

Data Analysis to Determine Incremental Measure Costs (IMCs) for the Retail Plug Load Portfolio (RPP)

May 28, 2015

PRESENTED TO

California Technical Forum

PRESENTED BY

Teddy Kisch, Eric Rubin, and Carolyn Richter

Energy Solutions

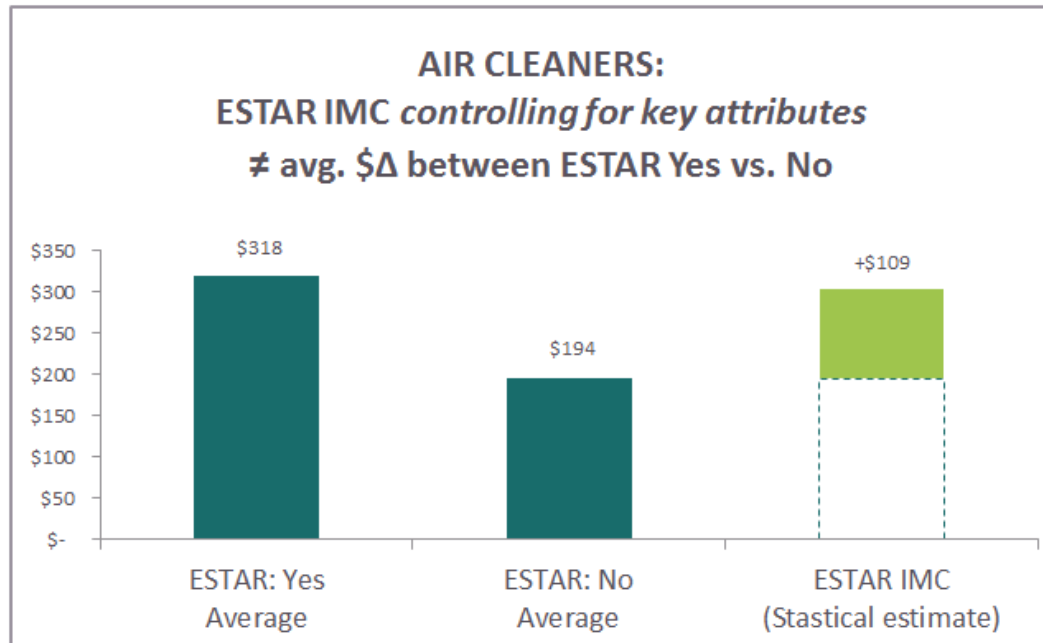
Presentation Overview

- Project Overview and Goals
- Terminology and Concepts Overview
- Methods
 - Overview
 - Product Example: Air Cleaners
- Results
 - Best Model Results: All Products
 - IMC Results: All Products
- Next Steps
 - Identify any items which require follow up clarification
 - Obtain Cal TF approval for the selected IMC values



Project Overview and Goals

- Used approved web harvesting approach
- Similar analysis methodology to Measure Cost Study using hedonic price modeling
- Goal:
 - Identify product attributes that are the *key* drivers of retail price
 - Estimate IMC of ENERGY STAR®, *controlling for those key attributes*



Terminology and Key Concepts Overview

- “Model”

- Multiple regression *model* should not be confused with the *model* of a specific product
- Equation that predicts price based on a combination of product attributes

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			

- **Controlling for variables using multiple regression**

- $\text{Price} = \text{Constant} + \beta_{\text{CADR}}(\text{CADR}) + \beta_{\text{COVERAGE}}(\text{Coverage}) + \beta_{\text{ESTAR}}(\text{ESTAR Qualified})$
- Model will estimate coefficient (β) for each term, even if it does not have a statistically significant effect on Price



Terminology and Key Concepts Overview

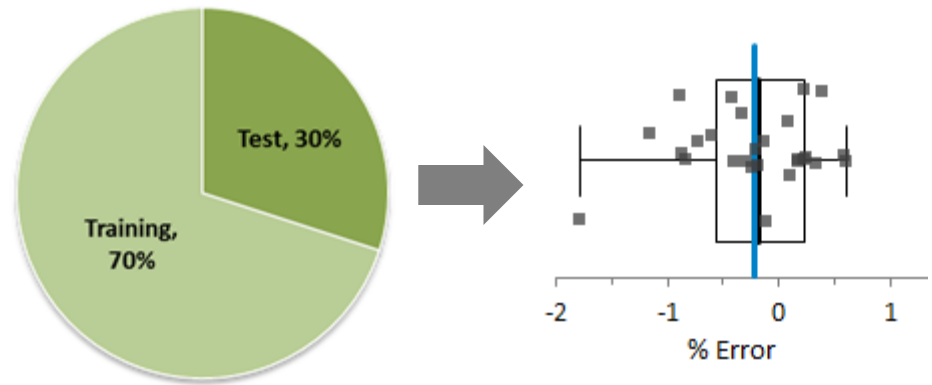
- **Significance of coefficients (p-value)**
 - p-value for each coefficient (β) is based on **Null Hypothesis Significance Testing (NHST)**:
 - “What is the likelihood of this evidence affecting Price, assuming no effect exists?”
 - **Null hypothesis**: Attribute does not have a unique influence on price, beyond that of other attributes in the multiple regression model
 - **Thought experiment**:
 - Imagine you collected many samples of data with this *same sample size* and analyzed the *same combination of attributes*
 - Assuming the null hypothesis is true (no unique effect of the attribute on price), in what fraction of those randomly-selected samples would you see such strong evidence of an effect, simply due to chance (the *p* value)?
 - **With a large enough sample size, p-values will be very small, and we can reject the null hypothesis, even if the effect is small (e.g., IMC of \$1)**



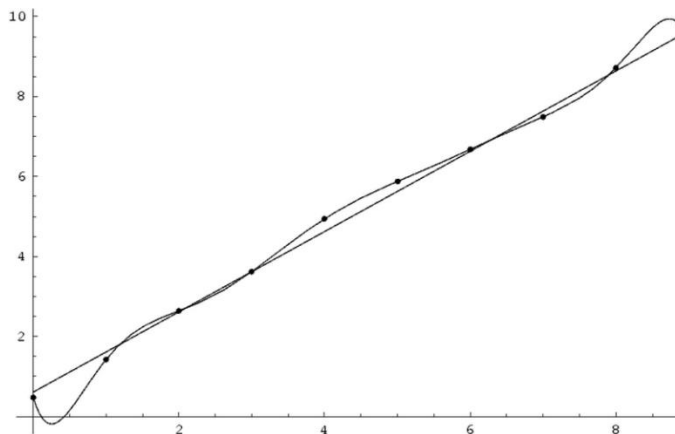
Terminology and Key Concepts Overview

- **Model Validation**

- Model is developed or “trained” on 70% of the data, then tested on remaining 30%
- Testing on new data catches “overfitting”
- Results tell us how accurate the model is and can help choose between possible Best Models



Conceptual illustration of overfitting



- **Overfitting:** Adding more product attributes will always improve model fit in the Training data
- **Model Validation** can identify overly complex models

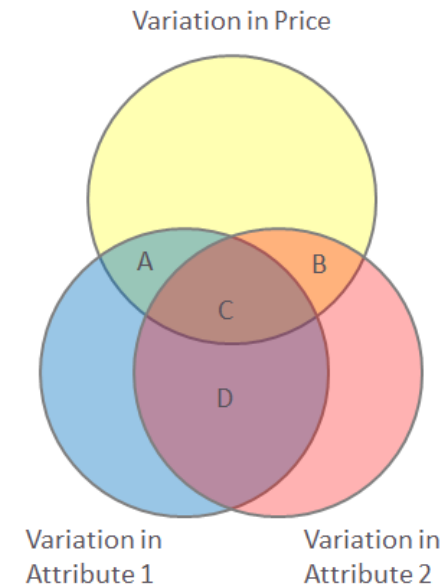


Terminology and Key Concepts Overview

Other Key Terms

- **R^2**
 - Percent variation in Price explained by the attributes in the model
- **Adjusted R^2**
 - Model selection tool
 - Penalizes R^2 of more complex models to account for overfitting (makes R^2 smaller)
- **AICc**
 - Model selection tool
 - Penalizes complexity; tells us likelihood of models being best relative to one another
- **(Multi)collinearity problems**
 - When one or more product attributes are highly correlated with one another
 - May cause important attributes to appear insignificant, because they have less unique overlap with price

Highly collinear attributes



Web Harvesting

- **Advantages**

- Web harvesting data collection method is better suited to rapidly-changing markets and RPP's portfolio approach
 - New products can be added as needed
 - Data can be collected faster and in higher volume over time
 - Cost is lower

- **Limitations**

- Data must be adjusted for any differences between brick-and-mortar and online price points
- Not all retailers sites are accessible to the web harvester



Methods Overview

STAGE

1. Web harvesting

2. Clean data & distill attributes

3. Multiple regression analysis

4. Model selection & validation

5. If not already in the model,
add ENERGY STAR to Best
Model to determine unique
effect on price

OUTCOME

1. Raw data

2. Likely key attributes that
influence Price

3. Identify combos of key
attributes (“models”) that
best explain variation in \$

4. Identify the Best Model

5. ENERGY STAR IMC
estimate
(β_{ESTAR}); measures of
evidence against the
null hypothesis ($\beta_{\text{ESTAR}} = 0$)



EXAMPLE: AIR CLEANERS



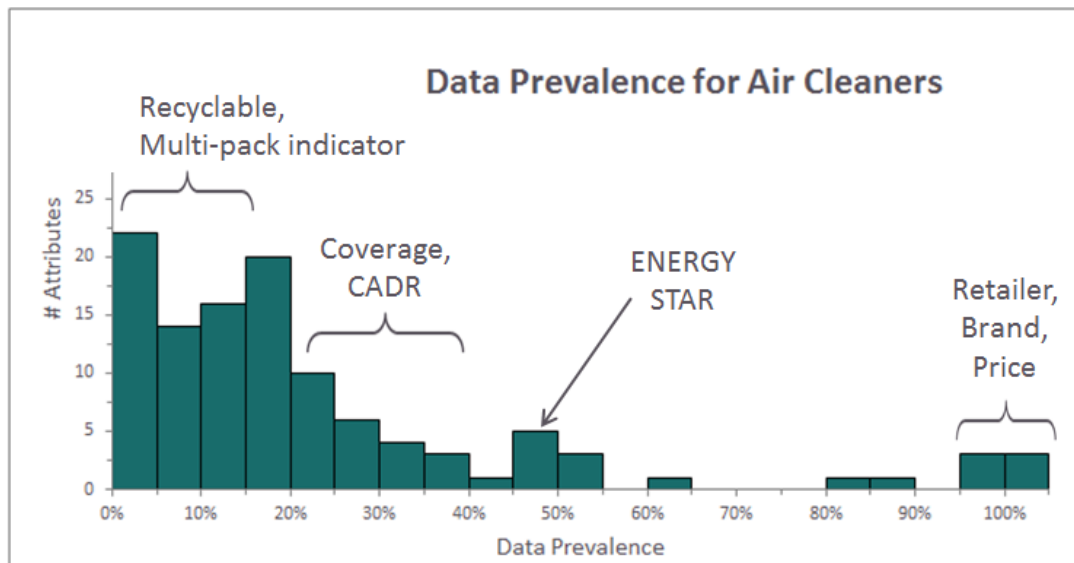
Air Cleaners: Web Harvesting & Pre-processing

