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Energy conservation potential uncertainty analysis

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ENERGY CONSERVATION POTENTIAL UNCERTAINTY ANALYSIS

BY

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DISSERTATION

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Date

This thesis is dedicated to my young family:

Meredith, Gage, and Asher,

who gave me this time, and have given to me daily throughout it.

I've not known joy so fully, nor breathed life so deeply,

as during these sparkling four years

of Springtime with you.

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ABSTRACT

ENERGY CONSERVATION POTENTIAL UNCERTAINTY ANALYSIS

by

Gregory A. Norris
University of New Hampshire, September, 1994

Previous studies which have generated estimates of the potential for cost-effective gains in energy efficiency have generally *acknowledged* the uncertainty in their inputs and conclusions, but none have gone beyond simple scenario analysis to *quantify* the uncertainties in their inputs or conclusions. This research develops and demonstrates methods for the explicit treatment of uncertainty in energy conservation potential analysis. New methods and critical data requirements are highlighted through application to the study of current weatherization potential.

Sensitivity analysis finds that, contrary to claims appearing in the literature, estimates of cost-effective conservation potential are more sensitive to uncertainties in empirical inputs than to variations in assumed discount rates. A taxonomy of the input uncertainties affecting estimates of current weatherization potential is developed. The availability of data to support estimates of each input uncertainty is found to be minimal. Estimates of annual energy savings are the most uncertain input to the analysis of current weatherization potential. This input's uncertainty is also significantly more complex to analyze and characterize than that of either installed cost or measure lifetime (for weatherization measures), because of the number of separate factors contributing to it.

Methods are demonstrated for translating probabilistic descriptions of input uncertainties into probabilistic measure-specific conclusions. Methods for aggregating and plotting these results in modified conservation supply curves are presented.

Ninety percent confidence intervals for population mean cost of conserved energy per weatherization measure are estimated to range from roughly 60% to nearly 400% of typical point estimates. Ninety percent confidence intervals for population mean annual energy savings per weatherization measure are estimated to be less wide but still significant, ranging from roughly 35% to 160% of "typical" point estimates. The most significant contributor to uncertainty in both of these outputs is uncertainty in estimates of annual energy savings per measure installation. Probabilistic conclusions about the supply curve as a whole, as well as confidence intervals for such summary results as the total technical potential and the total cost-effective conservation potential given a threshold price, all require specification of the statistical dependence of each uncertainty's influence upon separate measures.

INTRODUCTION

Residential and commercial buildings accounted for 36% of total US energy consumption, and 62% of US electricity consumption in 1992. (EIA 1993) How much of this energy could be conserved at what cost, using presently available technologies, without reducing the level of service provided by present energy consumption? Defining a *cost-effective* conservation investment as one whose cost is less than the present value of the investment's lifetime energy savings, what is the *cost-effective conservation potential* for a particular sector, a particular fuel, a particular end-use, and/or a particular region of the country?

Because of the priced and un-priced costs associated with extracting, importing, producing, distributing, and consuming energy, answers to the above questions are important to national and regional energy policy, environmental policy, utility regulation, and economic policy. Estimates of the magnitude and cost of present and future energy conservation potential provide a basis for strategies to reduce "greenhouse gas" emissions; they inform projections of the impacts (or debates about the economic efficiency) of energy tax proposals; they underlie electric and natural gas utility "Least-Cost Planning" regulation, practice, and evaluation; and they have come to the fore in emissions reduction strategies under the 1990 Clean Air Act Amendments as well.

The Uncertainty in Estimates of Conservation Potential Has Not Been Quantified

Many studies at national, state, multi-state, and utility service areas scales have developed detailed quantitative estimates of the potential for reducing energy consumption (and emissions) through implementing available efficiency technologies. The residential sector has been the most widely studied (Meier and Usibelli 1986), with over twenty five studies completed in the US and Canada during the past decade.[1] Few of the studies addressing the state or utility scale were ever published in the peer-reviewed literature; many are internal reports generated by and/or for either utilities or state regulatory commissions.

While many of these studies have *acknowledged* the uncertainties in their estimates, and some have enumerated sources of uncertainty considered to be most important, none have gone beyond simple scenario analysis (i.e., "best case/worst case/best guess" estimates) to actually *quantify* the uncertainties in their conclusions or the relative influence of different input uncertainties upon their conclusions.

There has been some mention in the general supply curve literature (e.g., Vine and Harris 1990; Meier and Usibelli 1986; Meier et al. 1983; Meier 1982) of the sensitivity of calculated estimates of conservation potential to variation in the inputs. The first came from Meier (1982) who derived the elasticities of "cost of conserved energy" (an index of energy conservation measure cost-effectiveness) with respect to its four determinants. The consensus of this literature has been that uncertainties in empirical inputs are not as important as differences in assumed discount rates. For example:

> The cost of conserved energy and, therefore, the estimate of cost-effective savings potential are both sensitive to variations in four key parameters: the cost of the measure (both initial and operating and maintenance costs), the annual energy savings, the amortization time, and the discount rate. Of all these variables, the discount rate has the greatest effect, [and] variations in assumed discount rates are often far greater than the uncertainties in lifetimes, energy savings, or investment costs. (Vine and Harris 1990, p. 19)

The view that the most influential "uncertainty" in estimates of current conservation potential is the assumed discount rate probably explains why a popular test of result "robustness" is to check for the impact of varying the discount rate between, say, 3 and 10%. (e.g., UCS 1991, NAS 1991, Rubin et al. 1992) In fact, sensitivity testing with the discount rate *should be done*, in order to evaluate whether the assumptions underlying its choice influence the conclusions of the analysis. However, as Chapter 1 will describe, the results of static sensitivity analysis do not support the use of discount rate sensitivity testing as a reliable evaluator of results robustness.

Confidence and Uncertainty in Prior Summaries of Conservation Potential Estimates

Several authors have pooled and compared the results of separate conservation potential studies, partly to derive a "mid-range" summary estimate and to guage indirectly the level of uncertainty in such estimates. These reviews of studies of conservation potential are summarized and compared below, together with a critique of their attempts to address indirectly the issue of confidence and uncertainty in conservation potential estimates. Each of the three reviews has attempted to standardize the major assumptions and scenario definitions underlying several independent conservation potential studies, and has demonstrated that the individual studies' results converge significantly after standardization. However, close-clustering of standardized point estimates cannot be mistaken for guidance about appropriate confidence intervals to attach to the results, individually or collectively.

Carl and Scheer (1987) reviewed eight studies of national and regional energy conservation potential for the US Department of Energy. Most of the studies they reviewed were actually forecasts rather than end-use-based engineering estimates of either technical or cost-effective conservation potential. To facilitate comparison of study conclusions, they standardized the studies by converting them to a common projection period, scaling them to common assumptions about gross national product (GNP), and extrapolating the two regional studies to national levels. They reported that "the consensus among the estimates [of conservation potential following normalization] supports the argument that these studies are still useful and a new study therefore is not necessary."

Komor and Moyad (1992) reviewed more than 6 studies which estimated the conservation potential in U.S. buildings, and found estimates ranging from 13% to 45% of "baseline" consumption. They attributed the majority of the estimate variation to differing analysis time frames (current potential versus potential in the years 2010 or 2015), different expected rates of future efficiency improvements absent new policy initiatives, varying scope of conservation measures or end-uses included, and some differences in assumed discount rate: "If one is willing to grant certain assumptions, then one can generate a savings estimate" (p. 132). They did not attempt a quantitative normalization of the estimates, but expressed a preference for the middle range estimate of 33% of consumption (in the year 2015) and stated that the factors mentioned above provided evidence suggesting that the lower and higher estimates were under- and over-estimates, respectively. They identified three areas needing further attention "before there will be general agreement on the cost-effective savings potential": 1) a better understanding of indirect costs (e.g., information costs, time costs, program administrative costs); 2) stronger empirical characterization of market imperfections (e.g., barriers to cost-effective investment decision-making); and 3) quantification of the societal benefits of energy conservation.

In support of the 1991 National Academy of Sciences study on *Policy Implications of Greenhouse Warming,* researchers at the Lawrence Berkeley Laboratory (LBL) compiled and compared nine conservation supply curves for the buildings sector. (Rosenfeld et al. 1993) Their compilation included several standardizing adjustments which minimized the impacts of differing assumptions among the nine studies. The resulting compilation found that six of the nine studies' adjusted estimates were within ±3% of an approximate mean estimate of 45% cost-effective current electricity conservation potential. An un-normalized comparison of the supply curves does not appear in Rosenfeld et al. 1993, but two of the curves (EPRI and an update from RMI) have appeared superimposed elsewhere, *un-normalized* (see, for example, Kahn 1991 or Joskow and Marron 1992); when un-normalized, the RMI estimate of cost-effective conservation potential was 3 times that of the EPRI estimate -- 60% of current consumption vs. 20%. As a result of their quantitative normalization, they reported a point estimate of current cost-effective conservation potential *to three significant digits,* but did not characterize the uncertainty associated with this estimate. Finally, studies for fuels other than electricity were found to be much more rare; the LBL compilation found the two available residential natural gas conservation supply curves to be in reasonably close agreement: one for the US (SERI 1981) and one for California (Meier et al. 1983), which estimated cost-effective conservation potential to be 55% and 44% of current consumption, respectively.

All three reviews cited above express greatest confidence in the mid-range of their pooled conservation potential estimates once assumptions are standardized. Both the LBL analysis and the earlier normalization by Carl and Scheer (1987) show significantly reduced variability among the estimates after standardization. But caution must be exercised: even if the normalized studies' *point estimates* were all found to be in *exact* agreement, this fact alone would say nothing about what the *confidence intervals* around this estimate should be. The range among published estimates of current cost-effective conservation potential should not be confused with even an "informal" confidence interval on this potential; but in the absence of quantitative uncertainty estimates, this distinction appears to have occasionally blurred. For example, a major inter-laboratory study of conservation potential, in discussing uncertainty of the results, stated "The range of uncertainty is illustrated by other published studies on energy conservation." (Carlsmith et al., p. 23)

In summary, several studies have attempted indirectly to gauge the reliability of point estimates of energy conservation potential, by normalizing and then comparing sets of separate estimates. The range among point estimates has narrowed significantly following normalization, which has lead to a tendency to attribute the lion's share of the variability among point estimates to differences in underlying assumptions. (e.g., Komor and Moyad 1992) Further, the narrowness of the range of normalized point-estimates has lead to a significant degree of confidence in the mid-range estimates, at least as reflected in the precision with which such mid-range estimates are reported. (e.g., Rosenfeld et al. 1993) The results of the present research indicate that the significance of empirical input uncertainties appears to have been widely underestimated.

The Potential Importance of Conservation Potential Uncertainty Analysis

The lack of attempts to quantify uncertainty in energy conservation potential does not stem from any lack of importance associated with such uncertainty. Several studies (e.g., Lesser 1990, Hirst and Schweitzer 1990, Hobbs and Maheshwari 1990, Hirst 1992a) have begun to examine the effects of uncertainty on utility planning. Actual *achievement* of some of the potential for energy conservation can *reduce* the magnitude of uncertainty in load forecasts. (Ford and Geinzer 1990) However, uncertainty about the energy savings achieved by such programs independently *increases* uncertainties in revenue requirements and electricity price. Hirst (1992a) found that whether the net effect of including conservation programs into utility resource plans was an increase or a decrease in total planning uncertainty depended strongly upon the magnitude of uncertainty associated with conservation program performance (p. 31). Yet given the scarcity of empirical data quantifying program performance uncertainty and the total absence of studies characterizing the uncertainty in conventional estimates of the size and cost of the efficiency potential, conclusions about the net effect of conservation planning upon total planning uncertainty appear difficult to draw.

Hirst has also continually reviewed and reported on both the average and cutting-edge state of practice in Utility Least-Cost Planning over the past several years. (e.g., Hirst 1992b, Hirst et al. 1991, Berry and Hirst 1990) He reported in 1992 that "neither the proponents nor the skeptics" of utility demand-side management (DSM) programs had yet quantified the effects of uncertainty in DSM program potential or performance upon their net value to utilities as a component of strategic load planning and resource acquisition. He cited a 1990 analysis by the New England Electric System (NEES) as a "rare" example of quantitative utility analysis of DSM program uncertainty. But the NEES study treated uncertainty in energy savings achieved by an entire DSM program rather than measure by measure, and top-level program performance uncertainties were characterized by "staff judgment" rather than by analysis based on estimates of individual input uncertainties. (Hicks 1994)

Noting that lower uncertainty about the impacts of conservation programs decreases the level of plant construction required to prevent capacity shortfalls with a given level of confidence, Sonnenblick (1993) focused on the potential for more effectively-targeted and better-synthesized program evaluation efforts to reduce conservation planning uncertainty. By defining the marginal cost of evaluation and the marginal benefits of capacity reductions, he showed how one might identify an optimum level of expenditure on evaluation (uncertainty reduction). In practice, the value of uncertainty reduction is partly a function of the baseline uncertainty (before further evaluations), which for studies of conservation potential, has not yet been identified. Thus, an initial attempt to characterize the uncertainty in energy conservation potential estimates can help indicate whether efforts to reduce the uncertainty in key inputs appear cost-effective.

