Optimal Market Transformation Program Planning and Evaluation

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ABSTRACT

Market transformation (MT) programs typically rely on indirect market mechanisms to achieve their goals. Thus, connections among program measures, target market changes and ultimate load/energy effects can be uncertain on many levels. Uncertainty is daunting. It may lead some program designers to rely on intuition and hope for the best, and may lead some evaluators to be content with measuring effort or intermediate outcomes rather than ultimate program goal achievement. These approaches will likely lead to empty outcomes for MT programs.

Unlike conventional MT efforts, *optimal* program design does not require us to hide, ignore, or apologize for uncertainty. Rather, uncertainty can be treated in a manner similar to financial portfolio analysis. Thus, we can select the most cost-effective program measures using a budget allocation that maximizes the expected net return from MT programs *at given levels of risk*.

Risk is, however, modifiable. It arises from our ignorance about connections among prospective program measures and the resulting market and energy use changes. Ignorance can be reduced by research, and we can design our research/pilot-program portfolio to get the most useful (risk-reducing) information possible for our research expenditures.

Finally, we can balance expenditures across program measures and research to obtain optimal combinations of risk and expected net return from MT programs.

Although the *innovations* in the paper concern theoretical methods, the *focus* of the paper is upon showing the techniques and information necessary for applying these methods to design optimal real-world programs.

Introduction

In this paper, we first describe the most important features of the market transformation program environment, and then discuss the implications of this environment for calculating expected program outcomes. After this, we consider the role of risk in program design and analysis. This is followed by a discussion of the control of program outcomes and risk using a procedure to optimally balance expenditures on program implementation and program-related research and pilot programs. Finally, we offer some thoughts about extending this procedure.

The Market Transformation Program Environment

We might think of a market for energy-related goods as a network with nodes representing the major types of market actors. For example, consider the market for air-

[1] Thanks are due to the anonymous referee for valuable presentation suggestions.

conditioners. This market would typically contain sequential supply nodes such as manufacturers, distributors, HVAC contractors, and consumers; with each node, except the last, supplying goods and/or services to the following node in the sequence.

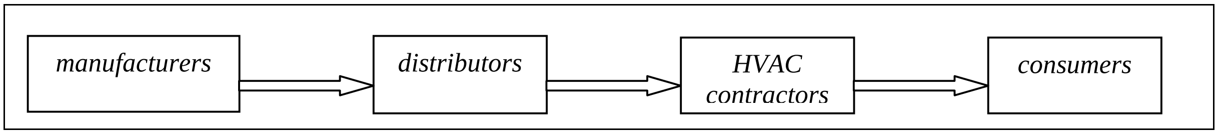

Figure: A Market Structure Example For Air-Conditioning

Of course, changes in the decisions of the market actors at any node can affect, directly or indirectly, the expectations of, and market conditions facing, market actors in other nodes. For example, information about the introduction of a utility program designed to offer consumers rebates for efficient air-conditioners may induce manufacturers to change the mix of air-conditioners they produce. The same information may cause distributors to try to stock more efficient air-conditioners and also cause HVAC contractors to try to attract potential customers by promoting the program. Furthermore, competition and demonstration effects can cause market actors to affect the decisions of their within-node neighbors.

Interestingly, any one of these nodes, or any combination of these nodes, might be used as the focus of a market transformation program. Suppose, for example, that we are designing a program that is intended to reduce residential energy consumption by encouraging the installation of more efficient air conditioners. The following table contains a summary of some of the possible design strategies for each node.

Table: Examples Of Air-Conditioning Energy Conservation Program Design Strategies

Direct Target Node	Examples Of Design Strategy Alternatives
Manufacturers	a. offer them a direct financial incentive to produce a greater proportion of efficient air-conditioners b. include their efficient air-conditioner models on an approved list that is distributed to consumers and HVAC contractors
Distributors	a. offer them a direct financial incentive to stock a greater proportion of efficient air-conditioners b. offer them sales brochures designed to show HVAC contractors the marketing advantages of efficient air-conditioners
HVAC contractors	a. offer them a direct financial incentive to install a greater proportion of efficient air-conditioners; b. include them on an approved list of conservation contractors if they install a target proportion of efficient air-conditioners
Consumers	a. offer them a direct financial incentive to buy more efficient new or replacement air-conditioners; b. implement a consumer education program that makes use of TV/Newspaper/Radio advertising to acquaint consumers with the benefits of using more efficient air-conditioners

Of course, a policy directed at any node can lead to changes in market signals (e.g., prices charged, quantities ordered) and other information flows presented to the related nodes. Thus, if our MT policy is directed toward distributors, we need to understand how the policy will also affect manufacturers and contractors as well as (ultimately) the equipment purchase and usage behavior of consumers. Furthermore, we need to account for any market feedback effects that may interfere with, or reinforce, the ultimate desired policy outcome.[2]

Apart from the *complexity and interdependence* of market responses for such programs, a market transformation program needs to account for the *duration or persistence* of these responses. In fact, some would restrict the definition of market transformation programs to those for which a permanent change in the market results from a limited-time application of program resources. The optimal energy policies that we discuss in this paper can function with such restrictions. Note, however, that we will generally find lower cost solutions for equivalent program outcomes if we keep open the questions of program time-limits and the duration of program effects, and allow them to have their *unrestricted optimal* values.