Web Harvesting

- 516 initial product models
- ~110 initial attributes

Data Prevalence

- Most attributes have prevalence < 50%

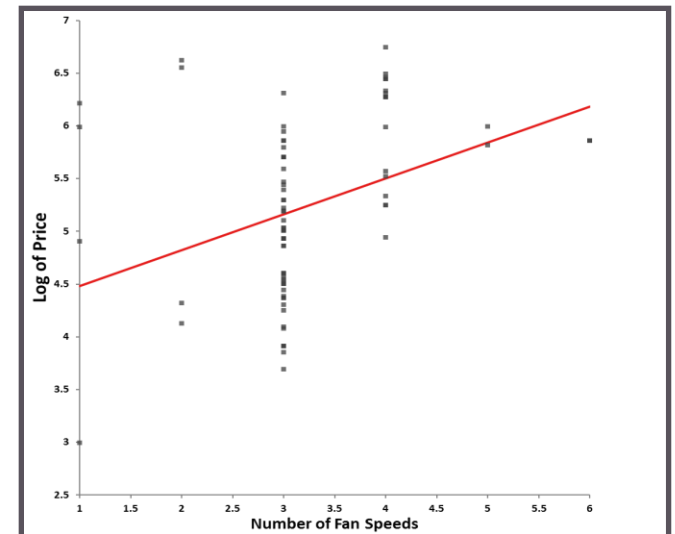
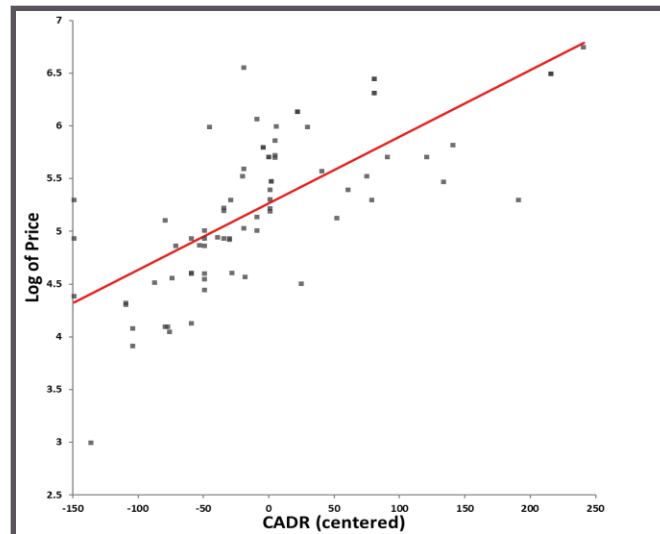
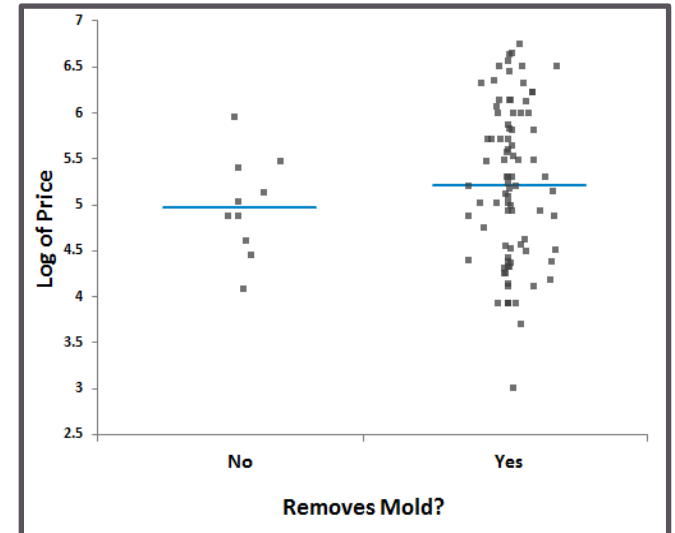
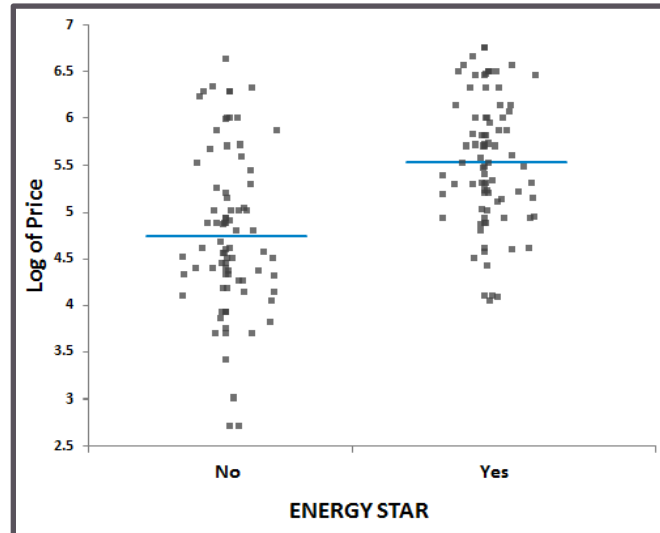


Attribute	Prevalence
Source	100.00%
Model	100.00%
Manufacturer	99.81%
Brand	99.81%
SKU	85.82%
Weight	81.80%
Name	63.98%
Width	53.45%
Depth	52.87%
Height	52.49%
Number of Customer Reviews	49.81%
Energy Star	49.62%



Air Cleaners: Distill Initial Attributes

- **Single variable correlations** with price help identify likely key attributes
- **Expert interview** indicated importance of CADR, filter type, and fan speeds, among others



Air Cleaners: Stepwise Regression

- Supervised backward stepwise regression
 - 3 candidate Best Models
 - 1. Estimated multiple regression model with all attributes
 - 2. Removed attributes with multicollinearity
 - 3. Removed least significant attributes based on p-values*

ATTRIBUTE		MODEL 1	MODEL 2	MODEL 3
CADR				
Coverage				
ESTAR				
Removes Bacteria				Importance
HEPA Filter			p-value: least significant	
Wall Mountable		p-value: least significant		
UVGI Filter		p-value: least significant		
CADR/W			Collinear: ESTAR	
Remote Control			Collinear: CADR + Coverage	
# of Cleaning Stages			Collinear: Coverage + Remote Control.	
Brand			Collinear: Coverage + CADR	

*'Removes Bacteria' was less significant than CADR in Model 2, but collinearity between CADR and coverage suppresses the significance of CADR



Air Cleaners: Interaction Term

Observed potential effects of interaction term

- Effect of ENERGY STAR on price appeared to be moderated by CADR in the training data
 - i.e. larger IMC for more powerful models

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			

ATTRIBUTE	MODEL 1x	MODEL 2x	MODEL 3x
ESTAR x CADR bin			
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			



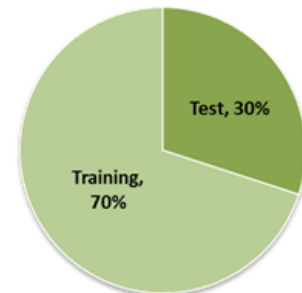
Air Cleaners: Model Validation & Selection

- Of six candidate models, model 1 and 1x yielded the best model validation results
 - $R^2 = 0.54$ for *new* data (i.e., the remaining 30% of models not analyzed)
- Model 1 was favored by AICc
 - 78:22 odds compared to Model 1x
- Interaction effect was very weak in full dataset
- Selected Model 1 as Best Model

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			

ATTRIBUTE	MODEL 1x	MODEL 2x	MODEL 3x
ESTAR x CADR bin			
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			

Model	N	R ²	Adj. R ²	AICc	Relative Likelihood
1	67	0.81	0.79	-124.5	78%
1x	67	0.81	0.79	-122.0	22%



Model validation results (re-parameterized to the full dataset)



Air Cleaners: Evaluate ENERGY STAR IMC

- **Selected Best Model as IMC Model**
- **Recommended IMC = β_{ESTAR}**
 - 56% of cost or +\$109 relative to base case average
 - Very significant term in the IMC Model
 - p-value < 0.00001
 - Highly significant and large difference without controls (ANOVA)

Model	ESTAR IMC		95% CI	
	Small CADR	Large CADR		
1	56%	56%	33%	78%
1x	59%	63%	17%	100%

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			

ATTRIBUTE	MODEL 1x	MODEL 2x	MODEL 3x
ESTAR x CADR bin			
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			



ALL PRODUCTS: BEST MODEL RESULTS



All Products: Best Model Results

Sample size (n); Variation in price explained by the Best Model (R^2);
Accuracy of the model (*distribution of % error*); Attributes included in the Best Model

Product	N	R ²	Model Validation Average % Error	% Error 95% Confidence Interval		Variables Included
Air Cleaners	67	0.81	3%	-11%	17%	Clean Air Delivery Rate (CADR); Coverage; ENERGY STAR; HEPA Filter; Removes Bacteria
Dryers	202	0.73	1%	-1%	4%	Brand, Drum Material, Drying Rack, Stackable, Steam, Window, Wrinkle-Free
Upright Freezer	116	0.89	10%	1%	19%	Brand; Capacity; Defrost
Chest Freezers	94	0.94	0%	-5%	6%	Brand; Capacity
Soundbars	71	0.63	-15%	-43%	14%	Number of Channels; Bluetooth & Wireless Capability; Active vs. Passive Subwoofer
HTIB	-	-	-	-	-	-

