# No Evidence for Energy Efficiency Market Saturation Leading to Higher Costs

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**Abstract**

A 2015 working paper by Richard Stevie asserts that no other study has illuminated the relationship between energy efficiency program costs and market penetration, and purports to itself demonstrate that market saturation causes higher efficiency program costs. We find that Stevie's study provides no usable evidence of a market saturation-program cost relationship and *ipso facto* no such relationship has as yet been demonstrated. The results of Stevie's working paper have impacted resource decisions proposed by electric utilities in at least three states (Indiana, North Carolina, and South Carolina). Stevie's analysis erroneously suggests that there exists evidence of efficiency market saturation significantly driving up programs costs. We find, in contrast, that the evidence presented is insufficient and inaccurate. We are aware of no reliable evidence for higher energy efficiency market penetration leading to higher efficiency costs. Inclusion of a baseless inflation of efficiency program costs in the name of market saturation results in higher energy efficiency costs than would otherwise be expected. Implementing Stevie's suggestions would lead utilities to select less energy efficiency than is optimal.

## 1. Background

Projected energy efficiency cost and savings levels are an important input to electric utilities' modeling of future resource additions and retirements. These projections are used in Integrated Resource Plans and other, similar filings submitted to state utility commissions for their approval. Some contend that the future cost of saved energy is influenced both by historical costs and by patterns in the relationship between the cost of saved energy and other factors, including: The amount of new efficiency savings in a given year, and the cumulative amount of savings that has built up over time (after adjusting for efficiency measures that have "sunset" at the end of their measure life).

In many jurisdictions around the United States, projected energy efficiency costs are used to determine utilities' efficient or otherwise optimal investment in energy efficiency and other resources in the next few years. An expectation of high costs, rising costs, or both can reduce investments in energy efficiency. Studies that overestimate the future cost of efficiency programs—and thereby result in lower levels of planned efficiency—deprive electric customers of low (and often least) cost efficiency measures while simultaneously pushing states towards an electric resource mix with higher costs and higher emissions of greenhouse gases and other pollutants.

Richard Stevie's 2015 analysis of these relationships has been used by utilities in Indiana, North Carolina, and South Carolina to justify a future cost of saved energy that rises with higher energy efficiency market penetration (that is, the higher the cumulative efficiency savings, the higher the efficiency cost).[1] The rationale for this purported relationship—as discussed in Stevie's paper—is market saturation and diminishing returns:

> *[A]s market penetration increases, energy efficiency implementation costs are expected to rise at higher levels of penetration of the market. The degree of impacts on program costs, from these factors, is a question to be empirically analyzed. (p.9)*

Stevie provides a review of some of the existing literature exploring the relationship between efficiency costs and savings levels and finds it wanting:

> *In summary, this review of past studies on the costs of energy efficiency reveals that a significant void exists in our understanding of how the implementation costs of energy efficiency are affected by the level of market penetration. (p.7)*

Having noted this gap, Stevie performs regression analysis using data voluntarily reported by utilities to the U.S. Energy Information Administration (EIA) and concludes somewhat heroically that:

> *From the review of other studies, it is apparent that little to no evidence exists on the relationship between program costs, program size, and market penetration. But now, the research conducted in this study provides an initial insight into this relationship…It should be obvious that further research in this area is warranted. As mentioned, this study is the first to investigate how costs can rise with increases in program size and market penetration. The findings point to the existence of cost efficiencies with respect to program size, but rising costs as market penetration increases. (p.21)*

Stevie's regression analysis—and the conclusions drawn from it that have been used to inflate the cost of saved energy—are the subject of this review. We found that Stevie's analysis:

- Is based on highly questionable data sources (Section 2),
- Relies on regression analysis that is sensitive to the inclusion or exclusion of problematic data entries, and seems to depend on unusual choices in variable and model specification (Section 3), and
- Is applied incorrectly and incompletely in the utility filings for which we were able to review workpapers (Section 4).

The result of these errors and omissions is higher energy efficiency costs than would otherwise be expected in utility planning and, consequently, less efficiency chosen in optimal resource planning.

