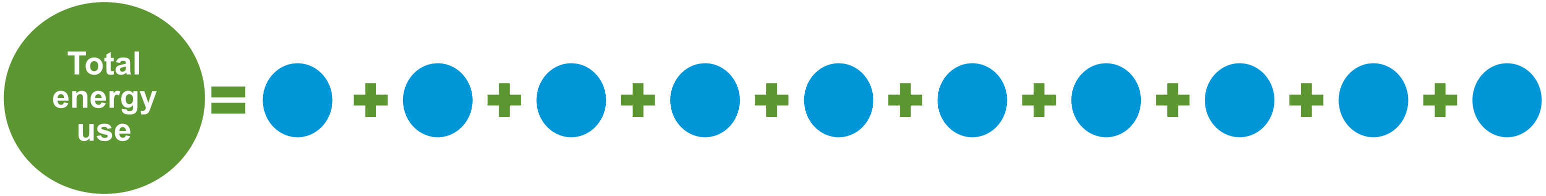
Questions, questions (importance)

- What role did more energy efficient equipment play?
- Did changes in behavior also play a role?
- What are the success stories?
- What policies may be the most impactful?
- What can we learn from others experience?

End-use estimation is a meaningful disaggregation of the billing totals to begin to answer these questions



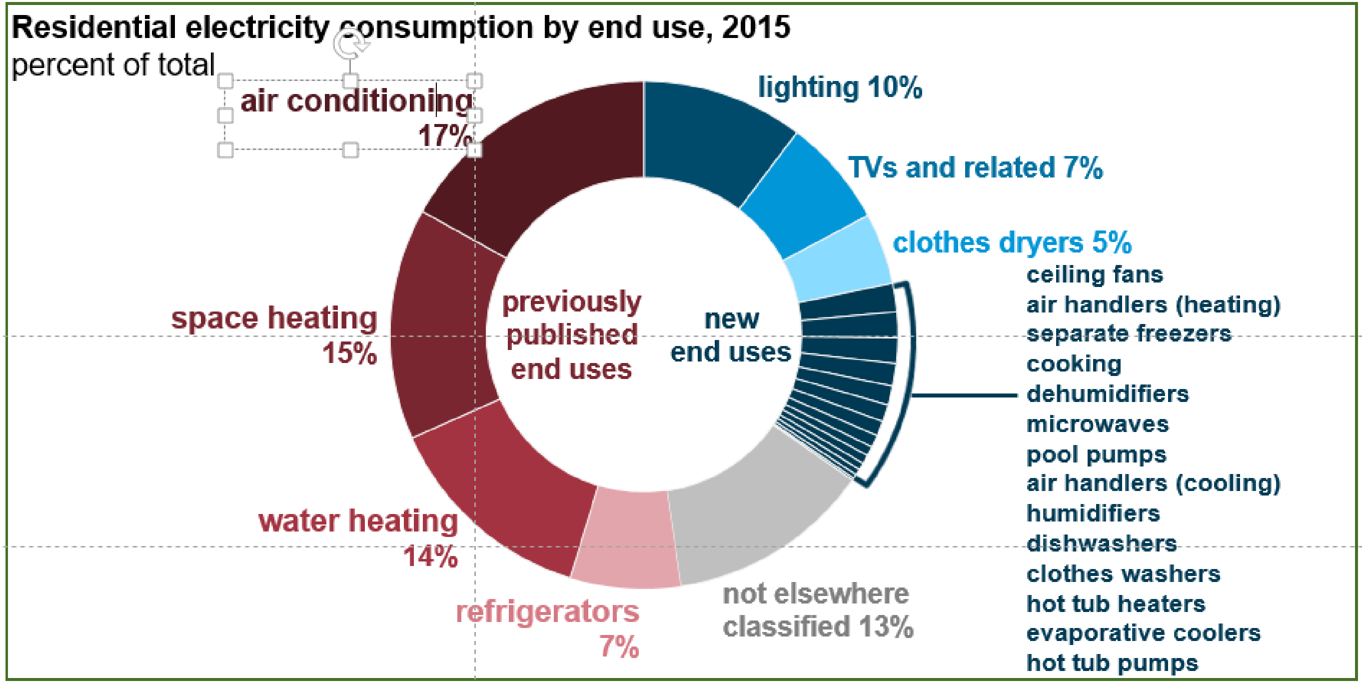
What end use categories are included in CBECS?



ENERGY SOURCE	Space heating	Space cooling	Ventilation	Water heating	Lighting	Cooking	Refrigeration	Computing	Office equipment	Other
Electricity	X	X	X	X	X	X	X	X	X	X
Natural gas	X			X		X				X
Fuel oil	X			X		X				X
District heat	X			X		X				X

Commercial end uses model: http://www.eia.gov/consumption/commercial/estimation-enduse-consumption.cfm

What end use categories are included in RECS?