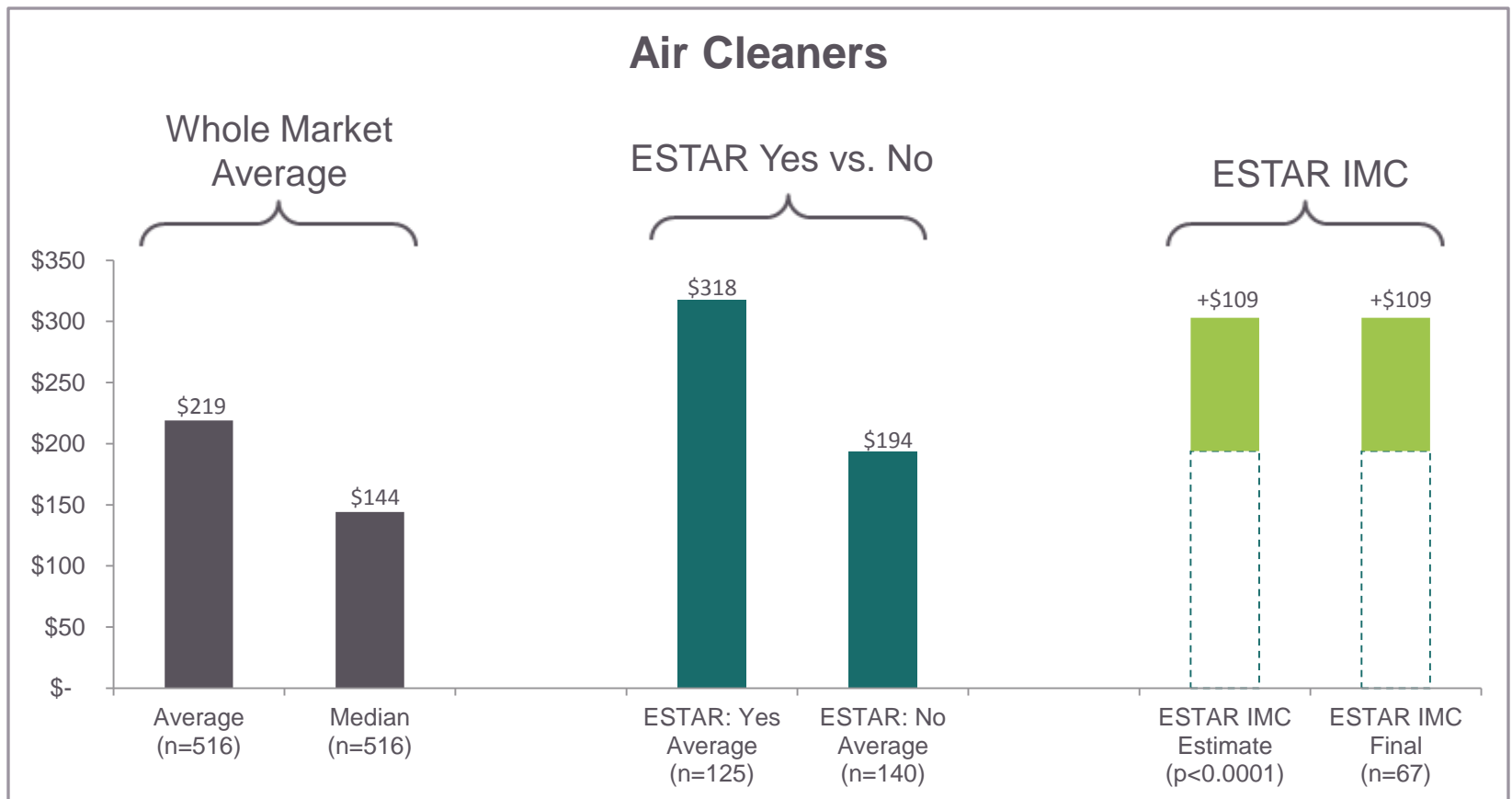


MARKET AVERAGES & IMC RESULTS BY PRODUCT



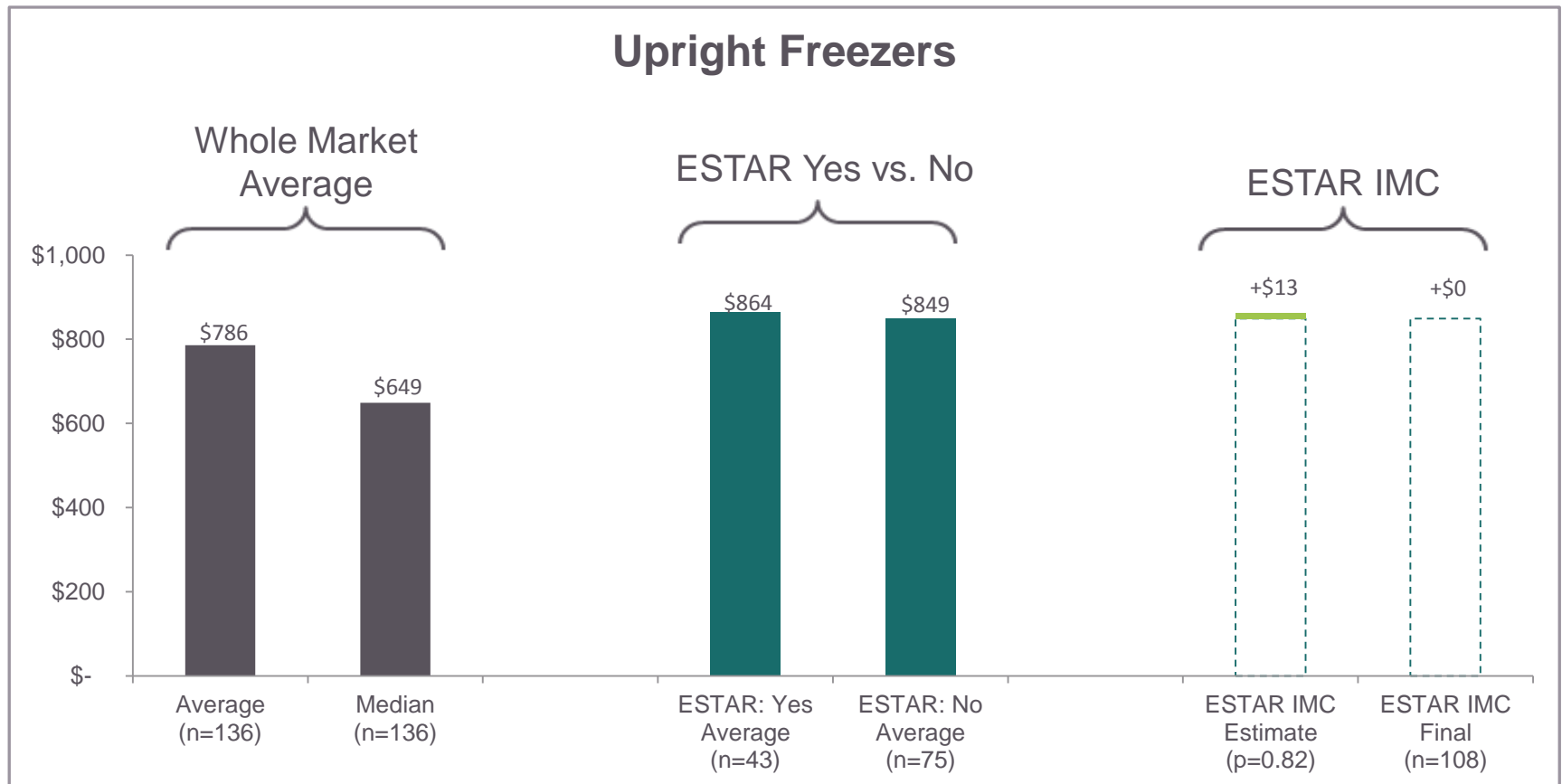
IMC Results: Air Cleaners

- ESTAR products are, on average, more expensive than non-ESTAR (*teal bars*)
- The unique effect of ESTAR accounts for \$109 of this difference (*green bars*)
- There is sufficient evidence to reject the null hypothesis (*right green bar $\neq 0$*)



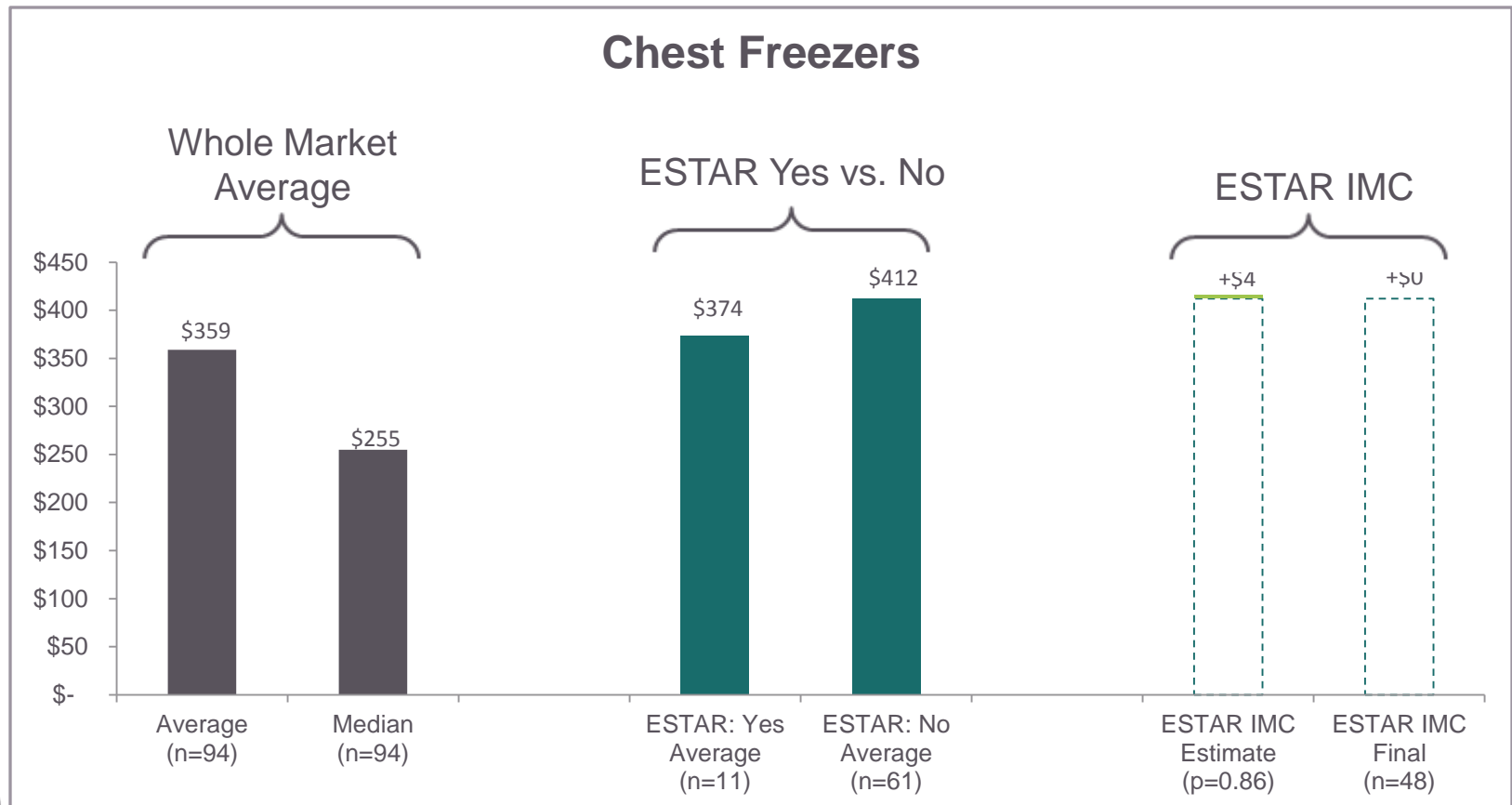
IMC Results: Upright Freezers

- ESTAR products are only slightly more expensive than non-ESTAR (*teal bars*)
- The estimated unique impact of ESTAR is +\$13 (*left green bars*)
- But there is insufficient evidence to reject the null hypothesis (*right green bar = 0*)



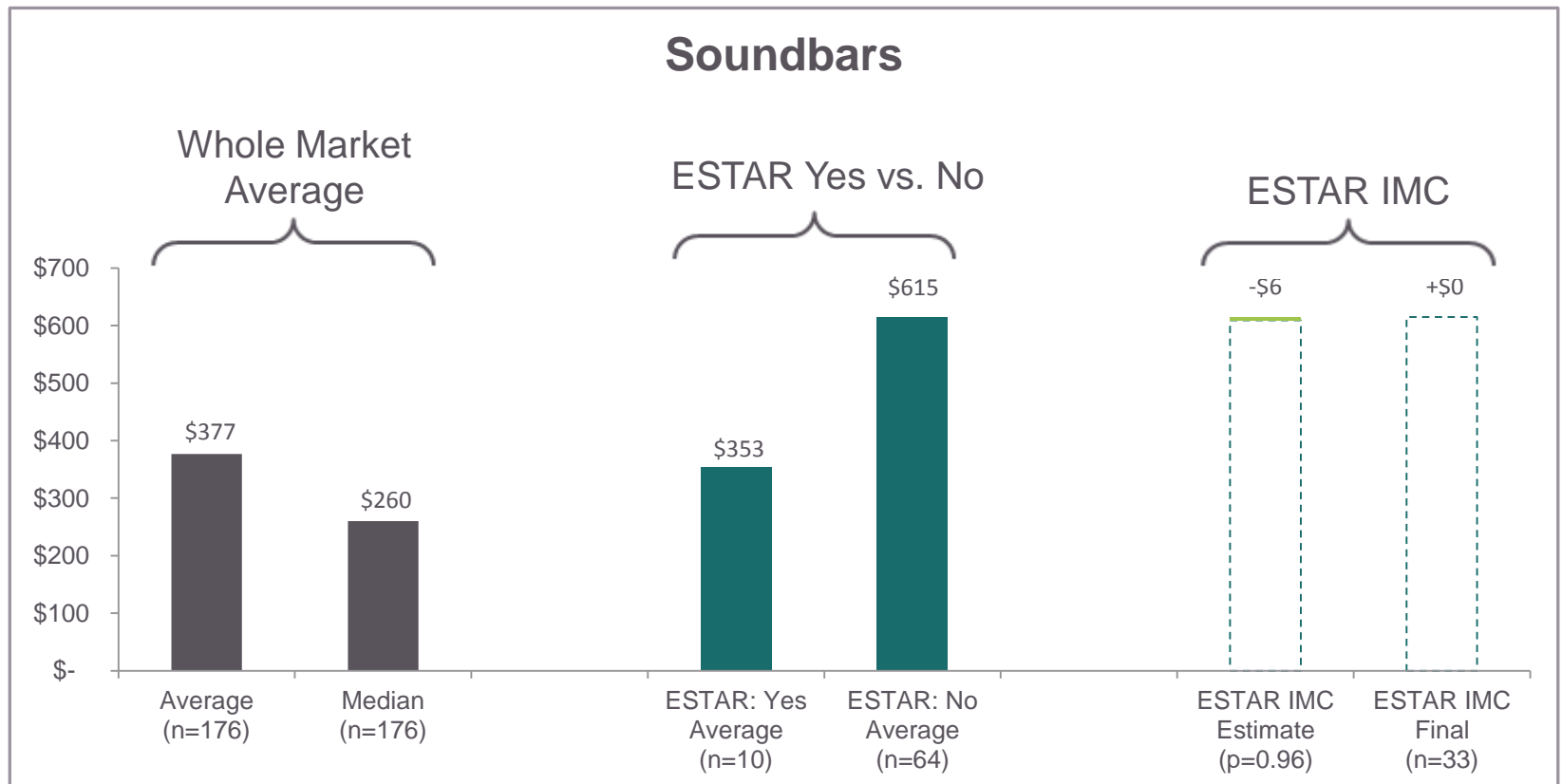
IMC Results: Chest Freezers

- ESTAR products are, on average, *less expensive* than non-ESTAR (*teal bars*)
- The estimated unique effect of ESTAR is +\$4, controlling for Capacity and Brand (*left green bars*)
- But there is insufficient evidence to reject the null hypothesis (*right green bar = 0*)