[1] Stevie, Richard (2015) "Energy Efficiency Program Costs, Program Size, and Market Penetration." Draft Working Paper. Integral Analytics. http://www.integralanalytics.com/files/documents/Projecting%20Energy%20Efficiency%20Program%20Costs%202015.pdf.

## 2. Data Sources

In regression analysis, variations in the value of one data point or "variable" (here, program costs) are explained through patterns in the values of other related variables. Stevie bases his analysis on the presumption that energy efficiency program costs can be explained using the values of several other variables, which he aggregates to the state level.

The dependent or explained variable in Stevie's regressions is:

- Program Cost: "the level of direct program spending (dollars) on energy efficiency programs only. Indirect costs are not included."(p.10); "For the purposes of this study, only the direct program costs including incentive payments to participants will be considered in the analysis."(p.15); Stevie reports that his data for direct spending on energy efficiency program are taken from EIA Form 861 (p.13).

Stevie's explanatory variables are:

- Program Size: "the current year achievement of energy impacts as a percent of current year retail kWh sales"(Stevie (2015), p.11); Stevie reports that his data for incremental energy efficiency (or current year annualized impacts) are taken from EIA Form 861 (p.13).
- Market Penetration: "the cumulative achievement of energy efficiency sales as a percent of retail kWh sales"(p.11); Stevie reports that his data for cumulative energy efficiency (called "annual" in the EIA data set) are taken from EIA Form 861 (p.13).
- Electric Rate: "the cost of power ($/kWh) to customers in an area"(p.11); Stevie reports that his data source for total revenue and total retail sales are taken from EIA Form 861.
- "Unemployment Rate"(p.12): Stevie gives no data source for his unemployment rate measure, instead noting that, "Data on national inflation and unemployment may be found from numerous sources"(p.14), and mentions but does not directly cite a secondary data source for these measures, "See the website Freelunch.com sponsored by Moody's Analytics for general macroeconomic data including inflation and unemployment."(p.14, fn.21).

While Stevie relies exclusively on EIA Form 861 for his data on energy efficiency spending, Stevie himself notes that EIA Form 861 data have limitations that impede their ability to correctly characterize the relationship between energy efficiency savings and the cost of saved energy. While Stevie's list of concerns is not comprehensive, it provides an overview of this data set's flaws, including: (1) a lack of data on the life of efficiency measures; (2) various known reporting errors (incorrect or mislabeled responses, inconsistent treatment of free riders, inconsistent classification of costs); and (3) changes in reporting requirements and instructions over time (p.14).

With respect to using these data to understand the effect of efficiency market penetration on costs, the most important issue is EIA Form 861's lack of information on the life of efficiency measures. Without this data point there is no way to measure the cost of saved energy, because this year's efficiency savings are not the only savings that will arise from this year's efficiency costs. The best and most commonly used measure for any energy resource cost is a "levelized" cost, which divides a resource's total fixed and variable costs by the total amount of energy that it will provide (or save) over its lifetime. EIA Form 861's cost and savings data are simply not sufficient to provide a measure of the levelized cost of saved energy.

Stevie acknowledges these data limitations. His stated solution is to limit his data set to the most recent three years of data available at the time of his study—a remedy that in no way addresses the problem of the mismatch between the cost and savings data available in EIA Form 861:

> *For this reason, the analysis conducted here looks at total annual spending relative to the first year impacts. Trying to compute a levelized cost requires knowledge that is just not available. While one might intuit an expected measure life for a portfolio, it is only a guess and could lead to misleading conclusions. In reviewing the EIA data, it is apparent that the reporting is not consistent. For example, kWh could be reported instead of MWh or dollars instead of thousands of dollars as specified in the instructions to the form. For this reason, the study will focus on the last three years of data for the years 2010 through 2012. Use of the most recent data should provide the best quality of data from the data base. (p.14)*

In addition, while EIA's Form 861 data are voluntarily reported by utilities—and are, therefore, available disaggregated by utility—Stevie makes the choice to aggregate these data:

> *Finally, to facilitate the research, costs and impact data is [sic] aggregated to a state level. This provides a useful data set for the 50 states plus the District of Columbia. (p.15)*

Stevie's choices to limit his data to three years and aggregate the data to the state level results in a very small dataset for his regression. While Stevie does not follow the convention of reporting the size of his data sets in his working paper, it would appear that his "Model 1" has 153 data points and his "Model 2"—which he further limits to just data for the year 2012—has 49 data points.[2] If this analysis were performed at the utility level, using these same data, its data points would number in the thousands. The small data set used by Stevie limits the reliability of his regression findings and call into question the confidence that can be placed in patterns observed in Stevie's study.

Our replication of Stevie's analysis uses his data and methodology to the greatest extent possible given his omission of some key details regarding variable specification and data sources:

- <u>Program Cost</u>: (dollars) EIA Form 861[3] 2010-2012 aggregated to 50 states plus the District of Columbia:

[2] Stevie notes in Fn.23 that, "Data for Delaware and Louisiana were deleted since the EIA data indicates [sic] essentially zero cumulative impacts for the year 2012."(p.16)

[3] EIA Form 861 data consists of multiple spreadsheets. For the years 2010 and 2011, "program cost", "program size", and "market penetration" data are taken from Form 3 and from the "dsm_2012" spreadsheet for 2012. While "electric rate" data are calculated from Form 2 for the years 2010 and 2011 and from the "retail_sales_2012" spreadsheet for 2012.

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- Program Size: (%) EIA Form 861 2010-2012 aggregated to 50 states plus the District of Columbia divided by EIA Form 861 2010-2012 aggregated to 50 states plus the District of Columbia states:

  *ENERGYEFFINCTOT / Total Sales*

- Market Penetration: (%) EIA Form 861 2010-2012 aggregated to 50 states plus the District of Columbia states divided by EIA Form 861 2010-2012 aggregated to 50 states plus the District of Columbia states:

  *ENERGYEFFANNTOT / Total Sales*

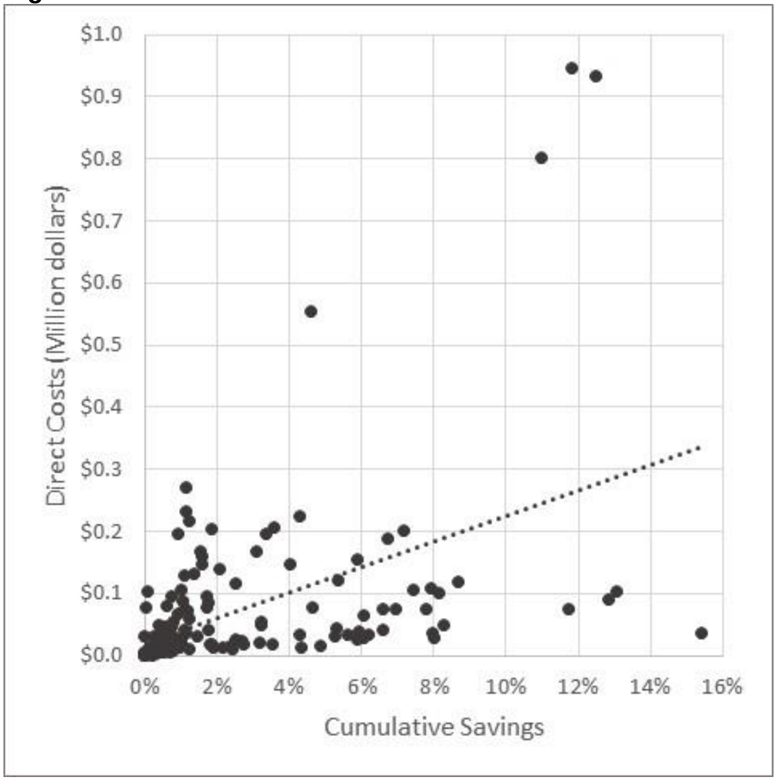
- Electric Rate: ($/kWh) EIA Form 861 aggregated to 50 states plus the District of Columbia states divided by EIA Form 861 2010-2012 aggregated to 50 states plus the District of Columbia states:

  Total Revenue / Total Sales

- Unemployment Rate: (%) U.S. Bureau of Labor Statistics (LNS14000000) Unemployment Rate, U.S. annual average

Using the data gathered from public sources to replicate Stevie's analysis, Figure 1 depicts the relationship between energy efficiency program costs and market penetration that Stevie recommends be used in forecasting future utility efficiency costs, claiming that: "It provides guidance on the expectation that as the market penetration of energy efficiency increases, the unit cost increases."(p.21)

**Figure 1. EIA Form 861 Direct Costs versus Cumulative Savings, 2010-2012**




***Note:*** *The line shown is a linear trendline, describing the relationship between the two variables: Direct costs and cumulative savings.*

Figure 1 provides a snapshot of several critical weaknesses in both Stevie's analysis and the data on which it was based:

- **The positive correlation between direct costs and market penetration (cumulative savings) is weak and appears to be driven by a few outliers.** Figure 1 above shows a dense cloud of data points with a few outliers, and not an obvious trend in which higher costs are associated with greater levels of market saturation. (Note that the data points do not congregate around the trendline but rather are found well above and below these lines.)

- **Larger programs have larger costs, and smaller programs have smaller costs.** Stevie's analysis offers little insight into the relationship between market penetration and the cost of saved energy. Stevie's puzzling choice of program costs in dollars as the dependent variable and percentage savings as the explanatory variable results in a regression analysis that points only to the obvious relationship between program size and program costs while failing to ask pertinent questions about how any one utility's repeated investments in efficiency over many years may impact its program costs.

- **A few years of state-level data cannot reveal an actionable expectation regarding efficiency program costs.** Stevie purports to identify a pattern among states over three years that can be applied to long-term projections of efficiency costs for individual utilities. Not only does Stevie's methodology suffer from well-known reliability issues arising from very small datasets, it also fails to track individual utilities over time, because his data are aggregated to the state level, and three years of data do not provide a pattern that can be applied to decades of projections. One year of data (as used in Stevie's Model 2) has no information whatsoever about the pattern of changes over time.

### 3. Regression Analysis

We attempted to replicate Stevie's regression analysis results using the data described in the previous section and the two regression equations reported in his working paper:

Model 1: $ProgCost\$_{it} = Intercept + \beta1 * ProgSize_{it} + \beta2 * MarketPen_{it} + \beta3 * ElecRate_{it} + \beta4 * Unemploy_{it} + \varepsilon_{it}$

Model 2: $ProgCost\$_{i} = Intercept + \beta1 * ProgSize_{i} + \beta2 * MarketPen_{i} + \beta3 * ElecRate_{i} + \varepsilon_{i}$

This exercise was successful for Stevie's Model 2 (2012-only) and achieved results that were similar but not identical to Stevie's Model 1 (2010-2012), as shown in Table 1. ("Original" is Stevie's reported regression results. "Replication" is our attempt to match his results using his data; "Replic_State" and "Replic_Year" are two different versions of our replication attempts, differentiated by the type of dummy variable.[4] "Public Data" is the corrected version of the EIA Form 861 data cited by Stevie. "Clean Data" is a subset of these Public Data, as discussed below.)

[4] Stevie appears to have assigned "dummy variables" to differentiate results by state. We attempted regression replications that differentiate results by state and, separately, by data year.

