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Disclaimer

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Estimating energy efficiency technology adoption curve elasticity with respect to government and utility deployment program indicators

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ABSTRACT

This study describes and demonstrates a method for estimating the accelerated adoption of energy efficient products that may be influenced by government and utility deployment programs. The method begins with the Bass adoption model and calibrates the dependence of model parameters on government and utility program indicators using an econometric analysis. Specifically, panel data exist for the market shares of efficient products in different U.S. states at different times. The different states have different intensities of government and utility deployment program activity, different energy prices, different incomes, *etc*. The method uses standard econometric techniques to estimate the correlation of the Bass adoption curve parameters with government and utility deployment program activity. The method is demonstrated with preliminary results for Energy Star clothes washers, dishwashers and refrigerators. The method reveals statistically significant correlations for clothes washers and dishwashers between rate-payer funded utility electric energy efficiency program spending and adoption. For refrigerators, the method indicates that income and energy prices may be more influential than utility spending.

1.   Introduction

Since the 1970's, governments and utilities have been implementing a wide range of energy efficiency and conservation programs to save consumers money and to help mitigate energy-related environmental impacts [1]. To accelerate climate change mitigation, governments are seeking improved means for accelerating the adoption of energy efficient technologies [2]. Inducing technological innovation in clean energy technology requires an integrated policy and program portfolio approach that combines research with policies that can accelerate market adoption of efficient products [3]. Induced innovation is accelerated by complementary environmental policies that accelerate the market adoption of energy efficient technologies, because accelerated adoption creates the market incentives that encourage private sector actors to invest more in research and development for environmentally beneficial technologies [4].

Consistent with the findings of policy studies on induced innovation, the U.S. Department of Energy (DOE) has invested in the development of a public investment technology prioritization tool for building sector energy efficiency measures [5]. This tool currently accounts for 770 energy efficiency technologies and measures, derived from literature reviews and expert input, and provides an accounting framework to estimate the relative impact potential of public investments in 411 of these 770 technologies and measures. One of the metrics of potential impact used to evaluate technologies in the public investment portfolio is an "adoption-based" energy savings that estimates the difference in energy consumption between a baseline and intervention scenario which have different rates of energy efficient technology adoption. Key drivers for the energy use estimates in the model scenario projections are the rates of adoption for different energy efficiency technologies as a function of public investments and policies. To characterize the technology adoption dynamics, the prioritization tool utilizes the well known model developed by Bass [6].

This study develops improved analysis techniques for empirically modeling the correlation between efficiency program indicators and efficient product adoption rates. The technique rewrites the adoption rate data in terms of a "hazard rate" function that allows estimation of adoption curve parameters using standard econometric techniques. The reformulation of the adoption parameter estimation problem as an econometric correlation analysis allows standard tools of statistical inference to be used to analyze patterns in available market data. Using this method, accounting for different program and policy activities in the 50 U.S. states, statistically significant correlations are found between state energy efficiency program activity levels and adoption rates for certain categories of Energy Star appliances.

2. Technology adoption modeling

In the Bass product diffusion and adoption model, if $F(t)$ represents the fraction of the market that has adopted a particular product by a particular point in time, then the rate at which this fraction increases over time is given by the following equation:

$$\frac{dF(t)}{dt} = (p + q \cdot F)(1 - F) \tag{1}$$

This equation has a particularly intuitive interpretation. First it assumes that the market consists of individuals who will eventually want a product once the purchasers know about it, and once it is available under conditions of sufficient accessibility or affordability. With this assumption, the rate at which the adoption increases is proportional to the product of two terms. One term is the fraction of purchasers who have not yet adopted the product (1-F), the population of people who can make a decision to adopt a new product. Then for those who have not yet adopted the product, there are two parameterized rate terms. One term is independent of the number of people who have adopted the product to date and may depend on such factors as advertising or some generally available type of information about the product being adopted. This is the term specified by the parameter p. The second rate term is proportional to the parameter q, and is sometimes referred to as the "contagion" term. It is proportional to the number of people who have already have "adopted" the product. This term represents the new adopters who are adopting the product because other people are adopting the product.

As illustrated in Fig. 1, at very early stages of market entry, the p term represents the early adopters and the initial adoption rate of a product at market entry. When fit to actual data on product adoption, the p parameter of a Bass adoption curve tends to be small compared to the q parameter. Also shown in Fig. 1, is how the q parameter of the Bass curve can have a dominant influence on the maximum adoption rate of a product, which is given by the expression $q(1+p/q)/4$.