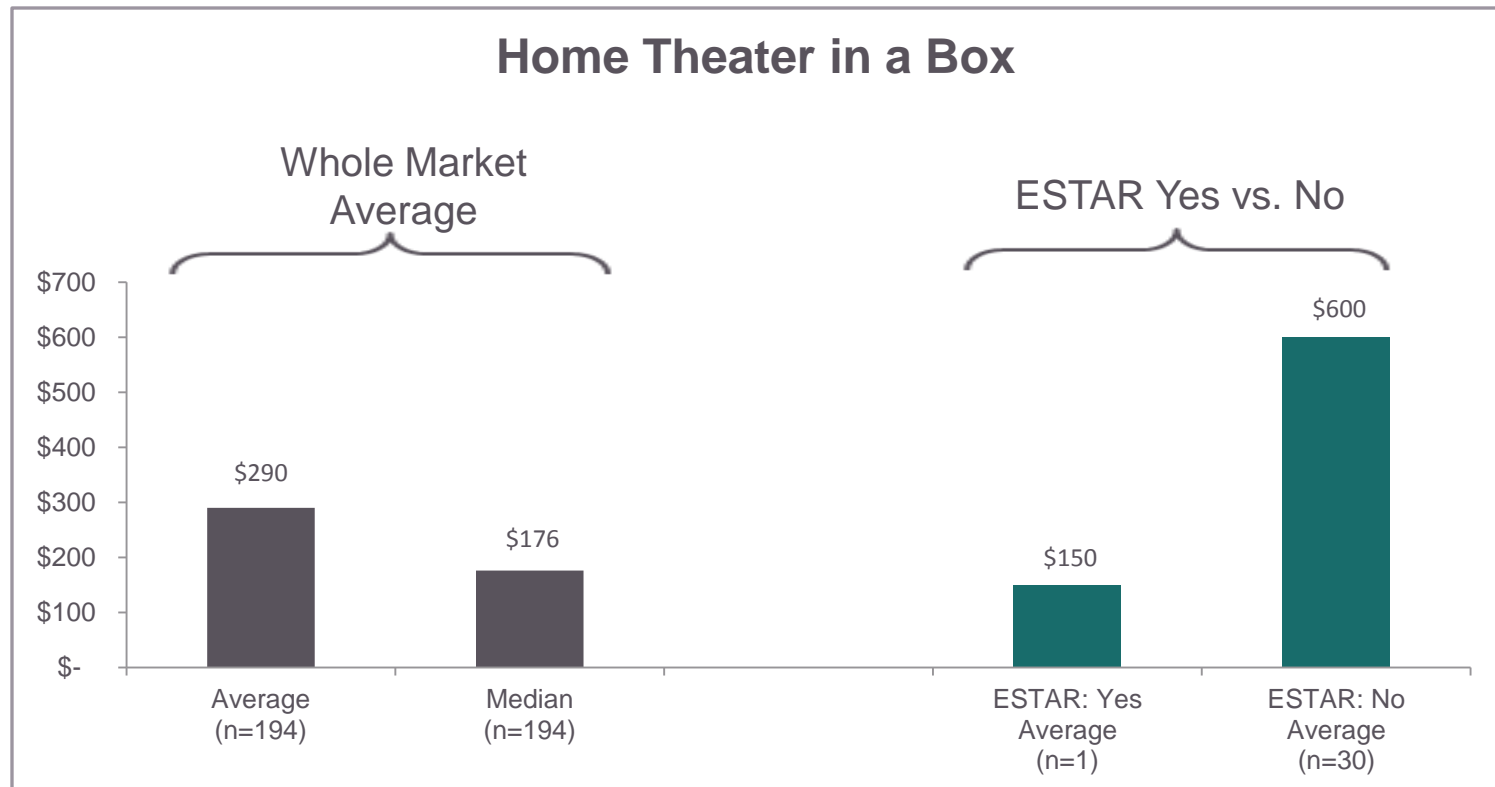
IMC Results: Soundbars

- The 10 ESTAR products are, on average, *less expensive* than non-ESTAR (*teal bars*)
- The estimated unique impact of ESTAR is *-\$6* (*left green bars*)
- But there is insufficient evidence to reject the null hypothesis (*right green bar = 0*)



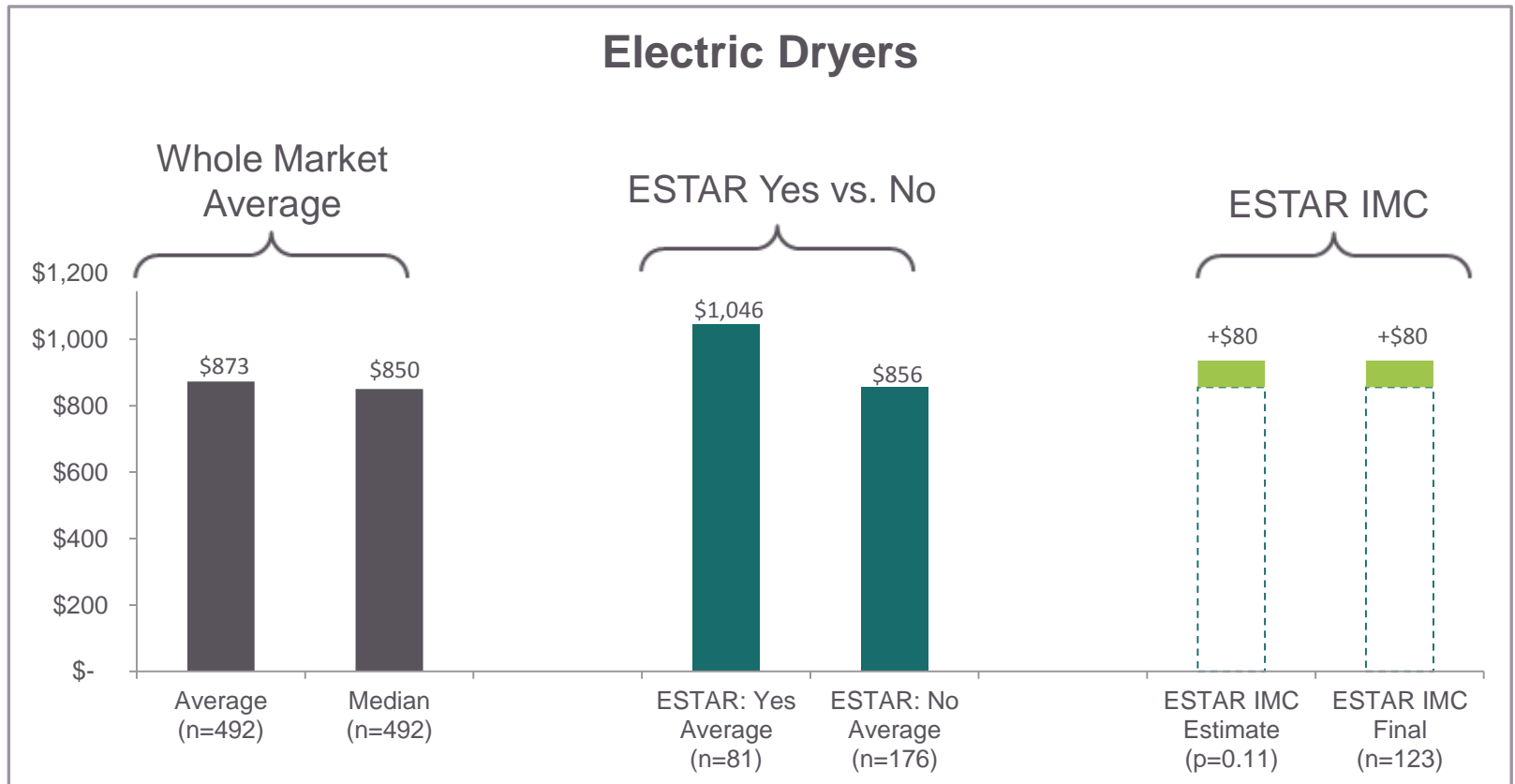
IMC Results: Home Theaters-in-a-Box

- Prevalence of ENERGY STAR data is too low to be able to determine an IMC for the Home Theater in a Box product category
- Only one product was listed as ESTAR-qualified
- Will assume an IMC of \$0 until more data become available



IMC Results: Electric Dryers

- ESTAR products are, on average, more expensive than non-ESTAR (*teal bars*)
- The unique impact of ESTAR accounts for \$80 of this difference (*green bars*)
- In consultation with PG&E, we recommend an IMC value for dryers even though the p-value of the ESTAR term is 0.11 in the IMC Model (*right green bar $\neq 0$*)

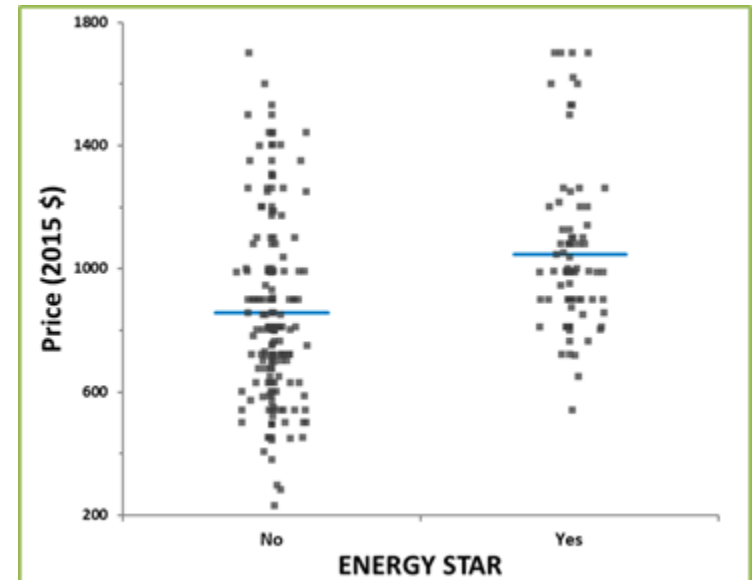


IMC Results: Electric Dryers

Recommendation of $IMC = \beta_{ESTAR}$ (\$80) over \$0

- **Prior evidence (against null hypothesis)**
 - RTF recommends a value of ~\$50
- **Limited statistical power**
 - Sample size of 123
- **High significance of β_{ESTAR} given different modeling decisions**
 - If we coded 'Door style' differently or if we remove 'Brand' instead of 'Control type' due to multicollinearity, ENERGY STAR survives the stepwise regression process and is significant
- **Narrow meaning of p-value**
 - Likelihood of evidence against the null hypothesis at least this strong, given the final model we chose and our sample size, if the null hypothesis were true

Δ_{ESTAR} is highly significant without controls (ANOVA)



**85% confidence interval
for β_{ESTAR} is +\$7 to +\$154**



All Products: Summary

Base case, measure case, and final recommended ENERGY STAR IMC for all products

Product	Base Case Avg. Price (\$)	Measure Avg. Price (\$)	ENERGY STAR IMC (%)	ENERGY STAR IMC (\$)
Air Cleaners	\$194	\$303	56%	\$109
Electric Dryers	\$856	\$936	9%	\$80
Upright Freezers	\$849	\$849	0%	\$0
Chest Freezers	\$412	\$412	0%	\$0
Soundbars	\$615	\$615	0%	\$0
HTIB	\$600	\$600	0%	\$0

*In consultation with PG&E, we recommend extending our electric dryers results to gas dryers, pending a separate gas dryers analysis.



Requests of CalTF / Next Steps

- Requests of CalTF
 - Are the methods and values adequately described?
 - Are there any aspects of the approach for which you would like clarification?
 - Does the CalTF endorse the *methods and values* proposed by the RPP team?
- Next Steps for PG&E:
 - Complete white paper detailing methods and results (to be included as an appendix in the white paper).
 - Approval of values produced by these methods.



QUESTIONS & DISCUSSION



APPENDIX A: SUMMARY TABLES FOR ALL PRODUCTS



All Products: Summary

Market average price for all products

Product	Average Price (\$)	Median Price (\$)
Air Cleaners	\$219	\$144
Electric Dryers	\$873	\$850
Upright Freezers	\$786	\$649
Chest Freezers	\$359	\$255
Soundbars	\$377	\$260
HTIB	\$290	\$176

*In consultation with PG&E, we recommend extending our electric dryers results to gas dryers, pending a separate gas dryers analysis.



All Products: Summary

*Average price of non-ENERGY STAR and ENERGY STAR products;
Estimated \$Δ due to ENERGY STAR in our IMC Model*

Product	Base Case Avg. Price (\$)	ENERGY STAR Avg. Price (\$)	Difference	ESTAR IMC Estimate	ESTAR IMC Estimate (%)	ESTAR IMC Estimate p-value
Air Cleaners	\$194	\$318	\$122	\$109	56%	<0.0001
Electric Dryers	\$856	\$1,046	\$190	\$80	9%	0.11
Upright Freezers	\$849	\$864	\$16	\$13	2%	0.82
Chest Freezers	\$412	\$374	(\$38)	\$4	1%	0.86
Soundbars	\$615	\$353	(\$262)	-\$6	-1%	0.96
HTIB	\$600	\$150	(\$450)	-	-	-

*In consultation with PG&E, we recommend extending our electric dryers results to gas dryers, pending a separate gas dryers analysis.



