Cost Analysis for the Portland Ecoroof Incentive

ENVIRONMENTAL SERVICES
CITY OF PORTLAND
working for clean rivers

Prepared by EcoMetrix Solutions Group, LLC.

December 2014

Table of Contents

Table of Figures

Table of Tables

Executive Summary

The City of Portland Bureau of Environmental Services' Ecoroof Program instituted an incentive that supported installations of ecoroofs for five years from 2009-2014. The program collected extensive data from the participants in the ecoroof incentive. One goal for the program was to support the use of ecoroofs by increasing the extent and rate of installation. The program also had the goal of reducing the cost of ecoroof installation through economies of scale and maturation of the industry through increased adoption of the technology. This report shares the results of an analysis of these data to understand if there was a change in the per-unit cost to install ecoroofs.

We conclude that the data do not support a statically significant relationship between the ongoing incentives distributed during the program and the installation per unit costs. This relationship was evaluated through a variety of techniques. We conclude that there is not a statistically significant relationship because either the relationship between the incentive and ecoroof costs is not direct or strong enough to affect a change, or that the data collected from participants in the program were not consistent enough to support statistical relationships.

Despite these conclusions, we find that the program dataset provides important information on the distribution of costs by installation type and land use. Descriptive statistics indicate that median installation costs range from approximately $6.00 per square foot for single-family residences up to $15.55 per square foot for institutional installations. The program included over 330,000 square feet of ecoroof installations with a total private investment of over $6 million.

The data collected through the incentive support several conclusions regarding the incorporation of ecoroof technology into the broader Portland community. First, these data help to facilitate a public understanding of the types and variations of ecoroof installation costs in the Portland area which helps guide future technological development. Second, the variation in cost data suggests other possible program tools may be more effective in increasing ecoroof adoption, such as credit and market based systems or reverse auctions. Finally, these data provide a strong foundation and lessons learned for future cost evaluation projects.

Introduction

The City of Portland's ecoroof incentive was developed as a means to expand the City's green stormwater management infrastructure by increasing the frequency and affordability of installing green roofs on private and public buildings within the City. Additionally, the City hoped that the incentive would promote the development of a small, local, industry of contractors and installers by decreasing installation costs while the industry developed. In an effort to assess the success of the incentive, the City collected data on the installation costs of each participating project. This report presents an evaluation of these data and attempts to identify relationships which suggest an installation cost benefit from the incentive. The primary benefit being assessed is a decreasing per-unit cost to install these facilities over time. The main hypothesis being tested in this analysis is whether or not these data suggest that the incentives program has caused a change in the per-unit cost over the duration of its implementation. Testing of this hypothesis includes time series analyses and requires some assumptions about the role of the City's incentives in the larger market.

Program Description and Background

The Ecoroof Program grew out of the Sustainable Stormwater Management Division that was formed in 2001. Program activities were focused on demonstration projects, technical assistance, and monitoring for stormwater performance.

The Ecoroof Program was expanded in 2008 by the Grey to Green Initiative, which provided a direct financial incentive of $5 per square foot to boost implementation. During this time, the Ecoroof Program hosted annual seminars and symposia to build awareness and connect willing property owners with ecoroof professionals. Leading researchers and policy makers from Portland, and around the globe, were invited to participate and share the most current information on successful green roof technology. The incentive helped to fund 134 projects with $1.9 million over 5 years.

In all, the ecoroof incentive allowed the program to leverage multiple partnerships, resources, and funding opportunities. The primary goal of the incentive was to reduce upfront costs so that more ecoroofs would be used in Portland and to jump start a forming industry.

The Ecoroof Program provided the incentive during a unique period in the US housing market and for the economy as a whole. The Portland housing market increased steadily through, and out of, the short 2001 recession but beginning in 2004 the rate of home price increased quickly. Home prices, as measured in the Case-Shiller Home Price Index, increased over 80% from 2000 to its peak in the beginning of 2008 when the Great Recession began. From this period forward home prices quickly fell. The Portland Ecoroof Incentive program data begins in 2009 and runs through 2014. Figure 1 shows the housing price data along with the duration of the Ecoroof data. As the index shows, housing prices go through a U-shaped curve over this time window. This curve may have influenced ecoroof costs and, if so, influenced them in two directions. This creates a challenge for analysis of the relationship between the real estate market and ecoroof costs.

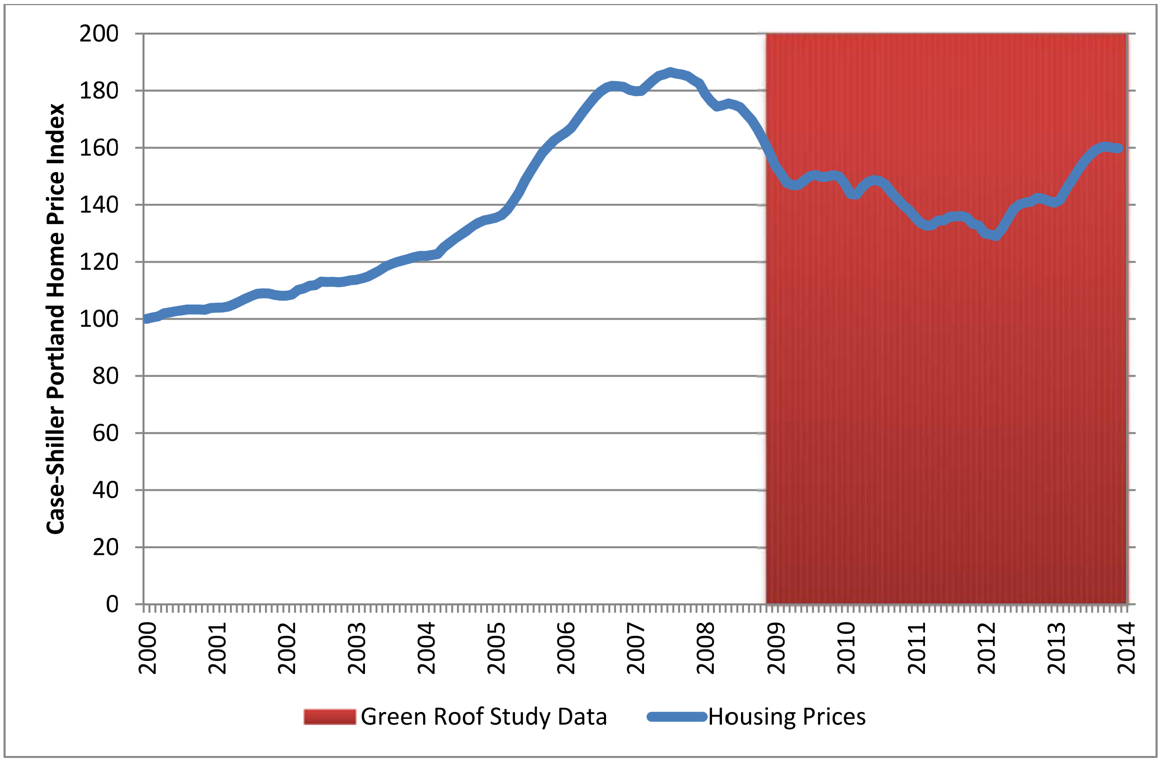

Figure 1: Housing Price Index and the Duration of the Ecoroof Incentive Program

Throughout this document the term ecoroof is preferred, but it is also the same as an extensive green roof. Green roof is a common term in the research literature, and the two are used interchangeably here. Further, there is a distinction between intensive and extensive ecoroof types (Rowe 2011). Intensive installations are larger and include public spaces, trees, and deep substrates. Extensive green roofs have shallower substrates usually using forbs, grasses or other smaller vegetation. Extensive installations are the type included in this study.

Data Description

The dataset used in this analysis consists of cost data for 105 ecoroof installations between June, 2009 and September, 2014. For each installation, additional descriptive information was collected for use in identification of trends within the dataset. These data included: Land Use Type (Residential, Multifamily, Commercial, Institutional, Mixed Use, and Hospital), Installation Type (New, Retrofit), Roof Installation Size (sf), and Completion Date. Additionally, a cost breakdown was provided for each installation in which incentive recipients and installers were asked to report costs specific to the Membrane, Root Barrier, Drain Mat, Drain Channel, Protection Board, Growing Media, Tray/Mat, Gravel, Edging, Irrigation Materials, Plants, Labor, and Other Costs. Additional notes were collected from incentive participants which further described the costs associated with the 'Other Costs' category and identified elements of the installation that might be unique to a particular install.

It is important to note that the type and nature of ecoroof installation varied considerably in the data. Some were smaller sized "do-it-yourself" installations on private residences while others were larger institutional installations that approached 30,000 square feet. The differences in costs, associated with these extreme variations, appear in the data and contribute to its variability. Larger installations may have required cranes or other mechanical tools not typically used for smaller installations, and may have also used higher cost prevailing wage labor. The smaller installations may have used volunteer labor and simple tools. These factors impacted the cost data, and our ability to assess change over time.