Finally, Henrion (1982, 1989) has developed formal methods for assessing the "expected value of including uncertainty" in policy analysis. From a list of several scenarios where he and a colleague consider uncertainty analysis to be "unquestionably called for" (Morgan and Henrion 1990), two are particularly relevant to the analysis of energy conservation potential:

1) cases when uncertain information from different sources must be combined to generate final estimates (e.g., information from different data samples, or from the opinions of different experts); and
2) cases when a decision is to be made about whether to buy new information -- recall observations about the implications of Sonnenblick (1993) above.

Finally, Morgan and Henrion point out that even if subsequent formal analyses do not explicitly analyze uncertainties, a prior "probability assessment process may be valuable in producing better estimates of the central values" used in subsequent non-probabilistic analyses (p. 320). In summary, probabilistic analysis of the uncertainty in estimates of energy conservation potential has not been conducted to date, but several factors point to the value of applying such techniques.

Outline of the Dissertation

This dissertation represents an initial exploration of the issues, data requirements, methods, and results of probabilistic analysis of energy conservation potential. It does so with a focus on the analysis of current weatherization potential.

The research begins by analyzing the sensitivity of the principal indices of conservation measure cost-effectiveness to variations in their inputs, presented in Chapter 1. It is found that claims in the literature about the dominance of variations in the discount rate are unfounded. In fact, the sensitivity of a conservation measure's cost of conserved energy (CCE) to variations in the discount rate is found to be *lower* than the sensitivity of CCE to variations in both annual energy savings and measure installed cost, regardless of the nominal values of either the discount rate or the measure lifetime. The sensitivity of CCE to variations in the discount rate is also exceeded by its sensitivity to variations in measure lifetime, for nominal measure lifetimes under approximately 20 years; the exact value of this nominal lifetime "cross-over point" is a function of the discount rate.

Chapter 2 develops quantitative estimates of the uncertainties in inputs to the analysis of current weatherization potential. On the way to these estimates, the state of available supporting data is reviewed, and a taxonomy of the factors which contribute to uncertainty in each input is developed. A principal conclusion of the chapter is that empirical data and/or analyses upon which to base quantitative estimates of input uncertainties are sparse. Of the four inputs, estimates of both measure life and annual energy savings appear to be especially in need of an improved empirical basis for estimating their uncertainty. The taxonomy of contributing factors demonstrates that (at least for measures addressing space-heating energy consumption), annual energy savings is by far the most complex input uncertainty to analyze; it is influenced by at least seven contributing sources of uncertainty. The chapter includes recommendations for near-term empirical and analytical research to strengthen the basis for estimates of input uncertainties related to current weatherization potential.

Chapter 3 begins the development of methods for probabilistic analysis of energy conservation potential, drawing upon the results of Chapter 2 to support illustrative numerical examples. Methods for converting probabilistic descriptions of input uncertainties into probabilistic descriptions of the outputs of conservation potential analysis are demonstrated. A generalization of conservation supply curves is developed which allows graphical summary of the results of probabilistic conservation potential analyses. The interpretation of such probabilistic conservation supply curves is discussed. It is found that estimates of weatherization measures' cost-effectiveness tend to be more uncertain than estimates of their annual energy savings potential. The separate influences of the three input uncertainties (measure life, installed cost, and annual energy savings) are compared; it is found that energy savings uncertainty is the most influential, followed by lifetime uncertainty. Development of confidence intervals for aggregate estimates of cost-effective conservation potential, and of confidence intervals for the supply curve as a whole, is found to require specification of the statistical interdependence of each input uncertainty's influence across the set of feasible measures.

Finally, a concluding chapter (Chapter 4) views the results of the entire dissertation as a whole, and from that perspective offers recommendations for further research which should improve the information basis for energy planning and policy.

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[1] Citations for twenty five studies completed during the past decade which have generated independent estimates of energy savings potential in the residential sector are listed below: WCDSR 1994, Boghosian and McMahon 1993, OTA 1992, UCS 1991, Koomey et al 1991, NAS 1991, EMR 1991, EIA 1990, Ontario Hydro 1990, Carlsmith et al 1990, EPRI 1990, Xenergy 1990, Boston Gas 1990, NPCC 1989, Bodlund et al. 1989, Miller et al. 1989, NEEPC 1987, Lovins 1987, Krause et al. 1987, NPCC 1986, Hunn et al. 1986, Geller at al. 1986, Lovins et al. 1986, Usibelli et al. 1983, Meier et al. 1983.

CHAPTER 1

ENERGY CONSERVATION POTENTIAL SENSITIVITY ANALYSIS

Introduction

Major studies which have generated estimates of the potential for cost-effective gains in energy efficiency in US buildings (e.g., Carlsmith et al. 1990; Koomey et al. 1991; UCS 1991; NAS 1991; OTA 1992) have generally *acknowledged* the uncertainty in their inputs and conclusions, but have not attempted to quantify either the input uncertainties or their net effect upon the uncertainty associated with the conclusions.

These studies typically estimate the "technical energy conservation potential" and also the fraction of the technical potential which is cost-effective -- that is, the total energy savings achievable by that subset of technically feasible measures which also each satisfy a given cost-effectiveness criterion. Finally, a few studies (e.g., Brown 1993, Nadel and Tress 1990, Krause et al. 1987) have estimated the "achievable energy conservation potential" -- that fraction of the estimated cost-effective potential which is considered to be realizable by programs and policies having prior precedent, in light of such programs' demonstrated levels of participation and effectiveness.

End-use/engineering estimates of cost-effective energy conservation potential rely on uncertain estimates of multiple inputs, including the annual energy savings achieved by each energy conservation measure, the lifetime and installed cost of each measure, future fuel prices, and the discount rate. Several authors, most recently Vine and Harris (1990) have contended that of all these inputs, estimates of cost-effective energy conservation potential are most sensitive to variations in the discount rate. The present chapter examines this contention directly by deriving and comparing the sensitivities of the major energy conservation measure cost-effectiveness indices to variations in their inputs. Multiple authors, notably Meier (1982), Meier, Wright and Rosenfeld (1983), and Vine and Harris (1990), have also claimed (as did Vine and Harris on p. 19) that "variations in assumed discount rates are often far greater than the uncertainties in lifetimes, energy savings, or investment costs." This issue is taken up separately in Chapter 2, through the development of empirically-based estimates of the uncertainty in estimates of mean litetimes, energy savings, and installed costs for residential weatherization measures.

Sensitivity analysis in the context of energy planning or policy analysis has been defined in slightly different terms by different authors (e.g., EPRI 1991b, Lesser 1990, Hirst and Schweitzer 1990, Morgan and Henrion 1990). Nevertheless, there appears to be widespread agreement on two points:

a) sensitivity analysis entails characterizing, for each input variable, the effect of its variation upon the output or outcome variable(s) of interest; and

b) sensitivity analysis is non-probabilistic, in that it does not employ estimated probability distributions to characterize the uncertainty in each input, and therefore its results do not yield probabilistic estimates for the output variable(s).

Although probability distributions are neither utilized nor produced by sensitivity analysis, the *range* of variation for each input may reflect judgments about "upper and lower bound values." (EPRI 1991b) Sensitivity analysis is a useful first step in uncertainty analysis, which can help focus subsequent efforts to obtain data to characterize the input uncertainties probabilistically.

A sizable literature exists which treats methods for addressing uncertainty in utility resource planning; reviews of issues and techniques are found for example in the four references cited above, as well as (Hobbs and Maheshwari 1990). Marshall (1988, 1991) has surveyed techniques for treating uncertainty in the economic evaluation of energy investments in buildings. Brown (1993) illustrated the application of "scenario analysis" (defined in the Introduction) in an attempt to bracket the range of uncertainty affecting projections of the fraction of cost-effective conservation potential which is "achievable" by actual programs and policies. Finally, three reviews have attempted to summarize and normalize the results of multiple national conservation potential studies in order to draw conclusions about the reliability of the estimates (Carl and Scheer 1987; Komor and Moyad 1992; Rosenfeld et al. 1993); however, the spread among point estimates cannot be construed as offering any real information about appropriate confidence intervals for conservation potential point estimates, nor the magnitude of uncertainty associated with such estimates.

Sensitivity Analysis of Cost-Effectiveness Indices

The cost effectiveness criteria addressed in this paper include the cost of conserved energy (CCE), cost-benefit ratio (CBR) and its inverse, benefit-cost ratio (BCR), and net present value (NPV). Another popular index of energy conservation measure cost-effectiveness is the "simple payback time" (SPT); since SPT neglects the time value of money and is blind to energy savings which occur after cumulative savings have surpassed the measure cost, it is not recommended for use as more than a casual "rule of thumb," and so is not examined here. Cost-effectiveness criteria used in the evaluation of building energy conservation measures are reviewed in, for example, (ASTM 1992) and (Schlegel and Pigg 1989).

In the simple static case involving constant annual energy savings E (ex., in Btu/year), constant real price for the displaced energy P ($/Btu), measure installed cost C ($), measure lifetime n (years), and discrete annual discounting at a rate d (% per year), the four conservation measure cost-effectiveness criteria take the forms indicated below.

$$\text{Cost of Conserved Energy (CCE)} = \frac{C*crf}{E} = \left(\frac{C}{E}\right)\left(\frac{d}{1-(1+d)^{-n}}\right) \qquad (1)$$

$$\text{Cost-Benefit Ratio (CBR)} \quad = \quad \frac{C*crf}{E*P} = \left(\frac{C}{E*P}\right)\left(\frac{d}{1-(1+d)^{-n}}\right) \tag{2}$$

$$\text{Benefit-Cost Ratio (BCR)} \quad = \quad \frac{E*P}{C*crf} = \left(\frac{E*P}{C}\right)\left(\frac{1-(1+d)^{-n}}{d}\right) \tag{3}$$

$$\text{Net Present Value (NPV)} \quad = \quad \left(\frac{E*P}{crf}\right) - C = (E*P)\left(\frac{1-(1+d)^{-n}}{d}\right) \tag{4}$$

The term *crf* appearing in equations (1) through (4) is the "cost recovery factor." Multiplying the measure cost C by *crf* converts the purchase price into an annuity, and yields the effective value of equal annual payments to be made n times over the life of the conservation measure. That is, from the perspective of time $t=n$, the value of each effective annual payment is escalated by an amount which acknowledges that each could (at least in principle) have instead been invested in its year of payment at a fixed rate of return d until the year $t=n$.[1] Conversely, dividing the value $E*P$ of the annual revenue (savings) stream by *crf* (in the expression for NPV) generates the discounted present value of the revenue stream over the full measure life.

While the assumptions of constant real E and P are restrictive, they are common, and the results provide an instructive starting point . This analysis need only be performed once for the "research community," since the results are a property of equations (1) through (4), are not affected by characterizations of the input uncertainties, and the parameter-dependence of the results is of low enough dimension to be given exhaustive treatment.

A standard approach to sensitivity analysis involves calculating the elasticities of the output of interest with respect to each of its inputs. In general, the elasticity of an output y with respect to its "ith" input x_i is defined as

$$\eta^{y}_{x_i} = \frac{\partial y}{\partial x_i} * \frac{x_i}{y} \tag{5}$$

When evaluated for a given set of values of the inputs, an elasticity approximates the percent change in the output variable due to a 1% change in x_i, all other inputs held constant. When plotted over relevant ranges of the input variables, the results allow assessment of the relative strengths of influence of the input variables upon the output.

The elasticities of CCE, CBR, and BCR with respect to their inputs are presented in Table 1.1, along with plots over the range of typical energy conservation measure lifetimes, for discount rates of 3%, 5%, and 10%. The elasticities of CCE and CBR with respect to their inputs are equivalent, except for the fact that CCE is independent of the price of displaced energy, ***P***. Note also that the elasticity of the inverse of an expression is equal to the negative of that expression's elasticity:

$$\eta_x^{y^{-1}} = -\eta_x^y \tag{6}$$

Therefore, the elasticities of the benefit-cost ratio (BCR) to its inputs are equal to the negatives of the corresponding elasticities of CBR.