APPENDIX B: METHODOLOGY DRILL-DOWN



Methods Overview

STAGE

1. Web harvesting

2. Clean data & distill attributes

3. Multiple regression analysis

4. Model selection & validation

5. If not already in the model, add ENERGY STAR to Best Model to determine unique effect on price

OUTCOME

1. Raw data

2. Likely key attributes that influence Price

3. Identify combos of key attributes (“models”) that best explain variation in \$

4. Identify the Best Model

5. ENERGY STAR IMC estimate
(β_{ESTAR}); measures of evidence against the null hypothesis ($\beta_{\text{ESTAR}} = 0$)



1. Web Harvesting Data Collection

- Data collection methods include screen scraping and API integration

SPECIFICATIONS

■ DIMENSIONS

Assembled Depth (in.)	36.86 in	Height to Top of Case (in.)	75.32
Assembled Height (in.)	75.32 in	Height to Top of Door Hinge	72
Assembled Width (in.)	36.38 in	Minimum Side Air Clearance (In)	3
Depth (Excluding Handles)	32.86	Product Depth (in.)	27.5
Depth (Including Handles)	36.86	Product Height (in.)	72
Depth With Door Open 90 Degrees (In)	59.625	Product Width (in.)	34.25

■ DETAILS

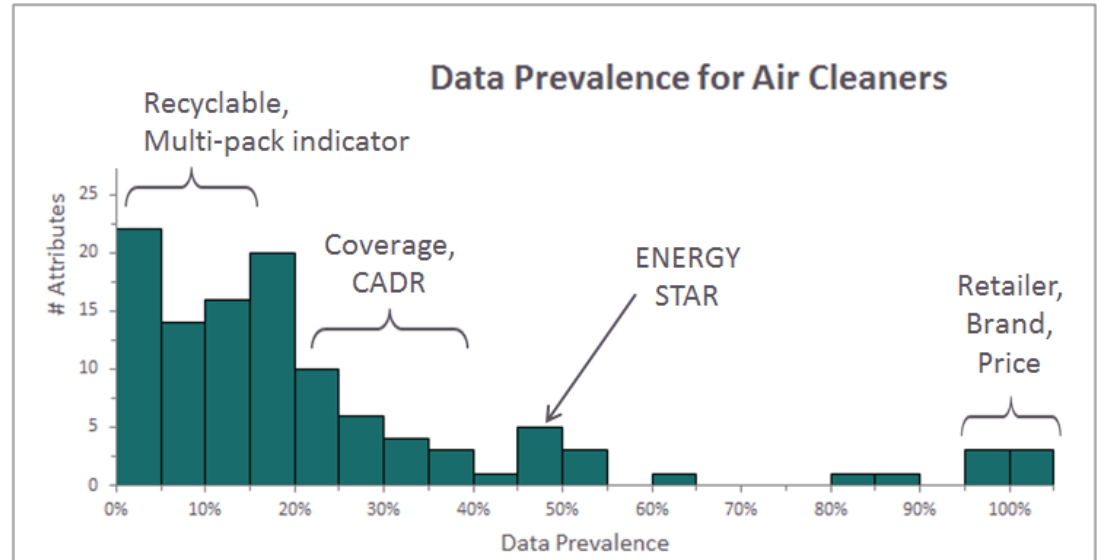
Appliance Type	Upright Freezer	Freezer Features	Adjustable Leveling Legs,Adjustable Temperature Control,LED Light Type,Power On Light Indicator,Safety Lock
Bulk Storage Baskets (number)	0	Freezer Type	Upright
Capacity (cu. Ft.) - Freezer	20.3	Minimum Back Air Clearance (In)	3
Color/Finish	White	Number of Shelves	4
Color/Finish Family	White	Product Weight (lb.)	210 lb



2. Clean Data & Distill Attributes

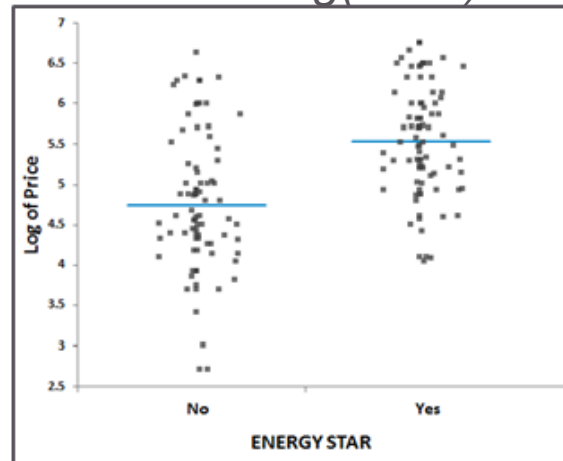
- Identify likely key attributes before stepwise regression to reduce:

- Spurious correlations
- Multicollinearity
- Loss of data

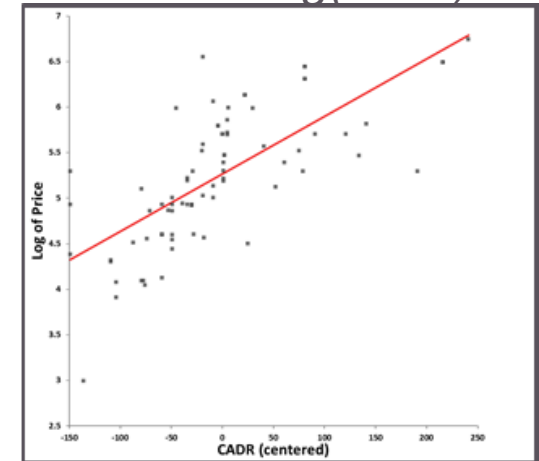


- Our toolkit
 - Data prevalence
 - Expert interview
 - Single variable correlations

ESTAR vs. $\log(\text{Price})$

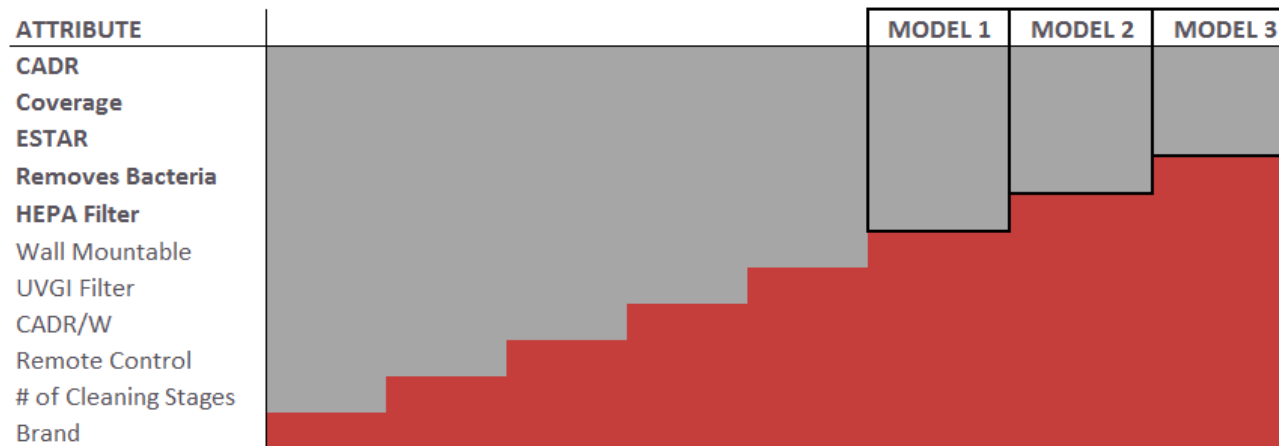


CADR vs. $\log(\text{Price})$



3. Supervised Backward Stepwise Regression

- Pare down likely key attributes to candidate Best Models of price



Unsupervised

- Software *automatically* removes least significant attributes
- Performs poorly in the face of multicollinearity

Supervised

- Account for multicollinearity
- Leverage understanding of attribute relationships
- Diagnostics and “reality-check” at each iteration

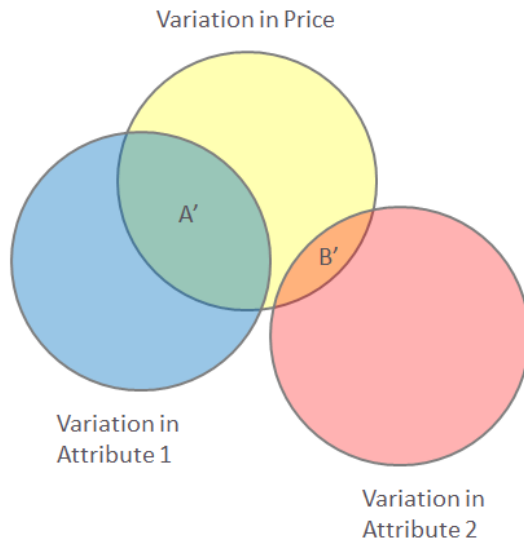


3. Supervised Backward Stepwise Regression

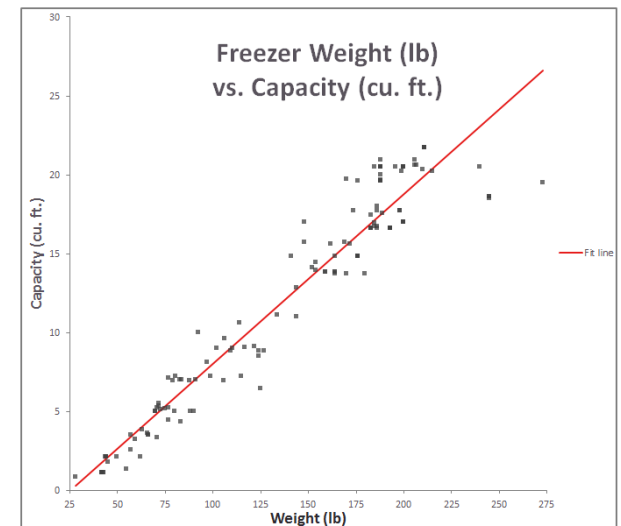
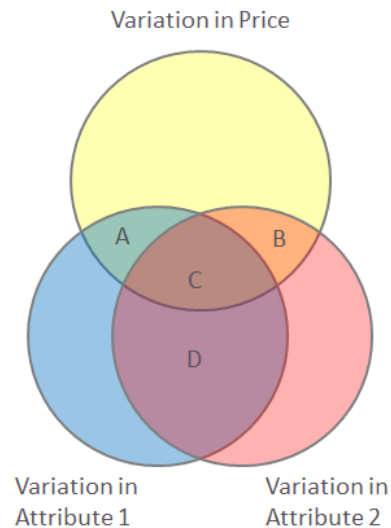
(Multi)collinearity

- When attributes are correlated with each other, they have less unique covariation with price
 - This reduces the significance of those attributes

No collinearity



Highly collinear attributes

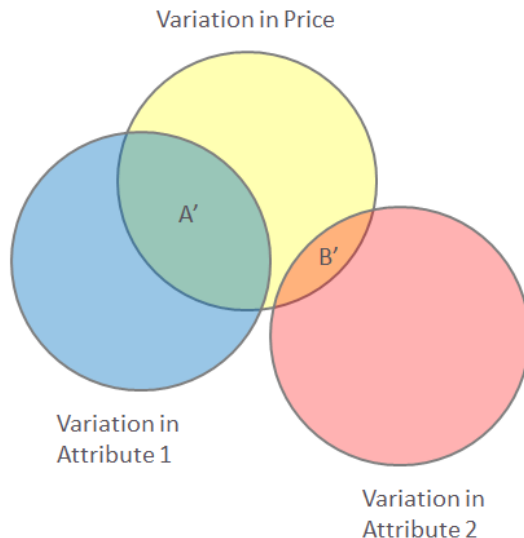


3. Supervised Backward Stepwise Regression

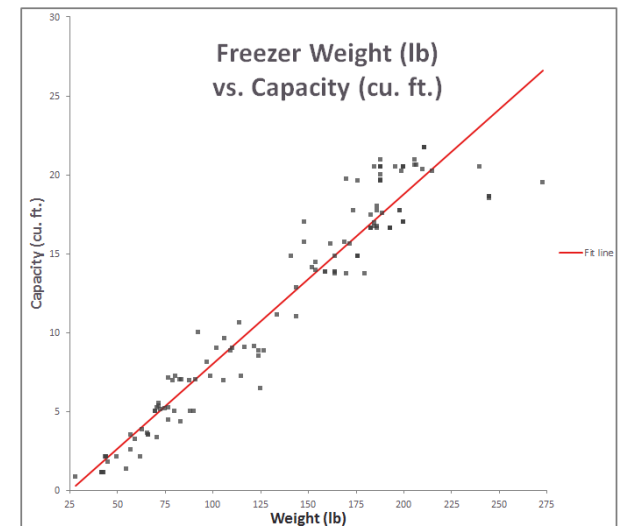
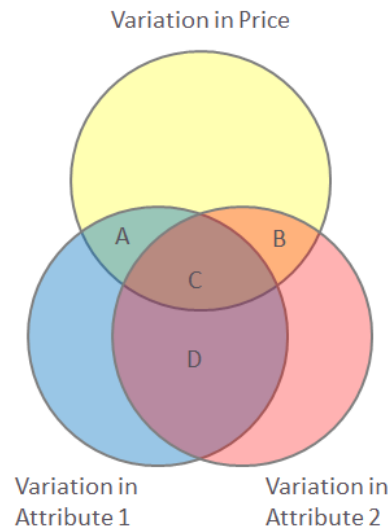
Supervised Solutions