Data Preprocessing

Throughout the initial cost analysis, several decisions were made which had impacts on how the final analysis would be conducted. While other options were explored, the following decisions resulted in the most appropriate application of these data to the cost analysis process. First, the installation costs that were considered did not include the membrane cost. When included, the membrane cost contributed significantly to the noise and outliers of the dataset, the removal of these costs provided the first step in normalizing the comparison between data. Second, the six land use categories were re-evaluated and generalized into three new categories which were similar in design and installation criteria, but contained more sample points, which increased the potential to identify significant trends. The three new groups are Single Family Residence (SFR) containing 59 installations; Mixed-use, Commercial, and multi-family residence (MXDMFR) containing 36 installations; Institutional and Hospital (INST) containing 10 installations. While an initial analysis was conducted which assessed the potential for trends in each of the land use categories throughout the duration of the project, only the Residential category had sufficient samples during the initial analysis, across the entire timespan of the project, to support a potentially significant trend. Third, several outliers were identified and investigated, which resulted in the implementation of corrections to the initial data collection or transcription process, further helping to support the analysis. These pre-processing steps were necessary to provide the highest potential for identification of trends within the dataset.

Research Question: Public Incentive Programs for Ecosystem Services

The management of stormwater, air and water pollutants, and urban heat island effect are three classes of environmental goods and services that ecoroofs provide (Rowe 2011). These environmental goods and services are supplied by the natural biophysical system as ecosystem services, until development occurs (Bolund and Hunhammar 1999; Hassan et al. 2005). With development, replacement of these services is required, normally this is accomplished through engineered solutions. In the context of impervious surfaces, new conveyance and treatment facilities are required for stormwater. Ecoroofs represent a hybridization of engineered and natural systems to replace services lost to development while retaining the benefits of urban development. This is a form of urban “domestication” of natural systems to better serve human communities (Kareiva et al. 2007).

The benefit of ecoroofs has been a growing object of empirical and modeled research. A recent meta-analysis of existing research identified a wide suite of benefits from these green roof technologies (Rowe 2011). These benefits include the above mentioned stormwater, air and water pollution filtration, and urban heat island effect reductions. For example, one square meter of green roof removes the same amount of particulate matter as that produced by the average automobile (Rowe 2011:2102).

Stormwater reductions can range from 50-100% depending on local climactic and design considerations (Rowe 2011:2104). Other benefits include reducing building heating and cooling energy requirements, urban noise, and reduced life-cycle costs of roofing materials. Longer range modeling of green roof installation shows large reductions in life cycle costs. Using Washington, DC's 20-20-20 initiative to develop 20 million square feet of green roofs, Niu et al. found that green roofs would be 30-40% less costly in net present value (2010). Based on this modeling, the break even for using green roofs over conventional roofing would occur after 7 years.

Based on these findings, local jurisdictions are seeking policy tools to expand the rate and extent of ecoroof adoption. For ecosystem services and environmental programs there are several existing policy tools. These range from command type tools that require particular design standards, to voluntary subsidy or incentive programs and on to market based solutions (Tietenberg 2006). Green roof programs have focused on the first two options, with more applying incentive programs (Carter and Fowler 2008; Mees et al. 2014). The City of Portland fits these models through its Ecoroof incentive. This leads to the basis of the research question, how effective can the incentive be at increasing the adoption of ecoroof technology?

More specifically for this report, the hypothesis is: The public incentive reduced the per-unit installation costs for ecoroofs in the City of Portland while it was active. This hypothesis is based on an assumption that the incentive provides a price effect through changing demand, increasing quantities of installation, and developing benefits from economies of scale and industry maturity. This process assumes the following steps: First, the subsidy shifts the demand curve to the right where more quantities of goods are produced for the same price. Next, this shift in the demand curve is realized by consumers (or building owners) as a decrease in price per square foot. Finally, the increase in the quantity of installations then introduces economies of scale and maturation in the industry. Economies of scale and maturity are seen through increases in contractor firms, improvement of installation skills, and decreases in material and labor costs as the technology moves from an emerging technology to a common application. These assumptions are supported by empirical data showing US costs of installation are higher in comparison to conventional roofs, while in Europe the two types are marginally similar (Blackhurst, Hendrickson, and Matthews 2010:142). As the European market for ecoroofs predates that of the United States, this observation suggests policy measures may close the gap between the two technology types.

The following sections review descriptive statistics from the City's program to understand the general trends and distributions of values in the dataset. The first section provides a basis for characterizing the cost of installations across multiple land use and installation types. While these data show some mixed results, they are informative for future program development. The next section seeks to test the above hypothesis using several different approaches. The statistical models do not reject the null hypothesis that there is no effect. Therefore we cannot settle the question of whether the incentive had an effect on installation costs. However these data provide insight on possible progress in other policy tools. The final section concludes by reviewing what was learned from the analyses and proposes several options for future research and policy development.

Section 1 – Descriptive Statistics

Initial Descriptive Statistics

Following preprocessing, a descriptive statistical analysis was performed to characterize general trends in these data and help to provide a sound foundation for additional model evaluation during the next phase of the analysis. The first analysis performed was an examination of the descriptive statistics around the installation cost in units of dollars per square foot. These first statistics were performed on the entire dataset and the results presented in Table 1 provide a comparison between the costs with or without installation of a membrane.

Data	n	Mean	Std Dev	Skew	Min	Median	Max	IQR
Membrane	105	$16.37	$14.49	2.49	$2.93	$11.25	$85.40	$12.80
w/o Membrane	105	$10.34	$8.06	1.56	$0.81	$8.38	$40.38	$8.07

Table 1: Basic Descriptive Statistics on Installation Costs per Square Foot

The skewedness and standard deviations are reduced with the membrane costs excluded. The remainder of these analyses are presented with the membrane costs excluded. When viewed in a histogram showing the frequency of installations over the unit cost (Figure 2), it becomes clear that the mean value ($10.34) reasonably fits these data while the skew (1.56) and large standard deviation ($8.06) are due to a number of projects on the expensive end of the spectrum. The IQR ($8.07), or Interquartile Range, is the size of the range that covers 50% of the installations, centered on the median value. In other words, 50% of all cases are within $4.03 of the $8.38 median cost.

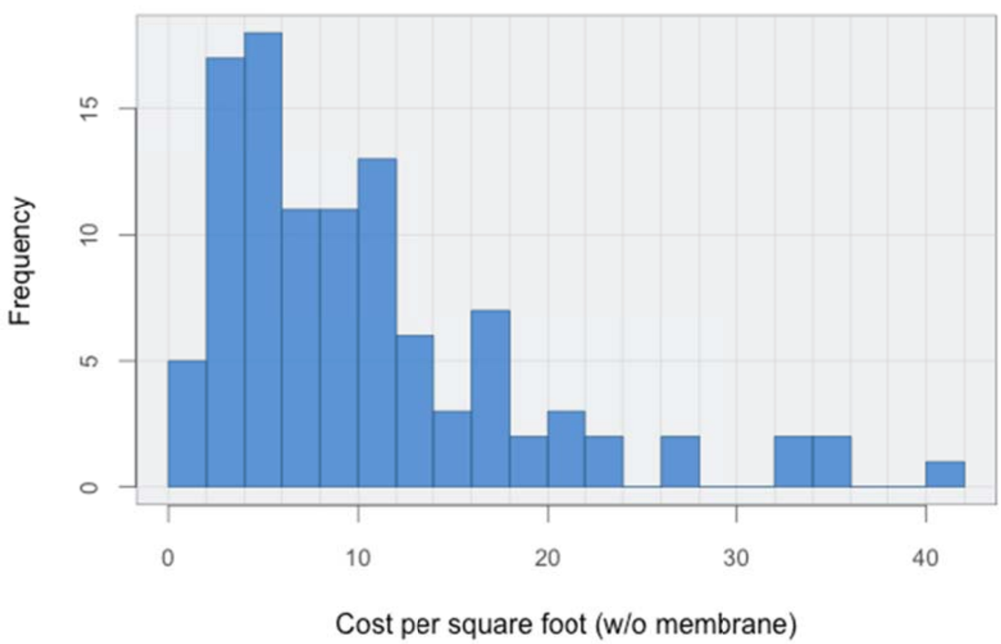

Figure 2: Histogram of Installation Costs per Square Foot

Additionally, the distribution in Figure 2 shows that the installation costs are grouped towards the left, while a little over 10% of the installations show costs greater than $20 per square foot which draws the tail out to the right. From this summary, these data do not meet the initial requirements for a regression analysis as the skewedness will bias the findings. In section 2, and the technical appendix, we present the methods used to address these issues.

Time Series Analysis

The next analysis was to determine whether or not there were any significant trends over time in these data. In order to better isolate trends, an initial breakdown of total installation area across the various land use or structure types was performed to identify land use categories that might support independent cost trend analyses (Figure 3 and Table 2). These land use types include commercial, hospital, institutional, mixed use, residential, and multifamily residential.

