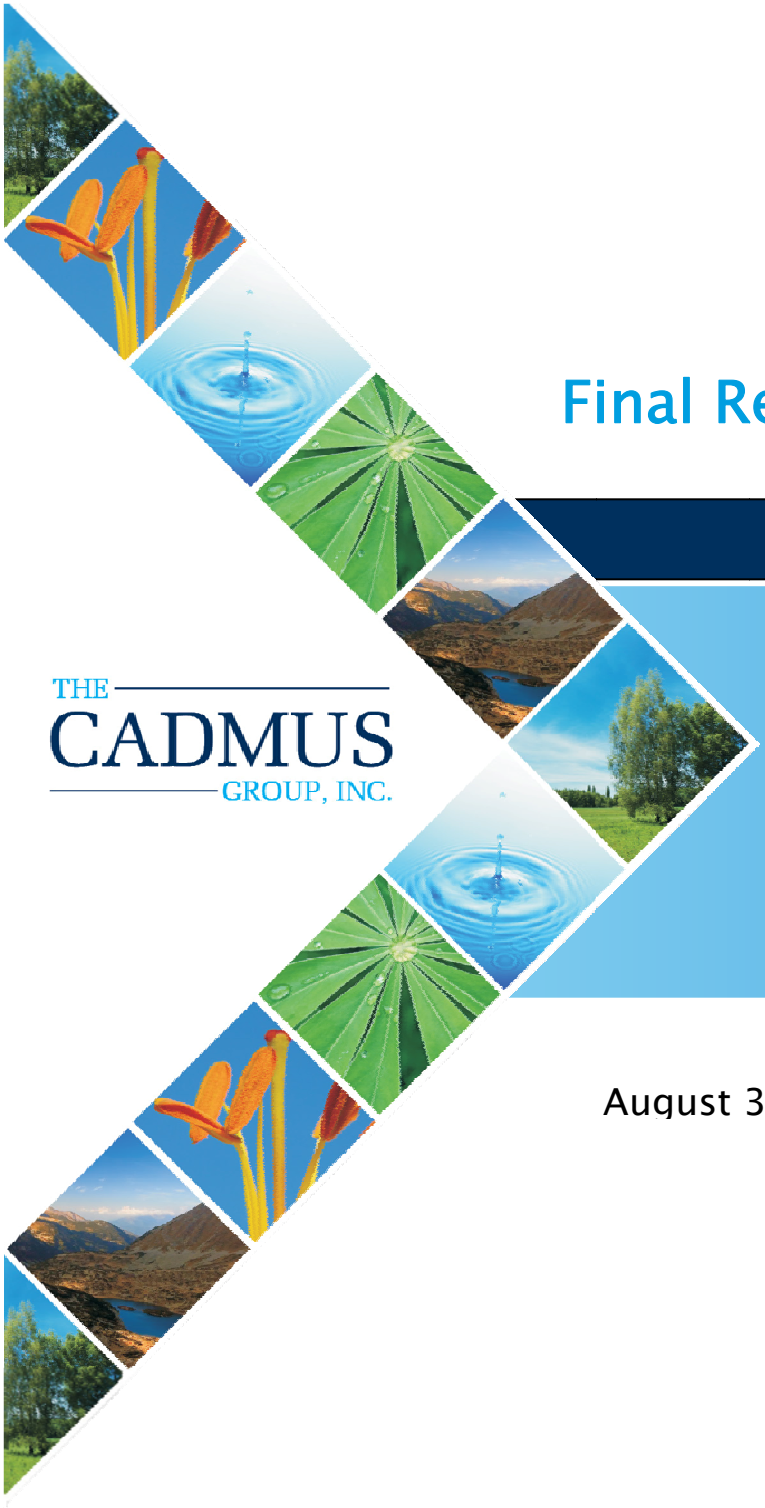

THE CADMUS GROUP, INC.

Final Report

2010 Great Refrigerator Roundup Program—Impact Evaluation

August 31, 2011

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Executive Summary

The Ontario Power Authority's (OPA) Great Refrigerator Roundup Program (GRRP) serves as a province-wide energy-efficiency initiative, designed to remove older, inefficient appliances from the homes of residential electricity consumers. While the GRRP focuses on the removal of full-size refrigerators or freezers, it also recycles older, unwanted, but operable window air conditioners and dehumidifiers. The program's appliance pick-up and decommissioning agent, ARCA Canada, Inc., decommissions all participating appliances in an environmentally-responsible manner.

To evaluate the 2010 GRRP, the OPA contracted with The Cadmus Group, Inc. (Cadmus) to undertake the following three evaluation tasks:

1. Estimating 2010 gross and net program savings.
2. Assessing impacts from the Energy Efficiency Act of 1995 on future GRRP cost-effectiveness.
3. Estimating market saturations of program-eligible appliances within Ontario based on past, current, and future GRRP efforts.

In keeping with the OPA's guiding principle of using resources as effectively and efficiently as possible, the 2010 GRRP evaluation builds upon and leverages Cadmus' previous 2007, 2008, and 2009 GRRP program evaluations.

Gross and Net Savings

To estimate average gross per-unit energy savings for the 2010 GRRP, Cadmus utilized *in situ* metering data, collected for 82 participating appliances as part of the 2008–2009 GRRP evaluation. Allowing a more robust analysis than that possible for the 2008–2009 evaluation, Cadmus also leveraged *in situ* metering data recently gathered through a similar evaluation of Consumers Energy, a Michigan-based electric utility.

Including data from Consumers Energy yielded two significant benefits:

- The additional 45 Consumers Energy metered appliances increased the pool of total metered appliances, allowing Cadmus to employ a more sophisticated and dynamic approach to estimating savings.
- As Consumers Energy did not include minimum age requirements for participating appliances, the Consumers Energy metering dataset included several appliances manufactured after enactment of the United States National Appliance Energy Conservation Act. Including these post-standard appliances in the analysis allowed Cadmus to quantify impacts of appliances manufactured following Canada's Energy Efficiency Act of 1995 participating in future GRRP program cycles.

Note that while the analysis leveraged Consumers Energy data, gross and net savings presented in this report are specific to the OPA's 2010 GRRP. As detailed in the report's Gross Savings chapter, Cadmus employed a two-step approach for estimating savings. First, we ran a regression model using metered energy consumption with each metered appliance's characteristics (i.e., size, age,

configuration, usage type [primary/secondary]) as the explanatory variables. This model quantified individual impacts of each characteristic on observed energy consumption.

Upon understanding these relationships, Cadmus applied model results to detailed information collected by ARCA Canada about each participating appliance to estimate energy consumption for every appliance recycled through the program. Once applied, a simple average of expected energy consumption yielded the program's per-unit gross savings.

Table ES1 summarizes *ex post* per-unit and total gross and net energy savings, by appliance type.

Table ES1. 2010 GRRP—*Ex Post* Gross and Net Energy Savings

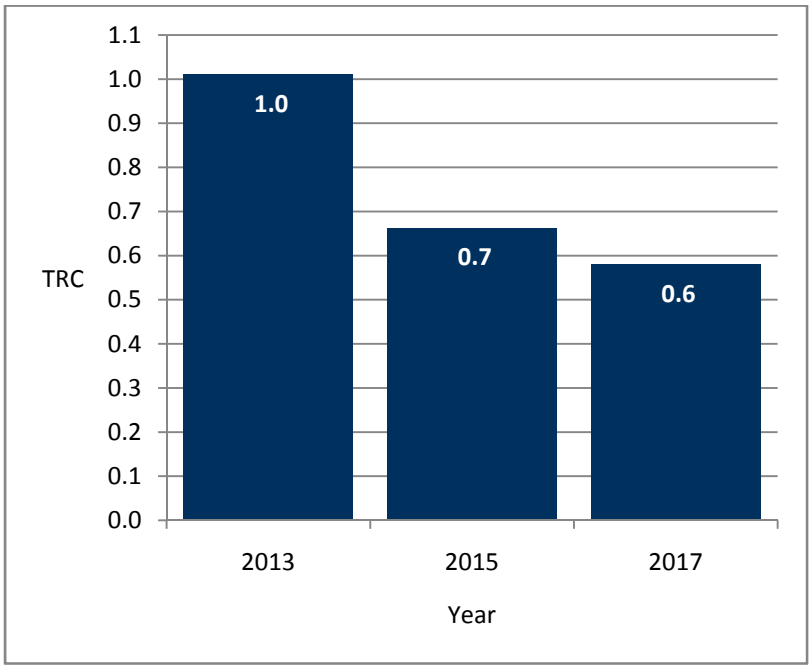
Appliance	2010 Participants	Per-Unit Energy Savings (kWh)	Annual Energy Savings (MWh)	NTG Ratio	Annual Net Energy Savings (MWh)
Refrigerator	48,887	1,126	55,047	0.54	29,725
Freezer	16,584	1,045	17,330	0.52	9,012
Window Air Conditioner	1,233	371	457	0.36	165
Dehumidifiers	1,118	964	1,078	0.36	388
Total	67,822		73,912		39,290

Cost-Effectiveness Forecast

To assess future cost-effectiveness, Cadmus developed a series of models to forecast the composition of participant populations for 2013, 2015, and 2017, as well as the change in average per-unit energy savings over the same time frame (leveraging the gross savings analysis detailed above). This, combined with the market saturation forecast, was used to predict future program cost-effectiveness.

Figure ES1 presents the analysis results.

Figure ES1. Forecasted TRCs for 2013, 2015, and 2017

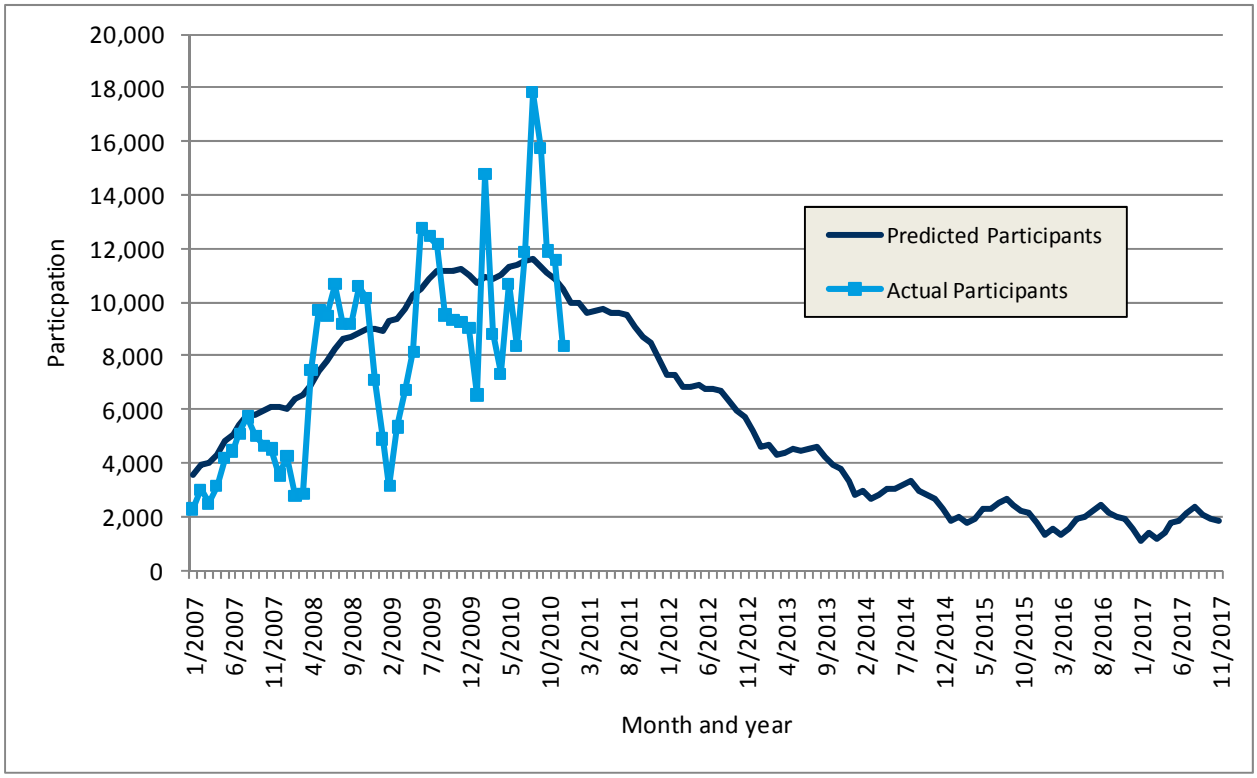


When evaluating the GRRP's forecasted cost-effectiveness, it is important to note that appliance recycling programs can positively impact residential energy efficiency portfolios beyond the energy savings they generate. Since appliance recycling programs typically enjoy extremely high levels of satisfaction (95% of GRRP participant's rated their satisfaction as an 8, 9, or 10 on a 10-point scale as part of the 2008-09 evaluation), the programs can function as a 'gateway' to further program participation. Specifically, participants encouraged by their positive experience in GRRP may be more likely to enroll in another OPA or local distribution company energy efficiency program.