**Table 1. Comparison of regression results**

| Model 1 | | | | | | |
|---|---|---|---|---|---|---|
| **Results** | | **Original** | **Replic_State** | **Replic_Year** | **Public Data** | **Clean Data** |
| **Number of Observations** | | 153 | 153 | 153 | 153 | 105 |
| **Adjusted $R^2$** | | 0.76 | 0.76 | 0.73 | 0.19 | 0.57 |
| **Coeff.** | **(Constant)** | -17.82 | -18.62 | 14.72*** | 1.55 | 12.92*** |
| | **LOG (UR)** | 2.44 | 2.15 | - | 2.92 | 1.06 |
| | **LOG (EE/kWh)** | 0.61*** | 0.61*** | 0.56*** | -0.74 | 0.43* |
| | **LOG (CUMEE/kWh)** | 0.28** | 0.28** | 0.28*** | 0.72 | 0.39 |
| | **LOG (REV*CPI_I/kWh)** | -11.98 | -11.99 | -0.08 | -0.21 | 0.24 |
| **Model 2** | | | | | | |
| **Results** | | **Original** | **Replication** | | **Public Data** | **Clean Data** |
| **Number of Observations** | | 49 | 49 | | 51 | 46 |
| **Adjusted $R^2$** | | 0.54 | 0.54 | | 0.08 | 0.57 |
| **Coeff.** | **(Constant)** | 12.02*** | 12.02*** | | 3.22 | 12.1*** |
| | **LOG (EE/kWh)** | 0.00 | 0.00 | | -0.76* | 0.36 |
| | **LOG (CUMEE/kWh)** | 0.90*** | 0.90*** | | 0.52 | 0.61* |
| | **LOG (REV/kWh)** | -0.84 | -0.84 | | -1.93 | -1.16 |
| ***P ≤ 0.001 ; **P ≤ 0.01 ; *P ≤ 0.05 | | | | | | |

The coefficients ("coeff.") in Table 1 are Stevie's main regression result and can be interpreted as for every 1 percent change in Variable X expect a β percent change in Stevie dependent variable, energy efficiency program costs. For example, using the "Original" results from Stevie's Model 1 would suggest that every 1 percent change in cumulative efficiency savings was associated with a 0.28 percent change in program costs.

After careful review, we believe that three key factors interfere with replication and interpretation of Stevie's results: unexplained changes by Stevie to EIA Form 861 data; data quality issues in EIA 861 data not properly addressed by Stevie; and Stevie's specification of the dependent variable.

*3-a. Unexplained changes by Stevie to EIA Form 861 data*

Our review of Stevie's regression analysis workpapers revealed widespread, large-scale inconsistencies between EIA Form 861 source data and the actual data on which Stevie based his regressions.[5] These inconsistencies take two forms:

1. Stevie's working paper mentions only one adjustment made to EIA data (the removal of two states in the 2012-only regression). We can offer no possible explanation for a large share of Stevie's data entries being different from those calculated directly from EIA data as state weighted averages (see Table 2). Still more puzzling is the finding that some of Stevie's data are exactly identical to EIA data—meaning that whatever factor is causing this inconsistency is only present in some of Stevie's data extraction. It should also be

[5] We were provided access to Stevie's workpapers, including his underlying data and regression results, on April 12, 2016, through the IRP stakeholder process.

noted that these data errors were not small in scale: the average error for program costs was 32 percent; current year savings, 34 percent; cumulative savings, 31 percent; and total sales, 31 percent.

**Table 2. Share of erroneous data entries**

| | % non-match | | |
|---|---|---|---|
| | **2010** | **2011** | **2012** |
| **Program Costs ($)** | 65% | 27% | 4% |
| **Current Year Savings (kWh)** | 67% | 27% | 8% |
| **Cumulative Savings (kWh)** | 65% | 24% | 6% |
| **Total Revenue ($)** | 0% | 0% | 0% |
| **Total Sales (kWh)** | 31% | 31% | 31% |

2. Stevie has, without explanation, replaced zero current-year and cumulative savings, and zero program costs with the value 0.00001. This type of change makes it possible to use these data in regression analysis and can be a necessary tactic in logarithmic regressions (since the logarithm of zero is undefined). In this instance, however, data entries with zero savings do not offer information to an analysis of energy efficiency programs and should be removed, as Stevie himself does with such entries in his 2012-only analysis.

Given these serious issues, we reran Stevie's regressions using the correct public data ("Public Data" in Table 1 above) and found that this correction resulted in changes to both coefficient values and the level of their significance. As shown in Table 1, using corrected data, only one coefficient in one model was significant at the 5 percent level and no coefficients were significant at the 1 percent level. These low levels of statistical significance indicate that the regression findings used by Stevie in various utility dockets represented relationships between the data that cannot be distinguished from happenstance.