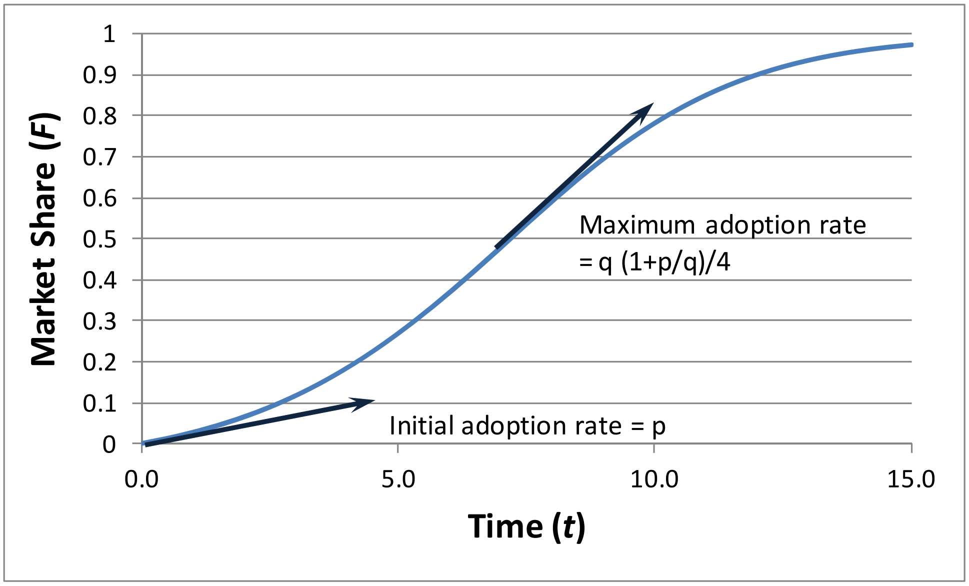

Figure 1: Standard Bass adoption curve with p=0.025 and q=0.4. At market entry the adoption curve begins with an initial adoption rate of p for a new product, and then accelerates to a maximum adoption rate of $q(1+p/q)/4$, the curve converges exponentially to a maximum market share of 1 after it passes the maximum adoption rate point.

Changing economic and market conditions can cause purchasers to change their probability of purchasing any particular product. Therefore in the 45 years since the Bass model was formulated, a fairly large number of extensions and generalizations of the Bass model have been developed to model these effects (see Mead and Islam [7] for a review).

This study examines the simplest extension of equation (1) that allows the parameters of the adoption rate to vary with a set of observable economic variables:

$$\frac{1}{(1-F)}\frac{dF(t)}{dt} = h(t) = p(\vec{X}) + q(\vec{X}) \cdot F \tag{2}$$

where $\vec{X}$ is the vector of observable economic variables that is used to model variations of p and q between markets and over time, and $h(t)$ is known as the "hazard rate" in the diffusion modeling literature.[1] The hazard rate is used because it is linear in p, q, and F and thus can be modeled conveniently using econometric methods.

3. Econometric formulation of Generalized Bass Model

To fit the model to equation (2), a set of panel data[2] is assembled for Energy Star product markets covering all 50 states. The primary data that is available are estimates of Energy Star product sales,

[1] See Mead & Islam 2006

[2] The term "panel data" is the term used in statistics and econometrics for multidimensional data involving measurements over time. In biostatistics the term used is "longitudinal data" where one is sampling over a usually large population, but over a relatively small number of time steps. In the present study, the population is the

market share by quarter, and by state.[3] Energy efficiency policy and program data is also available by state in aggregate form since the 1990s.[4] Additional economic information that is available state-by-state that can be incorporated into the econometric model includes income, energy prices, and new housing construction.