Market Saturation

To assess future market saturation, Cadmus used a hybrid forecasting methodology, drawing from primary and secondary data sources. This approach estimated long-run, steady-state participation and short-run participation deviations from the long-run equilibrium resulting from the program's relative infancy. These segments were modeled separately—the former through secondary research and the latter through diffusion curve analysis. Figure ES2 shows the final analysis results.

Figure ES2. Seasonally-Adjusted Forecasted Total Participation (All Appliances) 2007-2017



As shown, Cadmus predicts the GRRP just recently passed peak participation, and anticipates participation over the next four program years will begin to decline towards its long-run steady-state level.

Recommendations

Based on this evaluation's findings, Cadmus offers the following recommendations for program improvements and for enhancing future evaluation activities:

- As recommended in the 2008–2009 evaluation, additional *in situ* metering should be conducted no later than 2012; at that time, the program will be collecting significant numbers of appliances manufactured after enactment of the Energy Efficiency Act of 1995. To maximize evaluation resources, future metering efforts should focus on newer appliances, not captured in the 2008–2009 metering study.
- While the quality of appliance age data contained in the program's tracking database improved dramatically from 2009 to 2010, further improvement remains possible. Cadmus recommends collecting ARCA record appliance ages using mutually-exclusive, three-year intervals (i.e., 15-17, 18-20). Intervals should start at 15 and continue to 40. All units over 40 years old should be entered into a single ">40" category. As noted in the previous evaluation (and indicated by the model used to estimate savings for 2010), recording accurate appliance characteristics proves essential for accurately estimating program savings.
- Though Cadmus forecasts predict declining GRRP participation and for the program not to be cost-effective as soon as 2015, we believe GRRP could continue to play in important role in the province's long-term residential energy efficiency portfolio for two primary reasons. First, since the bulk of program costs are per-unit expenses, program costs will also decline with participation. It is also likely that other costs, such as advertising, could be reduced as the program awareness increases. Second, since appliance recycling programs typically enjoy extremely high levels of satisfaction, the programs can encourage participants to enroll in another OPA or local distribution company energy efficiency program they otherwise may not have.
- Cadmus recommends dropping the 15-year minimum age requirement for program eligibility. Our forecasts indicate that unit age will steadily decline over time and continuing to impose such an age requirement will further shrink an already declining participant base. In addition, after 2010 the 15-year age minimum will no longer ensure participating appliances were manufactured prior to the Energy Efficiency Act of 1995.

Introduction

The Ontario Power Authority's (OPA) Great Refrigerator Roundup Program (GRRP) serves as a province-wide energy-efficiency initiative, designed to remove older, inefficient appliances from residential electricity consumers' homes. While the GRRP focuses on removing full-size refrigerators or freezers, it also recycles older, unwanted, but operable window air conditioners and dehumidifiers. The program's appliance pick-up and decommissioning agent, ARCA Canada, Inc., decommissions all participating appliances in an environmentally-responsible manner.

To evaluate the 2010 GRRP, the OPA contracted with The Cadmus Group, Inc. (Cadmus) to evaluate the following three tasks:

1. Estimate 2010 gross and net program savings.
2. Assess impacts of the Energy Efficiency Act of 1995 on future GRRP cost- effectiveness.
3. Estimate market saturation of program-eligible appliances within Ontario, based on past, current, and future GRRP efforts.

In keeping with the OPA's guiding principle of using resources as effectively and efficiently as possible, the 2010 GRRP evaluation builds upon and leverages Cadmus' experience in evaluating the 2007, 2008, and 2009 GRRP programs.

Report Structure

Six chapters comprise this report:

1. ***Introduction.*** Discusses the program and evaluation objectives.
2. ***Gross Savings***. Estimates per-unit and overall gross 2010 GRRP savings, as determined by analyzing appliances metered prior to being recycled.
3. ***Net Savings***. Estimates per-unit and overall net 2010 GRRP savings, as determined through surveys with participants and nonparticipants, conducted as part of the 2008–2009 GRRP evaluation.
4. ***Forecasting Cost-Effectiveness***. Analyzes appliance standards' and other program trends' impacts on program cost-effectiveness for 2013, 2015, and 2017.
5. ***Assessing Market Saturation***. Assesses current and forecast market saturations.
6. ***Recommendations***. Provides guidelines for improved future program and evaluation efforts.

Gross Savings

To estimate average gross per-unit energy savings for the 2010 GRRP, Cadmus utilized *in situ* metering data, collected for 76 participating refrigerators and 25 participating freezers as part of the 2008–2009 GRRP evaluation.[1] That evaluation provided significant details regarding the metering study methodology, including sampling, recruitment, and metering equipment used.

To allow a more robust analysis, Cadmus also leveraged *in situ* metering data gathered through a recent, similar evaluation of Consumers Energy, a Michigan-based electric utility, conducted in late 2009 and early 2010. Including Consumers Energy data yielded two significant benefits:

- Adding the 45 refrigerators metered through the Consumers Energy evaluation sufficiently increased the pool of available metered appliances, allowing Cadmus to employ a more sophisticated and dynamic approach to estimating refrigerator savings than that used possible for the 2008–2009 evaluation.
- As Consumers Energy did not include a minimum age requirement for appliance participation, the Consumers Energy metering dataset included several appliances manufactured after the 1990 enactment of the United States National Appliance Energy Conservation Act (NAECA).[2] As NAECA imposed efficiency standards very similar to those dictated by Canada's Energy Efficiency Act of 1995 (EEA),[3] including these post-standard appliances in the analysis allowed Cadmus to quantify the likely impacts of allowing post-EEA appliances to participate in future GRRP program cycles.

While the refrigerator sample was large enough to fit a full regression model describing annual energy consumption as a function of multiple appliance characteristics, the number of freezer observations (25 for the OPA and 18 for Consumers Energy) proved too small a sample to fit a detailed model. Because of this, freezer energy saving is modeled as the weighted average of energy consumption by appliance configuration (upright or chest) determined through both metering studies.

Note that while Consumers Energy data were leveraged in this analysis, gross and net savings presented in this report are specific to the 2010 GRRP. As detailed below, Cadmus employed a two-step approach for estimating savings for participating refrigerators.

First, we used *in situ* meter data to model energy consumption as a function of appliance characteristics (e.g., size, age, configuration, usage class). The model sought to quantify each characteristic's individual impact on observed energy consumption (e.g., each additional cubic foot in capacity increased consumption by 24 kWh annually). Once these relationships were understood, Cadmus applied model results to the detailed information collected by ARCA Canada about each participating appliance, estimating energy consumption for every appliance recycled through the

[1] http://powerauthority.on.ca/sites/default/files/new_files/2009%20Great%20Refrigerator%20Roundup%20Program%20Evaluation.pdf Accessed July 2011.

[2] http://ees.ead.lbl.gov/node/2. Accessed July 2011.

[3] International Energy Agency (2003). *Cool Appliances: policy strategies for energy efficient homes*, IEA Energy Efficiency Policy Profiles. http://www.iea.org/papers/2008/cd_energy_efficiency_policy/3-Appliances%20and%20equipment/3-cool_appliance2003.pdf

program. Once these results were applied, a simple average of expected energy consumption for each of the 48,887 refrigerators yielded the program's per-unit gross savings for each measure.

Consumers Energy metering data were used only to increase the model's explanatory power in relating appliance characteristics to metered consumption; savings listed in this report are unique to specific appliances recycled by the GRRP in 2010.

Program Summary

Before conducting the gross savings analysis, Cadmus explored data collected by ARCA Canada for the 2010 program. Collected appliances included: 48,887 refrigerators, 16,584 freezers, 1,233 window air conditioners, and 1,118 dehumidifiers. Table 1 provides detailed count information, as well as age and size averages.

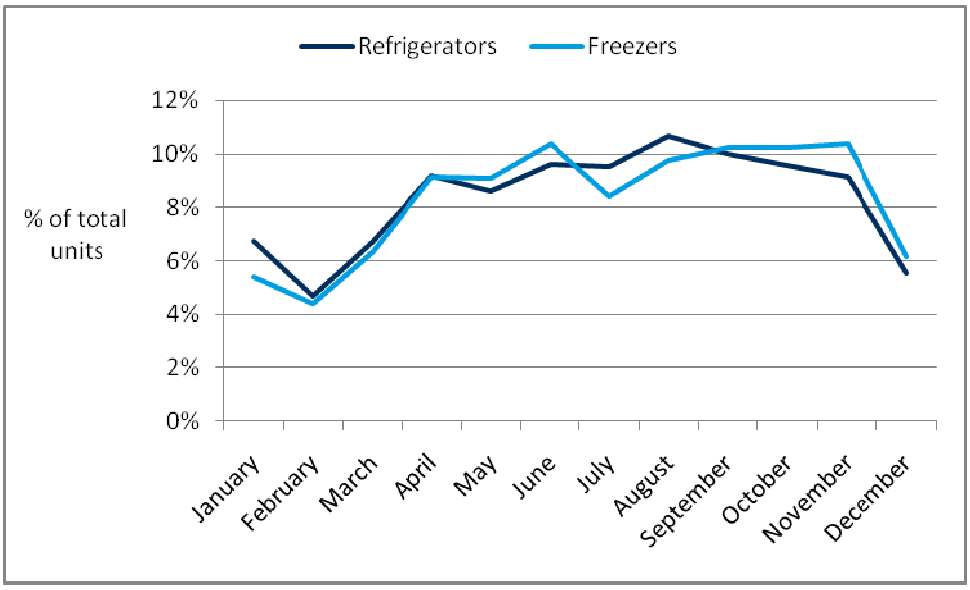
Table 1. 2010 GRRP Participation Summary

Configuration	Recycled Units	Average Age	Average Size	Percent primary
Refrigerators				
Single-door	6,278	30.3	14.1	88.2%
Bottom-freezer	546	23.2	18.8	94.9%
Top-freezer	37,454	24.3	16.1	88.5%
Side-by-side	4,609	23.3	19.7	96.4%
Overall	48,887	24.9	16.2	89.3%
Freezers				
Upright	2,666	26.8	15.9	-
Chest	13,918	27.8	16.4	-
Overall	16,584	27.6	16.3	-
Other				
Window air conditioner	1,233	24.5	-	-
Dehumidifier	1,118	24.6	-	-

The final energy consumption model for refrigerators primarily used characteristics included in this table as explanatory factors, although many other potential variables were considered. The "Estimating Annual Energy Consumption" section, below, describes this process in greater detail.

To inform the forecasting model, we also explored appliance recycling's seasonal nature. Figure 1, below, shows a clear seasonal trend, with relatively few appliances recycled between December and March, and a sharp increase from April through November.

Figure 1. 2010 GRRP—Appliance Pick-up by Month



Estimating Annual Energy Consumption

Our general approach used annualized *in situ* metering data to model annual unit energy consumption (UEC) for refrigerators and freezers as a function of individual appliance characteristics, and then used a regression model to explain annual usage in terms of individual appliance characteristics (only for refrigerators).

To annualize the sampled units' metering data, we first calculated average hourly usage for each appliance type and each demand category observed (summer peak, summer mid-peak, summer off-peak, and, for some units, shoulder mid-peak and shoulder off-peak). We then extrapolated results to annual averages, using the OPA appliance demand curve described in the GRRP 2008–2009 evaluation report. This resulted in annualized energy consumption estimates for the Consumers Energy sample consistent with those from the OPA 2008–2009 sample. Annualized OPA energy consumption estimates initially developed through the 2008–2009 evaluation remained unchanged.

Before annualizing with this approach, Cadmus explored other modeling schemes to account for appliance door openings, weather variations, and appliance locations (especially conditioned versus unconditioned spaces). However, we were unable to reliably estimate these factors' influences as their contributions to energy consumption were relatively small compared to observed variations in day-to-day energy consumption.