- Use metrics and heuristics to identify (multi)collinearity
- Try to understand *why* attributes are partially collinear
- Prioritize elimination of “redundant” attributes, then least significant
- Be cognizant of omitted variable bias, *especially* with ENERGY STAR

No collinearity



Highly collinear attributes



4. Model Selection & Validation

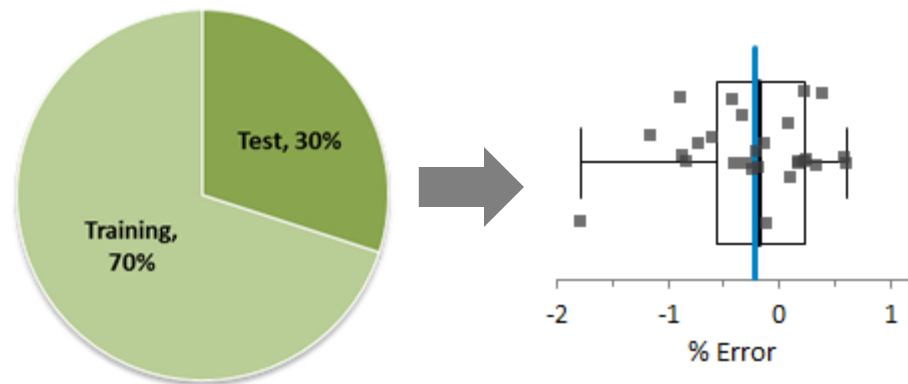
Model Selection

- Select Best Model based on:
 - Metrics that reward goodness of fit and penalize complexity
 - Adjusted R^2
 - AICc
 - Expert interview
 - Model validation results

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3
CADR			
Coverage			
ESTAR			
Removes Bacteria			
HEPA Filter			

Model Validation

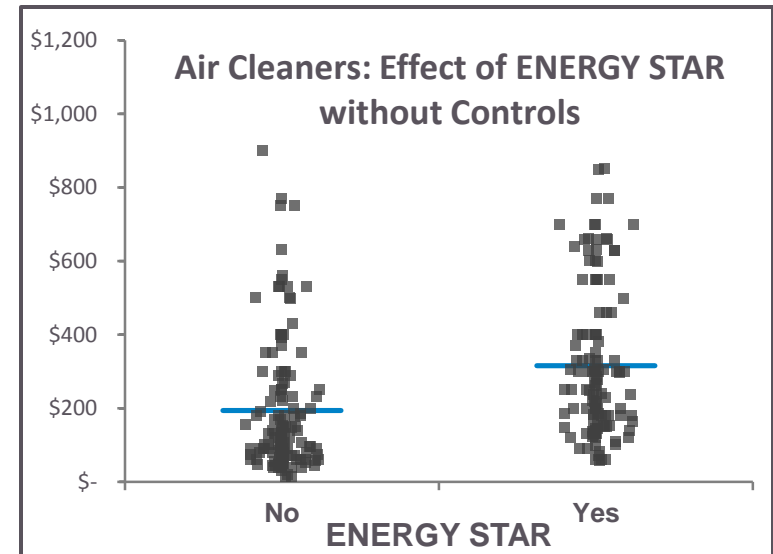
- Model is trained on 70% of the data, then tested on remaining 30%
- Testing on new data catches “over-fitting”



5. Evaluate Unique Effect of ENERGY STAR

ANOVA

- One-way ANOVA → effect *without* controls
- Gives us a hint of attribute relationships with price
- Covarying attributes may confound true effect



Generate IMC Models

- If Best Models do not include ENERGY STAR, force it into the candidate Best Models

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
ENERGY STAR					
Brand					
Window					
Drying Rack					
Drum Material					
Wrinkle-Free					
Stackable					
Steam					
Capacity					

Electric Clothes Dryers Backwards Stepwise Regression



5. Evaluate unique effect of ENERGY STAR

Evaluate IMC

- ENERGY STAR coefficient (β_{ESTAR}) is the estimated unique average effect on Price, controlling for most important attributes

$$\log(\text{Price}) = \text{Constant} + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \dots + \beta_{\text{ESTAR}}(\text{is_ESTAR})$$

- Analyze stability and significance of β_{ESTAR} between models
- Select IMC Model
 - In all cases, we selected the Best Model + ENERGY STAR
- Recommend IMC = 0 or β_{ESTAR} based on
 - p-value
 - Degree of multicollinearity
 - Statistical power of the model
 - Prior knowledge

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
ENERGY STAR					
Brand					
Window					
Drying Rack					
Drum Material					
Wrinkle-Free					
Stackable					
Steam					
Capacity					



Caveats and Limitations

- Sample Size Limitations
 - Limited sample size due to attribute data gaps
 - Ability to detect subtle IMCs will grow over time with increased sample size
- We cannot control for factors that are not listed online
- We did not impute missing ENERGY STAR data
 - Likely would increase our ability to detect IMC, because ESTAR [blank] tends to be cheaper than ESTAR 'Yes'
- The precise subset of attributes in the Best Model depends on:
 - The specific observations in a sample of data, especially with small samples
 - Prioritization of (multi)collinear attributes
 - Coding of attributes



APPENDIX C: PRODUCT-SPECIFIC METHODS & RESULTS



Freezers: Separating Chest & Upright Datasets

- Chest and Upright freezers are inherently different product types
 - Energy efficiency standards separate freezers based on whether they are chest or upright
- Tried treating Chest/Upright as a categorical variable
 - Chest/upright moderated the impact of other variables
- Separated freezers into two datasets, treating Chest and Upright freezers as different product categories

Product	Average Price (\$)	Median Price (\$)
Upright Freezers	\$786	\$649
Chest Freezers	\$359	\$255



Chest Freezers: Web Harvesting & Pre-Processing

Web Harvesting

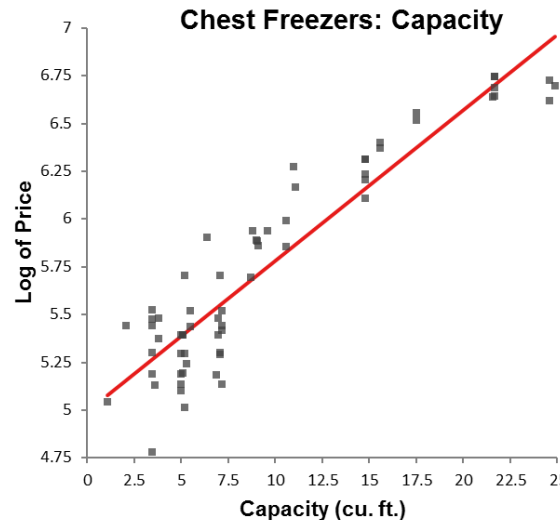
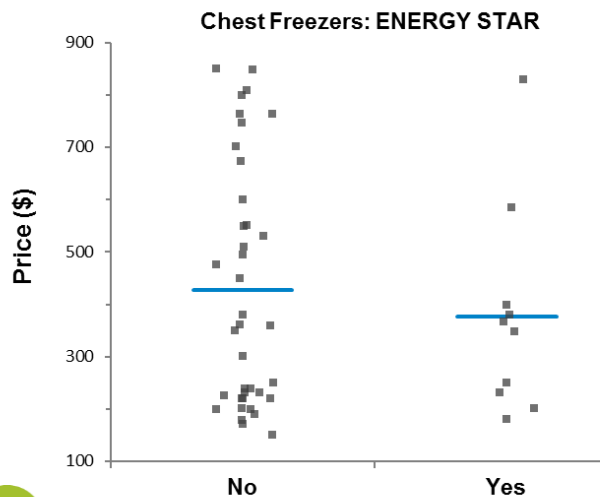
- 97 initial product models
- ~80 initial attributes

Data Prevalence

- Most attributes have prevalence < 60 %

Example high-prevalence attributes

Attribute	Prevalence
Source	100%
Manufacturer	100%
Brand	100%
Capacity (cu. ft.)	100%
Height	84%
Width	84%
Energy Star	83%
Depth	83%
Defrost	76%
Temperature	74%
Control	70%
Unit Price	65%
Color	63%
Color Family	62%
Weight	59%
Yearly Energy Consumption (kWh)	59%



Chest Freezers: Hierarchical Regression

Only 2 likely key attributes: Capacity and Brand

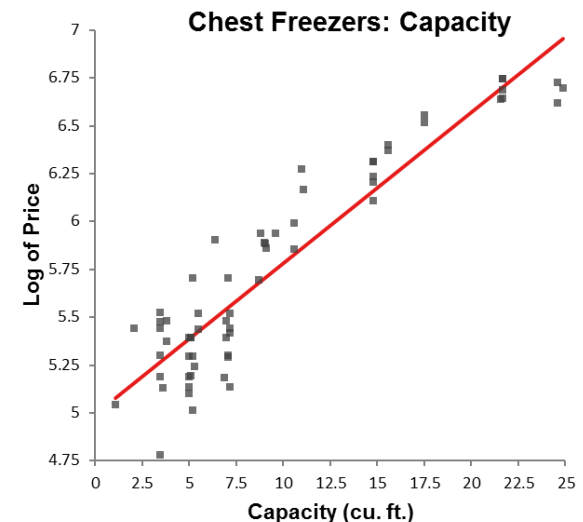
- Low data prevalence, especially in combination
 - Exacerbated by separating data into Chest and Upright freezers
- Categorical variables with many different levels, unclear functional categories
- Retailer was inadmissibly collinear with Brand
- All chest freezers sampled were manual Defrost

Hierarchical regression

- Pre-determined order
- Enter attributes in order of causal priority
 - Brand after Capacity

→ 2 candidate Best Models

ATTRIBUTE	MODEL 1	MODEL 2
Capacity		
Brand		



Chest Freezers: Model Validation & Selection

Selected Model 2 as Best Model based on Adjusted R² and AICc

- Both attributes were highly significant

ATTRIBUTE	MODEL 1	MODEL 2
Capacity		
Brand		

Model 2 performed very well in model validation

- R² = 0.90 for *new* data
- Average % Error = 0% with 95% CI: - 5% to 6%

Model	Training Data Adjusted R ²	Relative Likelihood (AICc)
1	0.93	1%
2	0.95	99%

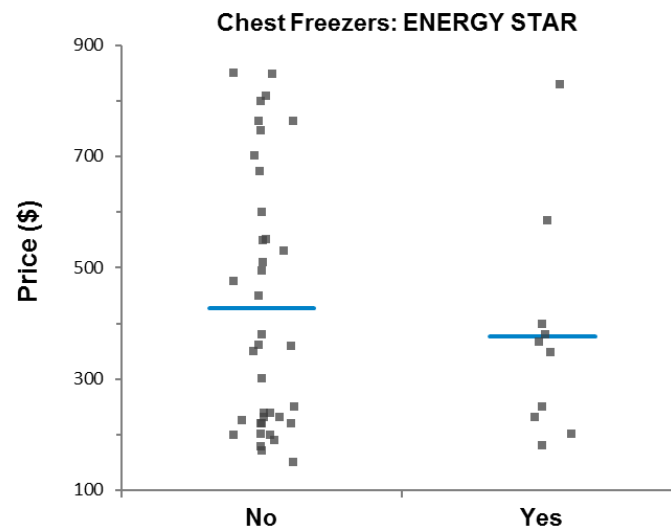
Model	Model Validation R ²	Avg. % Error	Avg. % Error 95% CI	Full Data Adjusted R ²
2	0.9	0%	-5% 6%	0.92



Chest Freezers: Evaluate ENERGY STAR IMC

Recommended IMC = \$0

- ENERGY STAR IMC is not significant
 - p-value = 0.86
- Insignificant difference in average price without controls (one-way ANOVA)
 - p-value = 0.53