From the expressions and plots appearing in Table 1.1 it is evident that in fact CCE, CBR, and BCR are *not* most sensitive to variations in the discount rate. Rather, these cost-effectiveness indices are *less sensitive* to variations in the discount rate than to variations in either measure cost ***C*** or annual energy savings ***E***, (and, for CBR or BCR, variations in the cost of displaced energy ***P*** as well) over all possible combinations of ***n*** and ***d***. At discount rates at or below 7% and measure lifetimes below 20 years, the cost-effectiveness indices are in fact *least sensitive* to variations in the discount rate, among all inputs. The sensitivity of cost-effectiveness to a percent change in ***d*** increases at higher discount rates and longer measure lifetimes.

When using CCE to evaluate energy conservation measure cost-effectiveness, measures whose CCE is less than the fuel price ***P*** are considered cost-effective, while measures with CCE greater than ***P*** are considered not cost-effective. Likewise, values of CBR less than 1.0 indicate cost-effectiveness, values of BCR greater than one indicate cost-effectiveness, and values of NPV greater than zero indicate cost-effectiveness. That portion of the estimated technical potential for energy conservation which is met by measures that satisfy these cost-effectiveness criteria is defined as the cost-effective energy conservation potential.

The "cost-effectiveness thresholds" or "break-even points" for an energy conservation measure is thus given alternatively by CCE=P, CBR=1, BCR=1, or NPV=0. It turns out that for all four criteria listed above, the definitions of these thresholds are algebraically equivalent, and represent that combination of values of C, P, E and n (given d) at which the present value of the measure's lifetime benefits are exactly equal to its costs:

$$PE\left(\frac{1-(1+d)^{-n}}{d}\right)=C \tag{7}$$

Because NPV is equal to zero at this cost-effectiveness threshold, the elasticities of NPV to its inputs are undefined at this threshold, and approach infinity near it. Another difficulty arises because the elasticities of NPV are nonlinear functions of E, P, and C (in addition to n and d). For example:

$$\eta_C^{NPV}=\frac{1}{1-\left[\left(\frac{EP}{C}\right)\left(\frac{1-(1+d)^{-n}}{d}\right)\right]} \tag{8a}$$

$$\eta_E^{NPV}=\eta_P^{NPV}=\frac{1}{1-\left[\left(\frac{C}{EP}\right)\left(\frac{d}{1-(1+d)^{-n}}\right)\right]} \tag{8b}$$

This nonlinear dependence precludes normalizing the elasticities with respect to E, P, and C. The result is excessive "dimensionality" of the expressions, making them impossible to portray comprehensively in two- or even three-dimensional plots.

Both of these difficulties make it more helpful for purposes of sensitivity analysis to examine and compare the expressions for the *absolute* (rather than *percent*) change in NPV due to a 1% change in each of its inputs, defined as

$$\delta_{x_i}^{y}=\frac{\partial y}{\partial x_i}*x_i \tag{9}$$

For NPV, these expressions are defined as follows:

$$\delta_C^{NPV} = -C \tag{10a}$$

$$\delta_E^{NPV} = PE\left(\frac{1-(1+d)^{-n}}{d}\right) \tag{10b}$$

$$\delta_P^{NPV} = PE\left(\frac{1-(1+d)^{-n}}{d}\right) \tag{10c}$$

$$\delta_n^{NPV} = nPE(1+d)^{-n} \tag{10d}$$

$$\delta_d^{NPV} = \left(\frac{PE}{d}\right)\left[nd(1+d)^{-n-1} + (1+d)^{-n} - 1\right] \tag{10e}$$

Equations (10a) - (10e) are plotted in Table 1.2. Note first that equations (10b) through (10e) are linear in the product ***PE***, allowing normalization. Note also that equation (7) and equation (10a) together enable representation of δ_C^{NPV} versus n rather than C. Equation (7) reveals that near the cost-effectiveness threshold, $-\delta_C^{NPV}$ is approximately equal to δ_E^{NPV} (which is identically equal to δ_P^{NPV}). Since C will always be ≥ 0, then $-\delta_C^{NPV}$ will always be non-negative. For cost-effective measures, then, we can write:

$$0 \leq -\delta_C^{NPV} < PE\left(\frac{1-(1+d)^{-n}}{d}\right) \tag{11a}$$

while for non-cost-effective measures, the following will hold:

$$-\delta_C^{NPV} > PE\left(\frac{1-(1+d)^{-n}}{d}\right) \tag{11b}$$

Again, for measures near the cost-effectiveness threshold (cases when sensitivity of NPV to uncertainty in its inputs is most likely to be of importance), $-\delta_C^{NPV}$ is approximately equal to δ_E^{NPV}.

The results in Table 1.2 clearly illustrate that as with CCE and CBR, the cost-effectiveness of an energy conservation measure based on NPV is *not* most sensitive to variations in the discount rate. In fact, over the range of measure lifetimes from 1 to approximately 20 years, NPV is *least* sensitive to variation in the discount rate.

Summary of Results and Conclusions

Prior estimates of the potential for cost-effective energy conservation have not quantified the uncertainty in their inputs or conclusions. The results of the present analysis indicate that the effects of input uncertainties upon estimates of cost-effective conservation potential may be significant and warrant further study. In particular, sensitivities of the four most common cost-effectiveness criteria were derived and plotted over plausible ranges of the discount rate and measure lifetime. The results of sensitivity analysis showed that variations in the empirical inputs were generally more influential than variations in the discount rate. For this reason, discount rate "scenario analysis" (testing the impact of different discount rate assumptions upon conclusions about the cost-effective energy conservation potential) may not be an adequate proxy for actual uncertainty analysis. The final contribution of input uncertainties to the total uncertainty in estimates of measure cost-effectiveness is a function of both the sensitivities (examined here) and the actual range of uncertainty in the estimates for each input. This latter topic is taken up in the next chapter.

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[1]An alternative view is that the conservation measure is paid for by borrowing the amount ***C*** at an interest rate ***d***; in this case, ***C*crf*** is the annual loan payment to be made each year during the measure life.

Table 1.1: Elasticities of CCE, CBR, and BCR with Respect to Their Inputs

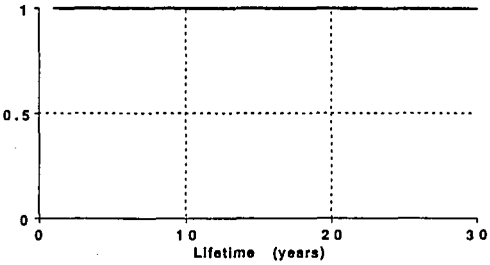
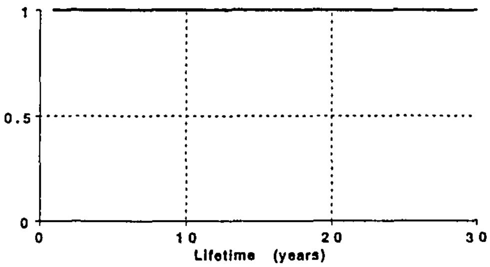
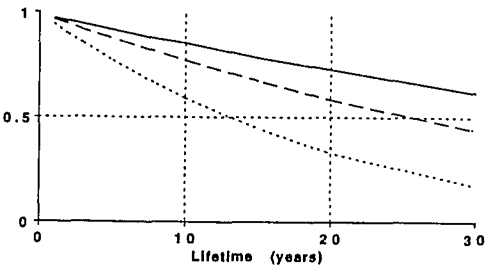
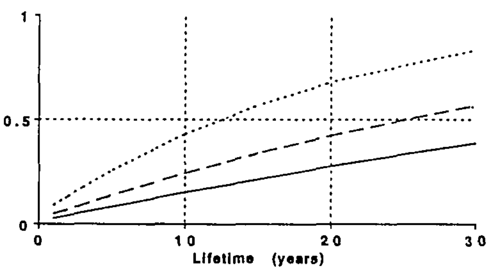
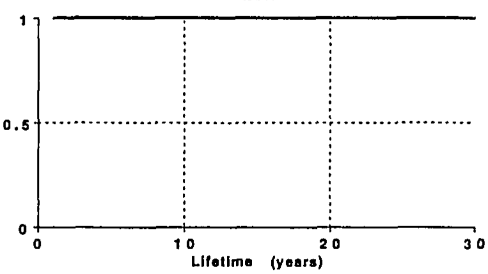
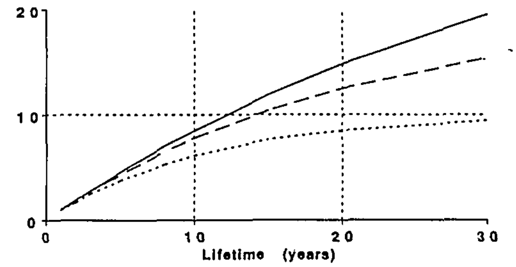
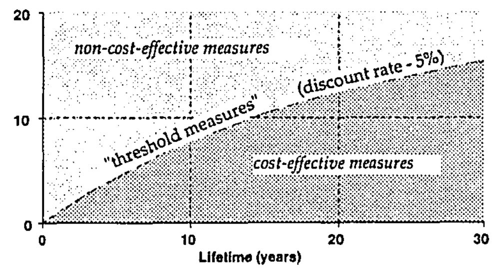
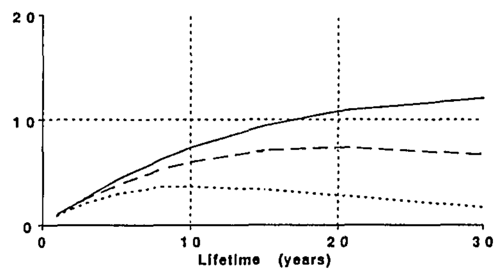
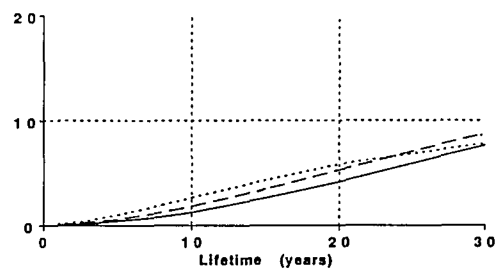
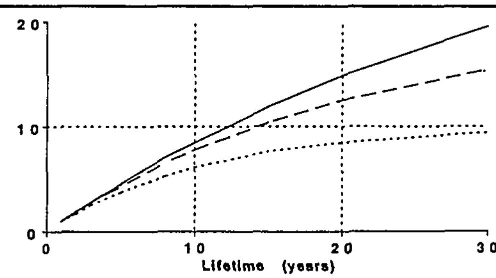
Elasticity with respect to:	Definitions of Elasticities	Plots of Elasticities versus measure lifetime, n Key: —— d=3% --- d=5% .... d=10%	
E (annual energy savings)	$\eta_E^{CCE} =$ $\eta_E^{CBR} = -\eta_E^{BCR} =$ -1	$-\eta_E^{CCE}$, $-\eta_E^{CBR}$, and η_E^{BCR}	
C (measure cost)	$\eta_C^{CCE} =$ $\eta_C^{CBR} = -\eta_C^{BCR} =$ +1	η_C^{CCE}, η_C^{CBR}, and $-\eta_C^{BCR}$	
n (measure lifetime)	$\eta_n^{CCE} =$ $\eta_n^{CBR} = -\eta_n^{BCR} =$ $\dfrac{n*\ln(1+d)}{1-(1+d)^n}$	$-\eta_n^{CCE}$, $-\eta_n^{CBR}$, and η_n^{BCR}	
d (discount rate)	$\eta_d^{CCE} =$ $\eta_d^{CBR} = -\eta_d^{BCR} =$ $1-\dfrac{nd}{(1+d)^{n+1}-(1+d)}$	η_d^{CCE}, η_d^{CBR}, and $-\eta_d^{BCR}$	
P (energy cost)	$\eta_P^{CBR} = -\eta_P^{BCR} =$ -1	$-\eta_P^{CBR}$ and η_P^{BCR}	