The same econometric model is used for both $p(\overrightarrow{X})$ and $q(\overrightarrow{X})$, which takes the form:

$$\mathrm{p}(\overrightarrow{X_S}) = p_0 + p_I \cdot \ln\left(\frac{I_S}{I_{US}}\right) + p_{PE} \cdot \ln\left(\frac{PE_S}{PE_{US}}\right) + p_{NHC} \cdot \frac{1}{Pop_S} NHC_S + p_{Plcy} \cdot Plcy_S + e_{p,S} \tag{3}$$

$$q(\overrightarrow{X_S}) = q_0 + q_I \cdot \ln\left(\frac{I_S}{I_{US}}\right) + q_{PE} \cdot \ln\left(\frac{PE_S}{PE_{US}}\right) + q_{NHC} \cdot \frac{1}{Pop_S} NHC_S + q_{Plcy} \cdot Plcy_S + e_{q,S} \tag{4}$$

The variables in these equations are *I*, income, *PE*, the price of electricity, *NHC*, new housing construction (in units per year), population, *Pop*, and *Plcy*, a policy or program indicator variable. This study uses only one policy variable, but in principal several different policy indicator variables for different policies could be used. The subscripted *p*s and *q*s are constant coefficients, and $e_{q,S}$ and $e_{p,S}$ are error terms. Each variable varies by state, as indicated by the subscript *S*; the subscript *US* refers to the average value of variable for the United States as a whole. The econometric equations use logarithmic functions for income and energy price, consistent with recent econometric studies of energy savings [8]. Since appliance purchase rates per capita may have a portion that is induced by new housing construction rates, the new housing construction term is proportional to new housing construction per capita.

The primary purpose of this work is to test if it is possible to discern a statistically significant correlation between state efficiency spending and the adoption rate of energy efficient technologies. To make the model simple and robust with regard to energy efficiency program activity, the model uses a simple binary variable (*Plcy*) to represent the policy/program environment in each state.[5] The calculation starts with data on total state funding for rate-payer funded utility electric energy efficiency and rank states based on their per-capita funding level. The policy variable then takes the value +0.5 for states with above average per capita utility energy efficiency spending rates, and -0.5 for states where those spending rates are below average.

In the demonstration of the method, one additional, more or less stylistic change is made to the econometric model. The method calculates the <u>marginal</u> impacts of economics and policy on the adoption parameters, by referencing the value of *F* (which varies by state) to the national average value (F_{US}). The reason that this is done is that as economic and program influences change over time, and the adoption parameters can also change over time. The adoption parameters shown in equation (2) are

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different states of the US, which are sampled over a few years during which the Energy Star efficiency level definition is stable.

[3] http://www.energystar.gov/index.cfm?c=partners.unit_shipment_data_archives. Date accessed: 7 February 2012

[4] http://aceee.org/sector/state-policy/scorecard. Date accessed: 9 November 2012

[5] In appendix A of this report, an alternative, non-binary rank-order policy variable is also presented which results in very similar correlation coefficient estimates.

referenced to a market share of $F=0$ at the time of market entry. But between the time of market entry and the time of measurement, the adoption parameters may have changed. The method therefore references the hazard function equation to the average market share at the time being studied (F_{US}). The equation for the marginal changes in adoption parameters during the period of data collection can thus be written as follows:

$$\begin{aligned} &\frac{1}{(1-F_S)}\frac{dF_S(t)}{dt} = p'(\overrightarrow{X_S}) + q(\overrightarrow{X_S})\cdot(F_S - F_{US}), \\ &p'(\overrightarrow{X_S}) = p(\overrightarrow{X_S}) + q(\overrightarrow{X_S})\cdot F_{US} \end{aligned} \tag{5}$$

3.1. Sources of economic data

The economic data used in the econometric correlations derive from a diversity of sources. The market share data for Energy Star appliances was downloaded from the Energy Star website.[6] Two distinct official sources exist for population data. One source provided by the US Census is estimates of civilian non-institutionalized population by state at monthly resolution.[7] Another source for both state-level annual population and income is the Bureau of Economic Analysis.[8] Electricity price data is provided by the Energy Information Administration. Annual housing construction activity is indicated by U.S. Census total residential building permits data.[9] For the utility energy efficiency program spending indicator, the statistical model uses total utility electricity energy efficiency program spending data as compiled by the American Council for an Energy-Efficiency Economy in its State Energy Efficiency Scorecard reports.[10] In these reports, data are provided for the years 2000 to 2011 inclusive except for 2001, 2002, 2005, and 2008. For those four years, values are imputed for each state using linear interpolation from the nearest years where data is available.

3.2. Calculation of the hazard rate

To estimate the hazard rate described in equation (2) the calculations need to estimate the time derivative of $F(t)$ for each state. This is done by using the quarterly data for F for one year and calculating the slope of $F(t)$ with respect to time using a linear least squares fit of the four data points. The linear least squares slope combined with the average value of F for the four quarters provides the estimate of the hazard rate for the year that is used in the statistical model given by equations (3), (4) and (5).