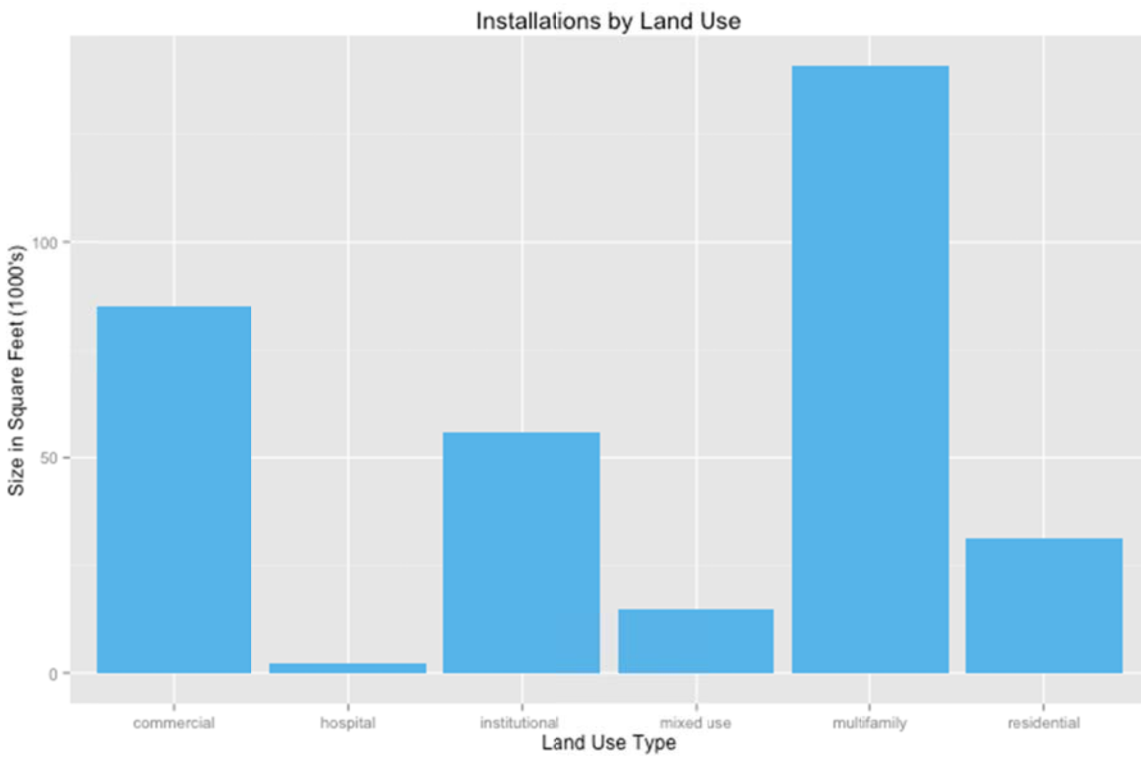

Figure 3: Size of Installations by Land Use Type

	Commercial	Hospital	Institutional	Mixed Use	Multifamily	Residential
Count	18	2	8	3	15	59
Area (sq ft)	85,026	2,254	56,034	14,858	140,783	32,173

Table 2: Count and Total Area by Land Use Type

We combined the types into three new categories based on input from City staff: Single Family Residence (SFR); Mixed-use, Commercial and Multi-Family (MXDMFR); and Institutional and Hospital (INST). Figure 4 shows the distribution of all installations in the dataset by these new land use categories. The combination of uses into MXDMFR will allow a more specific analysis of these categories, though the dataset is still small and it may not be possible to isolate trends within the Institutional installations due to the small number of observations in that class (n=10).

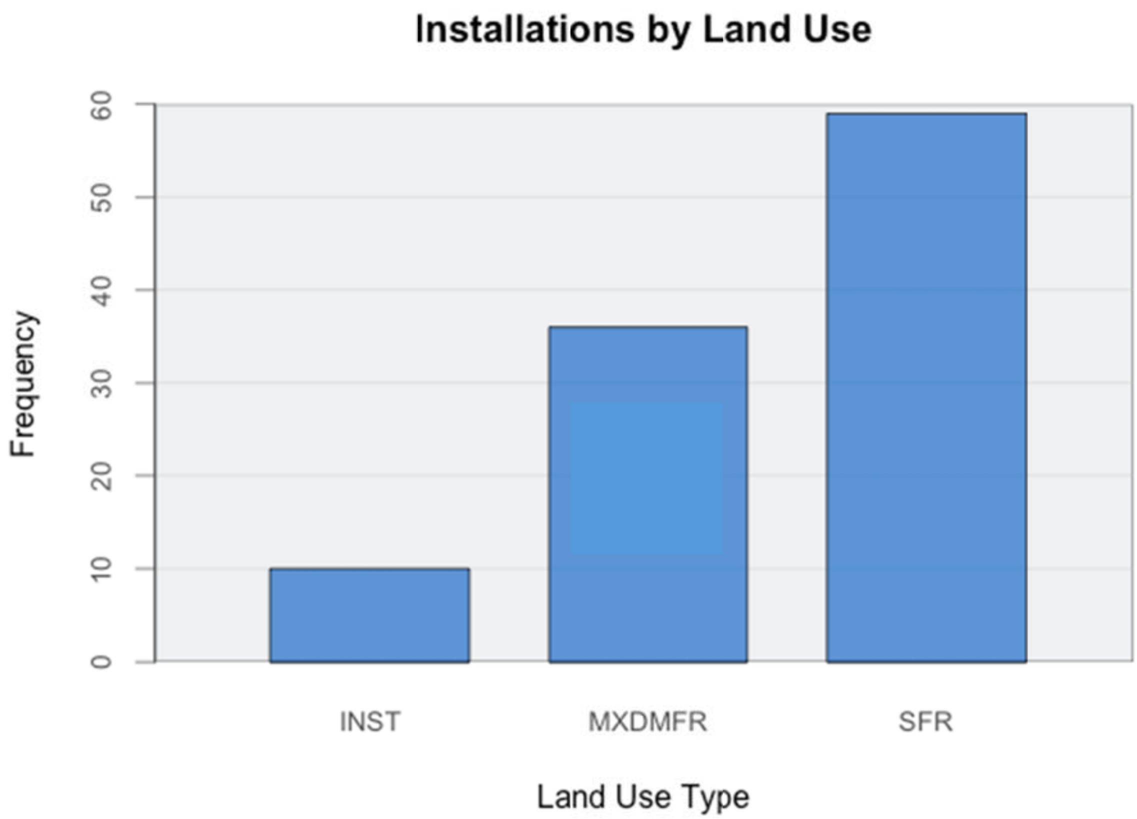

Figure 4: Installation by Land Use Type (Grouped Types)

A preliminary data assessment from 2009 to 2013 shows a mixed set of trends in installation costs across all land use categories and in the residential-only installations (Figure 5). These graphs do not support a clear trend in these data. Data from 2014 were omitted due to the small sample size for that year (n=2).

	Institutional	Multi-Family/MXD/Commercial	Single Family	Totals
Number	10	36	59	105
Area (square feet)	58,288	240,667	32,173	331,128
Number of sites 1000 sq ft or less	2	9	48	59
Number of sites 10000 sq ft or more	2	7	0	9
Total Cost*	$1,126,436	$4,557,921	$359,829	$6,044,186
** includes membrane costs*				

Table 3: Count of Installations by Land Use Type and Sum of Area

Table 3 provides a summary of the count, area and total cost for each land use grouping.[1] Of these installations, nine are 10,000 square feet or larger. Institutional large installations provide 44,621 square feet of green roof and multi-family/MXD/commercial installations provide 151,595 square feet. These large installations comprise approximately 60% of the area installed through the incentive. Of all of the installations, 61 were new and 44 were retrofit.

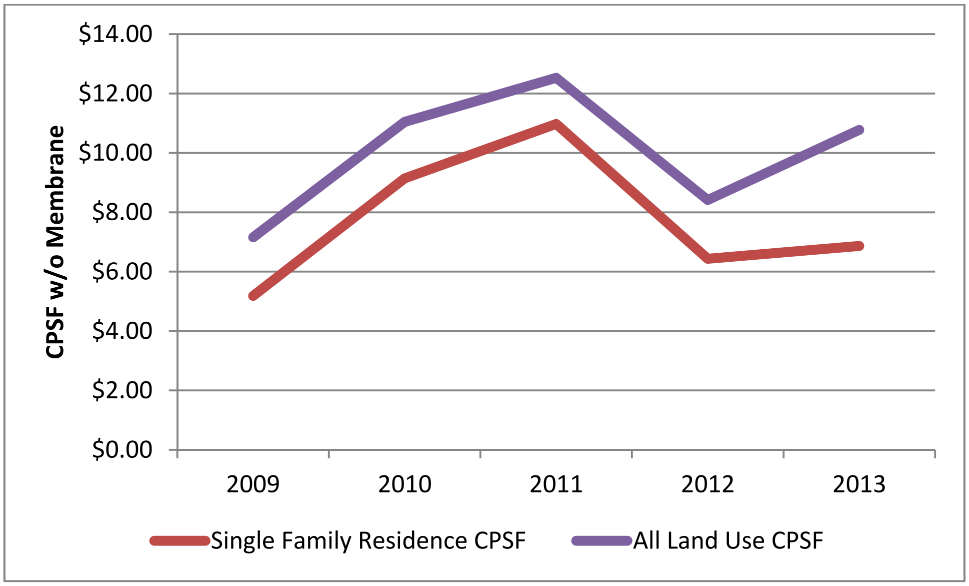

Figure 5: Cost per Square Foot by Project Over Time

A scatterplot of these data suggests that the SFR installations may show a slight decline. Figure 6 shows the distribution of installation costs for each year in a scatterplot and by land use type. Also included are simple regression lines to indicate any directionality – though not with a measure of significance.