Using the annualized energy numbers, we built a regression model to describe appliance energy consumption as a function of individual appliance characteristics. This model quantified impacts of specific appliance characteristics on annual energy consumption. We restricted possible characteristics to those captured in ARCA's participant data; allowing the *in situ*-based model to estimate annual usage for each appliance described in ARCA's database. Once specified, the model provided energy consumption estimates for every appliance recycled by the GRRP in 2010, based on its unique set of characteristics.

Design of the regression model for estimating annual refrigerator energy consumption factored in the following considerations:

- In selecting explanatory variables for the model, we considered several combinations of appliance characteristics, including configuration, age, size, location, primary/secondary designation, and a pre-/post-NAECA indicator.
- Sensible interaction terms were considered, but none were found to have coefficients that differed significantly from zero at the 0.05 level, after controlling for effects of their base additive terms.
- Weights applied to model inputs accounted for overrepresentation of certain configurations in the sample, relative to the 2010 GRRP participant database.
- All models considered were evaluated in terms of explanatory power, logic of coefficient signs, statistical significance of fitted coefficients, and general fit to the data.

The final refrigerator model captured: age, size, primary/secondary designation, manufacture date relative to NAECA implementation, and configuration. Table 2 presents model fit results. As noted, we could not justify an equally detailed explanatory model using the freezer data. Consequently, we applied participation weighted configuration averages.

Table 2. Determinants of Refrigerator Energy Consumption (Dependent Variable = Annual kWh, R2 = 0.23)

Variable	Parameter	St. err.	Pr > |t|
Intercept	672.9	277.92	0.02
Primary Appliance Dummy	147.2	83.41	0.08
Post-NAECA Dummy*	-474.9	123.33	0.00
Appliance Size (cubic feet)	24.4	13.23	0.07
Appliance Age (years)	2.6	4.85	0.60
Bottom Freezer Dummy	413.2	354.13	0.25
Side-by-Side Dummy	106.1	131.63	0.42
Single Door Dummy	-98.3	105.91	0.36

*Applies only to Consumers Energy refrigerators as none in the OPA metering sample were manufactured after Canada's equivalent appliance standard in 1995.

To extrapolate model results to the program population, we applied model coefficients to the average appliance characteristics of participating units. As presented in Table 3, the average for each of the model's independent variables was determined using ARCA's complete 2010 GRRP database. While we developed the cross-sectional regression model using OPA and Consumers Energy *in situ* metering data, note that the inputs we used to estimate savings for the GRRP were only those from the OPA participant population.

Table 3. Refrigerator Participant Characteristics

Independent Variable	2010 OPA Value
Primary Appliance (% of Total)	89%
Post-EEA (% of Total)	2%
Average Appliance Size (ft^3)	16.21
Average Appliance Age (years)	24.93
Bottom Freezer Configuration (% of Total)	1%
Side-by-Side Configuration (% of Total)	9%
Single Door Configuration (% of Total)	13%

Applying the above, average participant characteristics into the regression models estimated *in situ*-based annual energy consumption for the average participating appliance. Specifically, refrigerator consumption was calculated as:

Refrigerator Consumption = (672.9) + (147.2)(89% percent primary appliances)- (474.9)(2% percent post-EEA manufactured appliances) +(24.4)(16.21 average cubic feet squared) + (2.6)(24.93 average age) + (413.2)(1% percent bottom freezer configuration) + (106.1)(9 percent side-by-side configuration) - (98.3)(13 percent single door configuration) =1,255 kWh

Table 4 shows the modeled *in situ*-based estimate of annual energy consumption for an average refrigerator GRRP recycled in 2010.

Table 4. *In situ*-based Annual Refrigerator Energy Consumption

Appliance	Average Annual Energy Consumption (kWh/year)*
Refrigerators	1,255

* The value presented does not represent per-unit gross savings as part-use has yet to be accounted for.

As available metering data for freezers were insufficient to support a similar approach to estimate freezer consumption, Cadmus used a weighted average (based on 2010 GRRP freezer participation by configuration) to extrapolate the metering sample averages to the larger 2010 freezer program population (as detailed in Table 5**)**.

Table 5. *In situ*-based Annual Freezer Energy Consumption

Freezer Configuration	2010 GRRP Freezer Participation (Percent of Total)	Metering Sample Estimated Annual Energy Consumption (kWh/Year)
Chest	83.9%	1,156
Upright	16.1%	1,262
Overall		1,173

* The overall value presented here does not represent per-unit gross savings because part-use has yet to be accounted for.

Replacement

The 2007 and 2008–2009 GRRP evaluations applied a replacement factor to adjusted savings to account for whether or not the participant recycling the appliance had the following attributes:

- Did not replace the participating appliance;
- Replaced the participating appliance with a new ENERGY STAR® unit;

- Replaced the participating appliance with a new standard efficiency unit; or
- Replaced the participating appliance with a used unit.

To align this evaluation with evaluation-industry best practices for appliance recycling programs and to report the most accurate estimation of gross savings possible, Cadmus recommends not applying a similar replacement factor in 2010; savings for appliance recycling programs preferably should be assessed at the grid-level (or, in the case of the OPA, the overall province), not the household level.

This concept can be best explained through an example:

> *Suppose a customer chooses to buy a new refrigerator to replace an older, existing appliance. The customer informs a friend who lives across town of this intention. The friend shares that he'd been considering a second refrigerator for his garage and would gladly take the soon-to-be replaced appliance if the customer does not have other plans for it. The customer agrees to give the appliance to his friend.*
>
> *However, before transferring the appliance, the customer learns about the GRRP and decides the convenience of the GRRP's free pick-up service outweighs the significant effort required to remove the appliance from his own basement, load it in a truck, and assist in relocating it to his friend's garage. As a result, he enrolls in GRRP and notifies his friend of his decision.*

As the example indicates, the program's availability successfully prevented the appliance from being transferred to another customer for continued use. Instead, the appliance was properly decommissioned and permanently removed from the electrical grid. In short, one less appliance would be operating within the province due to the program. Though the customer would have replaced the participating appliance with or without the program's intervention has no bearing on savings generated by the program. Thus, continued application of a replacement factor for evaluating the GRRP proves inappropriate.

The above example also highlights the program's objective of not only encouraging Ontarians to quit using their older, expensive-to-operate secondary appliances, but also of ensuring those appliances are not transferred to other Ontarians. This concept underscores the appropriateness of assessing program savings at the grid level rather than the household level. In accordance with this approach, savings attributable to the program equal consumption of the recycled appliance (as it would have continued to operate in the friend's garage), and not the difference between the participating appliance and its replacement within the participating home.

Cadmus has also provided the OPA with a separate memo, describing in greater detail Cadmus' position on excluding a replacement factor. While the memo provides evaluated 2010 GRRP savings and cost-effectiveness with and without replacement for comparison purposes, 2010 gross and net savings values presented in this report do not apply a replacement factor.

Finally, in the above example, the participating appliance would have been transferred to a new customer for continued use in the program's absence. Other possible scenarios, independent of the program, include the customer keeping the appliance or discarding it in a way leading to its destruction. Unlike replacement factors, which adjust gross savings estimates, issues related to whether the participating appliance would or would not have

continued to operate in the program's absence are accounted for in the net-to-gross (NTG) analysis, detailed in the subsequent section.

Part-Use

As part of the 2008–2009 GRRP evaluation, Cadmus conducted telephone surveys with 800 program participants. These surveys provided information for calculating the program's part-use factor, which accounts for participating appliances that have not been in use throughout the entire year prior to being recycled. While part-use can change as a program matures, insufficient time has passed since the previous survey effort to observe such changes or to merit the cost of conducting additional surveys. Consequently, part-use factors used for the 2008–2009 evaluation have been applied to estimate gross savings associated with the 2010 evaluation.

Table 6 illustrates how part-use factors for each of the three usage categories were applied to estimate average pre-unit gross energy savings for refrigerators and freezers. Window air conditioners and dehumidifiers were not included in the part-use analysis as such appliances typically were turned off and on, unlike refrigerators and freezers. As a result, part-use has already been embedded in their energy savings estimates.

Table 6. Gross Energy Savings (After Part-Use)

Self-Reported Use Patterns	Refrigerator			Freezer		
	Pct of Units	Use Factor	Per-Unit Unit Savings (kWh)	Pct of Units	Use Factor	Per-Unit Unit Savings (kWh)
Not Running	3.0%	-	-	4.5%	-	-
Running Part Time	11.8%	0.38	478	8.7%	0.26	305
Running All Time	85.2%	1.00	1,255	86.8%	1.00	1,173
Gross Energy Savings (Weighted Average)	100.0%	89.7%	1,126	100.0%	89.1%	1,045

Coincident Demand Reduction

Using the methodology outlined by the OPA and the annual gross energy savings estimates presented in Table 6, Cadmus calculated summer and winter coincident peak savings (kW) for each appliance.[4]

These calculations were based on load shapes and coincidence factors provided by OPA. As with estimates of annual energy savings, we relied on the OPA-refrigerator and freezer load shapes modified through the 2008–2009 *in situ* metering study to calculate demand reductions. Load shapes for window air conditioners and dehumidifiers were not changed.

[4] OPA's APPENDIX A: Average Peak Demand Savings Methodology and Coincident Factors.

Table 7. Load Shapes

Load Shape	Winter			Summer			Shoulder		
	Peak	Mid	Off-Peak	Peak	Mid	Off-Peak	Mid	Off	Annual
	602	688	1614	522	783	1623	1305	1623	8760
Modified OPA Res Refrigeration*	5.91%	6.81%	16.92%	6.59%	9.79%	20.08%	14.08%	19.83%	100%
Modified OPA Res Freezer*	5.90%	7.30%	16.90%	6.50%	9.57%	20.11%	14.43%	19.29%	100%
OPA Res Space Cooling-Room**	0.0%	0.0%	0.0%	22.6%	21.3%	52.5%	0.6%	3.0%	100%

*OPA load shapes were modified to reflect actual energy consumption patterns of metered appliances during the observation period.
**Also used for dehumidifiers.

Table 8. Coincidence Factors

End-Use Profile	Winter	Summer
OPA Res Freezer	1.189	1.118
OPA Res Refrigeration	1.258	1.104
OPA Res Space Cooling - Room	N/A	2.338

Summary

Table 9 presents *ex post* per-unit gross energy savings and demand reductions impacts determined for each 2010 GRRP. Applying per-use savings to the 2010 GRRP participation yielded the program-level energy savings and demand reductions detailed in Figure 8.

Table 9. 2010 GRRP—Per-Unit Gross Energy and Demand Impacts

Appliance	Annual Energy Savings (kWh)	Winter Demand Reduction (kW)	Summer Demand Reduction (kW)
Refrigerator	1,126	0.139	0.157
Freezer	1,045	0.122	0.145
Window Air Conditioner	371	0.000	0.376
Dehumidifiers	964	0.000	0.976

Table 10. 2010 GRRP—Program Gross Energy and Demand Impacts

Appliance	Units	Annual Energy Savings (MWh)	Winter Demand Reduction (MW)	Summer Demand Reduction (MW)
Refrigerator	48,887	55,047	6.8	7.7
Freezer	16,584	17,330	2.0	2.4
Window Air Conditioner	1,233	457	-	0.5
Dehumidifiers	1,118	1,078	-	1.1
Total	67,822	73,912	8.8	11.6

Net Savings

When determining net savings attributable to energy-efficiency programs, gross savings must be adjusted to account for participants' actions independent of the program. For appliance recycling programs such as the GRRP, NTG analysis focuses on what would have happened to a participating appliance had it not been recycled through the program (e.g., it would have been kept, transferred to another user for continued use, or discarded and destroyed).

Similarly to the part-use analysis, the NTG value used for this evaluation was determined using surveys conducted for the 2008–2009 evaluation. In addition to participant surveys previously noted, the NTG analysis relied on 415 nonparticipant surveys. Nonparticipants were defined as Ontarians discarding a GRRP-eligible appliance independently of the program. Insights from these nonparticipants' actual appliance disposal methods were used to mitigate the socially desirable response bias often inherent in participant self-report NTG assessments.

The 2008–2009 evaluation report provided significant detail regarding the methodology used to estimate NTG, specifically how nonparticipant responses were utilized. As the 2008–2009 NTG analysis was robust and completed relatively recently, Cadmus applied that effort's results to the 2010 evaluation rather than incur the unnecessary expense of conducting additional participant and nonparticipant surveys. Application of the last evaluation's NTG values, as shown in Table 11, was further supported by GRRP program design changing very little between 2009 and 2010.