4. Regression results

Tables 1 through 3 provide the regression results for the model represented by equations (3), (4) and (5). For each appliance (clothes washers, dishwashers and refrigerators) regressions were performed for the maximum number of years between 2000 and 2009 for which the product performance requirements were

[6] http://www.energystar.gov/index.cfm?c=partners.unit_shipment_data_archives. Date accessed: 7 February 2012
[7] http://www.bls.gov/lau/rdscnp16.htm. Date accessed 15 September 2012
[8] http://www.bea.gov/iTable/index_regional.cfm, Date accessed: 2 February, 2013
[9] http://www.census.gov/construction/bps/stateannual.html. Date accessed 21 February, 2013
[10] http://aceee.org/sector/state-policy/scorecard. Date accessed: 9 November 2012

unchanged. For clothes washers this was 2000 to 2004 inclusive, for dishwashers this was 2001 to 2004 inclusive, and for refrigerators it was 2002 to 2004 inclusive.

For clothes washers, there is a clear correlation between whether a state has above-average vs. below-average utility energy efficiency program spending and the observed adoption rate for Energy Star clothes washers from 2000 to 2004. For low spending states, the observed Bass adoption curve q parameter is 0.660-0.5*0.347=0.486, while for high spending states the observed Bass adoption curve q parameter is approximately 70% larger: 0.660+0.5*0.347=0.834. Correlations with the other economic parameters do not appear to be statistically significant, since the correlation calculation finds that p-values for non-zero coefficients to be greater than 10%.

For dishwashers there is also a clear correlation between whether a state has above-average vs. below-average utility energy efficiency program spending and the observed adoption rate for Energy Star dishwashers. Correlations with income or new housing construction rate do not appear to be statistically significant. There does appear to be a significant negative correlation between energy prices in a state and Energy Star dishwasher adoption rate. Exactly why such a correlation might exist is not immediately clear and warrants further investigation. Such investigation might explore the issue of which other economic and demographic variables might correlate with energy prices.

For refrigerators, adoption rates for Energy Star products are substantially slower than for dishwashers and clothes washers. The national average q parameter for refrigerators is less than ½ the magnitude of q for clothes washers. There does appear to be a statistically significant correlation between one of the adoption parameters (p') and income electricity price and the policy variable. States with relatively low per-capita income appear to be more inclined to adopt Energy Star refrigerators during 2002 to 2004 than states with high average per-capita income. States with high energy prices also appear to have a statistically significant positive correlation with adoption of Energy Star refrigerators during 2002 to 2004.

Table 1: Regression Results: Energy Star Clothes Washers

Variables	*p'*	*q*
Income	-0.051 (0.038)	0.053 (0.313)
Energy price	0.026 (0.022)	-0.431 (1.384)
New housing construction rate	-0.007 (0.009)	-0.116 (0.101)
Policy indicator	0.002 (0.012)	0.355*** (0.091)
Constant	0.098*** (0.005)	0.663*** (0.048)
Average national market share (F_{US})	0.193	
Observations	250	
R-squared	0.59	
Number of states	50	
Period of observation	2000 to 2004	

*** represents 1% statistical significance. Significance level is determined by the p-value for the coefficient.
Standard errors are indicated in parentheses

Table 2: Regression Results: Energy Star Dishwashers

Variables	*p'*	*q*
Income	0.064 (0.090)	0.063 (0.336)
Energy price	-0.094* (0.054)	-5.456*** (1.513)
New housing construction rate	0.006 (0.023)	0.033 (0.097)
Policy indicator	0.117*** (0.025)	0.541*** (0.095)
Constant	0.474*** (0.011)	1.444*** (0.052)
Average national market share (F_{US})	0.470	
Observations	200	
R-squared	0.843	
Number of states	50	
Period of observation	2001-2004	

* and *** represent 10% and 1% statistical significance respectively
Standard errors are indicated in parentheses

Table 3: Regression Results: Energy Star Refrigerators

Variables	***p'***	***q***
Income	-0.098** (0.039)	0.097 (0.446)
Energy price	0.010 (0.022)	-0.597 (1.891)
New housing construction rate	0.001 (0.009)	0.032 (0.146)
Policy indicator	0.020* (0.010)	-0.054 (0.129)
Constant	0.085*** (0.005)	0.323*** (0.069)
Average national market share (F_{US})	0.268	
Observations	150	
R-squared	0.24	
Number of states	50	
Period of observation	2002-2004	