Table 1.2: Sensitivities of NPV to Variations in Its Inputs

<table>
<tr><th>Sensitivity with respect to:</th><th>Definitions of Sensitivities</th><th colspan="2">Plots of Sensitivities versus measure lifetime, n.
Key: —— d=3%   – – – d=5%   · · · · d=10%</th></tr>
<tr><td>E
(annual energy savings)</td><td>$\delta_E^{NPV} =$
$PE\left(\frac{1-(1+d)^{-n}}{d}\right)$</td><td>$\frac{\delta_E^{NPV}}{P*E}$</td><td>
</td></tr>
<tr><td>C
(measure cost)</td><td>$\delta_C^{NPV} = -C$</td><td>$\frac{-\delta_C^{NPV}}{P*E}$</td><td>
</td></tr>
<tr><td>n
(measure lifetime)</td><td>$\delta_n^{NPV} =$
$nPE(1+d)^{-n}$</td><td>$\frac{\delta_n^{NPV}}{P*E}$</td><td>
</td></tr>
<tr><td>d
(discount rate)</td><td>$\delta_d^{NPV} =$
$\left(\frac{PE}{d}\right)*$
$\left[\begin{array}{l} nd(1+d)^{-n-1} + \\ (1+d)^{-n} - 1 \end{array}\right]$</td><td>$\frac{-\delta_d^{NPV}}{P*E}$</td><td>
</td></tr>
<tr><td>P
(energy cost)</td><td>$\delta_P^{NPV} =$
$PE\left(\frac{1-(1+d)^{-n}}{d}\right)$</td><td>$\frac{\delta_P^{NPV}}{P*E}$</td><td>
</td></tr>
</table>

CHAPTER 2

UNCERTAINTY IN EMPIRICAL INPUTS TO ANALYSIS OF CURRENT WEATHERIZATION POTENTIAL

Introduction

The uncertainty in estimates or projections of energy conservation potential has not been quantified. Major studies which have estimated the potential for cost-effective gains in energy efficiency in US buildings (e.g., Carlsmith et al 1990; Koomey et al. 1991; UCS 1991; NAS 1991; OTA 1992) have generally *acknowledged* the uncertainty in their inputs and conclusions, but no study has attempted to quantify either the uncertainty in the inputs or the conclusions. A few studies have tested the *sensitivity* of their conclusions to variations in the discount rate (UCS 1991; NAS 1991), and one study (Brown 1993) specified "optimistic" and "pessimistic" scenarios for program cost and effectiveness in order to bracket the range of uncertainty in projections of the fraction of technically feasible residential electricity conservation potential is *achievable* in the US by the year 2010. Sensitivity analysis can indicate the *potential* for input uncertainties to be influential, but it offers no insight about their *actual* influence upon conclusions. Scenario analysis does not provide guidance about the probability of particular outcomes or conclusions. Finally, the uncertainty in estimates of technical or cost-effective conservation potential, upon which projections of achievable potential are based, has not yet been studied even using non-probabilistic scenario analysis.

Three prerequisites to probabilistic energy conservation potential uncertainty analysis which have not yet appeared in the literature are:

1) probabilistic descriptions of the uncertainties in the empirical inputs to analyses of energy conservation potential;

2) procedures for propagating input uncertainties through conservation supply curve analysis in order to develop probabilistic estimates of energy conservation potential; and

3) methods for reporting probabilistic results in a modified supply curve framework.

Chapter 3 begins the development of (2) and (3). The present chapter begins the development of (1), with a focus on the input uncertainties affecting the analysis of ***current weatherization potential***. Three objectives of the present analysis are:

1) attempting to establish a taxonomy of the uncertainties affecting the empirical inputs to analysis of current weatherization potential;

2) reviewing the state of available data which can support estimates of these uncertainties; and

3) attempting to develop initial estimates of these uncertainties, derived from empirical data wherever possible.

As the final results of the present paper will indicate, empirical data from which to derive estimates of input uncertainties are virtually nonexistent for some of the parameters; thus, important topics for further research are identified.

Analysis of current weatherization potential is a subset of energy conservation potential analysis, both methodologically and physically. Methodologically, analyses of ***current*** energy savings potential differ from projections of future potential in that the former are unaffected by uncertainties concerning building stock evolution, turnover and replacement of equipment stocks, and autonomous investments in efficiency retrofits. Thus, the uncertainties affecting estimates of current potential are a subset of the uncertainties which affect projections of future potential.

Weatherization potential refers to that subset of total residential energy savings potential which is addressed by retrofit measures (rather than measures which address new construction), and whose measures target strictly space-conditioning energy consumption (rather than consumption in other end-uses such as water heating, lighting, appliances, etc.). Estimates of weatherization potential are impacted by many complexities which do not affect estimates of energy savings in other end-uses, due in part to space-heating's dependence on climate, its complex dependence upon building and equipment characteristics, and the heterogeneity of building stocks, equipment stocks, and climatic conditions. Space heating is the largest single end-use in both the residential and commercial sectors (in terms of primary energy consumed per year) (OTA 1992), and energy use in these two sectors combined accounts for roughly one third of total US energy consumption. (EIA 1993a)

The four empirical inputs which are used to generate non-probabilistic "best estimates" of the total technical potential for energy conservation, and of the fraction of technical potential which is estimated to be cost-effective, are the following, which must be estimated for each technically feasible conservation measure: its mean annual energy savings per installation $\overline{\Delta e}$, its total market potential N, its mean installed cost $\overline{C}$, and its mean lifetime $\overline{n}$. The estimates of each measure's mean annual energy savings per installation, together with the estimated market potential for each measure, determine estimates of total technical conservation potential.[1] The mean energy savings per installation, together with the mean installed cost, mean measure lifetime, projected fuel prices, and a selected discount rate, are jointly used to asses the mean cost-effectiveness of each conservation measure. The conservation potential associated with the subset of technically feasible measures which are estimated to be cost effective on average is generally used as the estimate of the total cost-effective conservation potential. These relationships are portrayed in Figure 2.1, which includes a schematic "conservation supply curve," the common means for graphically summarizing the results of measure-based studies of conservation potential.

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[1]Measure interaction complicates this computation; see, for example, Chapter 3.

Now, estimates of weatherization measures' mean installed cost, lifetime, energy savings, and market potential are uncertain. It is common to characterize the uncertainty in such estimates using estimated probability density functions, or "*pdf*s."[2]

> A [*pdf*] represents the relative likelihood of specific outcomes for an uncertain variable. The [*pdf*] quantitatively describes the state of information for the variable. In some cases the information may be based on actual experience (e.g., the unplanned outage rate for an existing type of generating unit). The results of a frequently repeated experiment define an objective [*pdf*]. In other cases little objective information may be available (e.g., the capital costs of a technology not yet commercialized), and the information base may consist primarily of judgment and opinion. In this case uncertainty is quantified as a subjective [*pdf*]. (EPRI 1991b, p. 6-3.)

Techniques for the development of objective *pdf*s are described in chapters 6 and 7 of Morgan and Henrion 1990; a bibliography on the topic is also provided in EPRI 1991b.

A central objective of the present chapter is to develop estimated *pdf*s for each of the four uncertain empirical inputs to analysis of current weatherization potential, $\overline{\Delta e}$, $\overline{C}$, $\overline{n}$, and N. Rather than attempt to characterize separately *for each weatherization measure* (e.g., wall insulation, attic insulation, etc.) the uncertainty in estimates for each of the four empirical inputs, this initial analysis will attempt to specify generalized estimates of the uncertainty in typical point estimates of each of the four inputs *for weatherization measures in general.* Thus, an attempt is made to estimate a "normalized" *pdf*s for each of the four empirical inputs, which can then be used in conjunction with a point estimate for a given input and a given weatherization measure, in order to derive an estimate of the uncertainty associated with that point estimate. The approach is outlined below, where the uncertainty in estimates of mean installed cost, $\overline{C}$, is used as an example.

Consider a random variable $J_{\overline{C}}$, whose *pdf* will be estimated as follows. Empirical data is obtained from weatherization program evaluations and other studies which

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[2]PDFs are sometimes simply referred to as "probability distributions"; however, use of the term "density function" helps avoid confusing PDFs with "cumulative distribution functions." The term "PDF" has been substituted for "probability distribution" in the excerpt which follows in the text.

report both predicted and actual mean installed costs for weatherization measures -- $\hat{\overline{C}}$, and $\overline{C}$, respectively.[3] This data is then plotted to form a *relative frequency histogram* (e.g., Walpole and Myers 1978, Hoel 1984) for the ratios of actual to predicted installed cost. The sample of ratios is treated as a simple random sample of observations of the random variable $J_{\overline{C}}$;[4] therefore, the *pdf* for $J_{\overline{C}}$ is estimated based on the relative frequency histogram and the statistics of the sample of values for the ratio $\overline{C}/\hat{\overline{C}}$

$$\textit{approximate relative frequency distribution of} \left[\overline{C}/\hat{\overline{C}}\right] \Rightarrow \; pdf\left[J_{\overline{C}}\right] \qquad (1)$$

Defined as in equation (1), the *pdf* for $J_{\overline{C}}$ will represent our best current estimate of the uncertainty associated with point estimates of mean installed cost which are used in analyses of current weatherization potential. Once this *pdf* for $J_{\overline{C}}$ has been estimated, it can then be used together with a new point estimate of the mean installed cost for measure *j*, $\hat{\overline{C}}_j$, in order to specify a *pdf* which characterizes the state of our information and uncertainty about the true value of $\overline{C}_j$. This is done by scaling both sides of the relationship in equation (1) by the value of the point estimate, $\hat{\overline{C}}_j$:

$$pdf\left[\hat{\overline{C}}_j * J_{\overline{C}}\right] \Rightarrow \; pdf\left[\overline{C}_j\right] \qquad (2)$$

By equation (2) it is *not* strictly meant that $\overline{C}_j$ is properly considered to be a random variable. Instead, $\overline{C}_j$ is considered to be a theoretically knowable fixed parameter, about

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[3]Note that it is important that the methods and data sources used to develop each of these studies' estimates of mean installed cost be representative of the methods and data sources which are used in "typical" studies of conservation potential. This point is addressed later in the present chapter.

[4]The assumption that the summary data from a set of program evaluations obtained via a literature search represents a simple random sample of all possible such results is a rather strong one. Its relaxation entails the use of meta-analytic techniques, (for example, Violette et al. 1992; Greene et al. 1993; Karr et al. 1993; Lagerberg et al. 1993, and Green and Violette 1994.), which are beyond the scope of the present analysis, but whose application is recommended as part of further extensions of the results and methods described here.

which we have some information but remain uncertain. The *pdf* of $\hat{\overline{C}}_j * J_{\overline{C}}$ specifies our "beliefs about the relative likelihood of each possible value of the variable, based on the state of [our] information." (EPRI 1991b, p. 6-3) The same approach is then taken to estimate *pdf*s for $J_{\overline{\Delta e}}$, $J_{\overline{n}}$, and J_N, which characterize the uncertainty in typical point estimates of the other three empirical inputs, $\overline{\Delta e}$, $\overline{n}$, and N.