Calculating Expected Program Outcomes

Since the linkages among market nodes may be somewhat complex, we need to assure ourselves that there is a plausible *overall* connection between MT policy measures and desirable outcomes. To do this, program designers need to describe the links that are expected to connect the policy measures with their outcomes. This description should be detailed enough to build an Excel spreadsheet that would allow planners to simulate expected outcomes from alternative policies.[3] It is important to emphasize that if such a simulation cannot be performed, the MT program will most likely be poorly conceived and extremely risky.

To show how such a simulation might be specified consider a program design example based upon the table in the previous section. If we focus program financial resources to affect the production plans of manufacturers, we might imagine the methods they would use to induce distributors to order more of the efficient air-conditioners. One such method would be a lowering of the price of efficient air-conditioners relative to the price of inefficient air-conditioners. Of course the extent of the price lowering would be subject to negotiations between the manufacturers and distributors. If this relative price is lowered, distributors would have an economic incentive to increase their proportionate purchases of efficient air-conditioners, and this incentive may very well be transferred to the actors at subsequent nodes: HVAC contractors and the ultimate consumers. Thus for each node, we may imagine a set of market-clearing equations[4] in which quantities and relative prices of efficient v. inefficient air-conditioners are determined. Furthermore, market

[2] Consider, for example, a possible perverse short-run price increase that might result from a rebate for efficient air-conditioners given to HVAC contractors. Such a rebate may cause a short-run decline in distributors' efficient air-conditioner inventories and encourage them temporarily to raise the prices of these units.

[3] The idea of using a spreadsheet for this purpose is only illustrative. Better alternatives might be to use a dedicated simulation package, or a high-level programming language such as one of the variants of C or BASIC.

[4] We can think of these nodal market-clearing equations as summarizing a set of negotiations between buyers and sellers in which the prices and quantities of the goods (and other variables such as delivery times) are determined. The right-side variables in these equations would be exogenous variables for the market node, including any program-related incentive directly applied to each relevant node. In the formal economic literature these equations would be referred to as reduced-form equations. For competitive markets (not a requirement here) these would be solutions to the supply and demand relationships at each node.

clearing solutions of prices and quantities at subsequent nodes may cause a renegotiation of prices and quantities at preceding nodes in the market supply sequence (see figure 1).

Interestingly, the same set of nodal market clearing equations must be at work no matter which node or nodes are initially selected as the direct targets of an MT program. The input variables for these equations would, however, depend on the MT program configuration. Of course, the ultimate outcome of the market-clearing prices and quantities will depend upon the timing and allocation of program resources across the market nodes.

These sequential nodal market-clearing equations can be imbedded in an MT program simulation to assess the impact of alternative program resource configurations. Given a particular application of program resources across market nodes we can compute the solution to the chain of market clearing equations, and establish a relationship between the program budget allocated to each market node, and the final *net* program outcome. We will call the net result of the program resource allocation μ. A general equation for the program outcome can be written as follows:

1. $\mu = \mu(BI)$;

where BI is the budget allocation vector ($BI_1, \ldots BI_N$) with each element showing the program implementation budget for each market node (*1* through *N*).

The use of simulations is common in diverse fields such as weather forecasting and airplane design. In each case simulations require estimates of the important parameters affecting the system linkages. For the case of MT program simulations, I suggest we begin with consensus estimates of the required cross-node and within-node market linkage parameters (price effects, etc.) and plausible estimates of their ranges.[5] These ranges reflect any lack of confidence we have in our consensus estimates. This issue is important because greater uncertainty in the consensus estimates of market linkage parameters can be expected to result in greater uncertainty in the achievement of MT program goals. We will address this issue in the next section.

Quantifying Risk In Program Outcomes

Of course, other things equal, we would prefer less uncertainty[6] in the outcome of MT programs, and this preference can be reflected in our choice of programs if we quantify the uncertainty of our program estimates. We can build this type of calculation into our analysis by performing a number of simulation runs in which we calculate the expected benefits from a program using values of the parameters selected at random[7] from their plausible ranges. This type of analysis will result in a distribution of values of program outcomes that reflect the uncertainty in the market linkage parameters, and we can compute measures of dispersion (e.g., the variance) of program outcomes due to this uncertainty. These measures of dispersion can be viewed as indicators of the risk associated with each program.