[1] Note that some totals vary slightly between figures as the analysis moves to the hypothesis testing. In the statistical analysis some cases were removed after review with City staff, others were removed based on outlier analysis. The data presented here has the larger dataset before excluding any data for analytical purposes.

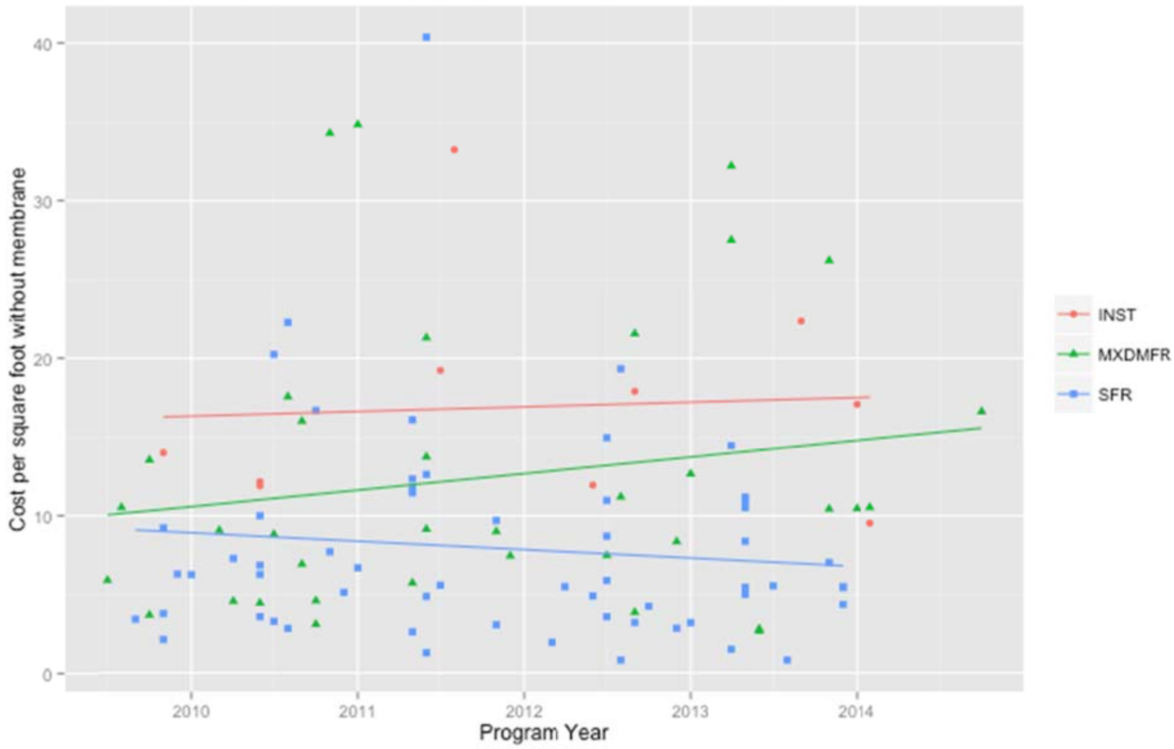

Figure 6: Scatterplot of Installation Costs by Program Year

Another look at these data is presented by boxplot. Figure 7 shows the three land use types for each year of the program. The box measures the interquartile range for each land use for each year. The whiskers reach to the end of the range of values unless there is an outlier. The median is represented by the dark line in the middle of the box. For Institutional installs, 2009, 2010, and 2014 only have one install, causing just the median to plot. The same is true for Single Family Residence in 2014. Table 4 accompanies Figure 7 and shows the number of installations included in that figure for each install type across the years of the incentive.

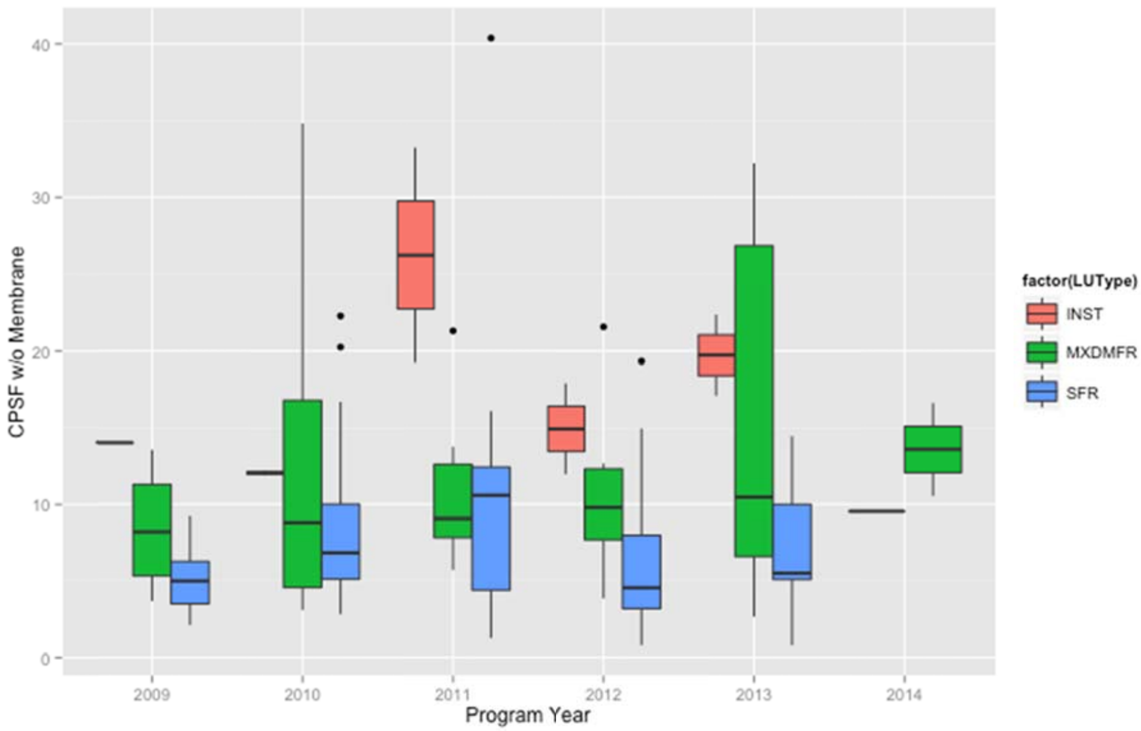

Figure 7: Box plot of install cost by type and year

Year	2009	2010	2011	2012	2013	2014
Institutional	1	2	2	2	2	1
MXDMFR	4	11	6	6	7	2
SFR	6	13	12	14	14	0
Note: For years and land uses with low counts, (n <5) the box plot may not be a reliable measure of distributions (Krzywinski and Altman 2014). This is true for all institutional installations and years 2009 and 2014.						

Table 4: Count of Installations by Land Use and Year

	Institutional	Mixed/MFR/Commercial	Single Family Residential
Median Cost per Square Foot	$15.55	$9.79	$6.07
Middle 50% range	$12 to $18.90	$5.86 to $16.17	$3.62 to $10.85

Table 5: Median Cost per Square Foot by Land Use Type

Table 5 reports the median cost per square foot without membrane costs, by land use group. The range reported in the second line is the 25th percentile value to the 75th percentile value. This represents the middle 50% of the data. This range is not exactly centered on the median value due to skewed distributions within the data. Figure 8 below shows a boxplot of costs per square foot for all installations across the three consolidated land use types. Like Figure 7, the box plot's median values are the dark black lines in each box. The box's size indicates how close the costs are to the median. Single family residence shows a narrower grouping, but with some notable outliers and a skew towards the higher cost values.

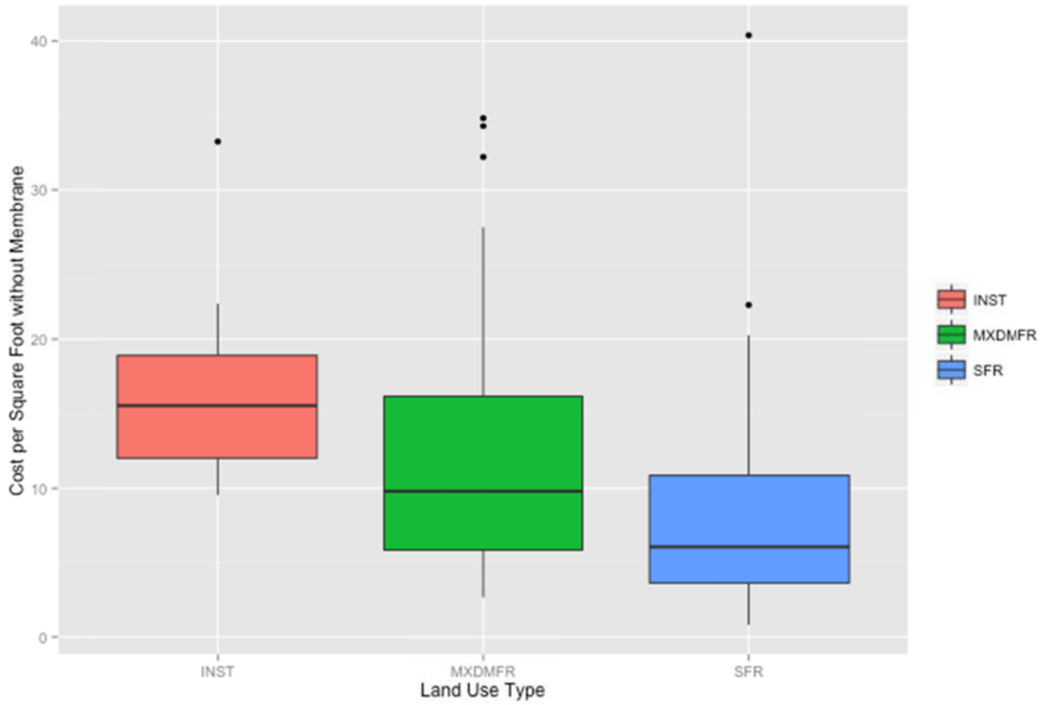

Figure 8: Cost per Square Foot by Land Use Type

Section 2 – Model Hypothesis Testing

Assumptions and Limitations

The starting hypothesis for this project is that the City incentives for ecoroof installation allowed for an increase in installations and a decrease in the per-unit cost. Section 1 reviewed the descriptive statistics to begin exploring this hypothesis. The descriptive data revealed that for all installations there did not appear to be a decrease over time. There may be some decreases over time, however, within subsets of installation based on the land use, size, and technology used. The descriptive statistics also revealed some of the technical challenges for regression models with the installation data.