Table 11. 2010 GRRP NTG Ratios*

Appliance	Overall NTG Ratio
Refrigerator	0.54
Freezer	0.52
Window Air Conditioner	0.36
Dehumidifier	0.36

*As determined through the 2008–2009 GRRP evaluation.

Summary

Applying the above NTG ratios to *ex post* 2010 GRRP gross savings yielded the program's annual net energy savings and demand reductions. Multiplying these values by each measure's remaining useful life (RUL) provided the program's lifetime energy savings, as shown in Table 13.

Table 12. 2010 GRRP—Program Net Energy and Demand Impacts

Appliance	NTG Ratio	Annual Net Energy Savings (MWh)	Net Winter Demand Reduction (MW)	Net Summer Demand Reduction (MW)
Refrigerator	0.54	29,725	3.7	4.1
Freezer	0.52	9,012	1.1	1.3
Window AC	0.36	165	-	0.2
Dehumidifier	0.36	388	-	0.4
Total		39,290	4.7	6.0

Table 13. 2010 GRRP—Lifetime Net Energy and Demand Impacts

Appliance	RUL	Lifetime Net Energy Savings (MWh)
Refrigerator	5.0	148,625
Freezer	4.0	36,048
Window Air Conditioner	3.0	660
Dehumidifier	4.0	1,164
Total		186,497

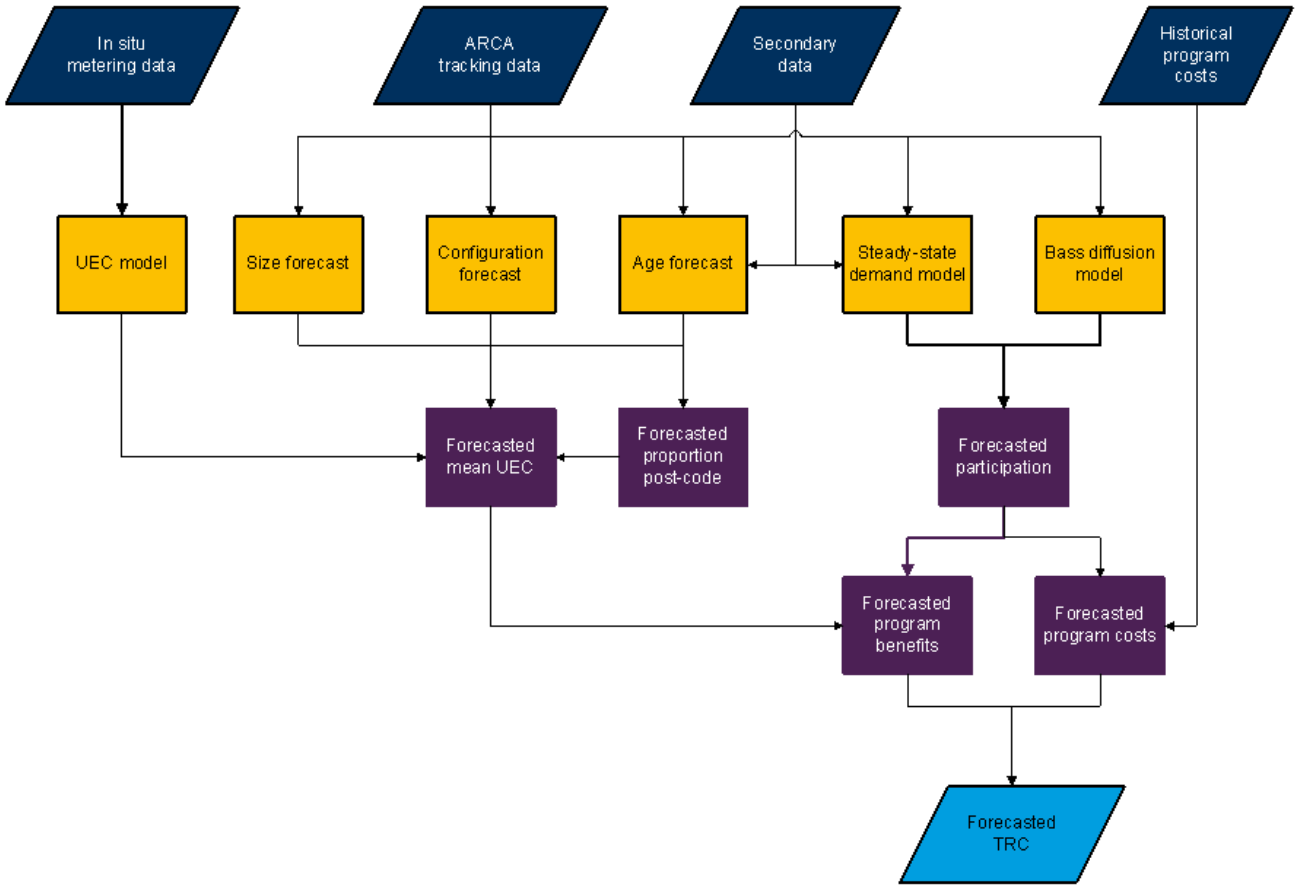
Forecasting Cost-Effectiveness

Currently, GRRP eligibility requirements stipulate participating refrigerators and freezers must be a minimum of 15 years old. In 2010, this meant all participating appliances had to have been manufactured prior to or the same year as the enactment of Energy Efficiency Act (EEA) of 1995. However, beginning in 2011, increasing numbers of post-EEA appliances will be recycled through the program. To understand the implications of this change, the OPA asked Cadmus to forecast expected savings—and consequently expected program cost-effectiveness—for 2013, 2015, and 2017.

Methodology

Due to the variety of factors affecting unit savings, we utilized a hybrid approach for forecasting unit savings and subsequent cost-effectiveness. This approach combined primary and secondary data sources from historical GRRPs and other programs. Models were chosen both for their appropriateness for a given prediction and the specificity of given input data. While significant detail is provided below regarding our approach, the methodology is summarized graphically in Figure 2.

Figure 2. Summary of Cost-Effectiveness Forecasting Methodology



As the program implementer, ARCA Canada has tracked a great deal of unit data for the GRRP. As seen in Table 14, however, these data were not necessarily consistent throughout the program's duration. Due to these inconsistencies, certain adjustments were necessary to the analysis.

Table 14. ARCA Canada Data Quality by Year and Type

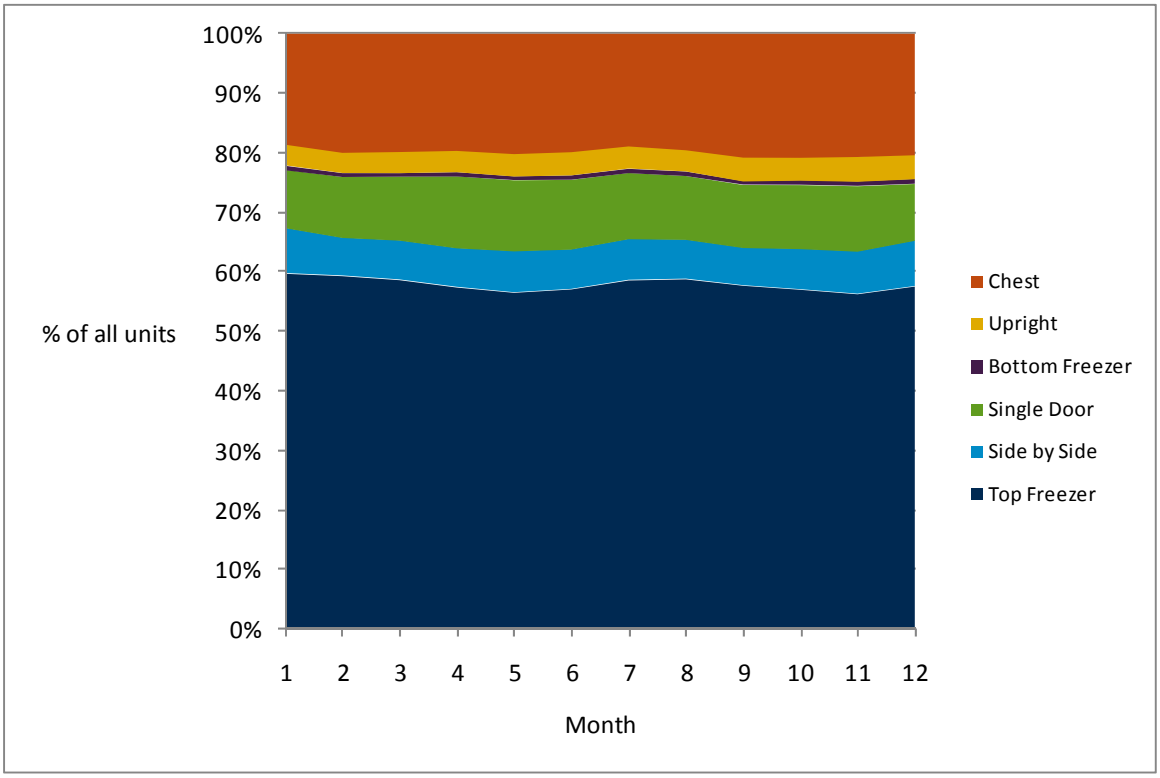
Year	Configuration	Size	Age	Primary/Secondary	Pick-Up Date
2007	Good	Good	Poor	Good	Missing
2008	Good	Good	Poor	Good	Good
2009	Good	Good	Poor	Good	Good
2010	Good	Good	Good	Good	Good

As discussed in the gross savings section, above, many appliance characteristics determine unit savings. Factors affecting consumption include age, size, configuration, and primary/secondary distinction. To estimate how the GRRP participant population's composition may change in this regard, we specified a series of time-series models for relevant characteristics.

Where possible, we specified time-series models based on the ARCA Canada database. As pickup dates were not available in the 2007 data, they were excluded from analysis. When age data were inconsistently collected, secondary data sources were used.

All models using ARCA Canada data controlled for the program's inherent seasonality. Though variations in the population's composition was not dramatic across months (see Figure 3), we controlled for this variation to avoid potential omitted variable biasing.

Figure 3. Example: Average Unit Configuration Distribution by Month (2008–2010)



Logistic Regression Models

Adequate data were available across the program's full life for configuration, size, and primary/secondary designation. As size was specified as ranges and not actual values, all these fields were categorical and exhaustive. As such, we felt time-series logistic regression analysis was the most appropriate approach for estimating changes in these variables over time.

Logistic regression analysis models the conditional probability of an event, given a set of explanatory variables. This method uses a maximum likelihood estimator of the logistic function (as shown below) to estimate the marginal impact on the probability of the event in question from each explanatory variable:

$$f(z) = \frac{1}{1 + e^{-z}}$$

For this analysis, the probability of each configuration, size category, and primary/secondary designation was modeled individually as a function of the month in which it was recycled and a monthly linear time trend. That is:

$$probability\ of\ having\ characteristic, j, in\ time, t = \frac{1}{1 + e^{-z_j}}, where\ z_j$$
$$= \beta_{0,j} + \beta_{1,j} t + \sum_{i=2}^{12} \beta_{i,j} month_{i,t} + \varepsilon_{t,j}$$

Where:

t = an incremental time trend increasing by 1 for each successive program month, and

$month_i$= a dummy variable equaling 1 if the time period is during the given month number (where January equal 1, February equals 2, etc.), and 0 otherwise.

For our purposes, this probability could be interchangeably treated as the predicted proportion of the population belonging to a given group. With this set of models, we could forecast the change in each probability over time. In the case of size, which had an underlying continuous distribution, we also predicted the change in age over time by assigning a median value to each size category, and then taking the weighted average of these values using the predicted distributions in each month.

Table 15. Values Assigned to Each Size Category for Forecasting[5]

Category	Value
<10	7.5
10-14	12.5
15-19	17.5
>19	25.0

[5] Age categories of "20-24," "25-27," and ">27" where conflated into one category due to relatively small sample sizes in each individual category.

Once we forecasted monthly, seasonally-adjusted values through 2017, these values were annual averages, calculated for each prediction year in question.

Secondary Research

As age was not adequately collected for the majority of the GRRP's lifetime, we relied on secondary data to estimate changes in program age over time. As these data often were not reported over multiple years, it was difficult to obtain a large set of input data. As such, estimates from this analysis should be interpreted cautiously.