In the modern analysis of financial assets it is common to discuss trade-offs between risk and expected return. There is a similar issue in the current context since we can expect alternative MT programs to differ in risk and expected net benefits. The rules for trading off

[5] We might think of these ranges as estimates of 99% confidence intervals for the parameters.
[6] Analysts may want to limit this to downside uncertainty.
[7] Analysts can decide upon the appropriate distributions for each application.

MT program risk against the expected net benefits are political decisions that, probably, can be best determined in a public regulatory environment.[8] Once we have set down these rules, we can define a score for each program alternative given its expected net outcome and its expected level of risk. As noted, the policy makers' score for each program will rise with its expected net benefits and fall with its level of risk. This benefit/risk program ranking approach is important for choosing among competing programs and can also be of use in helping to determine an optimal program research strategy.

Following a typical approach in the asset allocation literature, we might write such a ranking function as

2. $R = R(\mu, \sigma)$

where R represents an MT program score or rank, as above, μ represents the expected net program benefit, and σ is a measure of program risk. In general we suppose that benefits are good and risk is bad; i.e.,

3. $\frac{\partial R}{\partial \mu} > 0$; and

4. $\frac{\partial R}{\partial \sigma} < 0$.[9]

Equation 3 expresses the idea that we would expect policy makers to give higher scores to programs with greater net benefits (energy/peak savings), other things equal. Equation 4 expresses the idea that we would expect policy makers to give lower scores to programs that are more risky, other things equal.

It should be stressed that this approach does not rely on a simple hit-or-miss diversification of program elements to minimize risk. Rather, the current approach relies on optimized program and research/pilot-program expenditure allocation to enhance the risk-reducing benefits of diversified program design.

Controlling Outcomes and Risk: An Integrated Design/Research Strategy For MT Programs

Conservation program research is generally performed to confirm or deny assertions about program effectiveness. In the current context, however, we take a somewhat more

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[8] We might think of a point system for ranking MT programs. The idea here is that the program would receive more points if it had higher net benefits and fewer points if it were more risky. Note that the net benefits would probably be measured as a net present value for most programs, since this would allow us to compare differing time streams of costs and benefits for alternative programs. In addition, we can also consider program ranking procedures that would take into account possible program goals such as longevity and privatization. Note, however, that adding these particular goals would duplicate, somewhat, the functioning of the net present value ranking criterion, since this criterion would already take into account the length of the benefit streams as well as the magnitude of the stream of public costs.

[9] In the asset allocation literature, there are also generally assumptions about the sign of the second derivative of R with respect to σ.

general approach and view MT program research as a means to reduce the overall uncertainty attached to the program. For many research projects the projected reduction in the range of error will depend upon the size, and therefore the cost, of the research sample. Of course, the research projects can take many forms ranging from estimation of simple means of market characteristics from surveys to analysis of full-program pilot projects.[10] Since the resources for program research may be viewed as competing with program implementation, it seems appropriate to find an optimal resource allocation for research. In this setting, the total costs for a program are treated as the sum of the implementation costs and the research costs.

The solution of any optimal resource allocation problem requires a careful specification of means and ends, and optimal resource allocation for social policy is no exception to this rule. In the current setting, the resource allocation optimization problem might be phrased as follows*: find the allocation of expenditures on MT program implementation activities and research that maximizes the benefit/risk ranking score obtainable from a given budget*. Solving this optimization problem will likely require the use of iterative numerical techniques that take account of the benefit/risk scoring method described above, the market simulation model described above, estimates of the relationships between research elements and uncertainty reductions, and the unit costs of alternative program and research elements.

To show how such a joint program implementation/research optimization procedure would take place, it may be useful to cast this the problem in a simple analytical setting. Consider a one-node conservation-program example. In this case there is only one element in the program implementation budget vector *BI*; but how do we allocate our total budget, *B*, between program implementation, *BI*, and research, *BR*. For this example we will suppose that both the expected savings from the program and its riskiness rise with increasing *program implementation* expenditures. In addition, suppose that program riskiness falls with increasing *program research* expenditures. Then we can write,

5. $\mu = \mu(BI); \quad \frac{\partial \mu}{\partial BI} > 0$;

6. $\sigma = \sigma(BI, BR); \quad \frac{\partial \sigma}{\partial BI} > 0; \quad \frac{\partial \sigma}{\partial BR} < 0$;

and,

7. $B = BI + BR$

where *B* represents the total program-related budget, *BI* represents the budget component allocated to program implementation, and *BR* represents the budget component allocated to program-related research. In general, the information necessary to specify the relationship between expected program savings and the implementation budget (equation 5) will be obtained from the market clearing equations discussed in section III above and any technical

[10] The latter might be particularly useful for uncovering market characteristics which might have been overlooked by program designers.