*3-b. Data quality issues in EIA 861 data not properly addressed by Stevie*

Stevie's working paper reports only two data points removed from Model 2 ("since the EIA data indicates [sic] essentially zero cumulative impacts for the year 2012"(p.16)). From this we can infer that all 153 data entries are included in Stevie's 2010-2012 regression and 49 in his 2012-only regression.[6]

Our review of the 2010-2012 data showed that 25 entries include zero values for current-year savings, incremental savings, or both. State-years without energy efficiency savings cannot offer useful information to the analysis and should be removed. In addition, our review found another 23 data entries with obvious data quality issues: some with $1 entries in program costs or other obvious errors, and some states where there were unambiguous inconsistencies between reported incremental and cumulative savings (for example, 2011-2012 incremental

[6] Stevie's workpapers show that out of 153 possible data entries in this analysis, he used 153 in his Model 1 regression and 49 in his 2012-only Model 2 regression.

savings that, when added to 2010 cumulative savings, resulted in a value far greater than the reported 2012 cumulative savings[7]).

These apparently erroneous data comprised the majority of data outliers shown in Figure 1 (above); the remaining high program cost outliers are three-years of program data for California. We reran our "Public Data" regression with this smaller, corrected data set (called "Clean Data") to examine its sensitivity to changes in the underlying data. In the "Clean Data" regression, coefficient values were dramatically different from those in the "Public Data" regression (see Table 1 above) but the statistical significance of the regression remained very low.

*3-c. Stevie's specification of the dependent variable*

Program costs in dollars are impacted by the scale of savings, not because of market saturation but—more fundamentally—as a result of the size of the state or utility itself. Program costs on a per kWh basis, however, are far more likely to show meaningful impacts of current year program size and cumulative savings. Using the improved (but very small) dataset described above ("Clean Data"), we examined the sensitivity of Stevie's results to his unusual choice of dependent variable by comparing (1) the correlation of program costs in dollars to market penetration to (2) the correlation of program costs per kWh to market penetration (see Table 3, which presents the degree of correlation between variables in percentages).

**Table 3. Correlation matrix using EIA Form 861 data with obvious errors removed**

| | *ProgCost$* | *ProgCost$/kWh* | *ProgramSize* | *MarketPen* | *ElectricRate* | *UnemploymentRate* |
|---|---|---|---|---|---|---|
| **ProgCost$** | 100% | | | | | |
| **ProgCost$/kWh** | 60% | 100% | | | | |
| **ProgramSize** | 91% | 51% | 100% | | | |
| **MarketPen** | 94% | 57% | 90% | 100% | | |
| **ElectricRate** | 32% | 18% | 18% | 31% | 100% | |
| **UnemploymentRate** | 27% | 22% | 28% | 26% | 24% | 100% |

Both program size and market penetration are less correlated with program costs in $ per kWh than they are with program costs in dollars. Any conclusions that might be drawn from that finding should, however, be considered in light of the following caveats: (1) these regression models have too small of a sample size and therefore may not be statistically significant (i.e., discernable from happenstance), and (2) Stevie's choice to limit his regressions to model just a few years of data makes it impossible to discern data patterns that can have any application to long-term changes in efficiency costs.

Overall, our review of Stevie's regression analysis calls into question the quality of his data, the significance of his results, and whether or not any results produced using this methodology can be said to add meaningful insight to the projection of future efficiency costs.

## 4. Application of Stevie's Analysis in Utility Planning

[7] We recognize that some utilities will have correctly adjusted for sunsetting measures in their cumulative savings, and for this reason we removed only gross differences between these reported and calculated values.

We also had the opportunity to review Stevie's workpapers in which the results of his regression analysis were applied to an electric utility's 20-year projection of energy efficiency program costs. The coefficients resulting from a logarithmic regression can be interpreted as elasticities, that is, a 1 percentage point change in the value of an explanatory variable can be said to be associated with a β percentage point change in the value of the dependent variable, where β is the coefficient value for the explanatory variable.