Finally, in a subsequent chapter it will be of interest to characterize the uncertainty associated with estimates which are themselves *functions* of the uncertain empirical inputs $\overline{\Delta e}$, $\overline{n}$, $\overline{C}_j$ and N. For example, the estimate of the mean cost of conserved energy for measure j, $\overline{CCE}_j$, is calculated from the empirical input estimates as:

$$\hat{\overline{CCE}}_j = \left[\hat{\overline{C}}_j \Big/ \hat{\overline{\Delta e}}_j \right] \left(\frac{d}{1-(1+d)^{-\hat{\overline{n}}}} \right) \tag{3}$$

How can a *pdf* be developed which characterizes the uncertainty in this estimate of $\overline{CCE}_j$, given the characterizations of the uncertainty in estimates for the empirical inputs on which it is based, $\overline{\Delta e}$, $\overline{C}$, and $\overline{n}$? The simplest and most straightforward way is to use the point estimates $\hat{\overline{C}}_j$, $\hat{\overline{\Delta e}}_j$ and $\hat{\overline{n}}$ together with the estimated *pdf*s for the random variables $J_{\overline{\Delta e}}$, $J_{\overline{C}}$ and $J_{\overline{n}}$ directly in an "uncertainty propagation analysis," employing techniques of Monte Carlo simulation. From Morgan and Henrion (1990):

> In crude Monte Carlo analysis, a value is drawn at random from the distribution for each input. Together this set of random values, one for each input, defines a scenario, which is used as an input to the model, computing the corresponding output value. The entire process is repeated *m* times producing *m* independent scenarios with corresponding output values. These *m* output values constitute a random sample from the probability distribution over the output induced by the probability distributions over the inputs. One advantage of this approach is that the precision of the output distribution may be estimated from this sample of output values using standard statistical techniques. (p. 199)

Thus, the estimated "*pdf* for $\overline{CCE}_j$" developed through Monte Carlo analysis of the following expression, will characterize the uncertainty in estimates of the true value of $\overline{CCE}_j$ based on our estimates of the uncertainty in the "input" estimates $\hat{\overline{C}}_j$, $\hat{\overline{\Delta e}}_j$ and $\hat{\overline{n}}_j$:

$$\textit{Monte Carlo simulation of}\left\{\left[\frac{\hat{\overline{C}}_j * J_{\overline{C}}}{\hat{\overline{\Delta e}}_j * J_{\overline{\Delta e}}}\right]\left(\frac{d}{1-(1+d)^{-(\hat{\overline{n}} * J_{\overline{n}})}}\right)\right\} \Rightarrow pdf\left[\overline{CCE}_j\right] \qquad (4)$$

Neither the method described above nor its results require that any particular assumptions be made about the function form of the *pdf*s for $J_{\overline{\Delta e}}$, $J_{\overline{C}}$ and $J_{\overline{n}}$ (e.g., they need not be assumed to be normal, lognormal, etc.)[5] The estimated *pdf* for $\overline{CCE}_j$ will not generally be of any particular functional form either. The uncertainty propagation analysis will, however, provide an estimate of the expected value for $\overline{CCE}_j$ given the point estimate $\hat{\overline{CCE}}_j$. It will also generate estimates for the *pdf* and the cumulative distribution function of $\overline{CCE}_j$, which in turn can be used to estimate confidence intervals for the true value of $\overline{CCE}_j$, based upon its point estimate. Uncertainty propagation for energy conservation potential analysis is the subject of Chapter 3. Such an analysis requires estimates for the *pdf*s of $J_{\overline{\Delta e}}$, $J_{\overline{n}}$, $J_{\overline{C}}$ and J_N, whose development is the purpose of the present chapter.

An assumption being made at the outset of this analysis is that forms of standard practice can be identified with respect to both conservation potential analysis and estimation of input parameters. The standard practice of energy conservation potential analysis is described in Chapter 3. The assumption of standard methods for input estimation is examined recurrently in the present chapter.

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[5]It *is* important, however, that any correlations among input uncertainties be correctly characterized prior to the analysis. Failure to do so can lead to substantial biases in resulting estimates of the output mean, variance, and/or fractiles. Smith et al. (1992) describe these problems in more detail, and identify the circumstances under which statistical dependencies among the input parameters can be safely ignored.

There are several reasons to attempt a relatively basic characterization of empirical input uncertainties at present. First, empirical data allowing measure-specific probabilistic characterization of uncertainty are not yet available for each of the inputs for all weatherization measures. In fact, before a major attempt is made to develop and gather such data, it is prudent to attempt an initial analysis with existing data in order to determine the most important data requirements of later more detailed analyses of uncertainty in conservation potential estimation. It has been persuasively argued (Morgan and Henrion 1990) that quantitative uncertainty analysis should be conducted in an iterative process of data and model refinement. Initial results based on simple and readily available data indicate which empirical input uncertainties appear to be most influential, and how such uncertainties can best be described to provide inputs to probabilistic analysis. These results, in turn, help prioritize and focus subsequent data gathering efforts, and help guide re-allocation of analytical detail toward the most critical uncertainties.

Uncertainty Versus Variability, and the Use of "Binning"

The focus of the present study is the uncertainty in estimates of mean values ($\overline{\Delta e}$, $\overline{C}$, and $\overline{n}$), as well as in estimates of the market potential N, which together are used to develop estimates of total technical conservation potential and to estimate the fraction of technical potential which is cost-effective on average. In addition to concerns about the *uncertainty* in estimates of total potential and mean cost-effectiveness, policy and program decision-makers may *also* be interested about the expected *variability* in per-home or per-installation savings. For example, policy-makers may request estimates of the fraction of the participating houses which can be expected to experience negative savings, even in cases where predicted mean savings are positive.

Variability and uncertainty are not independent. There are two principal ways in which variability contributes to the uncertainty in estimates of conservation potential.

First, variability in population characteristics contributes to uncertainty in sample-based estimates of population means; the present paper includes efforts to estimate this impact of variability upon uncertainty. Secondly, variability in the factors which govern the cost-effectiveness of each technically feasible energy conservation measure causes most measures to be cost effective for only some fraction of the eligible population. Estimation of this fraction would require frequency distributions which characterize the estimated variability in each contributing factor, including estimates of the co-variation among the factors.[6] This influence of variability upon uncertainty in estimates of conservation potential is not analyzed in the present paper. It remains an important area recommended for further research.

In lieu of probabilistic treatment of the variability in population characteristics, "binning" is an important technique which is sometimes employed to at least partially account for variability's effects upon non-uniform cost-effectiveness for a given measure. Binning entails division of the physically eligible population into sub-groups with different mean characteristics. It is a way of trying to separately identify both the fraction of the eligible population for which a measure is cost-effective and the remainder of the physically eligible population for which it is not. In the evaluation of weatherization potential, binning is accomplished by the development of multiple prototypes to represent the population of houses physically eligible for a given measure.

Binning clearly increases the *resolution* of an analysis of conservation potential; it will lead to a conservation supply curve with a greater number of smaller steps, and can help identify measures which appear to be cost-effective for some fraction of the population even though they are not cost-effective on average for the whole population. On the down side, by increasing the number of prototypes, binning will tend to increase

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[6]For example, both the *cost* of insulating walls and the *energy savings* from insulating walls will increase with wall area.

sampling error uncertainty and the uncertainty in estimates of number of households represented by each prototype.

Whether binning enhances the accuracy of results as a basis for planning and policy depends in part upon whether measure installation will be preceded by some screening procedure such as a professional audit (or by reasonably accurate homeowner assessment of measure cost-effectiveness). The presence of a screening procedure is partly a function of program design, but also is partly tied to the type of measure. Some measures, such as compact fluorescent light bulbs, which are either low-cost or for which the cost-effectiveness is either reliable or difficult to assess with a pre-installation audit, are generally promoted to the entire eligible population without an audit. (In some programs, particular fixtures within individual houses are targeted for initial installation.) Weatherization measures, on the other hand, are generally only installed after an audit. Thus, a single-prototype-based analysis of weatherization potential will overestimate the mean "*to-be-actually-installed*" cost of conserved energy for all measures which are not cost-effective for some fraction of the physically eligible population. It will over-estimate the size of the "*to-be-installed*" market potential for these measures as well. For simplicity, conservation potential uncertainty analysis will be investigated initially under the simplifying assumption of one prototype per measure. As discussed later in the section on "errant prototype specification," it is still generally a generous characterization of standard practice to assume that a *single but different* prototype is specified to separately characterize the mean characteristics of the sub-population eligible for each measure.

A Note on "Conservative Under-Estimation" of Empirical Uncertainty

The present paper represents a departure from the literature's tradition of leaving input uncertainties un-quantified and un-analyzed. For this reason, where judgment is often called for in deriving estimates of input uncertainty based on published data, the conservative approach is deemed to be an attempt to err on the side of *underestimating* the magnitude of empirical uncertainties at present. Still, every effort is made to comprehensively *identify* the principal factors contributing to uncertainty, and to indicate for each of these factors whether it has been included or omitted in the process of deriving estimates of the total uncertainty in each of the inputs to conservation potential analysis.

Overview of Remaining Sections

The four sections which follow examine in turn the uncertainty in estimates of mean installed cost per measure, mean lifetime per measure, market potential per measure, and mean annual energy savings per measure. Energy savings uncertainty is described last because energy savings estimates, and thus their uncertainty, are considerably more complex than those of the other empirical inputs.

Mean Installed Cost per Measure

Three aspects of measure installed costs make the level of uncertainty in their estimates strongly dependent upon both the perspective and geographic scale of the conservation potential analysis. These aspects are:

1) measure costs may be controllable to varying degrees by program designers and/or implementers;
2) labor rates are partially a function of whether the crews are non-profits or for-profit; and,
3) labor and material costs for weatherization measures often vary considerably among and within states;

Each of these factors is considered briefly before available data are examined in order to develop estimates of measure installed cost uncertainty.

Control of Measure Installed Cost

The two principal agents of existing weatherization programs are utilities (electricity and natural gas) and the federally-funded, state-administered low-income Weatherization Assistance Program (WAP). For utility-sponsored programs the cost per installation is strongly dependent upon program design, and depends upon the type of program, the level of fixed expenditures allocated to marketing, administration, and evaluation, the level of participation achieved, and the perspective from which cost is evaluated (utility, participant, rate-payer, society, etc.). Thus, for purely marketing-or information-based programs, the uncertainty in direct program costs *to the utility* per installation is entirely a function of the uncertainty in projections of participation levels. For proven rebate-based programs with low administrative, marketing, and evaluation overhead, the utility cost per installation may be nearly certain, but if measure installed costs are uncertain then participant and societal costs for such programs will be uncertain as well.

The focus of the present study is measure-based (rather than program-based) analysis of conservation potential, for which installed costs are generally the sole costs considered, and in which possible effects of alternative program designs upon cost per installation are not generally considered. Several authors (e.g., Berry 1989, Krause et al. 1987, Nadel 1990, Koomey et al. 1991) have recommended and/or applied a "rule of thumb" that the "societal" cost of conserved energy should be increased by 10 to 20% to reflect the net effect of utility program costs upon average costs per measure-installation. However, Koomey et al. (1991) caution that "Program costs for particular end-uses may be lower or higher than these crude averages, [and] individual programs for specific end-uses may differ from these overall averages." (p.4)

In the case of WAP, current federal guidelines specify a maximum average expenditure per house, but no cost limits per measure. States have not adopted their own cost limits per measure either, in part because of significant geographic variability in material and labor rates within states. (e.g., Chapman 1994; Beachy 1994; Costello 1994) Some agencies or programs administered over smaller geographic scales such as a single metropolitan area do exercise effective control over costs per measure. An example is the Project Insulate Standards and Prices manual published by the Saint Paul Neighborhood Energy Consortium (1993), which specifies highly detailed cost limits for each weatherization measure. Such cost limits are generally derived from an iterative process of information exchange with contractors in the region. In fact, many WAP subgrantees (local non-profit agencies which administer the WAP for a given sub-state region) periodically solicit measure-cost bids from area contractors and set cost limits based upon contractor input. (Chapman 1994)

Geographic Variability of Labor and Material Costs

Geographic variability of labor and material costs for energy conservation measures complicates cost estimates used in studies of conservation potential in several ways. First, cost estimates derived from large samples of cost data over multiple regions (such as developed by Boghosian and McMahon (1993)) must adjust each data point for regional (and temporal) cost variation before the data are combined to generate national current cost estimates. Likewise, cost data from one region may need to be adjusted before they are used as an estimate for another region. Next, if regional cost variability is significant within the area whose conservation potential is being estimated, then regional average costs will depend upon the geographic distribution of the eligible stock, and measure cost-effectiveness may vary by sub-region. Finally, geographic cost variation contributes to total *variability* in the cost-effectiveness of each measure, which is an issue beyond the scope of the present paper, as noted in the introduction.

The principle source of data on regional (and temporal) variability in residential retrofit costs is the series of reports published by R.S. Means (e.g., Means 1993), which provides contractor survey-based regional (and temporal) cost "multipliers" for converting national cost estimates into estimates for specific metropolitan areas within the US, and vice-versa. As an example, Means' regional multipliers for the metropolitan areas of New England are summarized in Table 2.1 and Figure 2.2. Total cost multipliers (weighted combinations of material and installation cost multipliers) exhibit standard deviations on the order of 5-10% of the mean, for New England as a whole as well as within the larger individual states. Installation (labor) costs vary most widely.