We estimated the change in age by looking at two ARP evaluations from the United States. The first was of the Energy Trust of Oregon's program for 2008-09. As a relatively young program, evaluation spanned the program's first and second years. The second evaluation was drawn from the 2006–2008 process evaluation of Southern California Edison's (SCE) ARP, a mature program, having started in 1993. Table 16 summarizes these programs' age distributions, along with their corresponding program years.

Table 16. Age Distribution of Input Data by Utility and Program Year[6]

	ETO		SCE		
Age Group	PY 1	PY 2	PY 13	PY 14	PY 15
Less than 10	7%	9%	9%	11%	13%
10 to 15	11%	10%	41%	57%	57%
Greater than 15	82%	81%	51%	33%	30%

Though certainly not exhaustive, these data spanned the range of program maturity over which we were forecasting. Using these data, we fit time-series, ordinary least squares, linear regression models for each age category to determine a linear trend over time. Though logistic models would have been ideal, they were simply not possible, given the sample sizes. As such, each model was specified as:

$$proporton\ of\ units\ in\ category, j, in\ program\ year, t = \beta_{0,j} + \beta_{1,j} t + \varepsilon_{t,j}$$

Where:

t = an incremental time trend increasing by 1 for each successive program year.

Table 17 shows estimates derived from these models.

Table 17. Model Estimates for Age Regression

Age Group	Intercept	Slope	R^2
Less than 10	0.073	0.003	0.538
10 to 15	0.054	0.033	0.956
Greater than 15	0.873	-0.035	0.945

[6] Source data: Reed, J. and Bailey, C. (2010). "An Evaluation of Energy Trust of Oregon's Refrigerator Recycling Program." http://energytrust.org/library/reports/1001_FridgeRecycling_Eval.pdf
Reed, J. et. al. (2010). "Process and Market Evaluation of Southern California Edison's Refrigerator Recycling Program 2006 - 2008." http://www.calmac.org/publications/scearpfinal041410.pdf

To ensure estimates remained within reasonable bounds and maintained exhaustiveness, we summed predicted values across the three categories. Consistent estimates of these proportions should sum to 100 percent.

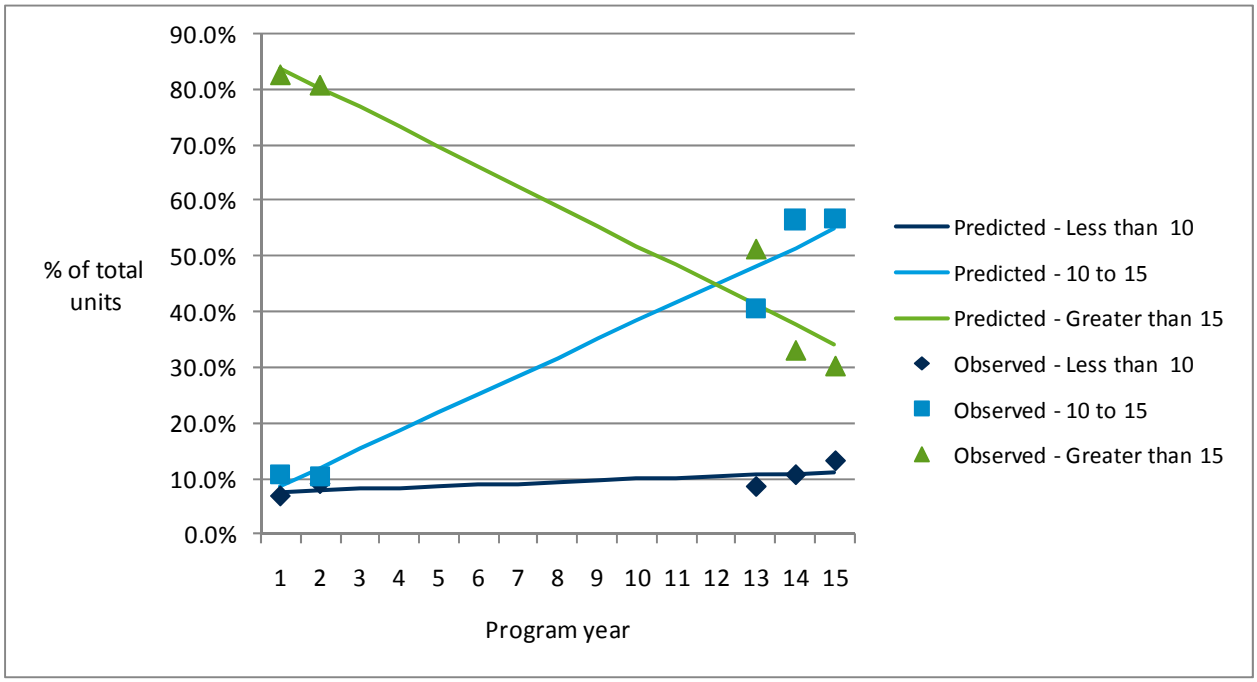
Table 18 shows cross-check results.

Table 18. Age Model Consistency Cross-Check

Program Year	Observed - Less than 10	Observed - 10 to 15	Observed - Greater than 15	Predicted - Less than 10	Predicted - 10 to 15	Predicted - Greater than 15	Sum of Predicted Values
1	6.8%	10.8%	82.4%	7.6%	8.7%	83.8%	100.0%
2	9.0%	10.5%	80.5%	7.8%	12.0%	80.2%	100.0%
3				8.1%	15.3%	76.7%	100.0%
4				8.3%	18.5%	73.1%	100.0%
5				8.6%	21.8%	69.6%	100.0%
6				8.8%	25.1%	66.0%	100.0%
7				9.1%	28.4%	62.5%	100.0%
8				9.3%	31.7%	58.9%	100.0%
9				9.6%	35.0%	55.4%	100.0%
10				9.9%	38.3%	51.9%	100.0%
11				10.1%	41.6%	48.3%	100.0%
12				10.4%	44.9%	44.8%	100.0%
13	8.5%	40.5%	51.1%	10.6%	48.2%	41.2%	100.0%
14	10.6%	56.5%	32.9%	10.9%	51.5%	37.7%	100.0%
15	13.1%	56.8%	30.1%	11.1%	54.8%	34.1%	100.0%

Despite the small sample sizes, the estimator seemed relatively consistent across the estimation period. The models showed increases in the younger categories and decreases in the higher category.

Figure 4. Predicted Change in Age Distribution



Once we modeled the change in the age distribution over the program lifetime, we could estimate the change in average age by taking the weighted average of each category's midpoints. Table 19 shows these midpoint designations.

Table 19. Values Assigned to Each Age Category for Forecasting

Category	Value
<10	7.5
10-15	12.5
>15	25.0

To ensure age forecasts remained consistent with OPA's program, we adjusted all forecasted average ages using an adjustment factor based on the ratio of the modeled age in 2010 (where age data were found reliable) to the predicted age in 2010.

Table 20. Age Adjustment Factor

Actual Age in 2010	Modeled Age in 2010	Adjustment Factor
25.1	21.2	1.184

Code Change

Once age distributions were forecasted, we used the lower and upper bounds of each cohort's age range to estimate the proportion which would have been manufactured after the 1995 EEA code change. As insufficient information was available on age distributions within each cohort, a uniform distribution was assumed.

To estimate the proportion for each year, the difference between the upper and lower age was adjusted with the factor shown in Table 20, and the year was calculated to determine the range of appliance vintages for a given year and age cohort. If both vintages fell before 1995, the proportion of post-code units for that cohort was set to 0. If both were on or after 1995, then the proportion was set to 1. If the range included 1995, the fraction of the range after 1995 was calculated as the proportion of that cohort manufactured on or after code implementation. The final proportion of all units for a given year was then the weighted average of each cohort's post-code proportion. Table 21 shows this calculation for the "10 to 15 years old" cohort.

Table 21. Example: Post-Code Calculation

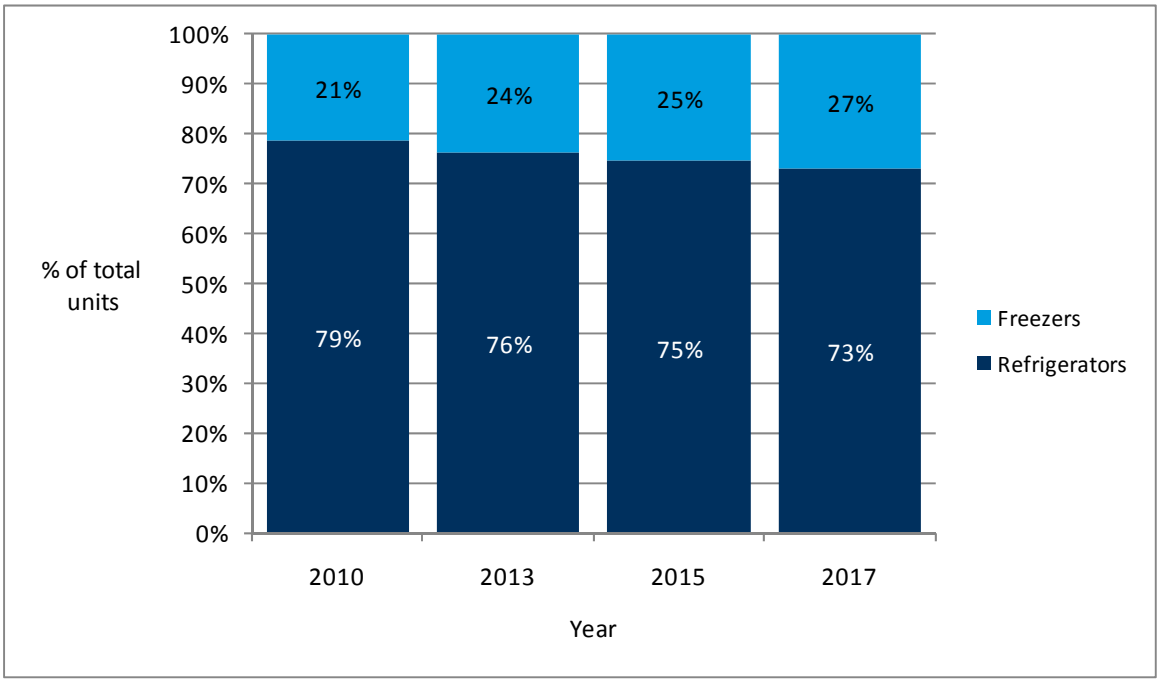
Year	Max. Vintage	Min. Vintage	Adj. Max. Vintage	Adj. Min. Vintage	Proportion of Cohort Post-Code	Proportion of All Participating Units	Proportion of All Participating Units Post-Code
2007	1997	1992	1995.2	1989.2	0.390	0.087	0.034

Findings

Configuration

Estimation of logistic models provided us with forecasts for a variety of characteristics. Of particular interest were results for configuration and appliance type. Figure 5 shows, over time, expected slight declines in proportions of refrigerators overall, compared to freezers.

Figure 5. Forecasted Appliance Type for 2013, 2015, and 2017



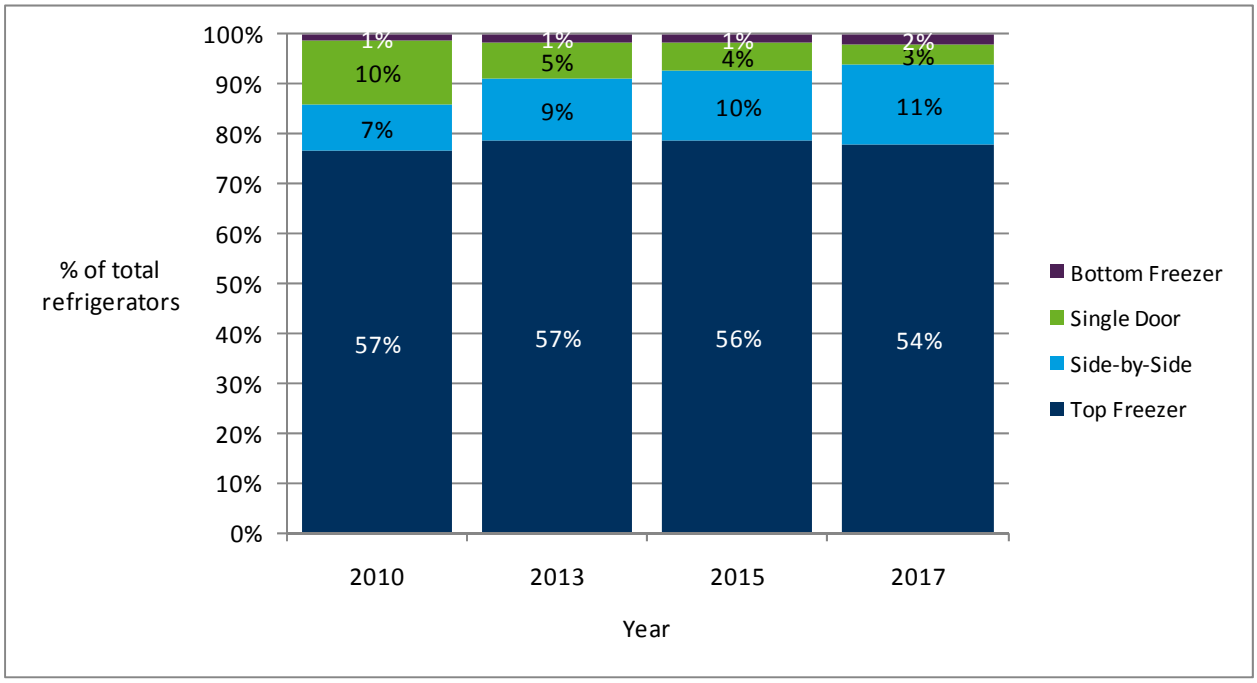
As can be seen in Table 22, this appliance-type trend has been driven by two factors. First, chest freezers steadily increase, gaining 6 percent of the market over the next seven years.