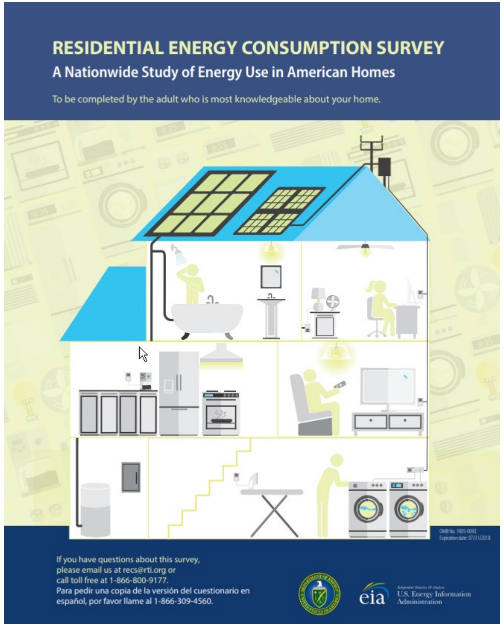


What information is needed for estimating national end-use consumption?

- Sadly, no submetering data across a representative, national sample
- Hence, end-use consumption must be ***Estimated*** from available information:
  - **Billing data (required)**
  - **Building characteristics data (required, but detail can vary)**
  - **Administrative data (Not always necessary, but can improve results)**

  - **Wider Community Knowledge!**

Residential Energy Consumption: a tale of two surveys



Billing Date	kWh	Cost
1/7/2015	813	$194.44
2/5/2015	627	$133.11
3/9/2015	615	$122.90
4/7/2015	758	$143.89
5/7/2015	689	$149.44
6/8/2015	703	$148.03
7/8/2015	965	$228.99
8/6/2015	1302	$335.73
9/4/2015	1467	$386.86
10/6/2015	1584	$387.18
11/5/2015	1191	$300.21
12/8/2015	963	$223.40
Total	**11,677 kWh**	**$2,754**

The basics of end-use estimation

Use ***Calibration*** to synthesize available information:

- ***Task 1***: ***Expectations***, quantified by *Models*
  - Housing characteristics data
  - Weather data
  - Wider community knowledge
- EIA models each energy source separately
- ***Task 2***: ***Final measurements (control totals)***
  - Match to billing data

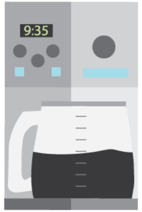
Options based on data and resource ability (approaches)

- ***Expectations***, quantified by *Models*
  - Statistical approach:
    - Regression analysis with nationally representative sample
    - Coefficient values used to determine values for individual observations
  - Engineering approach:
    - Calculations based on engineering formulas
- ***Final measurement (control totals)***, to match
    - Simple normalization (*e.g.*, prorate)
    - Minimum variance estimation (preferred)

End-use energy expectations set by modeling

- Example: the end-use model for coffee makers

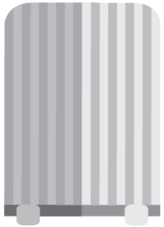
```
if COFFEE = 1
     Coffee_Consumption = P_coffee
else
     Coffee_Consumption = 0
end
```

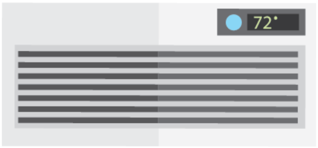


- Prior to the 2015 RECS, modeling was ***Statistical***
- The 2015 RECS used ***Engineering Models***

End-use energy expectations can get complicated

- A model for space conditioning clearly depends on many inputs





- Prior to the 2015 RECS:

  "*Does space heating consumption depend on the* square-root *of HDDs?*"

- In the 2015 RECS, calculate an underlying "load," and then consider the efficiency of fuel and equipment used to meet the load

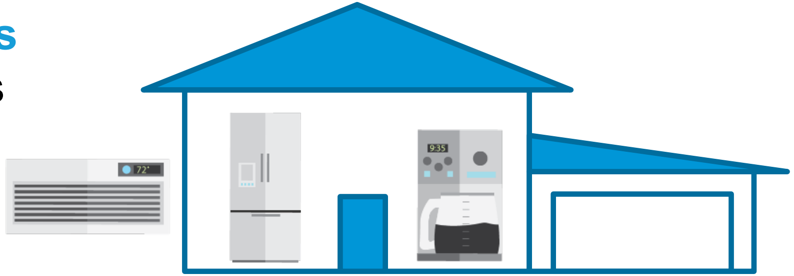
Calibration is capable of using more information, if one can provide it

- Prior to the 2015 RECS, the Calibration method was ***Simple Normalization***
  - Treats all modeled end uses as equally certain/valid

- In the 2015 RECS, the Calibration method follows a ***Minimum Variance Estimation*** approach
  - Does not treat all modeled end uses as equally certain/valid
  - Requires specifying the uncertainties of and correlations between end uses