Note that Means' data allow for cost comparison only among major metropolitan areas. While data comparing rural to non-rural residential retrofitting costs are sparse, anecdotal evidence indicates that rural labor rates are considerably lower, while rural material costs may be higher than those of moderately-sized metropolitan areas (due to increased distance to suppliers). Rural material and labor costs are both generally lower than those of the very large, hi-cost urban areas such as metropolitan New York or Boston.[7]

Non-Profits vs. Private Contractors

In the early 1980's nearly all WAP work was done by employees of non-profit agencies and community-based organizations. During the past decade, there has been a steady increase in the amount of weatherization work under the WAP which is subcontracted to professional contractors by the local agencies. (Brown et al. 1993) Private contractor installation costs, unlike installation costs reported by non-profits, include profit and overhead. As part of their residential retrofit cost data compilation, Boghosian and McMahon (1993) cited $20.00 per hour (1989 dollars) as the typical residential retrofit labor rate; their sources include a mix of utility programs, WAP programs, and research projects. Boghosian and McMahon's labor rate closely matches the R.S. Means' national bare labor rate estimate for residential weatherization

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[7]Based upon conversations with Bill Beachy (VA), Tim Lenahan (NH); and Pat Costello (NY); see references.

retrofitting; final Means-based labor plus material cost estimates per measure which include overhead and profit are approximately 10% higher than bare costs.[8] In fact, Means national cost estimates (including overhead and profit) exceed Boghosian and McMahon's estimated US average costs for insulation retrofits by about 10% on average.

Empirical Estimates of Uncertainty in Installed Measure Costs

In order to estimate the costs of shell retrofit measures as part of a national study of the potential for cost-effective single family thermal shell retrofitting, Boghosian and McMahon (1993) assembled measure installed cost citations from fourteen different sources nationwide and adjusted for regional- and temporal-based variation using the Means multipliers described above. Each reference provided cost citations for several individual measures, and in most cases, the cost citations were quotations for contractor work in a typical government retrofit program. Boghosian and McMahon noted that since regional and temporal cost-scaling multipliers are inexact, then imprecise scaling may contribute to some portion of the observed variability among cost estimates for a given measure. However, after testing alternative scaling approaches, they concluded that variation among reported costs for each measure after scaling appeared to be "caused by sources other than geographic, temporal, and labor-to-material cost differences." (p. 14) For each retrofit measure, Boghosian and McMahon used the arithmetic mean of the scaled cost estimates as the final estimate of the measure's installed cost.

The data from Boghosian and McMahon's compilation were analyzed statistically as reported in Table 2.2, to quantify the variability among reported measure installed costs, in an attempt to characterize the uncertainty associated with measure cost estimates used in conservation potential studies. For each measure with four or more cost quotes,

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[8]See rates for carpenter and for "Crew G-4" in the Means Repair and Remodeling Cost Data: Residential and Commercial (Means 1993).

the ratio of each quote to the mean of all such quotes for the given measure was calculated. Then, the estimate for the variance among these ratios (given by the sum of the squared errors divided by (n-1)) was calculated for each measure, as well as for each component (e.g., attic, walls, sub-floor), and for the dataset as a whole. Based on the results in Table 2.2, the cost quotes will be approximated as distributed in a bell-shaped fashion (not necessarily normally) about their mean (per measure) with a standard deviation equal to 20% of the mean.[9]

What does the variability among Boghosian and McMahon's retrofit cost quotes indicate about the uncertainty in installed cost estimates used in conservation potential studies in general? First, note that the Boghosian and McMahon compilation represents the most comprehensive published synthesis of retrofit cost estimates to date; most studies' estimates of mean retrofit costs appear to be derived from smaller samples. Second, the variability among cost quotes per measure did not appear to change significantly *between* measures. The following assumptions allow a first-order estimate of the uncertainty in "typical" estimates of mean cost per measure:

1) Assume that the variation among quoted or published costs exhibited in Boghosian and McMahon's data is indicative of the variability of per-measure cost estimates generally found in cost samples obtained by analysts of conservation potential -- that is, quotes or citations are distributed in a bell-shaped fashion about their mean per measure with a standard deviation equal to approximately 20% of the mean;

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[9]A standard deviation of 0.20 is a bit lower than found in the dataset. However, the ratios of individual quotes to the measure mean quotes exhibited a somewhat bimodal distribution (although the sample size (n=43) is not large enough for this to be definitive.) The bimodality might reflect the presence of data from both private and non-profit contractors (e.g., two sets of labor rates), so that some of the variability in quotes might in principle be corrected for. However, source identification provided in the report did not allow for testing of this hypothesis.

2) Assume that estimated mean costs per measure used in individual studies are typically based on four independent cost quotes per measure;[10]

3) Assume that each cost quote refers to the estimated mean installed cost across the entire population being studied; this assumption is based on fact that Boghosian and McMahon's data included corrections for geographic (as well as temporal) variation in costs; thus, the conservation potential analysts' estimate of the mean installed cost for each measure is set equal to the mean of the four quotes for the measure;

Then, from Boghosian and McMahon's data and the central limit theorem, analyst's quote-based estimates of the true mean costs per measure should be roughly normally distributed about the true mean costs with a standard deviation of $0.2/\sqrt{4} = 0.1$. In other words, true mean installed costs are expected to lie within approximately ±20% of the analysts' estimates approximately 95% of the time. Note that this estimate of $J_{\bar{C}}$, the uncertainty in estimates of mean installed cost per measure, is also based on the assumption that for studies whose geographic scope is large enough to lead to significant sub-regional cost variability (ex, state or national studies of conservation potential), analysts will make the same effort to normalize quotes for regional variation as was made by Boghosian and McMahon.

Data from a regionally-focused study provide a look at measure cost uncertainty when inter-temporal scaling, inter-regional scaling, and inter-regional cost variability are not confounding issues. The results of Ternes et al. (1991) provide data from a study where *local and current* material and labor rate estimates were available and were used to predict local and current per-measure and per-home installed costs. In their Buffalo, NY

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[10]Few conservation potential studies actually report this statistic; a rare example is Randolph et al. 1991. In fact, many (e.g., UCS 1991, Miller et al. 1989) rely on prior published summaries of cost data obtained for other regions (e.g., Krause et al. 1987, OTA 1982), which may be 5-10 years older than the studies using them (e.g., UCS 1991, p. A-52 and A-56.) Koomey et al. 1991 used Boghosian and McMahon's retrofit cost estimates.

evaluation of a single-family weatherization measure selection technique, local cost estimates were developed by obtaining quotes from several (approximately 2-4) local contractors for each measure. (Ternes 1994) The estimated installed costs were then compared with the actual per-measure and per-home costs of weatherizing 36 homes. Cost estimates for each made use of pertinent audit data, such as wall area in the case of the cost of wall insulation. The results describing cost prediction accuracy are summarized in Figures 2.3 and 2.4.

Figure 2.3 compares the mean predicted and mean actual costs per measure. For most measures, the actual cost per installation was higher than estimated, although the two under-prediction outliers reflected unexpected labor costs for very low cost measures (lower the hot water temperature setting, and insulate hot water pipes). The one significant over-prediction of costs (for air sealing work) was also explained, since the cost estimate was based on a protocol calling for more extensive sealing than the actual protocol used in the field. Even without these three outliers, the standard deviation of > 0.25 indicates the possibility for significant uncertainty in even local quote-based estimates of average installed costs per measure. Predictions of total weatherization cost per home fared a bit better than those of mean cost per measure (see Figure 2.4). The absence of prediction bias indicated that over- and under-predictions per measure tended to cancel out *on average* at the household level, and was aided by the fact that some higher-cost, frequently-installed measures had a small mean prediction error (e.g., wall and attic insulation).

In summary, the variability evidenced in Boghosian and McMahon's data set has been used to derive an estimate of the uncertainty in estimates of mean installed cost per measure which are used in state or national-scale studies of conservation potential. Clearly, actual uncertainty in cost estimates will depend upon the procedures, data, and sample size upon which each study's cost estimates are based. Variability among quoted costs may be less for smaller regions such as single metropolitan areas, but it is not clear how much this will actually reduce the uncertainty in quote-based estimates of mean installed cost per measure. In the future, it would be helpful if the estimation procedure and the variability among cost quotes (if they are used) were reported by each study to allow assessment of the reliability and uncertainty of estimates for mean installed cost per measure, and to allow meta-analytic synthesis of cost data from multiple studies. (e.g., Violette et al., 1992) Finally, estimates of total *program cost* per measure are likely to be more uncertain than estimates of installed cost if, as is typical, uncertain installed costs are multiplied by an uncertain percentage to derive program cost estimates, *unless* features of the program provide the opportunity to exercise significant control over cost variation and uncertainty.

Mean Lifetime Per Measure

The empirical basis for estimates of many energy conservation measure's lifetimes is slight. (e.g., Vine and Harris 1990; EMS 1993) Of the four empirical inputs to analysis of current weatherization potential, measure lifetime estimates are probably the least-supported by empirical data, and as will become clear, this lack of empirical data forces characterizations of lifetime estimate uncertainty to rely purely upon judgment. In fact, expert judgment is the major source of residential retrofit measure life point estimates at present. The virtual absence of any published quantitative estimates of measure life uncertainty leads us to recommend that future collaborative processes or expert elicitation exercises which develop measure life estimates based on expert judgment *also* seek experts' quantitative judgments about confidence intervals for mean measure life estimates.

Improvement of measure lifetime estimates has gained increased attention in recent years, and has become an integral part of studies of measure persistence; see, for example, (Vine 1992), which reviews persistence research. As most residential retrofit measure estimated lives exceed 10 years, the final results of studies designed to track measure longevity directly would obviously be a long time in coming.[11] In lieu of such long-term direct research, several recent studies have examined the assumptions and sources underlying current lifetime estimates, have assessed the realism of these assumptions and sources, and have recommended adjustments to lifetime estimates which take account of both field operating conditions and data on the incidence of premature removal for particular measures. (e.g., Skumatz et al. 1991; SRC 1992; EMS 1993; Granda 1992, and Wiggins and Boutwell 1991) Data on measure retention should continue to improve as program evaluations considering this topic proliferate.

It has become common to distinguish three definitions of measure lifetime (e.g., Gordon et al. 1988; Vine 1992; CEC 1993; EMS 1993)

a) Engineering Life is the average life of a measure under laboratory test conditions, which can be ideal for measure longevity. (CEC 1993) Engineering lifetime estimates are usually provided by the manufacturer.

b) Operating Life or Service Life is the average lifetime of a measure under typical operating conditions and average maintenance practices. Major sources for such estimates include ASHRAE manuals. (e.g., ASHRAE 1987)

c) Effective Life or Useful Life takes account of the combined effects of field operating conditions (which yield Service Life rather than Engineering Life) *and* the effects of premature removal due to customer dissatisfaction, building remodeling, renovation, demolition, occupancy changes (e.g., new tenants move in and remove measures), etc.[12]

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[11]As of 1991, the longest-running energy savings persistence studies covered only 7 years of data, and were based on billing analysis rather than physical monitoring of measures' performance or physical integrity.

[12]A California collaborative with representation from the state's major investor-owned utilities and the California Energy Commission determined that Effective Life could be quantitatively derived (from empirical data) as the elapsed number of years between the installation of a cohort

The importance of field operating conditions, poor maintenance, and premature removal appear to vary considerably among measures. For example, commercial lighting, residential lighting, and residential low-flow showerheads and faucet aerators have each shown significant incidence of premature removal; reported first-year removal rates have varied considerably for the same measure, and among measures. For some of the shorter-lived weatherization measures such as air sealing, caulking and weatherstripping, field studies are likely to be hampered by difficulties of measure identification. (Bordner 1994) Lifetimes of longer-lived shell insulation measures are primarily ended by structural demolition, although remodeling of attics or basements may also play a role.

Given the current dearth of empirical data on measure life, present assessments of the uncertainty in measure life estimates must come primarily from "expert judgment" -- as do many measure lifetime estimates themselves. (Messenger 1994) During a collaborative investigation of measure lifetime assumptions and their bases which involved representatives of the major California investor-owned utilities and the California Energy Commission, utility analysts were asked to rate their confidence in measure life estimates as either "very confident", "confident", "somewhat confident", or "low confidence". Unfortunately, these confidence levels were not given quantitative expression. The large majority of measure life estimates were rated as either "somewhat confident" or "low confidence." (EMS 1993) The final report of this collaborative study noted that "the utilities did not think their measure life estimates were wrong or baseless. However, in the absence of field studies... and with the knowledge that field studies are planned for the future, the utilities were generally hesitant to adopt a less-than-conservative confidence rating." (p. 5)

At this point it may be useful to recall decision theory's rule that additional information (e.g., better data on measure lifetimes) is only of value if it has the potential

of measures and the time when 50% of those measures have either been removed or have ceased to operate in the building environment in which they were originally installed (EMS 1993).

to change some conclusion or decision. In deterministic, measure-based studies of energy conservation potential, the sole influence of measure life is its effect upon the cost of conserved energy.[13] (Lifetime estimates' influence on program cost-effectiveness in utility integrated resource planning can become more complex when "efficiency resources" are projected to be sizable enough to potentially delay requirements for new supply-side resources.) Among the longer-lived measures, attic and wall insulation have been proven to save so much energy per year per dollar invested, that as long as their lifetime exceeds 5-15 years they are reliably cost effective measures at current energy prices. (e.g., Cohen et al. 1991) Secondly, as measure lives increase, the effect of a given percentage variation in measure lifetime upon the measure's CCE diminishes, due to discounting of out-year energy savings. For example, at a 5% discount rate and nominal measure life of 25 years, variations in measure life of ±20% lead to variations in CCE of only ±10%; at a 10% discount rate, the variations in CCE are reduced to ±3% (see, for example, Chapter 1). For shorter-lived weatherization measures such as air sealing or heating system retrofits, however, uncertainties in measure lifetimes have the potential to be quite influential. The potential for high nominal cost-effectiveness and discounting to lead to minimal influence of measure life uncertainty upon estimates of cost-effective conservation potential is examined in more detail in Chapter 3; however, such an investigation requires as an input at least first-order estimates of the range of uncertainty in measure life estimates.