Table 22. Forecasted Configuration Distribution (All Appliances) for 2013, 2015, and 2017

Year	Top Freezer	Side by Side	Single Door	Bottom Freezer	Upright	Chest
2010	57%	7%	10%	1%	4%	21%
2013	56%	9%	5%	1%	4%	23%
2015	55%	10%	4%	1%	4%	25%
2017	55%	11%	3%	2%	4%	27%

Second, decline single-door units decline precipitously. This population share drops considerably, from 10 percent of all units in 2010 to a mere 3 percent in 2017. As shown in Figure 6, this is part of a larger trend in the refrigerator recycling market, moving from single-door units toward more side-by-side units, an expected result, as single-door units are often older, while side-by-side units did not begin to gain popularity until the 1990s.

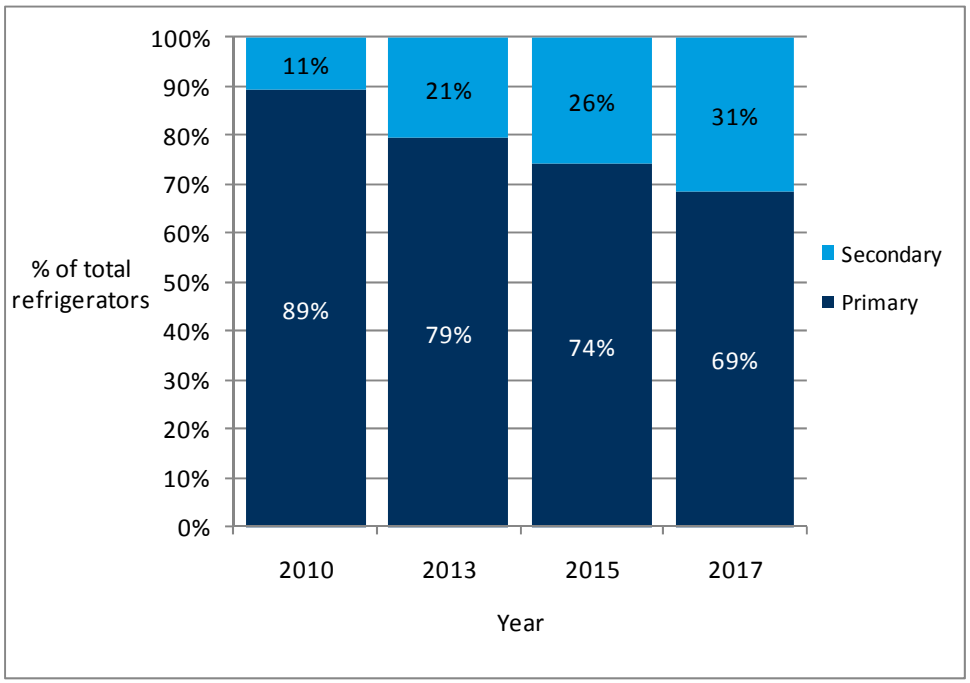
Figure 6. Forecasted Configuration Distribution (Refrigerators Only) for 2013, 2015, and 2017



Primary/Secondary Designation

The population's proportion of primary units is forecasted to decline over time. This will have a negative marginal impact on refrigerators' unit savings, as these units consume more energy, on average, than secondary units, holding all else equal.

Figure 7. Forecasted Usage Distribution (Refrigerators Only) for 2013, 2015, and 2017



Size and Age

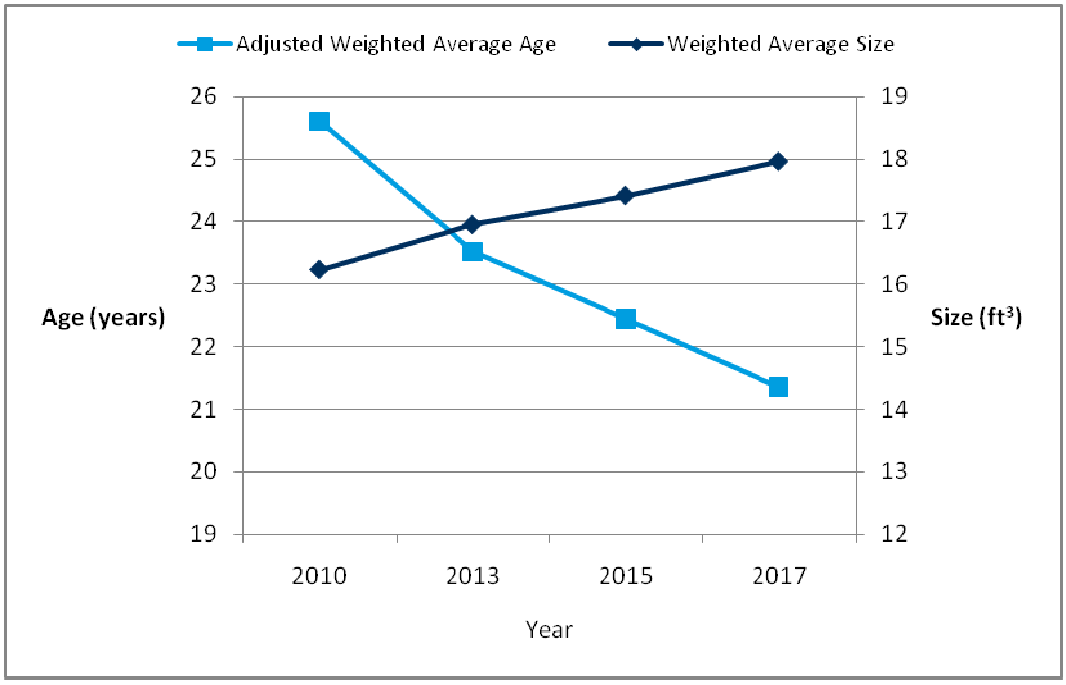
As discussed, relationships between unit size, age, and energy consumption can be complex. Over time, appliances have become larger; so average unit sizes will likely increase, leading to increased unit consumption. As the program matures, however, we expect particularly old units will be "cleaned out" of the population, replaced by younger, more efficient, units.

Table 23. Forecasted Age and Size Distributions (All Appliances) for 2013, 2015, and 2017

Size (ft^3)					
Year	Less than 10	10 to 14	15 to 19	Greater than 19	Weighted Average Size
2010	7%	29%	52%	12%	16.2
2013	6%	24%	57%	14%	16.9
2015	6%	20%	61%	15%	17.4
2017	6%	17%	65%	16%	18.0
Age (years)					
Year	Less than 10	10 to 15	Greater than 15	Weighted Average Age	Adjusted Weighted Average Age
2010	0%	2%	98%	25.6	25.6
2013	9%	28%	62%	19.9	23.5
2015	10%	35%	55%	18.9	22.4
2017	10%	42%	48%	18.0	21.4

Table 23 and Figure 8 show estimated trends in age and size. These forecasts support our theories regarding how appliance recycling programs evolve over time. Based on analysis results, we expect units will be approximately 2 cubic feet larger in 2017, but roughly four years younger.

Figure 8. Forecasted Average Age and Size (All Appliances) for 2013, 2015, and 2017



Code

Adding to the savings impact of younger units will be the increasing share of participating units that have been manufactured after the 1995 EEA code. As seen in Table 24, our forecasts estimate, by 2017, approximately three out of four participating appliances will have been manufactured post-code.

Table 24. Forecasted Percent of Units Manufactured after EEA Code (All Appliances) for 2013, 2015, and 2017

Cohort	Year	Adj. Max. Vintage	Adj. Min Vintage	% of Cohort Post-Code	% of Participating Units	% of Participating Units Post-Code
Less than 10	2013	2007.1	2002.3	100%	9%	9%
	2015	2009.1	2004.3	100%	10%	10%
	2017	2011.1	2006.3	100%	10%	10%
10 to 15	2013	2001.2	1995.2	100%	28%	28%
	2015	2003.2	1997.2	100%	35%	35%
	2017	2005.2	1999.2	100%	42%	42%
Greater than 15	2013	1994.0	1977.5	0%	62%	0%
	2015	1996.0	1979.5	25%	55%	14%
	2017	1998.0	1981.5	49%	48%	24%
Total	2013				100%	38%
	2015				100%	58%
	2017				100%	75%

Gross Energy Savings

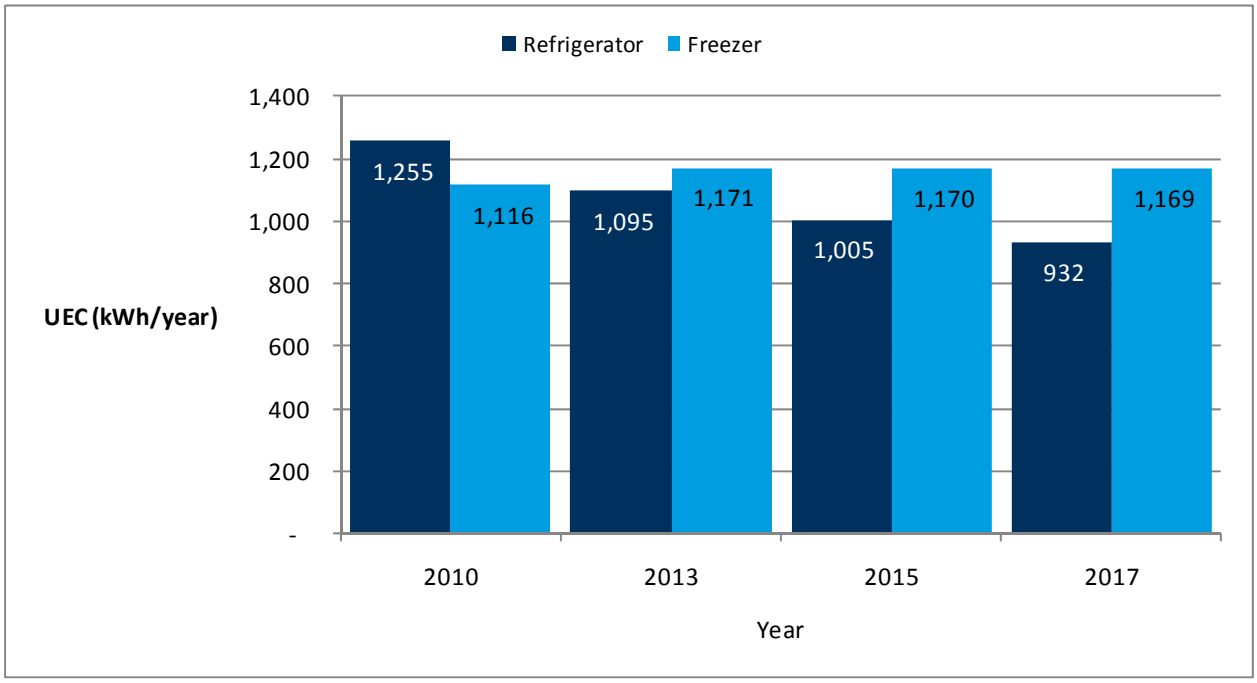
Using the described forecasts for various appliances characteristics, we estimated UECs for each study year. For refrigerators, this was done using coefficients estimated in the meter-data regression analysis.