Before discussing the models and techniques used in this report, the general challenges for statistical modeling need to be addressed. Once this background is established, the particular model choices can be explored in more detail. One of the most common regression techniques for this type of analysis is the ordinary least squares (OLS) (Burt and Barber 1996). Regression techniques such as OLS are based on four primary assumptions: normal distribution of variables; a linear relationship between dependent and independent variables; low or no measurement error; and errors are homoscedastic (Osborne and Waters 2002).

The first assumption means that the frequency of the variable observations centers on a mean value with equal increments of observations to the right and the left of the mean. The histogram in Figure 2 shows an example of examining a variable for normality. The figure shows a skewedness that must be addressed to perform an OLS regression. This can be accomplished with transformations. Transformations are the use of an equation to change the value of each observation such that the frequency becomes normal. For example, by raising the cost per square foot by 0.20, the distribution approximates normality, although this also makes interpretation of results more challenging as the coefficients from the regression model become relative, rather than absolute. As observed in Figure 2, normality in distributions is a challenge for these data. We try to address this in the models below with several techniques. Another related challenge to normality is the existence of outliers. Outliers have been a challenge in these data and we have removed some and corrected others as identified by the project team.

The second assumption (of a linear relationship) is a requirement based on the structure of OLS or multiple regression techniques. If the relationship is curvilinear it can be managed, but we did not detect this as a problem in these data.

The third assumption (low or no measurement error) is a challenge in this project. As discovered with the City of Portland team, the self-reporting of data appears to be a large and uneven source of error in the data. There is no technique to address this except to try and subset these data into categories where at least the error might be standardized. However, this is a large limitation of this study and needs to be kept in mind as the results are reviewed.

The final assumption on error homoscedasticity appears not to be a challenge in the models presented below. This assumption is based on the idea that the distribution of error is consistent across the analysis and would be violated if there were time windows in which the distribution was significantly tighter than others. We do explore the distributions of error as we evaluate various model and regression techniques.

While we have identified some tools to correct these data to meet the four assumptions, some of the distributional issues are being managed through transformation techniques. Alternatively there is a family of regression techniques known as robust regression. Robust regression methods have been developed to address the problems of outliers and to some degree issues of distributions (Andersen 2008). Several techniques are available for robust regression, based on the challenges faced in this study we have used M-estimator as the primary technique and this is supported by empirical research as a good fit for the data challenges present in this study.

Several models were crafted based on the subset of data used as well as the management of these data through transformations to address distributions and outliers.

The following models were tested:

- All installation types, cost per square foot over program
- Cost per square foot over program by land use type
- Cost per square foot over program by land use type and installation type
- Cost per square foot over program for large installations (>10,000 square feet)
- Labor costs per square foot for all installation types
- Labor costs per square foot by land use type

The goals for each of these models are to explore a refined subset of the data in an attempt to address the limitations discussed above. The subsets allow for testing that controls for some error types, or provide subsets which show better distributions. However this can also introduce new problems. By creating subsets of these data, the number of observations are reduced which can introduce new sources of error which represent a limitation for the analysis. As found in the descriptive statistics, the single family residence installations provide the most observations and thus allow for subsets on multiple variables. Other land use types do not have a large enough set of observations to address multiple variables. This strategy has allowed us to detect some new possible trends in these data.

Individual Model Testing Results

For all of the following models, we were not able to reject the null hypothesis. We present these findings to show how we tested these data. But the conclusion overall in these statistical tests is that we cannot claim the program's hypothesis of reducing per-unit costs can be supported or rejected. The Appendix provides detailed regression tables for the models tested.

All Installation Types by Cost per Square Foot over Time

Initial OLS results: positive correlation with time (increasing costs per square foot) but not statistically significant. Initial robust regression with power transformation of cost per square foot data: slight positive correlation over time. This model reports a 0 value for the R^2 and a p-value of over 0.58. This means that there is no explanation of the variance of data and the null hypothesis is more likely than the tested hypothesis.

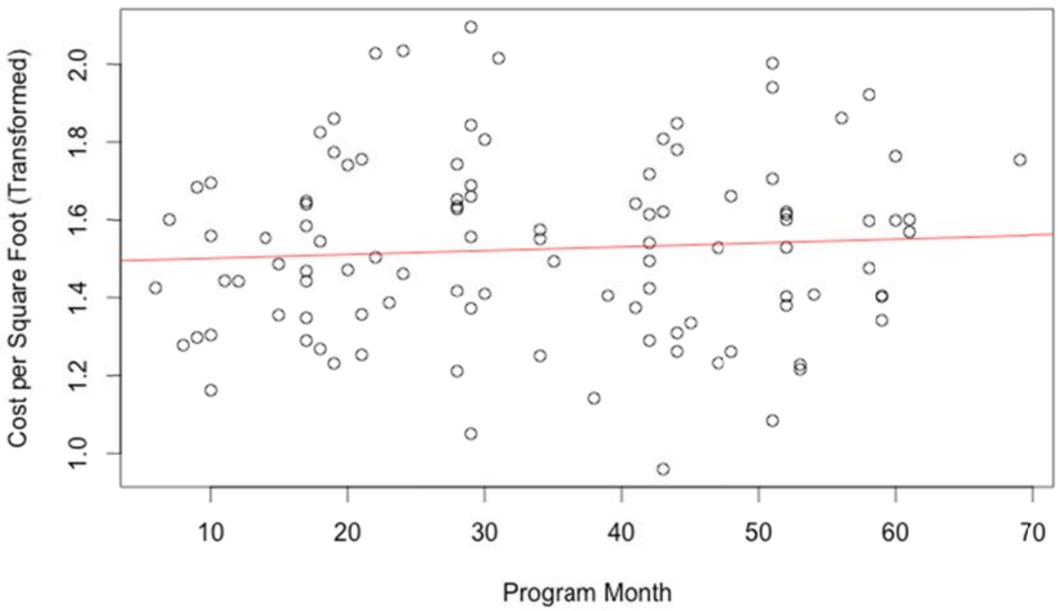

Figure 9: Scatterplot of Cost data and Robust Regression Model Plot

Cost per Square Foot by Land Use Type

SFR results show a very slight robust decline over time with a lower level of residual error, suggesting a better fit. However, like other models, this analysis does not show a statistically significant relationship and the reported R^2 is very small. This model reports a 0 value for the R^2 and a p-value of over 0.78. This means that there is no explanation of the variance of data and the null hypothesis is more likely than the tested hypothesis. Similar to all land use types, the cost data requires a power transformation to address the distributional issues in the variable.

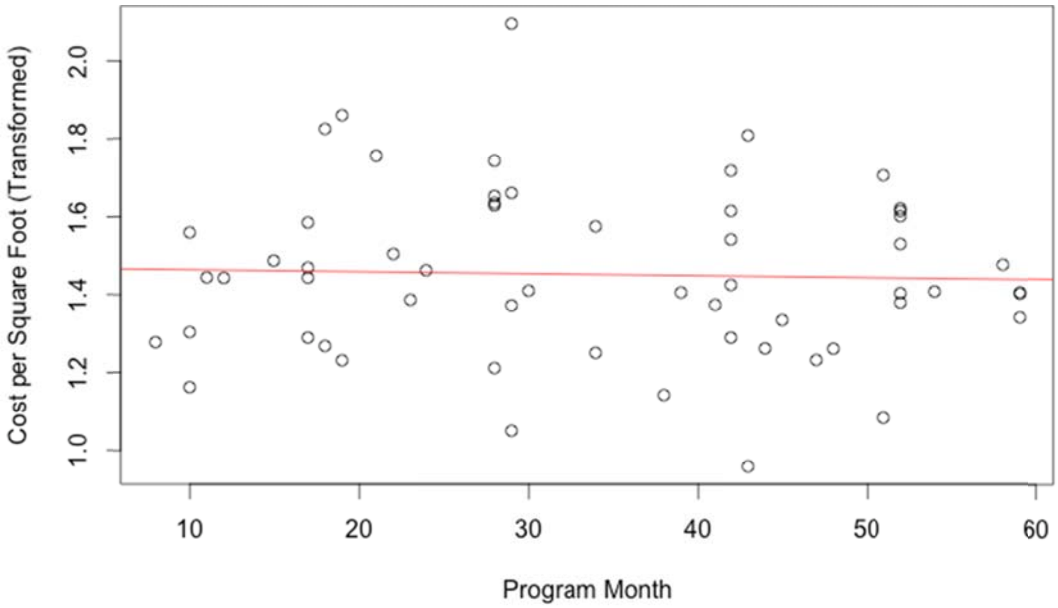

Figure 10: SFR Installation Scatterplot and Robust Regression Plot

Costs per Square Foot by Install Type and Land Use Type

This series of models examined the new and retrofit installations as well as the projects without tray-type technology. These subsets are meant to control for certain construction costs within the project dataset. New installs for all land use show a positive relationship between time and cost, while retrofitted installations are positive but not as strong. The retro installations have far fewer observations reducing the reliability of this assessment. Non-tray type installations show a decrease in costs over time. For both models we did not find a statistically significant relationship and R^2 values of zero.