ATTRIBUTE	MODEL 2
ENERGY STAR	
Capacity	
Brand	

Model	ENERGY STAR IMC	95% Confidence Interval	ESTAR p-value
2	1%	-11% 13%	0.86



Upright Freezers: Web Harvesting & Pre-Processing

Web Harvesting

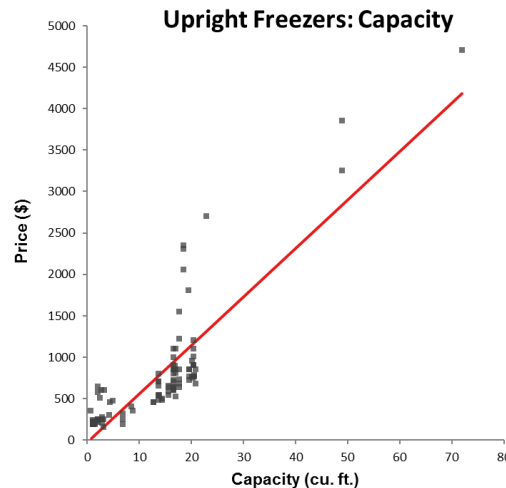
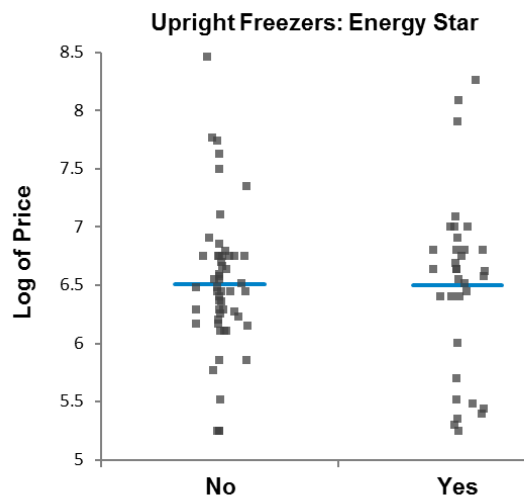
- 142 initial product models
- ~80 initial attributes

Data Prevalence

- Most attributes have prevalence < 30 %

Example high-prevalence attributes

Attribute	Prevalence
Source	100%
Manufacturer	100%
Brand	100%
Capacity (cu. ft.)	100%
Energy Star	87%
Defrost	86%
Temperature	78%
Control	74%
Color	72%
Color Family	72%
Weight	62%
Yearly Energy Consumption (kWh)	58%
UL Safety Listing	50%
CSA Safety Listing	48%



Upright Freezers: Hierarchical Regression

Only 3 likely key attributes: Capacity, Defrost, and Brand

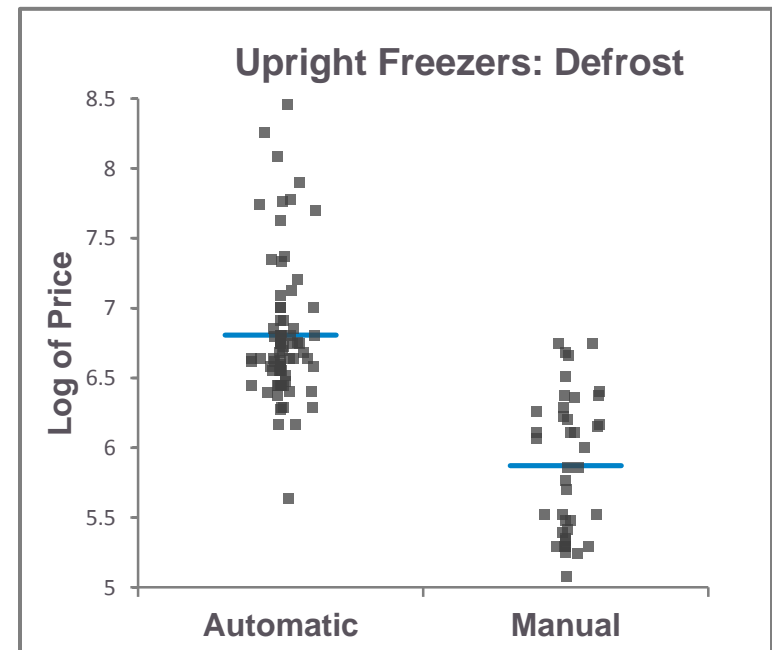
- Low data prevalence, especially in combination
 - Exacerbated by separating data into Chest and Upright freezers
- Categorical variables with many different levels, unclear functional categories
- Retailer was inadmissibly collinear with Brand

Hierarchical regression

- Pre-determined order
- Enter attributes in order of causal priority
 - Capacity first
 - Brand after more proximate effects

→ 3 candidate Best Models

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3
Capacity			
Defrost			
Brand			



Upright Freezers: Model Validation & Selection

Selected Model 3 as Best Model based on Adjusted R² and AICc

- All three attributes were highly significant

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3
Capacity			
Defrost			
Brand			

Model 3 validation results:

- R² = 0.76 for *new* data
- Average % Error = 10% with 95% CI: 1% to 19%

Re-parameterized to the full dataset, Adjusted R² is 0.87 for Model 3

Model	Training Data Adjusted R ²	Relative Likelihood (AICc)
1	0.71	0%
2	0.74	0%
3	0.87	100%

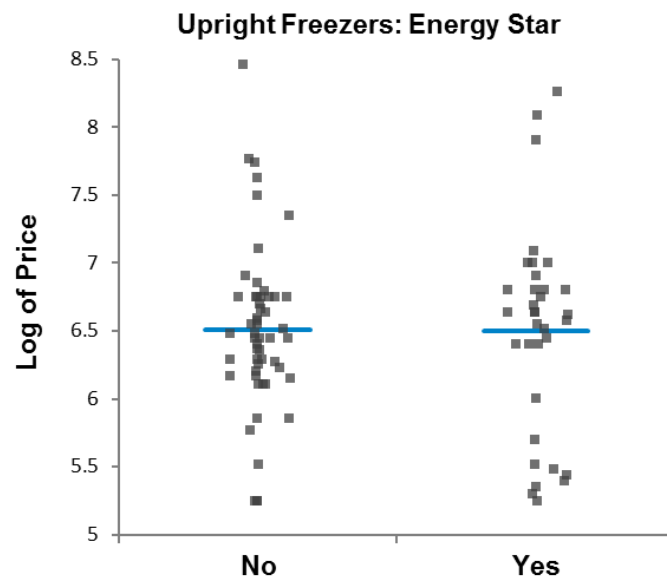
Model	Model Validation R ²	Avg. % Error	Avg. % Error 95% CI	Full Data Adjusted R ²
3	0.76	10%	1% 19%	0.87



Upright Freezers: Evaluate ENERGY STAR IMC

Recommended IMC = \$0

- ENERGY STAR IMC is not significant
 - p-value = 0.82
- Insignificant difference in average price without controls (one-way ANOVA)
 - p-value = 0.99



Model	ENERGY STAR IMC	95% Confidence Interval		ESTAR p-value
3	2%	-12%	15%	0.82



Electric Dryers: Web harvesting & Pre-Processing

Web Harvesting

- 492 initial product models
- ~130 initial attributes

Data Prevalence

- Most attributes have prevalence < 50 %
 - ~ 60% of attributes have prevalence < 30 %

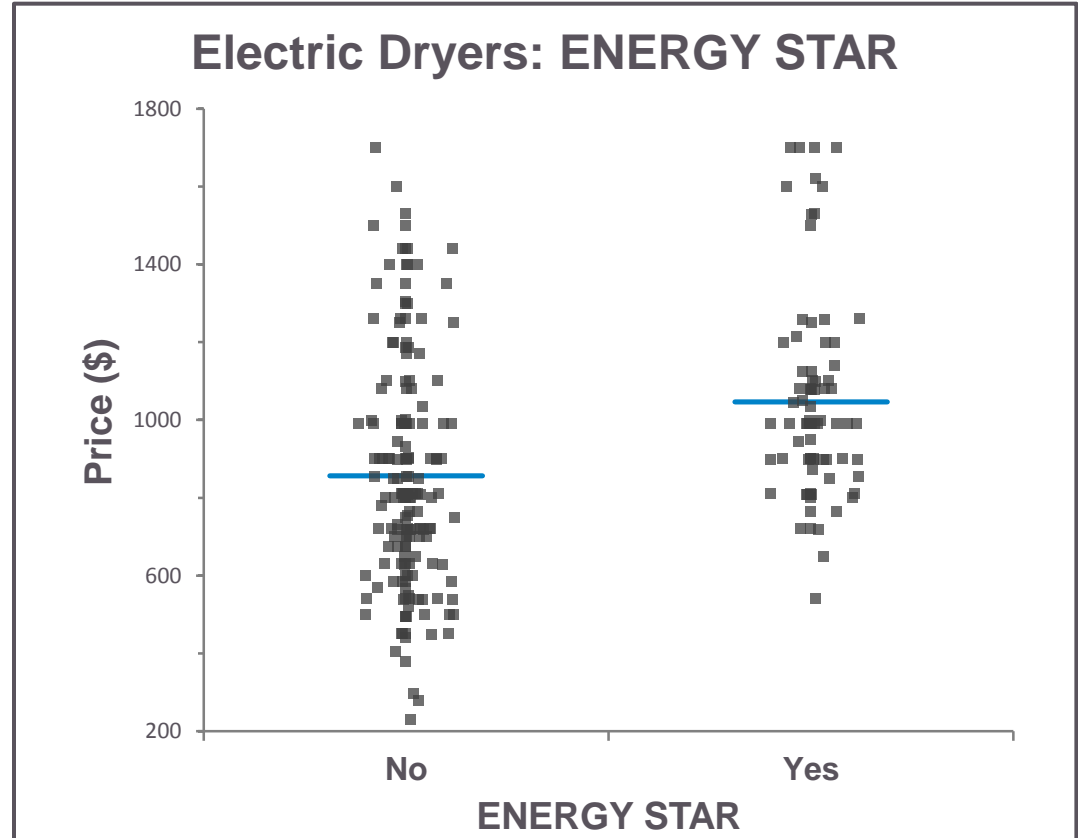
Example high-prevalence attributes

Attribute	Prevalence
Source	100%
Manufacturer	100%
Brand	100%
Capacity (cu. ft.)	99%
Height	97%
Width	97%
Drum Material	96%
Control Type	95%
Stackable	95%
Color	91%
Weight	77%
Interior Light	73%
Drying Rack	72%
Depth	70%
Steam	79%
Number of Temperature Settings	64%



Electric Dryers: Distill Initial Attributes

- **Single variable correlations** with price help identify likely key attributes
- **Expert interview** indicated importance of capacity, drum material, brand, and control type, among others



Electric Dryers: Stepwise Regression

Supervised backward stepwise regression

→ 5 candidate Best Models

- First removed attributes with problematic multicollinearity
- Then removed least significant based on p-values

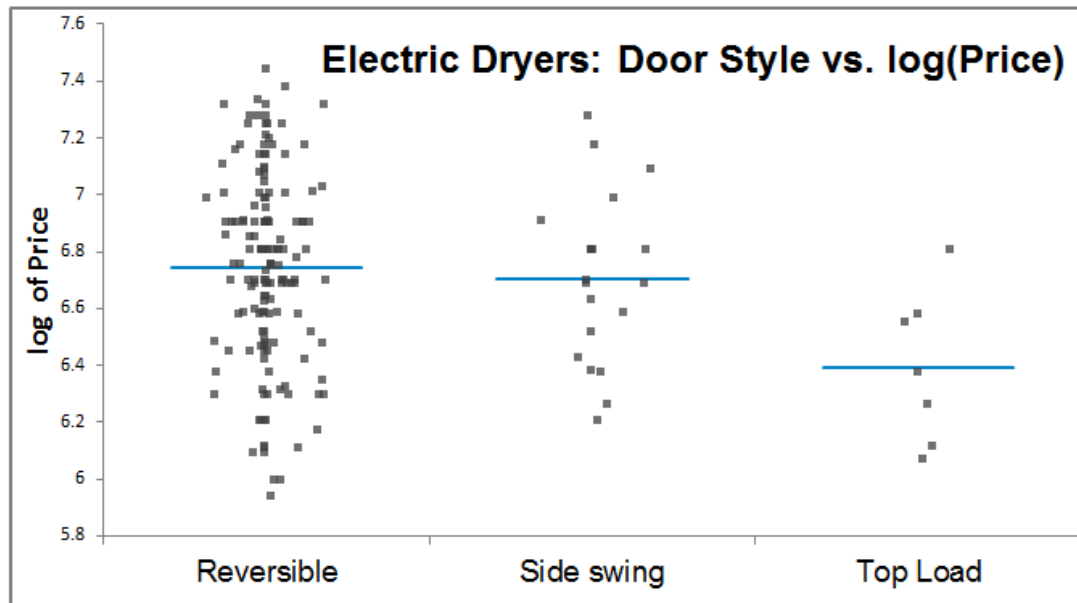
ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
Brand					
Window					
Drying Rack					
Drum Material					
Wrinkle-Free					p-value: least significant
Stackable				p-value: least significant	
Steam			p-value: least significant		
Capacity		p-value: least significant			
# of Drying Cycles	p-value: least significant				
Door Style		p-value: least significant			
Interior Light			p-value: least significant		
ENERGY STAR			p-value: least significant		
Auto Dry Cycle			p-value: least significant		
# of Temperature Settings		p-value: least significant			
Control Type	Collinear: Brand				