Summary of Residential Retrofitting Measure Lifetime Estimates

Recently published surveys or summaries of residential retrofit measure lifetimes are consolidated in Tables 2.3 and 2.4; Table 2.3 presents estimates for shell and heating system retrofits, while Table 2.4 presents estimated new-purchase heating appliance

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[13]In probabilistic analysis of conservation potential, measure life may also influence estimates of measure mean savings per year, as discussed in the section on energy savings uncertainty.

lifetimes, which are the basis for estimates of furnace/boiler replacement lifetime estimates. Only one of the five sources in Table 2.3 (EMS 1993) included sub-citations of the sources of the estimates; all but two of the ten measure lifetime estimates from this report were based on either the California Collaborative Process (5 measures) (also a separately-cited source of estimates in Table 2.3), or "engineering judgment based on experience with this technology" (6 measures). A majority of appliance-life sources reported low, median, and high lifetime estimates rather than single point estimates. This caused the ranges among appliance life estimates to be considerably larger than the variations found among most retrofit measure estimates: retrofit measure ranges are typically on the order of ±15-25% of the mean estimate, while appliance life ranges approach ±50% of the mean in some cases.

Neither the data summarized in Tables 2.3 and 2.4 nor the results of the collaborative California investigation provide a basis for quantitative estimates of the uncertainty associated with residential retrofit measure lifetime estimates. For the present analysis, a purely judgmental specification of J_n as normally distributed with mean 1.0 and standard deviation of 0.25 is adopted based on Tables 2.3 and 2.4.. This leads to 90% confidence intervals of approximately 50% of the point estimate. As recommended earlier, future collaborative processes or expert elicitation exercises which develop measure life estimates should also seek experts' quantitative judgments about confidence intervals for mean measure lives.

Market Potential per Measure

Estimates of measure market potential, as well as of the uncertainty in such estimates, come from household energy use surveys. Features of such surveys which are the major determinants of estimate uncertainty include the sample size, the age of the survey data, and the degree of geographic overlap between the sample area and the area for which conservation potential is being estimated.

The three principal sources of market potential estimates in the US are summarized below.

1) EIA's triennial Residential Energy Consumption Survey (RECS). (e.g., EIA 1992; 1993b; 1993c) RECS represents the only detailed national survey of residential equipment and building stock characteristics (particularly since the decennial census of population has paid successively less attention to energy-related building and appliance characteristics over the past three decades). Because RECS is national in scope, its sample size for particular census divisions is quite small (for example, less than 350 single-family houses in New England), and does not provide state-level estimates of stock characteristics.

2) Utility Residential Appliance Saturation Surveys ("RASSes"). An effort is underway at the Lawrence Berkeley Laboratory to synthesize the results from nearly 100 RASSes nationwide, partly to overcome the sample size/geographic detail limitations of RECS. Once this database becomes available, it may considerably reduce the uncertainty in estimates of residential retrofitting market potential, as the cumulative sample size of the full set of RASSes is over 90 times that of RECS (LBL/EED 1993).

3) State-level residential audit databases. Several states in the US have continued to provide for subsidization of free home energy audits following the termination of federal funding for the Residential Conservation Service audits in 1990. In some of these states, (for example, Massachusetts, Rhode Island, and Connecticut), mechanisms are either in place or under development to catalog electronically the results of the tens of thousands of residential audits completed annually. While the resulting audit databases suffer from some self-selection bias, their large sample size and comprehensive fuel coverage may make them an important complement to the RASS compilation described

above, and a potentially rich source of data for state-level conservation potential estimates.

Table 2.5 reports point estimates along with approximate relative standard errors (RSEs) for the market size (N_j) for selected weatherization measures, based upon data from the 1990 RECS. RSEs per measure vary both by measure and by region, ranging from 5% to 28% of the estimate. The average RSE for estimates of measure-eligible population sizes reported in Table 2.5 is 14%, and RSEs are generally larger for the smaller market size estimates. For the numerical examples in the present paper, the mean value RSE of 14% is adopted as a crude estimate of the uncertainty in RECS-based, census-region-scale, market size estimates in general; thus, J_N is estimated to be normally distributed with mean 1.0 and standard deviation 0.14. Since market sizes vary considerably by measure, it appears likely that market size estimate uncertainty will vary considerably as well. RECS-based market potential estimates for census divisions are more uncertain still. Future state-level estimates should benefit dramatically from the coming availability of the RASS database and/or residential audit program databases described above.

Mean Annual Energy Savings per Measure

Estimates of per-installation annual energy savings used in conservation potential analyses are based upon simplified models which utilize incomplete and errant data to characterize the stock of houses, their energy-using equipment, and the conservation measures themselves. Such estimates are also based upon estimated climate data for a long-term average ("normal") weather year, and they further neglect non-climate-induced year-to-year variability in annual energy savings (imperfect "persistence" of first-year savings. It is possible therefore to identify three separate factors contributing to uncertainty in estimates of mean annual energy savings per measure:

1) uncertainty in estimates of *first-year* savings, assuming normal climate years;

2) uncertainty in annual savings due to deviation of annual climates from normal; and,

3) uncertainty about persistence of (weather-normalized) first-year savings.

The first of these three factors clearly leads to a static uncertainty, in that a "one-time" parameter --mean first-year weather-normalized savings per measure -- is being estimated. The latter two factors are dynamic *factors*, in that persistence and climate are both expected to vary from year to year. However, neither the annual climate *estimate* nor the uncertainty of this estimate should change over the measure life (neglecting uncertainties about global climate change), so that climate uncertainty, like first-year savings uncertainty, is a static *uncertainty*. Persistence alone is potentially a dynamic *uncertainty*, in that the estimated effect of persistence, as well as the uncertainty in this estimate, may be different for different years during the measure life.

As discussed in the introduction, uncertainty in estimates of $\overline{CCE_j}$ will be characterized by a *pdf* developed through Monte Carlo analysis utilizing the *pdf*s of $J_{\bar{n}}$, $J_{\bar{C}}$, and $J_{\overline{\Delta e}}$, which characterize the uncertainty in $\hat{\bar{n}}_j$ as an estimate of $\bar{n}_j$, $\hat{\bar{C}}_j$ as an estimate of $\bar{C}_j$, and $\hat{\overline{\Delta e}}_j(y)$ as an estimate of $\overline{\Delta e}_j(y)$, respectively. The estimates $\hat{\bar{n}}_j$and $\hat{\bar{C}}_j$ are scalar quantities, and so their uncertainty is characterized by the *pdf* of single random variables $J_{\bar{n}}$ and $J_{\bar{C}}$. However, the discussion above pointed out two aspects which differentiate estimates of annual energy savings from these scalar estimates:

1) first, individual uncertain estimates are actually being made for the energy savings to occur in each year of a measure's life; and,

2) the uncertainty in these annual estimates may change from year to year.

For these reasons, it is necessary to consider energy savings estimates as a *vector* of estimates (of dimension y), $\hat{\overline{\Delta e}}_j(y)$, and to characterize the uncertainty in annual energy savings estimates as a *vector* (of dimension y) of *pdf*s for a vector of random variables,

$J_{\overline{\Delta e}}(y)$. The following discussion defines how these vectors are used in calculating the two quantities of primary interest in conservation potential studies (recall Figure 2.1): the energy savings potential associated with measure J, and the cost-effectiveness of measure j. Calculation of energy savings potential is considered first.

A standard assumption made to simplify calculations of energy savings potential is that the population-mean energy savings in year y achieved by measure j, $\overline{\Delta e}_j(y)$, is constant from year to year. A less restrictive approach which acknowledges the dynamic nature of the estimate yet yields the same simplicity of calculations, is to specify that calculations of the total energy savings potential associated with each measure, E_j, should be based on the temporal-mean (i.e., over the measure life) of the population-mean annual savings, $\overline{\overline{\Delta e}}_j$, which is given by

$$\overline{\overline{\Delta e}}_j = \frac{1}{n}\sum_{y=1}^{n} \overline{\Delta e}_j(y) \tag{5}$$

This allows us to define the energy savings potential associated with measure j as:

$$E_j = \overline{\overline{\Delta e}}_j * N_j \tag{6}$$

Given these definitions, the uncertainty in estimates of the quantities $\overline{\overline{\Delta e}}_j$ and E_j will be characterized by the *pdf*s obtained by Monte Carlo simulations ("MCS") of the following expressions:[14]

$$pdf\left[\overline{\overline{\Delta e}}_j\right] \Leftarrow MCS\left\{\frac{1}{\hat{\bar{n}} * J_{\bar{n}}} * \sum_{y=1}^{\hat{\bar{n}} * J_{\bar{n}}}\left(\hat{\overline{\Delta e}}_j(y) * J_{\overline{\Delta e}}(y)\right)\right\} \tag{7}$$

and

$$pdf\left[E_j\right] \Leftarrow MCS\left\{\frac{\hat{N}_j * J_N}{\hat{\bar{n}} * J_{\bar{n}}} * \sum_{y=1}^{\hat{\bar{n}} * J_{\bar{n}}}\left(\hat{\overline{\Delta e}}_j(y) * J_{\overline{\Delta e}}(y)\right)\right\} \tag{8}$$

[14]For compactness of notation, the functional notation "$MCS\{\ldots\}$" will be used to represent the estimated *pdf* which results from a set of Monte Carlo simulations.

Constant energy savings is also generally assumed in calculations of the mean cost effectiveness of each conservation measure. However, because of the use of discounting in calculating measure cost-effectiveness, it is not clear that the estimated temporal mean of the population mean energy savings should be used in estimating mean measure cost-effectiveness. In particular, it seems that uncertainties in later years should be discounted with respect to uncertainties in earlier years when estimating the uncertainty in estimates of measure cost-effectiveness. This concern is addressed below.