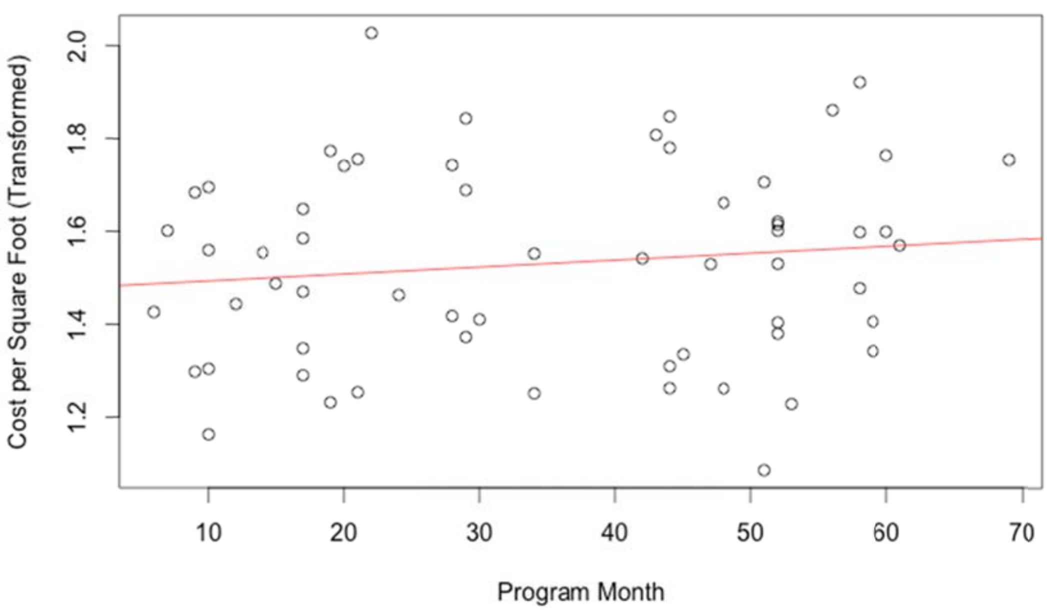

Figure 11: Cost Scatterplot for New Installs for All Land Uses and Robust Regression Plot

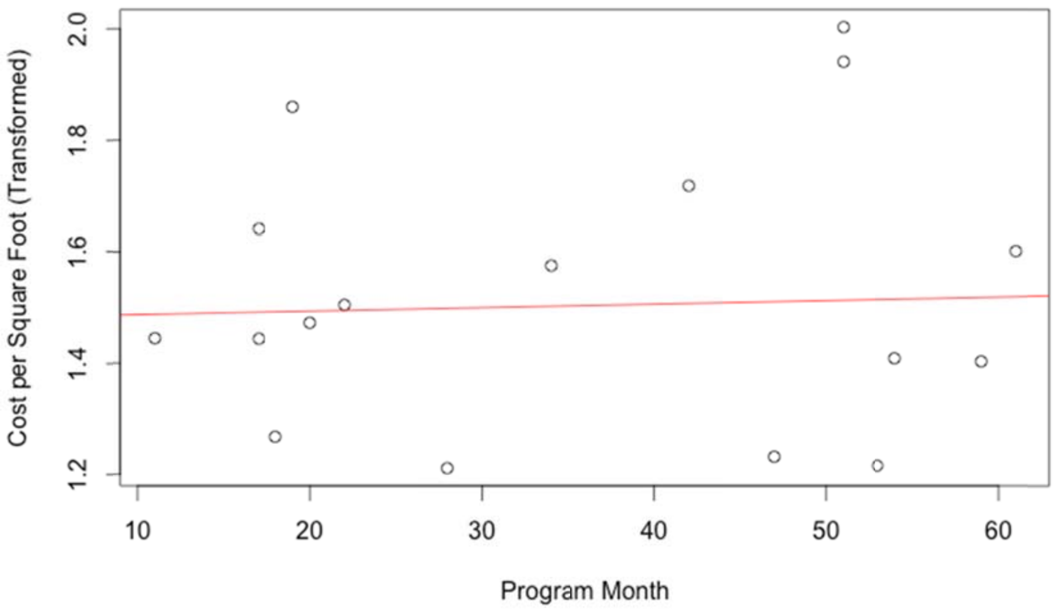

Figure 12: Cost Scatterplot for Retro Installations for All Land Use Types and Robust Regression Plot

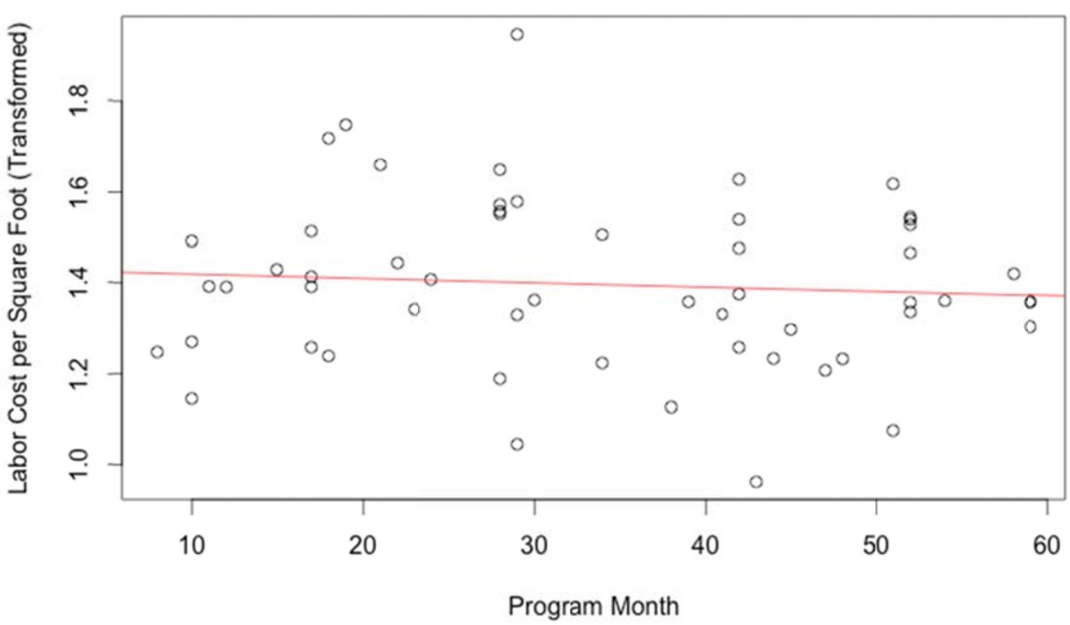

Figure 13: Cost Scatterplot for Single Family Residence Installations not Using Tray Type Technology and Regression Plot

Costs per Square Foot for Large Installations (>10,000 sq ft)

Only 9 cases exist that meet the definition of being a large installation, 10,000 square feet or larger. This limits the options for testing the data. This model reports a 0.02 value for the R^2 and a p-value of over 0.30. This model does not explain variation and we cannot reject the null hypothesis.