(engineering/empirical) information that relates program elements to ultimate goals. The relationship between program riskiness and the implementation and research budgets (equation 6) can be obtained from the simulation studies in section IV above, and from statistical studies relating sample size to parameter variances.

Given these relationships, we can find the allocation of budget elements *BI* and *BR* (i.e., the program implementation and research budget components) that will maximize the program's ranking score (see equation 2) for a given total budget *B*. One way to carry out such an optimization procedure is optimize the relevant Lagrangian function, L, as follows:

8. $L = R(\mu,\sigma) + \lambda \cdot [B - BI - BR]$

or substituting equations 5 and 6 into the *R* portion of the Lagrangian equation, we have.

8a. $L = R[\mu(BI),\sigma(BI,BR)] + \lambda \cdot [B - BI - BR]$

where λ is an undetermined Lagrangian multiplier. We can find the optimal budget allocation for program implementation and research (*BI* and *BR*) by setting the first derivatives of equation 8a. with respect to *BI*, *BR* and λ equal to zero and solving these derivative equations for *BI* and *BR*.[11]

It should be understood that the optimal allocation of expenditures on program implementation activities would very likely result in program actions and measures directed at a *combination* (portfolio) of market nodes rather than at *one* market node. Furthermore, we may want to consider several types of program implementation activities for each market node.[12] In the same way, it should be understood that the optimal allocation of research expenditures would very likely be directed at a *combination* (portfolio) of studies of market linkage parameters, rather than at *one* market linkage or one parameter. This diversification of program resources would be viewed as optimal in this sense: it allows us to obtain the optimal combinations of program return and risk levels for any given budget. *Without such an approach it would be difficult to know how much in the way of resources to devote to each program and research element.*

To carry out this more general type of optimization procedure we would write a more detailed version of equation 8a as follows:

9. $$\begin{aligned} L &= R[\mu(BI_{1,1},...,BI_{N,M}),\sigma(BI_{1,1},...,BI_{N,M};BR_{1,1},...,BR_{J,K})] \\ &+ \lambda \cdot [B - (BI_{1,1} + ... + BI_{N,M}) - (BR_{1,1} + ... + BR_{J,K})] \end{aligned}$$

where $BI_{n,m}$ (*n=1,…,N; m=1,…,M*) is the budget devoted to program implementation element *m* directed at market node *n*; and $BR_{j,k}$ (*j=1,…,J; k=1,…,K*) is the budget devoted to research element *k* of market-clearing or technical relationship *j*.

[11] A second derivative test is also necessary here to assure that these *BI* and *BR* values will yield a maximum *R* and not a minimum *R* or a *saddle point*.

[12] See, for example, the alternatives listed in the table in section II.

Other things equal, the optimization procedure can be expected to favor program implementation or research elements that are relatively inexpensive and/or relatively productive in increasing program returns or decreasing risk.

Extensions

The analytical approach in this paper has thus far cast the optimization problem in a simple static setting. If, however, we take the timing of each program element and benefit into account, we will be solving for optimal trajectories of program elements rather than their optimal static values. For such an optimization procedure we would find it useful to use a related optimal control approach rather than the static Lagrangian approach presented above.

In addition, note that the optimization problem is phrased in terms of a *given budget*; i.e., the size of the budget is an input, not an output, of the optimization procedure. This approach, however, does allow us to solve for the most effective combination of program elements that can be obtained from any budget size. This, in turn, would allow us to calculate a ranking increment for every expenditure level. Thus, the budget size is determined politically, although the public debate over efficient use of budgets can be informed by the current simulation framework.

A more general optimization framework, in which the budget size itself is determined by the optimization procedure, can be constructed if we are explicit about the social ends to be served by the MT policy. For example, we may wish to use MT energy policies to help solve air-pollution problems or to reduce vulnerability to collusion by foreign oil producers. If we can establish a comparable valuation rule for such social ends (e.g., express these problems/issues in dollar terms), we can include them in our benefit/risk program ranking approach. In this case we would be able to solve for the socially optimal level of total MT program expenditures as well as the allocation of expenditures across program measures and parameter research.

Finally, another very general optimization approach would be to embed the simulation model and the benefit/risk scoring method in an adaptive control loop. This approach would allow us to optimally adjust data collection, research and program measure implementation over time as we acquire more information and as the state of the market changes.