In the utility's projection of future efficiency program costs, the coefficients for Stevie's market penetration variable are applied to program costs for a recent historical year such that each incremental 1.0 percent increase in savings has the effect of adding the cost equivalent of 0.6 percent savings (calculated as the average of Stevie's Model 1 and Model 2 coefficients for market penetration: 0.278 and 0.897, respectively). Over the course of 20 years, the utility interprets this as resulting in a more than doubling of the program costs associated with a 1 percent incremental annual savings level: from 3 cents per kilowatt-hour in 2016 to 8 cents in 2036.

In summary, this utility application of regression findings to efficiency cost projections suffers from several errors in substance and logic, any one of which would, by itself, render the study's use in resource decisions inappropriate:

- **Errors, omissions, and misspecifications of data:** Stevie's data are taken—by his own admission—from a deeply flawed dataset, use an illogical combination of dependent and independent variables, are too few in number to provide meaningful results, and do not include the correct variables (or encompass sufficient years) to provide insight into changes to state's or utility's costs over time. In addition, our review of the data used in his regressions found serious unexplained errors and inconsistencies.

- **Weak significance and a lack of robustness in regression findings:** Stevie's overall model significance and significance for his key variable, market penetration, appear to be sensitive to removal of problematic data entries and corrections to his misspecified functional form.

- **Purported impact of electric rates on program costs is excluded from the application of regression findings:** Stevie's regression analysis also finds a significant impact of electric rates on program costs, but this effect is excluded from the utility's projection of future efficiency costs. Our calculations suggest that including this effect on a forecasted growth of electric rates ranging from 0.7 percent per year[8] to 3.2 percent per year[9] results in a <u>decrease</u> in the incremental change in program costs of 4 to 20 percentage points in each year averaged across Stevie's two models. Put into context, just this countervailing effect would reduce Stevie's 0.60 percent increase in annual incremental efficiency costs for each 1 percent increase in market saturation down to 0.40 to 0.56 percent.

[8] Vectren 2016 IRP Attachment 4.1

[9] 2016 Residential Bill Survey. Available at: http://www.in.gov/iurc/files/2016_Residential_Bill_Survey_Presentation.pdf

- **Averaging a coefficient from a full dataset with the same coefficient from a truncated version of the data set:** Stevie's explanation of the inclusion of Model 2 (which excludes all data entries from 2010 and 2011) is largely rhetorical: He—without substantiation—calls this method "traditional" and notes that it is "extremely useful" because it "provides a view into the long-run since the data contains multiple points along the continuum of experience"(p.16). This approach is neither traditional nor particularly useful, and a regression of data from various states (each unique in program size, market penetration, and electric prices) in the same year in no way provides a view into the long-run and cannot be said to contain multiple points along a continuum of experience. Indeed, the extent to which those multiple data points from various states do predict future performance would be mere coincidence. Averaging the regression result of the 2012 truncation with the full dataset does have one clearly observable result: It increases the assumed addition to program costs from 0.28 percent to 0.60 percent from each 1 percent increase to market penetration.

## 5. Findings and Conclusion

Stevie asserts repeatedly in his working paper that no other study has illuminated the relationship between energy efficiency program costs and market penetration. If this is the case, then that status quo remains unchanged: Stevie's study provides no usable evidence of such a relationship and *ipso facto* no such relationship has, as yet, been demonstrated.

This area of research is by no means purely scholarly or theoretical. To our knowledge the results of Stevie's working paper have impacted the resource decisions proposed by electric utilities in no fewer than three states. Stevie's analysis suggests, erroneously, that there exists evidence of energy efficiency market saturation driving up programs costs that is sufficient to justify a more than doubling of the direct cost per kWh over 20 years.

We find, in contrast, that the evidence presented in his working paper is insufficient and inaccurate. We are aware of no reliable evidence for higher energy efficiency market penetration leading to higher efficiency costs. Inclusion of a baseless inflation of efficiency program costs in the name of market saturation results in higher energy efficiency costs than would otherwise be expected in utility planning and, consequently less efficiency chosen in optimal resource planning.