*, ** and *** represent 10%, 5% and 1% statistical significance respectively
Standard errors are indicated in parentheses

Fig. 2 illustrates the results of the regression for Energy Star clothes washers in graphical form. The figure shows data for both high energy efficiency program spending and low energy efficiency program spending. The statistical results from table 1 indicate that the two sets of states have different values of the q adoption parameter: q=0.486 for a low spending state, and q=0.834 for a high spending state. The two adoption curves in Fig. 2 are calculated using equation (5), the same values of p', the same value of F_{US}, different values of q and different initial conditions in the year 2000. The initial condition we use for each curve is the median market share for the corresponding subset of states in the year 2000.

In the two adoption curves, we can see the faster growth in the market share in the states with the higher energy efficiency spending. The statistical correlation analysis shows that this difference in market share growth for clothes washers is not correlated to income, energy price, or new housing but is correlated with differences in utility spending between states. The existence of a correlation is not enough evidence to fully attribute the observed differences in Energy Star clothes washer adoption rates to utility program spending, but they do provide a significant observational test of the hypothesis that utility electricity program intensity may have an impact on energy efficiency product adoption rates. Further analysis and data collection would be useful to more clearly understand the relationship between utility spending and Energy Star clothes washer adoption rates.

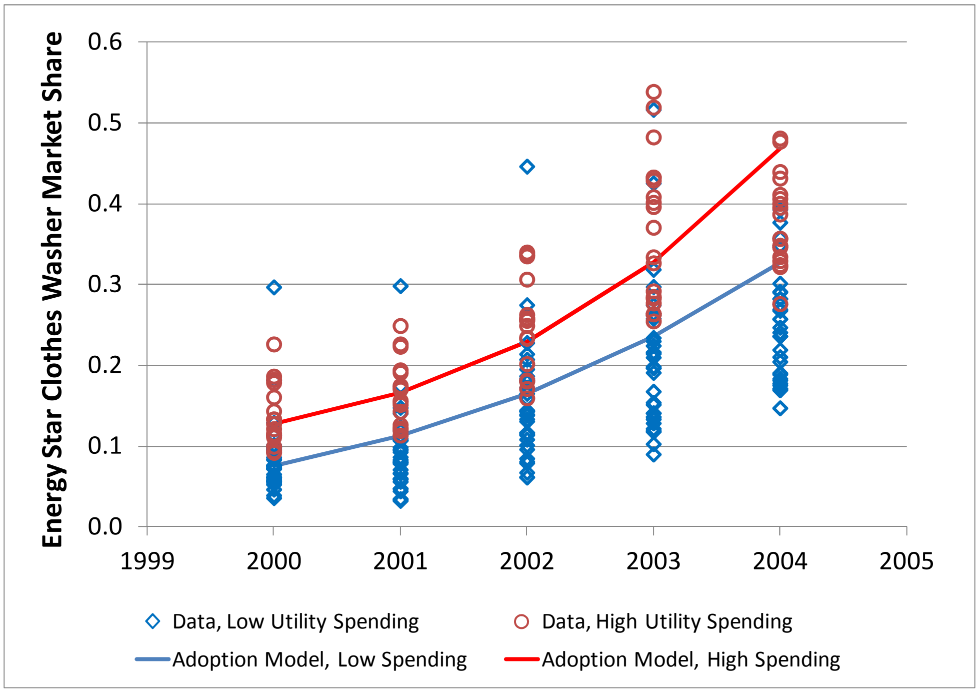

Figure 2: Statistical model results for Energy Star clothes washers in graphical form. Red open circles represent Energy Star market share data for states with high levels of utility energy efficiency program spending. The corresponding red curve is the adoption curve calculated from an adoption equation that uses the statistical results for high spending states shown in table 1. Blue diamonds represent the Energy Star market share data for states with low levels energy efficiency program spending, while the blue curve represents the corresponding adoption model calculated from the statistical estimate of adoption curve parameters in table 1.

5. Summary and conclusion

This study develops a form of a generalized Bass model that enables an econometric correlation analysis of the relationship between energy efficiency policies or programs and the adoption rate of energy efficient products. The analysis found that with this model there are statistically significant correlations between high and low state utility efficiency program spending levels and Energy Star product adoption rates for clothes washers and dishwashers.