Table 25. Forecasted Refrigerator Model Parameters (All Appliances) for 2013, 2015, and 2017

Year	Primary	Post-Code	Size	Age	Bottom Freezer	Side by Side	Single Door	Estimated UEC
2013	0.79	0.379	16.9	23.5	0.015	0.122	0.076	1,095
2015	0.74	0.583	17.4	22.4	0.018	0.141	0.054	1,005
2017	0.69	0.753	18.0	21.4	0.022	0.162	0.037	932

For freezers, we simply took the weighted average of the two configurations, using forecasted proportions for each year. Looking at consumption trends, we see freezers remain relatively constant across the study years, while refrigerators decline, from 1,255 kWh in 2010 to 932 in 2017.

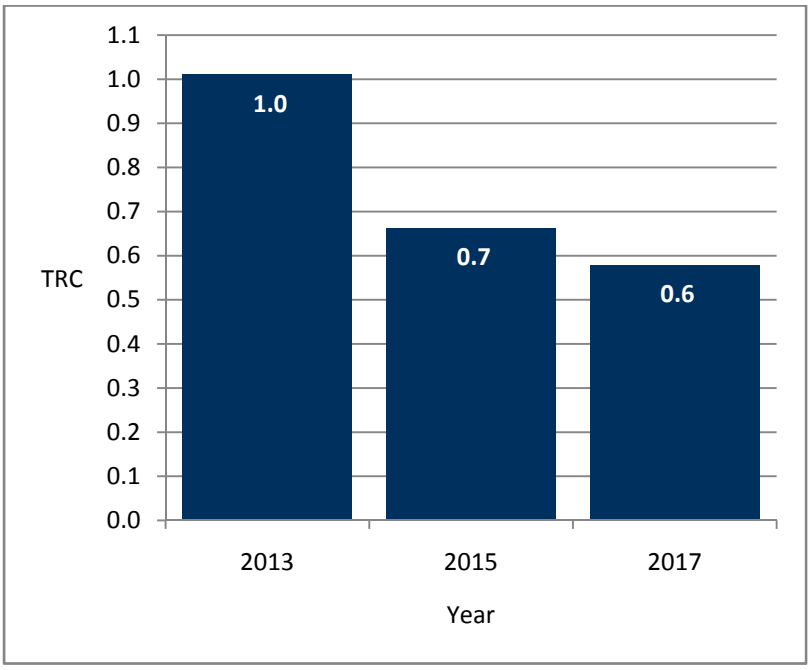
Figure 9. Forecasted UECs (All Appliances) for 2013, 2015, and 2017



Cost-Effectiveness

Using OPA's Conservation Program Resource Planning Tool, we calculated cost-effectiveness for the program years using; inputs included: forecasted energy consumption, program characteristics, and participation levels (discussed further, below). As expected, given declining energy consumption, we forecast program cost-effectiveness would decline over time. Figure 10 shows the decline for the study years. The largest impact occurs between 2013 and 2015, with a decline from 1.0 to 0.7.

Figure 10. Forecasted TRCs for 2013, 2015, and 2017



When evaluating the GRRP's forecasted cost-effectiveness, it is important to note that appliance recycling programs can positively impact residential energy efficiency portfolios beyond the energy savings they generate. Since appliance recycling programs typically enjoy extremely high levels of satisfaction (95% of GRRP participant's rated their satisfaction as an 8, 9, or 10 on a 10-point scale as part of the 2008-09 evaluation), the programs can function as a 'gateway' to further program participation. Specifically, participants encouraged by their positive experience in GRRP may be more likely to enroll in another OPA or local distribution company energy efficiency program.

Assessing Market Saturation

In our analysis of market saturation for appliance recycling in Ontario, we our research was guided by the theory that we should expect to see an initial increase in participation as information about the program spreads through the population eligible for the program in 2007 (this is the short run component of participation modeled using the Bass model). As this demand is exhausted, however, there should be a leveling-off of demand. At this steady-state demand, the program will recruit only those participants that enter the market in a given year.

Our subsequent modeling was guided by two main research questions:

- What is the long run steady-state demand for the program?
- At what point will the program settle on that level of demand? That is, when does participation return to long-run equilibrium?

Methodology

To answer these questions, we drew upon market research and previous evaluations of mature appliance recycling programs.

Steady-State Demand

A given economy presumably has an equilibrium demand level for appliance recycling programs, at which all potential participants eligible and likely to participate in the program each year do so. Although estimating this level for Ontario could be informed by characteristics of its economy and historical GRRP participation, data from a mature program was necessary to estimate a baseline participation level.

Typically, number of annual retired appliances of type, j, are estimated as[7]:

$$N_{Retired\ Appliance_j} = \frac{N_{Total\ Appliance_j}}{EUL_j}$$

Early in appliance recycling programs, however, we see appliances almost exclusively older than their EULs. This leads us to assume units being recycled in these programs are from a markedly older (and therefore smaller) portion of the population. To estimate this population's size (what we refer to as the "representative" population), we use this average age of units recycled in a given program in place of the EUL in the equation above:

$$N_{Representative\ Retired\ Appliance_j} = \frac{N_{Total\ Appliance_j}}{Mean\ Recycled\ Age_j}$$

Although a given appliance may be in the representative population, it is not guaranteed the given appliance will become a participating appliance. This may be due to factors such as structural

[7] This expression makes two assumptions: that the market for appliance disposal is in long run equilibrium and that the EUL captures the midpoint of the retied appliances' distribution of vintages.

barriers, preferences, or other unknown behavioral heuristics. Therefore, we need to estimate of the rate of uptake into the program:

$$Uptake\ Rate * N_{Representative\ Retired\ Appliance_j} = N_{Steady-State\ Participants}$$

To estimate this long-run value for OPA, we looked to a program in place long enough to be in a long-run equilibrium. SCE started its appliance recycling program in 1994.[8] Using data from the 2006–2008 process evaluation of SCE's program, we were able to estimate uptake rates.

Table 26. SCE Uptake Rates

Year	Total Appliances (Refrigerators and Freezers)	Average Age	Representative Retired Appliances	Participation	Uptake Rate
2006	19,434,402	16.0	1,215,147	69,052	5.68%
2007	19,434,402	14.1	1,382,989	60,315	4.36%
2008	19,434,402	14.3	1,357,699	90,242	6.65%
Average					5.56%

Given this program had been in place for 12 years at the onset of the study period, we felt the program was uniquely suited to providing estimates of long-run program behaviors. Average ages in Table 26 support this: they are quite close to the EUL for refrigerators (14 years for an ENERGY STAR® unit), implying market is in long run equilibrium. Therefore, we used the average uptake rate of the SCE study period as an estimate of OPA's long-run uptake rate.

This uptake rate was then used in estimating the GRRP's long-run annual participation. Using population growth forecasts from the Ontario Ministry of Finance[9] and appliance counts from the Office of Energy Use's 2007 Survey of Household Energy Efficiency,[10] we forecasted total appliances in Ontario through 2017. By combining this forecast with the long-run uptake rate and the age forecasts estimated for cost-effectiveness, we calculated steady-state level participation as follows for each year, t:

$$N_{Participants_t} = Uptake\ Rate * \left(\frac{N_{Total\ Appliance_t}}{Forecasted\ Mean\ Recycled\ Age_t}\right)$$

Where:

$$N_{Total\ Appliance_t} = N_{Total\ Appliance_{2007}} * \left(\frac{Forecasted\ Population_t}{Population_{2007}}\right)$$

Table 27 shows analysis results.

[8] In addition to SCE running their appliance recycling program longer, other programmatic differences also exist. For example, SCE offers participants an incentive ($35) and does not have a minimum age requirement. Despite these differences, SCE was selected since it is the longest running appliance recycling program in North America and provides the greatest insight into long-run appliance recycling trends.

[9] http://www.fin.gov.on.ca/en/economy/demographics/projections/. Accessed July 2011.

[10] http://oee.nrcan.gc.ca/publications/statistics/sheu07/section6.cfm?attr=0. Accessed July 2011.

Table 27. Forecasted Steady-State Demand (All Appliances) 2007-2017

Year	Total Appliances (Refrigerators and Freezers)	Average Age	Representative Retired Appliances	Uptake Rate	Steady-State Participation
2007	6,123,218	26.8	228,819	5.56%	12,730
2008	6,189,921	26.2	236,073		13,134
2009	6,253,390	25.7	243,506		13,547
2010	6,323,160	25.1	251,509		13,993
2011	6,399,706	24.6	260,138		14,473
2012	6,477,377	24.1	269,201		14,977
2013	6,556,255	23.5	278,731		15,507
2014	6,635,179	23.0	288,711		16,062
2015	6,714,154	22.4	299,173		16,645
2016	6,794,349	21.9	310,207		17,258
2017	6,875,740	21.4	321,854		17,906

Market Diffusion

Once the steady-state participation was established, we modeled the participation in the short run after the program was introduced. We expected this process would follow an S-shaped diffusion, seen in the marketing of other goods; so an initial growth in demand would be followed by decline, which asymptotically approaches the saturation level as existing appliances that were eligible and likely to participate become exhausted from the population.

To model this behavior, we fit a Bass diffusion curve to the participation data from the ARCA database from 2007 through 2010. The Bass diffusion model, widely used in forecasting new product marketing, has been found highly predictive in this context. For our purposes, the model could be described as:

$$\frac{f(t)}{1 - F(t)} = p + qF(t)$$

Where:

f(t) = the probability of participating in time, t,

F(t) = the cumulative probability of participating in time, t

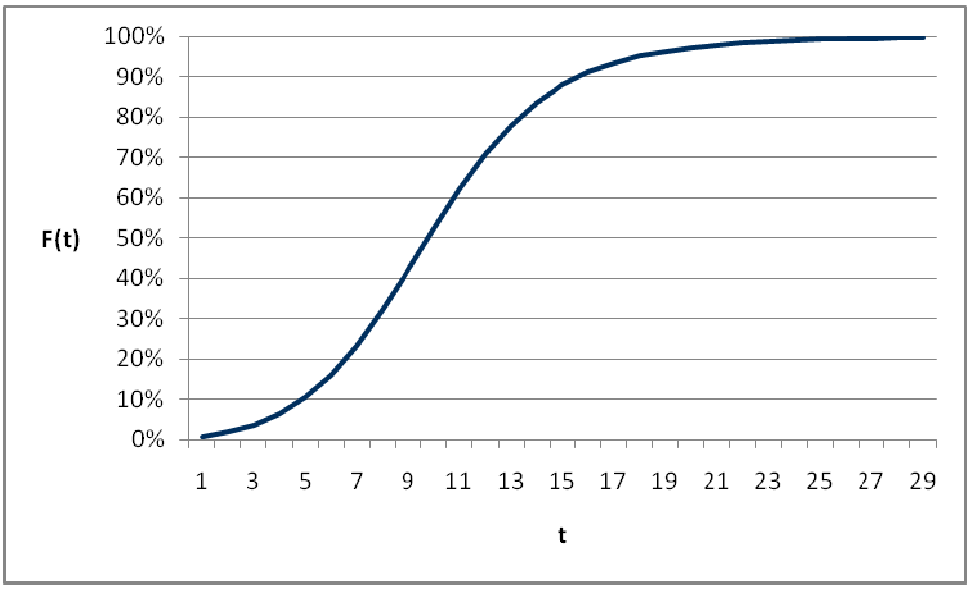
p = a coefficient representing the rate of early adoption,[11] and

q = a coefficient representing the rate of imitation.

For p and q, this function describes adoption behavior over time, assuming saturation approached in an S-shaped fashion, as shown in Figure 11.

[11] Also called the coefficient of innovation.

Figure 11. Example: Bass Diffusion Curve (p=0.005, q=0.2)



For data inputs, we first summed ARCA participation data at the monthly level for 2007 through 2010. As monthly data were not available for 2007, we distributed participation across the 12 months according to the mean distribution of participation in the other three program years for which data were available. These monthly weights are shown in Table 28.

Table 28. Monthly Participation Weights

Month	Weight
1	4.8%
2	6.3%
3	5.2%
4	6.5%
5	8.7%
6	9.3%
7	10.6%
8	11.9%
9	10.4%
10	9.7%
11	9.4%
12	7.4%

We then seasonally-adjusted the steady-state participation, estimated in the section above, and subtracted it from monthly participation data in each year. This provided us with the excess demand for each program month.