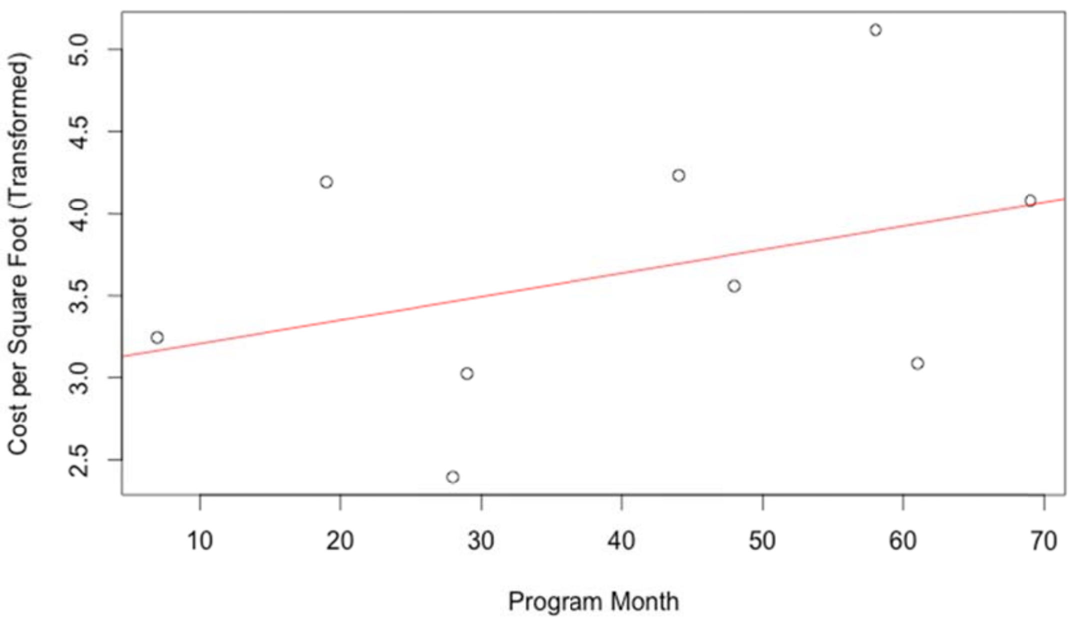

Figure 14: Cost Scatterplot for Large Installations (>10,000 sq ft) and Robust Regression Plot

Labor Costs per Square Foot by Land Use Type

One of the possible causal relationships for a reduction in costs over the life of the incentive is efficiencies in workforce skills. If the increased number of installations resulted in quicker, more problem-free installations the costs for labor would decline. To examine this possible explanation, labor costs per square foot were calculated for these data. The initial plot suggests a slight downward trend over time, however the data with labor costs is limited in the dataset. In the case of SFR labor the R^2 is zero and the p-value exceed 0.98. This is due to the very few points included in the analysis due to a lack of labor data.

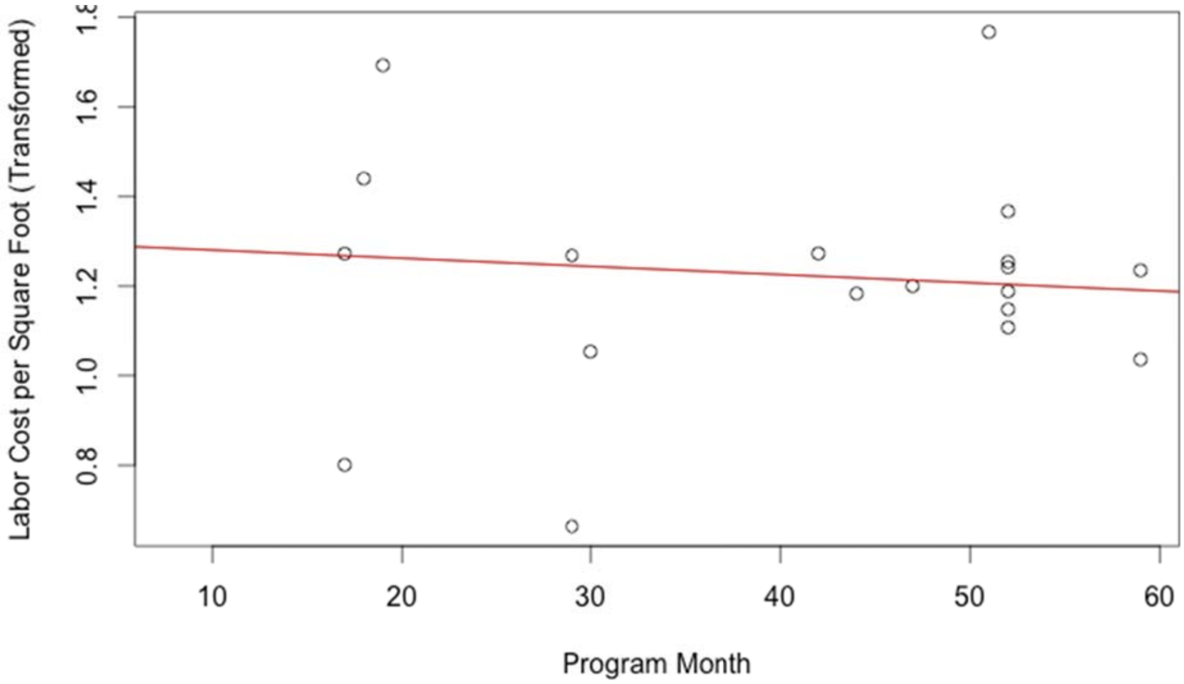

Figure 15: SFR Labor Costs per Square Foot Scatterplot and Robust Regression Plot (Non-Tray Type)

As noted in the in the introduction to this section, the models were created numerous ways to try and test the hypothesis as rigorously as possible. Despite the directionality shared on the plotted figures, none of the models met statistical standards for significance, or showed meaningful explanation of variance in the data. The following section discusses the implications and conclusions for the analysis as a whole.

Section 3 – Conclusions and Future Recommendations

This section briefly reviews the analytical results from Section 2, the interpretation of these results, and then shifts to understand what information these data do provide. This section also presents several data, program, and policy recommendations.

The results of the various models were not found to be statistically significant. Therefore the null hypothesis cannot be rejected. This means these data do not support the conclusion that the incentive decreased costs over time. There are several reasons why the hypotheses may not be supported. First is the possible lack of a causal relationship in the economic dynamics behind the cost of ecoroof installations. These costs may not be affected by the City's incentive. As discussed in the first section, the proposed causal relationship was based on seeing increased economies of scale and maturity in the ecoroof industry. While over 300,000 new square feet were supported with this program, 60% of that area was accomplished with 9 large projects. This may have limited the ability of economies of scale to be realized across the diverse set of installations.

It is also possible that the underlying costs benefited from economies of scale but these benefits did not influence much of the total costs. We tested for the maturation of the industry by using labor costs as a measure of possible efficiencies. Unfortunately, these metrics also failed to support a statistically significant relationship. One limitation for this analysis was that the labor data was not complete across the entire dataset.

Another reason for the possible lack of a relationship is that the set of projects included in the data collection are a unique sample of all projects installed in Portland. It is possible that property owners who chose to participate in the program were skewed by the available incentive, leading to a sample of projects with unique or non-representative costs. While the descriptive data does not suggest a per unit skewedness, there is a possibility of selection bias based on the incentive. To adjust for this, future data collection would need to randomly sample installations not participating in the incentive program to survey for similar cost data.

The last challenge for the analysis is data quality. As the descriptive statistics review was developed with City staff it was acknowledged that the reporting of the data from participating installers was not consistent. There was variation in how costs were included or excluded in the reporting, as well as how costs were categorized. We suspect this variation had a powerful impact on the data. It increased outliers and skewed data distributions. We attempted to control for this by subsetting data into categories where the error may have been more uniform, however these methods were also unsuccessful in the identification of statistically significant relationships. These efforts also created subsets of data with fewer cases and thus, further complicated developing statistical tests.

These two issues do not mean the data is not of some value for the City in evaluating the program. The data collected around these installations provides a valuable snapshot of the economics of ecoroof installation. This is a useful tool for future program development and policy adoption. Based on our review of the data we offer the following conclusions and their implications.

Conclusion 1: Data from Program Supports Better Policy and Public Information

Environmental programs to incent landowners or developers are often hampered by "information asymmetry" (Ferraro 2008). Information asymmetry is the situation where landowners or developers better understand the financial impacts of proposed regulations on their practices than regulating entities. This higher quality information allows for more successful negotiation to reduce costs for regulation as the agency often does not know the true "cost of doing business." By collecting these data, the City has a better understanding of how costs are distributed through the city, and can more appropriately compare these to other conventional costs. These conclusions have the same caveats as noted above in the data quality discussion. But we believe these data to be insightful at this level. Further, this first phase of data collection can be seen as a pilot for further data collection. A key role for government in speeding innovation and adoption of new environmental technology is to reduce information costs and make the findings from data a public good for all parties to use (Jaffe, Newell, and Stavins 2005). Findings from this program should be shared with the public and participating contractors to grow the body of knowledge among practitioners.

Conclusion 2: Cost Data is Highly Variable Within and Across Installation Types

The descriptive statistics show that installation costs vary considerably. This is true within, and across, land use types. We also did not see that variability declined over time. This difference means that some building owners have very low cost installations (typically single family) and others have higher costs (larger installations and institutional land uses). When large differences in cost are known to exist, one policy tool that can be effective is market based systems (Carter and Fowler 2008:154).

Conclusion 3: Data Collection Improvements Can Expand Usefulness of Program

As the previous two conclusions have shown, using the incentive to collect cost information from contractors is itself a public benefit. Further developing the cost data collection protocols can improve the quality and extent of the data for future evaluations. While this research did not directly review data collection practices, the team did discuss challenges experienced through the program. Self-reported data requires more protocols to guide the respondents. This is especially true for data that varies greatly on how the technology is used. For example the tray-type installations appeared to embed costs differently than other technologies. Another challenge was making sure that data was completed and checked for accuracy. Labor data, membrane costs, and other components were inconsistently reported or were missing from the data. Developing more involved protocols or instructional materials may improve data quality. Random selections of reports should be reviewed by staff over the phone or in person to assess data quality as well. This random calling would also provide an opportunity for qualitative data collection. A survey could be developed to allow for open-ended questions to explore drivers in costs or installation challenges. The results of these surveys and interviews could change how data is collected to better capture the information needed.