For refrigerators, the method indicates that income and energy prices may be more strongly correlated with adoption rates than per-capita energy efficiency spending levels. Specifically, income correlations were significant at a 99% confidence level, energy price and utility spending correlations were significant at a 90% confidence level.

This new method has therefore passed an initial test of being able to detect correlations between energy efficiency programs spending intensity, economic drivers and efficient product adoption rates.

Given these initial results, further research is recommended to explore the precision and power of this technique. Specifically, future research could examine the application of this method to providing forecasts of energy efficiency product adoption as a function of economic and program parameters.

Further investigation of the method with better and more precise data regarding utility programs and incentives is also likely to be useful, and may yield new insights regarding the potential impact of utility programs on energy efficient product adoption.

Appendix A. Selected sensitivity tests of the econometric correlations

This appendix presents the results of two sets of sensitivity calculations. The first set of calculations test the sensitivity of the correlation results to changes in the definition of the policy variable. The second set of calculations test if the correlation calculation results of a random subsample of the data can predict correlation coefficients calculated from the remaining out-of-sample data.

State rank-order policy variable correlation results

For the calculation that tests the sensitivity of the correlation results with respect to policy variable definition, the results using a continuous state rank variable is compared to the results from the binary policy variable calculation used in the main study. The new policy variable is a normalized rank of a state as measured by per-capita utility energy efficiency spending rate where the normalize rank is +1.0 for the state with the highest per-capita spending, is -1.0 for the state with the lowest per-capita spending, is 0.0 for the state with the median per-capita spending, and varies linearly as a function of the state rank order.

The results of the correlation analysis with the continuous rank order policy variable are show in tables A1 through A3. Qualitatively the results are very similar for the two different definitions of the policy variable with similar patterns of statistical significance and standard errors for the various correlation coefficients in the models with the binary policy variable and the rank-order policy variable.

Table A1: Regression Results: Energy Star Clothes Washers

Variables	***p'***	***q***
Income	-0.054 (0.038)	0.109 (0.313)
Energy price	0.022 (0.022)	-0.262 (1.383)
New housing construction rate	-0.006 (0.009)	-0.149 (0.100)
Policy indicator	0.003 (0.009)	0.256*** (0.066)
Constant	0.099*** (0.005)	0.606*** (0.048)
Average national market share (F_{US})	0.193	
Observations	250	
R-squared	0.59	
Number of states	50	
Period of observation	2000 to 2004	

*** represents 1% statistical significance
Standard errors are indicated in parentheses

Table A2: Regression Results: Energy Star Dishwashers

Variables	***p'***	***q***
Income	0.115 (0.095)	0.334 (0.349)
Energy price	-0.062 (0.056)	-4.872*** (1.602)
New housing construction rate	-0.004 (0.024)	-0.003 (0.102)
Policy indicator	0.077*** (0.026)	0.424*** (0.105)
Constant	0.445*** (0.013)	1.285*** (0.056)
Average national market share (F_{US})	0.470	
Observations	200	
R-squared	0.823	
Number of states	50	
Period of observation	2001-2004	

* and *** represent 10% and 1% statistical significance respectively
Standard errors are indicated in parentheses

Table A3: Regression Results: Energy Star Refrigerators

Variables	***p'***	***q***
Income	-0.091** (0.039)	0.006 (0.431)
Energy price	0.010 (0.022)	-0.571 (1.897)
New housing construction rate	-0.001 (0.009)	-0.028 (0.146)
Policy indicator	0.026* (0.013)	-0.001 (0.178)
Constant	0.072*** (0.007)	0.328*** (0.108)
Average national market share (F_{US})	0.268	
Observations	150	
R-squared	0.24	
Number of states	50	
Period of observation	2002-2004	

*, ** and *** represent 10%, 5% and 1% statistical significance respectively
Standard errors are indicated in parentheses

Comparison of randomly selected in-sample and out-of-sample correlations

This section presents the results of test that examines if the correlation analysis of a subsample of data has the ability to predict the statistical properties of the out-of-sample data.

In this test, the states were randomly assigned to be either in-sample or out-of-sample for the clothes washer correlation analysis presented in table 1 above. The random assignment was made by selecting a random number between 0 and 1 for each state, and then assigning the state to in-sample status if the random number was <0.5 and out-of-sample status if the random number was >0.5. Two correlations were then performed for each subset of states, and the out-of-sample correlation coefficients were compared to the in-sample correlation coefficients for the three correlation coefficients that were found to have a high degree of statistical significance in the main study, i.e. the variables p_0', q, and q_{Plcy}.