To estimate *p* and *q* econometrically, we used a WLS estimation of the equation from (Boswijk and Franses, 2002):[12]

[12] Boswijk, H. & Franses, P. (2002). *The econometrics of the Bass diffusion model*. UvAEconometrics

$$n_t - n_{t-1} = \beta_0 + \beta_0 N_{t-1} + \beta_0 N_{t-1}^2 + \beta_0 n_{t-1} + n_t - n_{t-1}\varepsilon_t$$

Where:

n = participation in month, *t*, for likely and eligible units in 2007, and

N = cumulative excess participation in month, *t*, for these eligible and likely units.

From this estimator, we derived p, q, the excess participation saturation level, and the time at which peak excess participation took place.[13]

Findings

Our initial secondary research provided the following steady-state participation forecast:

Figure 12. Seasonally-Adjusted Forecasted Steady-State Participation (All Appliances) 2007-2017

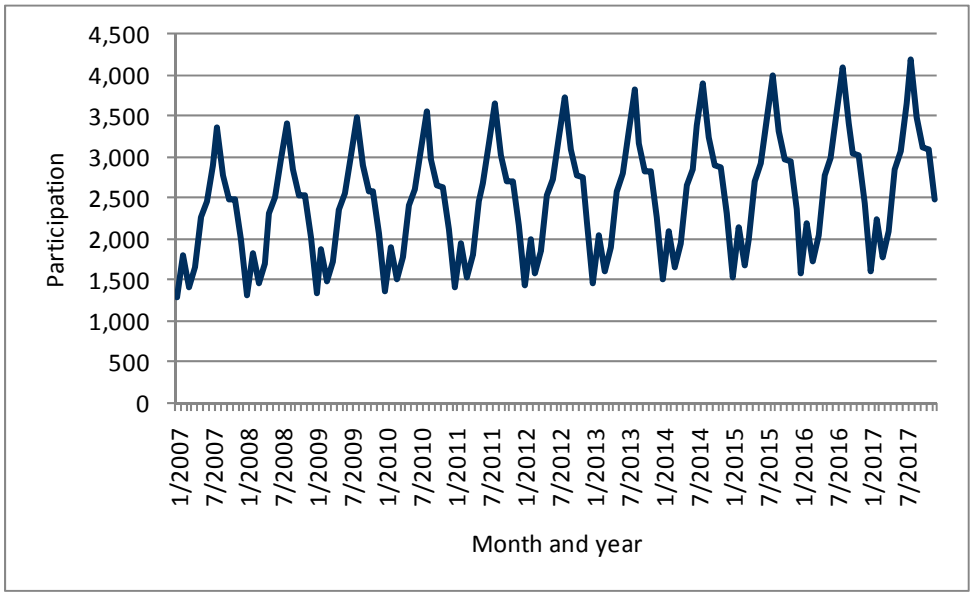


Table 29 shows diffusion model results, indicating peak participation of eligible and likely units from 2007 took place in mid-2010, and this total participation was estimated at approximately 600,000 units.

Table 29. Results of Bass Diffusion Model Estimation

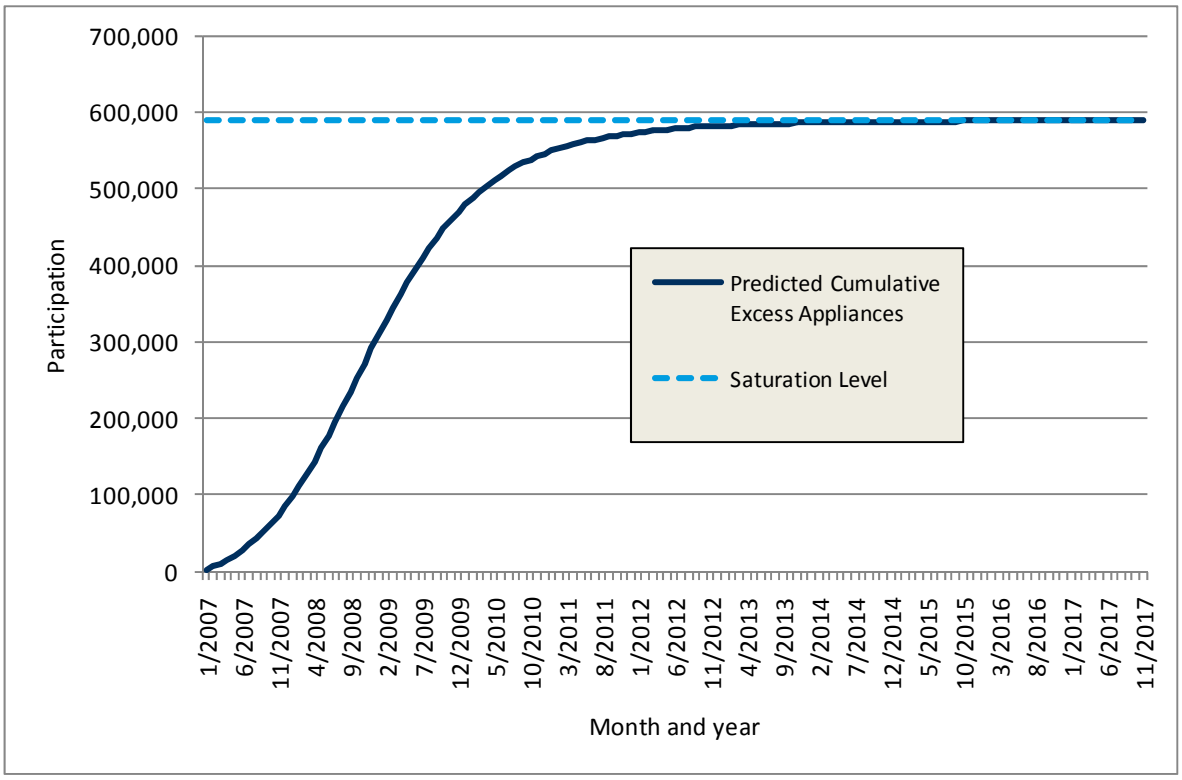
Saturation Level	Months to Peak Excess Participation	Coefficient of Early Adoption (p)	Coefficient of Imitation (q)
588,749	40	0.005	0.059

Discussion Paper 2002/12. Universiteit van Amsterdam.

[13] For details on the necessary calculations to derive these parameters as well as a thorough exploration of their consistency and efficiency, see Boswijk and Franses (2002).

Figure 13 shows forecasted cumulative participation eligible and likely units from 2007 over the program's lifetime. This diffusion curve indicates total demand in this population will be effectively exhausted by late 2012.

Figure 13. Diffusion Curve of GRRP Excess Participation



Combining the two forecasts provides a forecast of total participation through 2017. As seen in Figure 14, program participation settles somewhere between 1,500 and 3,000 units per month around 2013. At that point, participation should increase at a relatively gradual pace, roughly equal to the percent increase in population, divided by the percent decrease in average unit age (the theoretical growth rate of steady-state participation).

Figure 14. Seasonally-Adjusted Forecasted Total Participation (All Appliances) 2007-2017

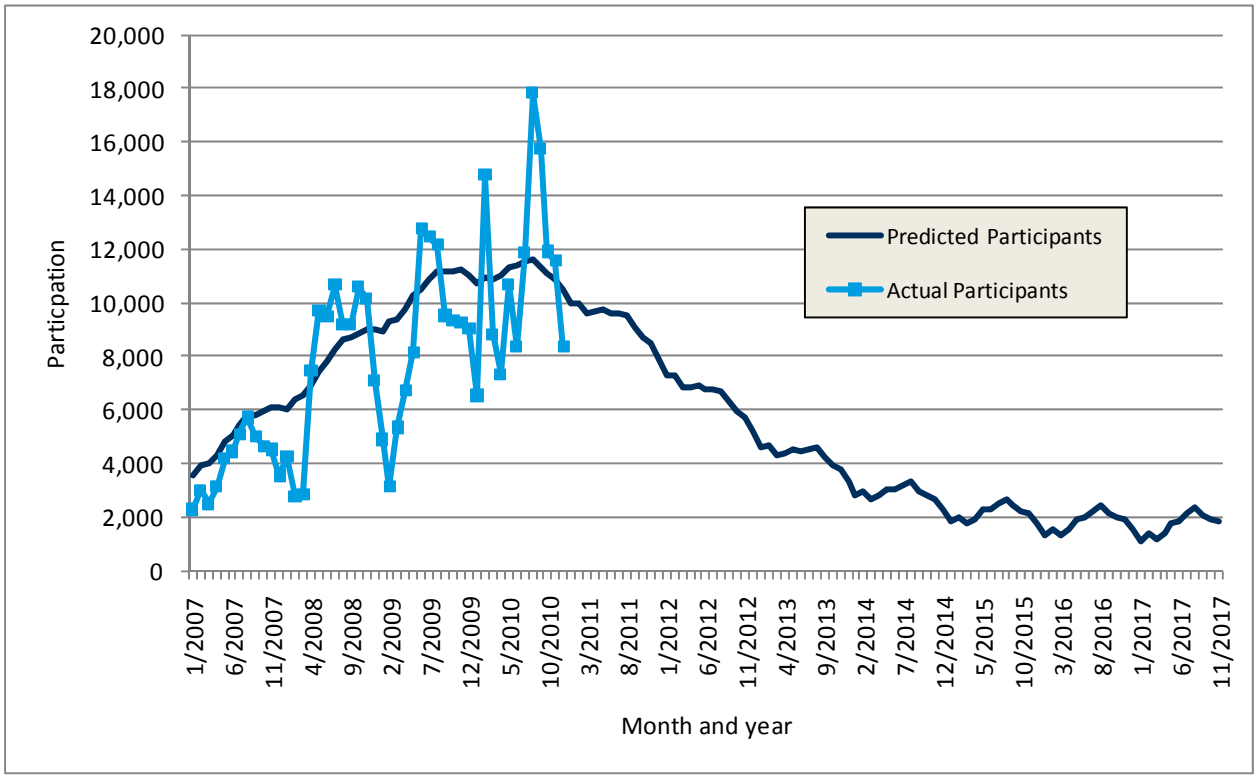


Table 30 shows these results, summarized for the study years. Results also break out by forecasted appliance type distribution, as discussed in the section above on cost-effectiveness.

Table 30. Forecasted Participation (All Appliances) 2013, 2015, and 2017

	2013		2015		2017	
Appliance Type	Proportion	Participation	Proportion	Participation	Proportion	Participation
Refrigerators	72%	37,068	71%	18,359	69%	14,168
Freezers	28%	14,173	29%	7,610	31%	6,298
Total	100%	51,241	100%	25,969	100%	20,466

Recommendations

Based on evaluation findings, Cadmus offers the following recommendations for improving the program and conducting future evaluation activities:

- As recommended in the 2008–2009 evaluation, Cadmus believes additional *in situ* metering should be conducted no later than 2012, when the program will be collecting significant numbers of appliance manufactured after enactment of the 1995 EEA. To maximize evaluation resources, future metering efforts should focus on newer appliances, not captured in 2008–2009 metering study.
- While the quality of appliance age data contained in the program's tracking database improved dramatically from 2009 to 2010, further improvement can be achieved. Cadmus recommends collecting ARCA record appliance age using mutually-exclusive, three-year intervals (i.e., 15-17, 18-20). Intervals should start at 15 and continue to 40. All units over 40 years old can be entered into a single ">40" category. As noted in the previous evaluation, and indicated by the model used to estimate savings for 2010, achieving accurate appliance characteristics proves essential for accurately estimating program savings.
- Though Cadmus forecasts predict declining GRRP participation and for the program not to be cost-effective as soon as 2015, we believe GRRP could continue to play in important role in the province's long-term residential energy efficiency portfolio for two primary reasons. First, since the bulk of program costs are per-unit expenses, program costs will also decline with participation. It is also likely that other costs, such as advertising, could be reduced as the program awareness increases. Second, since appliance recycling programs typically enjoy extremely high levels of satisfaction, the programs can encourage participants to enroll in another OPA or local distribution company energy efficiency program they otherwise may not have.
- Cadmus recommends dropping the 15-year minimum age requirement for program eligibility. Our forecasts indicate that unit age will steadily decline over time and continuing to impose such an age requirement will further shrink an already declining participant base. In addition, after 2010 the 15-year age minimum will no longer ensure participating appliances were manufactured prior to the Energy Efficiency Act of 1995.