Works Cited

Alma, Özlem Gürünlü. 2011. "Comparison of Robust Regression Methods in Linear Regression." *International Journal of Contemporary Mathematical Sciences* 6(9):409–21.

Andersen, Robert. 2008. *Modern Methods for Robust Regression*. Los Angeles: Sage Publications.

Blackhurst, Michael, Chris Hendrickson, and H. Scott Matthews. 2010. "Cost-Effectiveness of Green Roofs." *Journal of Architectural Engineering* 16(4):136–43.

Bolund, Per and Sven Hunhammar. 1999. "Ecosystem Services in Urban Areas." *Ecological Economics* 29(2):293–301.

Burt, James E. and Gerald M. Barber. 1996. *Elementary Statistics for Geographers.* New York: Guilford Press.

Carter, Timothy and Laurie Fowler. 2008. "Establishing Green Roof Infrastructure Through Environmental Policy Instruments." *Environmental Management* 42(1):151–64.

Ferraro, Paul J. 2008. "Asymmetric Information and Contract Design for Payments for Environmental Services." *Ecological Economics* 65(4):810–21.

Hassan, Rashid M., R. J. Scholes, Neville Ash, and Millennium Ecosystem Assessment (Program). Condition and Trends Working Group. 2005. *Ecosystems and Human Well-Being : Current State and Trends : Findings of the Condition and Trends Working Group of the Millennium Ecosystem Assessment*. Washington, DC: Island Press.

Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins. 2005. "A Tale of Two Market Failures: Technology and Environmental Policy." *Ecological Economics* 54(2–3):164–74.

Kareiva, Peter, Sean Watts, Robert McDonald, and Tim Boucher. 2007. "Domesticated Nature: Shaping Landscapes and Ecosystems for Human Welfare." *Science* 316(5833):1866–69.

Krzywinski, Martin and Naomi Altman. 2014. "Points of Significance: Visualizing Samples with Box Plots." *Nature Methods* 11(2):119–20.

Mees, Heleen LP et al. 2014. "A Method for the Deliberate and Deliberative Selection of Policy Instrument Mixes for Climate Change Adaptation." *Ecology and Society* 19(2):58.

Niu, Hao, Corrie Clark, Jiti Zhou, and Peter Adriaens. 2010. "Scaling of Economic Benefits from Green Roof Implementation in Washington, DC." *Environmental Science & Technology* 44(11):4302–8.

Osborne, Jason and Elaine Waters. 2002. "Four Assumptions of Multiple Regression That Researchers Should Always Test." *Practical Assessment, Research & Evaluation* 8(2):1–9.

R Core Team. 2012. *R: A Language and Environment of Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved (http://www.R-project.org/).

Rowe, D. Bradley. 2011. “Green Roofs as a Means of Pollution Abatement.” *Environmental Pollution* 159(8):2100–2110.

Tietenberg, Thomas H. 2006. *Environmental Economics and Policy*. 5th ed. Boston: Pearson/Addison Wesley.

Appendix: Technical Analyses

Following the evaluation of the descriptive statistics, the analysis team was concerned that the distribution of the variables and the change of the mean over time would not support a significant finding. We chose to explore these concerns through several OLS models and robust regression models (M-estimator). Due to the number of observations and the distributions we focused our models on single family residences where the assumptions of cost error estimation might be more similar, reducing measurement error effects.

The following tables work though the several models we have developed to explore these data. The first set of regression tables are the OLS results for three models with cost per square foot without membrane as the dependent variable: a univariate model with the program month; a multivariate model with program month and size of the installation in square feet, and a multivariate model adding a dummy variable for installation type to the previous model. The data was examined and identified skewedness in the dependent variable. Using the Box-Cox technique a power transformation was applied. Initial plots identified outliers that were reasonable to remove.

Based on these analyses we are not confident that the program duration and the incentives provided during it resulted in a change in cost per square foot for installations. As discussed in the conclusion there are a number of ways to understand this.

Following are the resultant tables for the three models using this single family residence data from the ecoroof master dataset:

MODEL 1: Univariate CPSF and Program Month

	Dependent variable: cpsf_wo_memb0.2
progmo	-0.0004
	(0.002)
Constant	1.475***
	(0.061)
Observations	55
R2	0.001
Adjusted R2	-0.017
Residual Std. Error	0.186 (df = 53)
F Statistic	0.073 (df = 1; 53)
Note:	*p<0.1; **p<0.05; ***p<0.01

MODEL 2: CPSF by Size and Program Month

	Dependent variable: cpsf_wo_memb0.2
progmo	0.002
	(0.002)
sizesf	-0.0001**
	(0.0001)
Constant	1.479***
	(0.058)
Observations	55
R2	0.109
Adjusted R2	0.075
Residual Std. Error	0.178 (df = 52)
F Statistic	3.188** (df = 2; 52)
Note:	*p<0.1; **p<0.05; ***p<0.01

MODEL 3: CPSF by Size, Program Month and Install Type

	Dependent variable:
	cpsf_wo_memb0.2
progmo	0.002
	(0.002)
sizesf	-0.0001**
	(0.0001)
newdummy	-0.002
	(0.050)
Constant	1.480***
	(0.062)
Observations	55
R2	0.109
Adjusted R2	0.057
Residual Std. Error	0.179 (df = 51)
F Statistic	2.085 (df = 3; 51)
Note:	*p<0.1; **p<0.05; ***p<0.01

In addition to the OLS models we attempted robust techniques to both examine outliers and leverage points as well as to assess the coefficients and standard errors under these methods. Due to the small dataset we chose M-Estimator as the most appropriate method (Alma 2011). The results are similar to OLS in that coefficients are very close to 0, thus suggesting the null hypothesis cannot be rejected. The power transformation should reduce this number as the transformation would approach a zero slope further to the right, on higher dependent values. Regardless, the low coefficient is still too low.

MODEL 4: Robust (M-Estimator) CPSF by Program Month

```
===============================================
                 Dependent variable:
              ---------------------------
                  cpsf_wo_memb0.2)
-----------------------------------------------
progmo                    -0.001
                          (0.002)

Constant                  1.469***
                          (0.070)
-----------------------------------------------
Observations                58
Residual Std. Error     0.243 (df = 56)
===============================================
Note:           *p<0.1; **p<0.05; ***p<0.01
```

MODEL 5: Robust (M-Estimator) CPSF by Program Month and Size

```
===============================================
                 Dependent variable:
              ---------------------------
                  cpsf_wo_memb0.2
-----------------------------------------------
progmo                     0.002
                          (0.002)

sizesf                   -0.0001***
                         (0.0001)

Constant                  1.466***
                          (0.058)
-----------------------------------------------
Observations                55
Residual Std. Error     0.186 (df = 52)
===============================================
Note:           *p<0.1; **p<0.05; ***p<0.01
```

MODEL 6: Robust (M-Estimator) CPSF by Program Month, Size and Install Type

```
================================================
                   Dependent variable:
                ---------------------------
                     cpsf_wo_memb0.2
-----------------------------------------------
progmo                     0.002
                          (0.002)

sizesf                   -0.0001**
                          (0.0001)

newdummy                   0.006
                          (0.050)

Constant                  1.463***
                          (0.062)

-----------------------------------------------
Observations                55
Residual Std. Error      0.183 (df = 51)
================================================
Note:              *p<0.1; **p<0.05; ***p<0.01
```

The analysis for this project was conducted in the R statistical scripting and analysis language using R Studio for a user interface (R Core Team 2012). The MASS and ggplot2 packages were used to support this analysis as well. The following code was used to generate these analyses from Section 2. Data was subsetted to new dataframes as needed for these analyses. The primary subsetting is listed below with dataframe name in parentheses:

- Observations with SFR Land Use Type (cleandataSFR)
- Large Installations => 10,000 sq ft (largeinstalldata)
- New installations (cleandata.allnewinstall)
- Retro installations (cleandata.allretroinstall)
- Tray type installations (traydata)

Regression Analyses:

Figure 9: Scatterplot of Cost data and Robust Regression Model Plot
rlm((cleandata$cpsf_wo_memb^.2)~cleandata$progmo)

Figure 10: SFR Installation Scatterplot and Robust Regression Plot
rlm((cleandataSFR$cpsf_wo_memb^.2)~cleandataSFR$progmo)

Figure 11: Cost Scatterplot for New Installs for All Land Uses and Robust Regression Plot
rlm(sfr.notray$laborsf^.18 ~ sfr.notray$progmo)

Figure 12: Cost Scatterplot for Retro Installations for All Land Use Types and Robust Regression Plot
rlm((cleandata.allretroinstall$cpsf_wo_memb^.2)~cleandata.allretroinstall$progmo)

Figure 13: Cost Scatterplot for Single Family Residence Installations not Using Tray Type Technology and Regression Plot
rlm(sfr.notray$cpsf_wo_memb^.18 ~ sfr.notray$progmo)

Figure 14: Cost Scatterplot for Large Installations (>10,000 sq ft) and Robust Regression Plot
rlm((largeinstalldata$cpsf_wo_memb^.5)~largeinstalldata$progmo)

Figure 15: SFR Labor Costs per Square Foot Scatterplot and Robust Regression Plot (Non-Tray Type)
rlm((cleandataSFR$laborsf^.2)~cleandataSFR$progmo)