Electric Clothes Dryers: Recoding Door Style

Conducted 3 backward stepwise processes in total

1. With Door Style coded as 'Reversible,' 'Side swing,' or 'Top load'
 - Door style has major multicollinearity issues and is eliminated quickly
 - ENERGY STAR survives the stepwise process and is highly significant
2. Coding Door Style as "Top load" or "Not top load" + removing Brand instead of Control Type in the beginning
 - ENERGY STAR survives the stepwise process and is significant, but Best Models perform poorly
3. **What we ultimately selected:**
 - Including Brand + Door Style = "Top load" or "Not top load"



- *Reversible is a specific type of side swing.*
- *Side swing vs. top load shows the most difference.*
- *Three-level coding produces major multicollinearity problems*



Electric Dryers: Model Validation & Selection

All candidate models performed similarly in model validation

- $R^2 = 0.63$ to 0.65 for *new* data
- 95% CI for average % error -1% to +4%

Selected Model 2 as Best Model based on adj. R^2 and AICc

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
Brand					
Window					
Drying Rack					
Drum Material					
Wrinkle-Free					
Stackable					
Steam					
Capacity					

Model	Model Validation R^2	Avg. % Error	Average % Error 95% CI		Full Data Adjusted R^2	Relative Likelihood (AICc)
1	0.63	1.4%	-1%	4%	0.70	40%
2	0.63	1.4%	-1%	4%	0.70	59%
3	0.65	1.5%	-1%	4%	0.69	0%
4	0.65	1.5%	-1%	4%	0.69	0%
5	0.65	1.6%	-1%	4%	0.65	0%



Electric Dryers: Evaluate ENERGY STAR IMC

Selected Best Model as IMC Model based on AICc

Recommended IMC = β_{ESTAR}

- 9% or +\$80 relative to the base case
- Although p-value = 0.11 in the IMC model, in consultation with PG&E we determined β_{ESTAR} is a more likely estimate of the true IMC than 0

ATTRIBUTE	MODEL 1	MODEL 2	MODEL 3	MODEL 4	MODEL 5
ENERGY STAR					
Brand					
Window					
Drying Rack					
Drum Material					
Wrinkle-Free					
Stackable					
Steam					
Capacity					

Model	ENERGY STAR IMC	95% CI		P-value	Relative Likelihood
1	5%	-7%	18%	0.38	40%
2	9%	-21%	2%	0.11	59%
3	8%	-3%	20%	0.16	0%
4	8%	-2%	19%	0.13	0%
5	9%	-1%	20%	0.09	0%

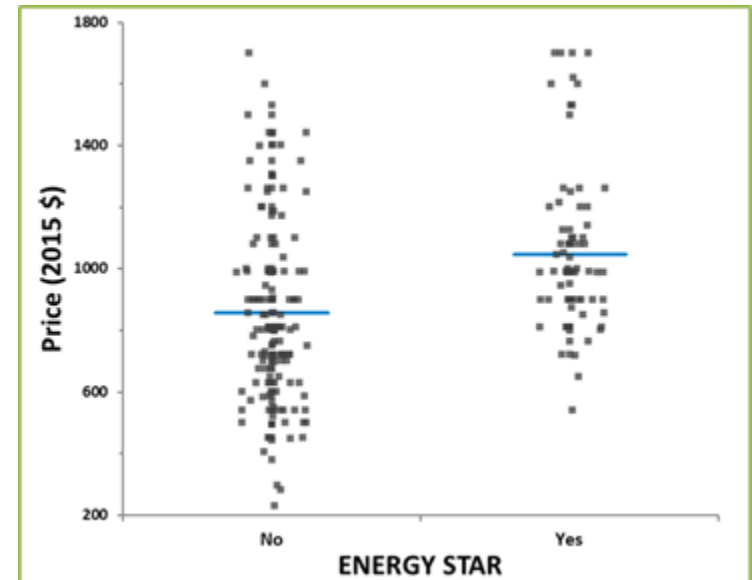


IMC Results: Electric and Gas Dryers

Recommendation of $IMC = \beta_{ESTAR} (\$80)$ over \$0

- **Prior evidence (against null hypothesis)**
 - RTF recommends a value of ~\$50
- **Limited statistical power**
 - Sample size of 123
- **High significance of β_{ESTAR} given different modeling decisions**
 - If we coded 'Door style' differently or if we remove 'Brand' instead of 'Control type' due to multicollinearity, ENERGY STAR survives the stepwise regression process and is significant
- **Narrow meaning of p-value**
 - Likelihood of evidence against the null hypothesis at least this strong, given the final model we chose and our sample size, if the null hypothesis were true

Δ_{ESTAR} is highly significant without controls (ANOVA)



**85% confidence interval
for β_{ESTAR} is +\$7 to +\$154**



Soundbars: Web harvesting & Pre-Processing

Web Harvesting

- 180 initial product models
- ~ 85 initial attributes

Data Prevalence

- Most attributes have prevalence < 40 %

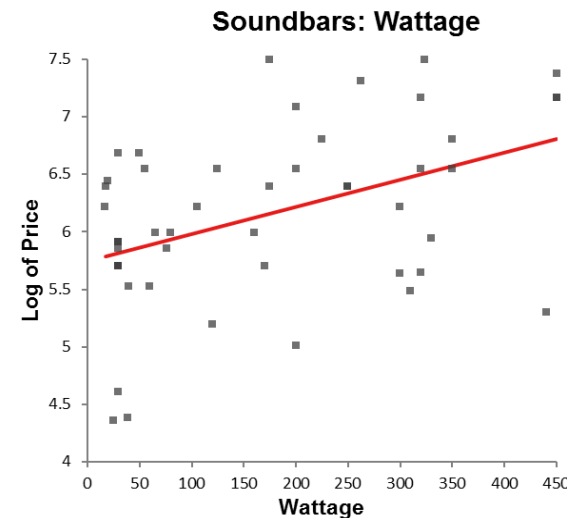
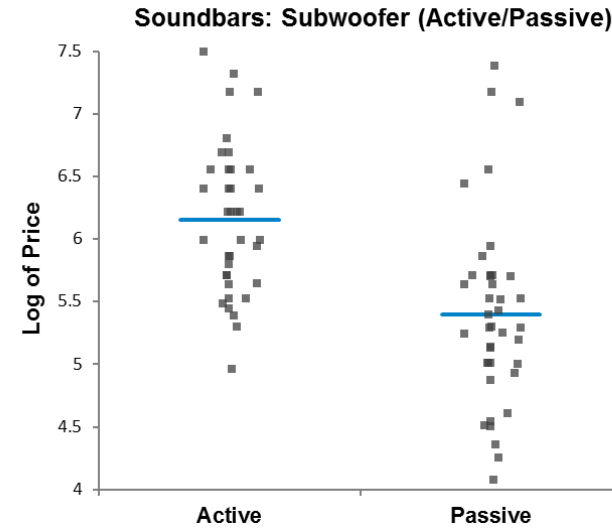
Example high-prevalence attributes

Attribute	Prevalence
Source	100%
Manufacturer	100%
Brand	100%
Subwoofer (No/Active/Passive)	100%
Subwoofer (Yes/No)	100%
Wireless (Yes/No)	76%
Number of Channels	59%
Bluetooth Enabled	58%
Wireless, Bluetooth	58%
Number Of Speakers	45%
Energy Star	41%
Speaker System (Active/Passive)	39%
Wattage	39%



Soundbars: Distill Initial Attributes

- **Single variable correlations** with price help identify likely key attributes
- **Expert interview** indicated importance of subwoofer (active/passive), # of speakers, # of channels, and wattage, among others



Soundbars: Stepwise Regression

Supervised backward stepwise regression

→ 2 candidate Best Models

- First removed attributes with multicollinearity*
- Then removed least significant based on p-values
- Added Wireless & Bluetooth capability back into final model based on:
 - Expert interview
 - Effect strength throughout the stepwise process
 - Single variable correlation with price

ATTRIBUTE		Model 1	Model 2
# of Channels			
Wireless, Bluetooth			
Wattage		p-value: least significant	
Subwoofer (Active/Passive)		p-value: least significant	
ENERGY STAR		p-value: least significant	
Low Frequency Channel		p-value: least significant	
Source	Collinear		
# of Speakers	Collinear; least significant		
Brand	Too many levels		

*Brand had so many levels relative to the sample size that the equation was overdetermined.



Soundbars: Model Validation & Selection

- All attributes were highly significant in Model 2
- Neither candidate model performed well in model validation
 - Model 2 favored with $R^2 = 0.38$ for *new* data
 - Low sample size
 - Test data: $n = 15$
 - Training data: $n = 52$
- Model 2 was favored by adjusted R^2 on the full dataset
- Selected Model 2 as Best Model

ATTRIBUTE	Model 1	Model 2
# of Channels		
Wireless, Bluetooth		
Subwoofer (Active/Passive)		

Model	Model Validation R^2	Avg. % Error	Avg. % Error 95% CI		Full Data Adjusted R^2
1	0.25	-34%	-56%	-11%	0.52
2	0.38	-15%	-43%	13%	0.60



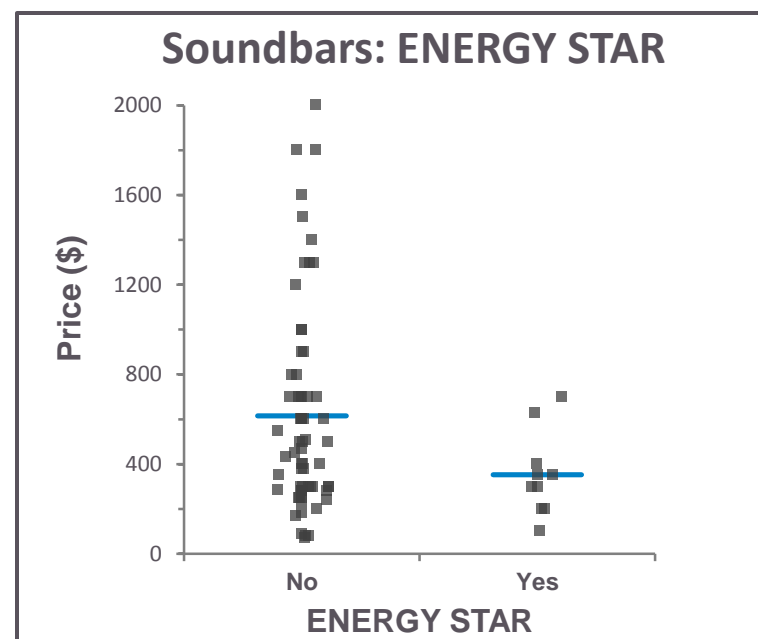
Soundbars: Evaluate ENERGY STAR IMC

Recommended IMC = \$0

- ENERGY STAR is not significant in either candidate model
 - p-values = 0.92 and 0.96
- Insignificant difference in average price without controls (one-way ANOVA)
 - p-value = 0.17

Model	ENERGY STAR IMC	95% Confidence Interval		ESTAR p-value
1	-2%	-39%	36%	0.92
2	-1%	-38%	36%	0.96

ATTRIBUTE	Model 1	Model 2
ENERGY STAR		
# of Channels		
Wireless, Bluetooth		
Subwoofer (Active/Passive)		



Home Theater in a Box: Web Harvesting & Pre-Processing

Web Harvesting

- 200 initial product models
- ~100 initial attributes

Insufficient ENERGY STAR prevalence to move forward

- 30 identified as not qualified
- 1 identified as ENERGY STAR qualified
- Unable to determine IMC for Home Theater in a Box products

Example prevalence

Attribute	Prevalence
Source	100%
Manufacturer	100%
Brand	100%
Bluetooth Enabled	100%
Weight	51%
Bluetooth, wireless	31%
Wattage	30%
Amplifier Channels	21%