The results of this analysis are illustrated in figure A1 which shows the out-of-sample correlation coefficients as a function of the in-sample correlation coefficients for the three statistically significant coefficients calculated for the clothes washer case. On a log/log plot like that shown in the figure, the scatter in the data is an indicator of the relative error in the in-sample to out-of-sample forecast. As expected the relative error in the forecast corresponds roughly to the estimated relative standard error of the subsample correlation analysis which averages in this analysis 8%, 12% and 48% for the subsample data for the estimates of p_0', q, and q_{Plcy} respectively.

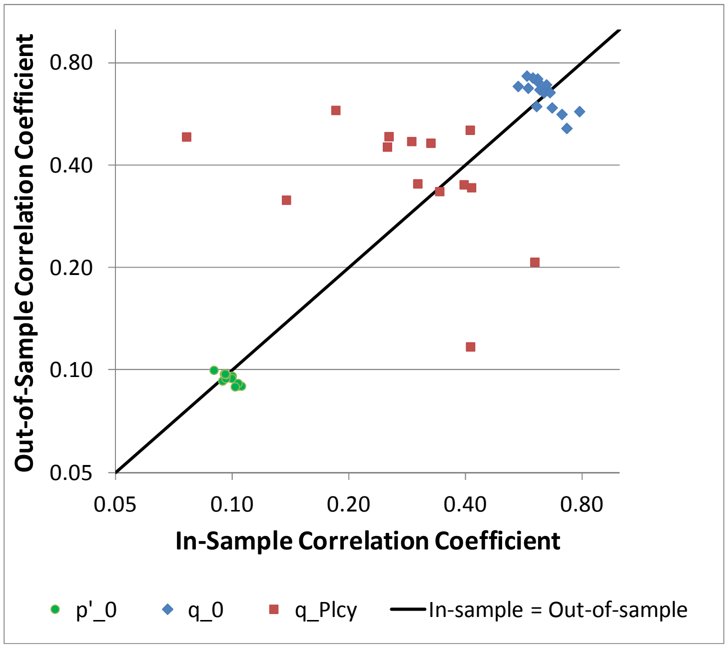

Figure A1: Comparison of in-sample correlation coefficients to out-of-sample correlation coefficients for the clothes washer correlation analysis presented in table 1 in the main study. Results are presented with a logarithmic scale on both axes such that the scatter of the correlation represents the relative error in predicting the out-of-sample correlation coefficients from the in-sample data.

The key implication of the in-sample versus out-of-sample comparison analysis is that the accuracy of prediction is likely to scale with the standard error of the econometric correlation estimates. Standard errors depend quite sensitively on the number of data values in the data set used for the correlation calculation. There are several ways in which market data sets can be expanded, including increasing either the geographic or the temporal resolution of the market data that is collected. Hence, there exists the possibility of creating increasingly precise forecasts of policy-correlated adoption of energy efficient products by continually expanding market data collection capabilities.

REFERENCES

[1] Geller, H., Harrington, P., Rosenfeld, A. H., Tanishima, S., & Unander, F. (2006). Polices for increasing energy efficiency: Thirty years of experience in OECD countries. *Energy Policy*, *34*(5), 556-573.

[2] IEA (2012). World Energy Outlook 2012 - Efficient World Scenario. International Energy Agency. Paris, OECD.

[3] Veugelers, R. (2012). Which policy instruments to induce clean innovating?. *Research Policy*.

[4] Newell, R. G. (2010). The role of markets and policies in delivering innovation for climate change mitigation. *Oxford Review of Economic Policy*, *26*(2), 253-269.

[5] Farese, P., Gelman, R., & Hendron, R. (2012). *A Tool to Prioritize Energy Efficiency Investments*. National Renewable Energy Laboratory.

[6] Bass, F. M. (1969). “A New Product Growth Model for Consumer Durables.” *Management Science*, Vol. 15 pg. 224.

[7] Meade, N., & Islam, T. (2006). Modelling and forecasting the diffusion of innovation–A 25-year review. *International Journal of Forecasting*, *22*(3), 519-545.

[8] Arimura, T. H., Li, S., Newell, R. G., & Palmer, K. (2011). *Cost-effectiveness of electricity energy efficiency programs* (No. w17556). National Bureau of Economic Research.