A Simple Example: the available information

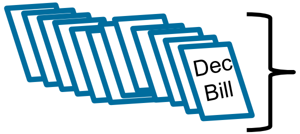
- **Housing Characteristics Survey** - only 3 end uses of Electricity:
  - AC
  - Refrigerator
  - Coffee Maker



- **Administrative Data**
  Weather data

Temperature,
Dew Point

- **Energy Supplier Survey**
  Annualized billing total of 2,000 kWh



Σ = 2,000 kWh

A Simple Example: end-use energy expectations

- Plausible model estimates for the end uses:
  - AC = **1,000 kWh**
  - Refrig = **500 kWh**
  - Coffee = **60 kWh**
- Sum of model estimates is **1,560 kWh**

This is **440 kWh** less than the annualized billing total of **2,000 kWh**

A Simple Example: simple normalization calibration

- Prorate the residual
  - AC = 1,000 kWh + (1,000 / 1,560) · 440 kWh = **1,282 kWh**
  - Refrig = 500 kWh + (500 / 1,560) · 440 kWh = **641 kWh**
  - Coffee = 60 kWh + (60 / 1,560) · 440 kWh = **77 kWh**

- These add to 2,000 kWh, but are all three model estimates equally valid?
  - Refrigerators are relatively easy to model
  - AC is difficult to model
  - Coffee Makers cannot be modeled beyond presence

A Simple Example: specify uncertainties and correlations

- Plausible, hypothetical estimates for the uncertainties and correlations:
  - AC has 50% relative uncertainty :: **1,000 ± 500 kWh**
  - Refrig has 20% relative uncertainty :: **500 ± 100 kWh**
  - Coffee has 100% relative uncertainty :: **60 ± 60 kWh**
  - All 3 are uncorrelated ::

Corr(AC, Refrig) = Corr(AC, Coffee) = Corr(Refrig, Coffee) = 0

  - Uncertainty Propagation ::

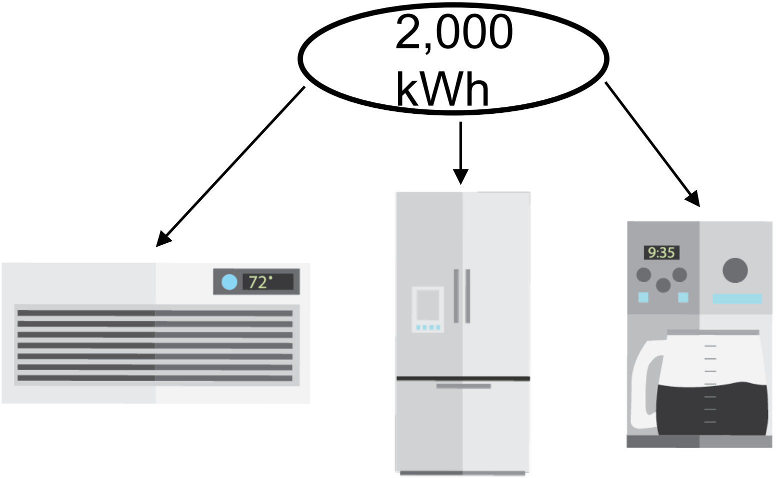
    Sum = AC + Refrig + Coffee = **1,560 ± 513 kWh**

A Simple Example: minimum variance estimation

- Full problem solved as optimization with constraints
  - Weight model estimates by inverse variance-covariance matrix
  - Assume annualized billing total has no uncertainty
  - Constraints to ensure no negative consumption

- This problem simplifies nicely
  - AC = 1,000 kWh + (250,000 / 263,600) · 440 kWh = **1,417 kWh**
  - Refrig = 500 kWh + (10,000 / 263,600) · 440 kWh = **517 kWh**
  - Coffee = 60 kWh + (3,600 / 263,600) · 440 kWh = **66 kWh**

A Simple Example: two calibration solutions



Simple Normalization	1,282	+	641	+	77	=	2,000
Minimum Variance Estimation	1,417	+	517	+	66	=	2,000

A Simple Example: comparing results

	Modeled	Simple Normali-zation	Relative Uncertainty	Absolute Uncertainty	Minimum Variance Estimation
AC	1,000	1,282	±50%	±500	1,417
Refrig	500	641	±20%	±100	517
Coffee	60	77	±100%	±60	66
Total	1,560	2,000			2,000

Most of the +440 kWh correction has been given to AC, the end use with the largest absolute uncertainty

Conclusions

- Two approaches for end-use modeling
  - Regression models
  - Engineering models
- Minimum data needs
  - Billing information from utility companies (or quantities consumed on the survey instrument)
  - Housing characteristics (common sense in survey design; can be extended later)
  - Weather information (spacing conditioning often greatest energy use)
- Common statistical techniques
  - But still a bit of an art that benefits from learning from others' practical experience and literature reviews
  - Can be viewed as doing the best with the data on hand with no uniformly "right" answer