Identifying Future Adopters

Our Objective...

Identify residential customers most likely to adopt Distributed Energy Resource (DER) measures
Identifying Future Adopters

Evergreen developed propensity models for four measures:

- Solar Photovoltaic (PV)
- Electricity Storage
- Plug-In Electric Vehicle (PEV)
- Green Power
Identifying Future Adopters

Our Approach...
Used logistic regression to develop propensity models to estimate probability a customer will adopt a DER measure.
Models are then used to “score” customers based on their estimated probability of adopting a DER measure. The utility can then ...

1. Target those customers most likely to adopt
2. Create messaging that appeals to subgroups of customers
3. Focus resources toward particular subgroups
Identifying Future Adopters

- Utility provided customer information
  - Address, home type
  - Participation in utility programs & services
  - Derogatory payment information

- Evergreen merged additional information
  - Zillow Home value indicators
  - Median income by zip code
  - Temperature data
Identifying Future Adopters

What we did...

1. Randomly selected 70% of customers for modeling and 30% for testing

2. Used logistic regression to create scoring models “probability that customer will adopt a DER measure”

3. Scored each customer in the test group

4. Compared probability scores to actual adoption rates

5. Examined relative importance of factors in a customer’s decision to adopt DER measure
Model Validation – PV Adoption

Targeting Model Identifies 57% of solar PV adopters among only 15% of customers
Factors Affecting PV Adoption

Positive Effect on PV Adoption

- Home area network (HAN)-enabled home
- Enrolled in peak period pricing
- Enrolled in online banking
- Non-English speaker*
- Years of tenure with utility*
Factors Affecting PV Adoption

Negative Effect on PV Adoption

- Enrolled in payment assistance program
- Derogatory payment history
- Percent rentals in zip code
Propensity models predict which customers are most likely to adopt based on the characteristics of customers that have already adopted.

Which means... scores are highest for customers with similar characteristics to past adopters.
Let’s focus on **low-Income** customers living in a **DAC**

<table>
<thead>
<tr>
<th>Single-Family Customer Segments</th>
<th>Customer Distribution</th>
<th>PV Adoption Distribution</th>
<th>% Adoption by Segment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Low-Income - DAC</strong></td>
<td>9.5%</td>
<td>3.6%</td>
<td>2.6%</td>
</tr>
<tr>
<td>Low-Income – Non-DAC</td>
<td>15.2%</td>
<td>8.2%</td>
<td>3.5%</td>
</tr>
<tr>
<td>Non-Low-Income – DAC</td>
<td>12.9%</td>
<td>10.6%</td>
<td>5.2%</td>
</tr>
<tr>
<td>Non-Low-Income – Non-DAC</td>
<td>62.4%</td>
<td>77.4%</td>
<td>7.7%</td>
</tr>
</tbody>
</table>

**Low-Income** - Customer received benefits from one or more income qualified assistance programs

**DAC** - Residence is located in a designated Disadvantaged Community
## Propensity Scoring - Option 1

1. Estimate single propensity model for all customers
2. Score customers with that model
3. Select customers with highest propensity scores

<table>
<thead>
<tr>
<th>Propensity Score Percentile</th>
<th>Proportion of Customers Targeted That Are Low-Income/DAC</th>
<th>Number of Customers (Out of 1,000,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1 Percentile</td>
<td>2.4%</td>
<td>235 of 10,000</td>
</tr>
<tr>
<td>Top 10 Percentile</td>
<td>4.3%</td>
<td>4,258 of 100,000</td>
</tr>
<tr>
<td>Top 25 Percentile</td>
<td>5.4%</td>
<td>13,429 of 250,000</td>
</tr>
</tbody>
</table>
Propensity Scoring - Option 2

1. Estimate segment-specific propensity models
2. Score customers w/ model specific to their segment
3. Select customers with highest scores independent of segment

<table>
<thead>
<tr>
<th>Propensity Score Percentile</th>
<th>Proportion of Customers Targeted That Are Low-Income/DAC</th>
<th>Number of Customers (Out of 1,000,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1 Percentile</td>
<td>0.0%</td>
<td>1 of 10,000</td>
</tr>
<tr>
<td>Top 10 Percentile</td>
<td>0.2%</td>
<td>177 of 100,000</td>
</tr>
<tr>
<td>Top 25 Percentile</td>
<td>1.0%</td>
<td>2,499 of 250,000</td>
</tr>
</tbody>
</table>
Propensity Scoring - Option 3

1. Estimate segment-specific propensity models
2. Score customers with model specific to their segment
3. Select customers with highest scores within each segment

<table>
<thead>
<tr>
<th>Propensity Score Percentile</th>
<th>Proportion of Customers Targeted That Are Low-Income/DAC</th>
<th>Number of Customers (Out of 1,000,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 1 Percentile</td>
<td>9.5%</td>
<td>950 of 10,000</td>
</tr>
<tr>
<td>Top 10 Percentile</td>
<td>9.5%</td>
<td>9,500 of 100,000</td>
</tr>
<tr>
<td>Top 25 Percentile</td>
<td>9.5%</td>
<td>23,750 of 250,000</td>
</tr>
</tbody>
</table>
### Accuracy

Segment-specific propensity models result in more accurate probability scores for individual customers.

### Efficiency

Targeting customers with the highest scores (regardless of segment) is the “globally” efficiency approach, but may be at the cost of equity.

### Equity

Targeting customers with the highest scores within each segment may be the most equitable and is a “locally” efficient approach.
Ted L. Helvoigt, Ph.D.
Vice President, Evergreen Economics

helvoigt@evergreenecon.com
541-954-8674
www.evergreenecon.com