In conservation potential studies, a cost-effectiveness index is used to rank-order the conservation measures prior to final calculations of their individual energy savings, in order to account explicitly for measure interaction and thus avoid double-counting of energy savings. The cost-effectiveness index is also used to evaluate what fraction of the final technical conservation potential is estimated to be cost-effective. Virtually all conservation potential studies have employed the "Cost of Conserved Energy," or CCE,[15] which can be defined in several different ways:

$$CCE = \frac{\overline{C} * \left(\dfrac{d}{1-(1+d)^{-n}} \right)}{\overline{\overline{\Delta e}}} = \frac{\text{annualized } \overline{C}}{\overline{\overline{\Delta e}}}$$

$$= \frac{\overline{C}}{\begin{array}{c}\text{present - valued}\\ \text{energy savings}\end{array}} = \frac{\overline{C}}{\sum_{y=1}^{n} PV\left(\overline{\Delta e}(y)\right)} = \frac{\overline{C}}{\sum_{y=1}^{n} \left(\overline{\Delta e}(y) * e^{-yd}\right)} \tag{9}$$

CCE is usually defined as the "ratio of annualized installed cost to (constant) annual energy savings" (e.g., Vine and Harris 1990, Rosenfeld et al. 1993, Meier 1982, EIA 1990); this definition is expressed in the first line of equation (9). An alternative definition of the same formula, expressed by the second and third lines of equation (9), is "the ratio of measure installed cost to present-valued energy savings." The measure installed cost is a

[15]The advantages and disadvantages of CCE compared with alternative cost-effectiveness indices are discussed in Chapter 3.

one-time, fixed, static, uncertain quantity. On the other hand, energy savings estimates are in fact a vector of estimates, one made for each year of the measure life (even when constant energy savings is assumed in the estimate). For this reason, the latter definition and formulation of CCE is preferred for the present analysis. Using this final expression for CCE, the uncertainty in $\hat{\overline{CCE_j}}$ as an estimate of $\overline{CCE_j}$ will thus be estimated via Monte Carlo simulation as follows:

$$pdf\left[\overline{CCE_j}\right] \Leftarrow MCS\left\{\frac{\hat{\overline{C}}_j * J_{\overline{C}}}{\sum_{y=1}^{\hat{\overline{n}}*J_{\overline{n}}}\left(\hat{\overline{\Delta e}}_j(y) * J_{\overline{\Delta e}}(y) * e^{-yd}\right)}\right\} \tag{10}$$

Defining the Three Constituents of Total Uncertainty in Annual Savings Estimates

As pointed out in the previous section, three separate factors contribute to the total uncertainty in estimates of mean annual energy savings per measure: uncertainty in estimates of *first-year* savings, assuming normal climate years; uncertainty in annual savings due to climate variability; and uncertainty about persistence of (weather-normalized) savings. A simplifying assumption to be made for this initial analysis is that the influences of these three factors are statistically independent.[16] The second major assumption to be made is that the total uncertainty in the estimate of a year's energy savings can be modeled as the product of the three contributing uncertainties. No assumptions about the functional form of the *pdf*s characterizing any of the uncertainties are required, however. Given these assumptions, the total uncertainty in estimates of energy savings per year will be characterized as:

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[16]This assumption requires the assumption that weather-normalized persistance is independent of climatic variation. Behavioral factors such as budget constraints may in fact lead to some degree of negative correlation between annual climate-induced variability in savings and annual viriability in weather-normalized annual consumption (which falls under the heading of persistance); this question should be investigated empirically.

$$pdf\left[\overline{\Delta e}_j(y)\right] \Leftarrow MCS\left\{\hat{\overline{\Delta e}}_j(n) * J_{\overline{\Delta e}(n)} * J_{HDD}(y) * J_{persist}(y)\right\} \tag{11}$$

where:

$\hat{\overline{\Delta e}}_j(n)$ is an engineering-based estimate of population-mean, first-year, weather-normalized energy savings due to measure *j*. In standard analyses of conservation potential, this quantity is used as the estimate of constant, population-mean, annual energy savings;

$J_{\overline{\Delta e}(n)}$ is a random variable whose *pdf* characterizes the uncertainty in engineering estimates of mean first-year, weather-normalized energy savings, for all weatherization measures in general; it will have a mean of 1.0 if engineering estimates are expected to be unbiased;

$J_{HDD}(y)$ is a random variable whose *pdf* characterizes the uncertainty introduced by using population mean normal annual heating degree days as an estimator of the actual population mean total heating degree days to occur during year *y*;[17] it will have a mean of 1.0 if the population-mean normal heating climate provides an unbiased estimator for future mean annual heating climates; and

$J_{persist}(y)$ is (a random variable whose *pdf* characterizes the uncertainty introduced by assumptions of perfect persistence of first-year, weather-normalized savings. If empirical data indicate that on average, weatherization savings persist perfectly over time, then $J_{persist}(y)$will have a constant mean equal to 1.0; if not, its mean will be different from 1.0, and may vary from year to year.

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[17]The present study will adopt the simplifying assumption that the ratio of actual to normal heating degree days in a given year is invariant accross all the eligible houses in the area of study. Variation among eligible houses in normal heating degree days is acknowledged, however.

Based on equation (7), the uncertainty associated with estimates of the temporal-mean of population-mean savings is thus a function of the uncertainties associated not only with estimates of annual population-mean energy savings, but also the uncertainties in estimates of measure life. This dual dependence upon measure life uncertainty and annual mean energy savings uncertainty is also true of the final uncertainty in estimates of the present value of the stream of annual energy savings. Synthesis of these empirical input uncertainties to characterize the final uncertainty in estimates of conservation potential is taken up in Chapter 3. The purpose of the present chapter is simply to establish a taxonomy of the uncertainties affecting the empirical inputs to conservation potential analysis, to review the state of available data which can support estimates of these uncertainties, and to develop initial estimates of these uncertainties.

The disaggregation of $J_{\hat{\bar{e}}}$ into its three independent constituents is portrayed graphically in Figure 2.5. That figure also illustrates how $J_{\hat{\bar{e}}_j(n)}$ is further disaggregated into the five independent factors which contribute to it, as will be discussed in the following sub-section.

Uncertainty in First-Year Weather-Normalized Savings Predictions

A host of characteristics of a house, its utilization by occupants, and its environment interact to determine its annual space-heating energy consumption. Energy conservation measures operate by altering one or more of the following characteristics which together determine annual energy consumption:

- area and thermal conductance of walls, ceiling, floor, windows, and doors;
- instantaneous flow rate and temperature of air infiltrating the heated space, and/or cavities in shell components such as walls, floors, etc.;
- combustion and cyclic efficiency of the heating appliance;

- efficiency of the distribution system;
- time-varying thermostat settings (settings during the day, at night, when occupants leave, etc., and timing of changes);
- time-varying operation of curtains, windows, exhaust fans, etc.
- instantaneous internal thermal gains (from occupants, appliances, etc.)
- instantaneous climatic influences (exterior temperatures, wind, and solar insolation).

Let the full set of all non-climatic characteristics and factors which influence the total annual space-heating energy consumption for house i during year y be designated as $S_i(y)$. Further designate the full set of climatic factors influencing total annual space-heating energy consumption for house i during year y as $K_i(y)$. The actual change in space-heating energy consumption during the first year after weatherization relative to the last year prior to weatherization (i.e., from year "0" to year "1) is a function of these two sets of factors before and after weatherization:

$$\Delta e_i(0 \rightarrow 1) = e_i[S_i(0),\ K_i(0)] - e_i[S_i(1),\ K_i(1)] \tag{12}$$

If the climate during years 1 and 2 had been equal to the long-term average or "normal" climate (typically based on 30 years of recent data), then the observed change in space heating energy consumption would have equaled the change in normal-climate annual heating energy consumption, $\Delta NAHC$:

$$\Delta NAHC = e_i[S_i(0),\ K_i(n)] - e_i[S_i(1),\ K_i(n)] \tag{13}$$

Although equation (12) represents the actual change in energy consumption occurring between years 0 and 1, it is estimates of (13) which are used in conservation potential studies, since the average climate over the past 30 years presumably provides a best estimate of the annual climate which will occur during the measure life. Secondly, empirical measurements of first-year energy savings (with which energy savings predictions have generally been compared to assess their accuracy) *also* include attempts to weather-normalize the observed change in energy consumption, in order to factor out the effects of climate variation between the two years. The standard source of measurement-based estimates of energy savings, $\Delta N\hat{A}HC_i$, has been the PRISM method (Fels 1986), which typically utilizes two years' fuel billing records (one year prior and one year following weatherization), together with data on heating degree days observed during each billing period and on the normal annual heating degree days for the region under study.

Conservation potential studies generally employ engineering-based predictions of the average per-installation change in weather-normalized annual heating energy consumption achievable by each measure. Below is an initial attempt to catalog the types of factors which contribute to the final uncertainty in the savings predictions used in conservation potential studies. The results are summarized in Tables 2.6 and 2.7, and in Figures 2.5 and 2.6. Such a catalog helps guide subsequent adoption and interpretation of empirical results characterizing the uncertainty due to various combinations of these factors, in order to estimate the total uncertainty associated with energy savings predictions.

Let $\tilde{k}_i(y)$ refer to a set of discretized (e.g., monthly, daily, etc.) measurements of climate characteristics, such as weekly heating degree-days, or even hourly measurements of outdoor temperature, wind speed, and insolation, estimated to be representative for house i during year y. Thus, $\tilde{k}_i(y)$ is a set of imperfect *measurements and/or estimates of a subset* of the full set of climatic characteristics $K_i(y)$ which influence house i's heating energy consumption during year y. Further let $\tilde{k}_i(n)$ refer to the long-term normal (e.g., 30-year average) measured values for this subset, and let $\hat{\bar{\tilde{k}}}_j(n)$ refer to the *estimated population means* of these measurable characteristics, for the population of houses eligible for installation of measure j, which is based on a sample of measurements taken for a subset of the eligible population. The notation for estimated means of measurable non-climatic characteristics, $\hat{\bar{\tilde{s}}}_j(y)$, is similar. In both cases, the notation indicates that input data are *sample-based estimates* ("^") of *population means* ("-") based on *imperfect measurements or reported values* ("~") of an *incomplete set* (*s* vs. *S*, *k* vs. *K*) of the characteristics which influence actual energy consumption and measure-induced energy savings.[18]

Finally, engineering-based energy savings predictions generally employ models (which can range from simple percent-savings formulations to hourly building simulation models) whose inputs are *based on*, but may not equal, the sample-based estimates of the mean characteristics of the eligible population, $\hat{\bar{\tilde{k}}}_j(n)$, $\hat{\bar{\tilde{s}}}_j(0)$, and $\hat{\bar{\tilde{s}}}_j(1)$:

$$\Delta\hat{\bar{e}}_j(0 \rightarrow 1,n) \;=\; \{\hat{e}[\hat{\bar{\tilde{s}}}_j(0)+\varepsilon,\, \hat{\bar{\tilde{k}}}_j(n)+v] \;-\; \hat{e}[\hat{\bar{\tilde{s}}}_j(1)+\varepsilon,\, \hat{\bar{\tilde{k}}}_j(n)+v]\} \qquad (14)$$

Factors 1, 2, and 3 listed in Table 2.6 are elements of modeling and parameterization error; together they yield the uncertainty associated with audit+model-based predictions of weather-normalized energy savings for an individual house. Factor 4 is aggregation error, which arises when mean energy savings are not equal to the energy savings associated with the "mean house." Factor 5 is due to sampling error in estimating the population mean values for climate and building characteristics. Finally, Factor 6 refers to errors introduced when prototype characteristics are not set equal to those indicated by the sample mean for the population of homes eligible for each measure . Following a

[18]The prediction error introduced by using heating degree-days as a simple proxy for all environmental determinants of heating energy consumption has been found to be quite minimal *if* predictions are made for total consumption within periods of approximately a week or longer, ***and if*** the house reference temperature is derived from analysis of consumption data rather than fixed arbitrarily at 65°F or 60°F, ***and if*** predictions are being made for other than especially mild periods with very few heating degree days (e.g., Hill et al. 1992). This is why PRISM models, which regress fuel bills on total heating degree-days per billing period, are usually able to achieve R^2 values > 0.95 when predicting consumption per billing period based upon heating degree days per billing period, given data covering the full heating season for a house (Fels 1986.) Thus, the lion's share of ommitted variable error in energy savings predictions is likely to be due to omission of important house+utilization characteristics rather than omission of climate/weather characteristics.

consideration of their interrelationships, each of these factors is examined in more detail below.

Relationships Among the Factors Contributing to Uncertainty in First-Year, Population-Mean, Weather-Normalized Energy Savings

Figure 2.6 portrays a "chain of inequalities" which accounts, one at a time, for five different sources of error and uncertainty in estimates of the mean (first-year) weather-normalized energy savings per eligible house, when such estimates are derived using the standard approach employing heating degree-day-based calculations and prototype house descriptions. Subsequent sections examine each of these sources of uncertainty in some detail, and attempt to summarize the empirical data pertaining to each, or to document its absence where necessary. The question addressed by the present section is how these five different sources of uncertainty should be aggregated to determine an estimate of the total uncertainty in prototype+HDDM-based predictions of mean first-year weather-normalized energy savings.

The simplest relationship is one of additive error. That is, it could be assumed that measurement-based estimates of mean ΔNAC were equal to the actual value plus an error term, the random variable J_o. Using the notation introduced by Figure 2.6 for simplicity, the implication of this model is that the final uncertainty equals the sum of the individual uncertainties:

$$B = A + J_o \tag{15a}$$

$$C = B + J_{123} = A + J_o + J_{123} \tag{15b}$$

$$\vdots$$

$$F = E + J_6 = A + \left\{ J_o + J_{123} + J_4 + J_5 + J_6 \right\} = A + J_{\overline{\Delta \hat{e}(n)}} \tag{15c}$$

The problem with this model is that in the present study, a single estimate is being developed to characterize the uncertainty in savings estimates for all weatherization measures in general. Clearly, the absolute magnitude of the uncertainty in prototype+HDDM-based estimates of energy savings for a very influential (e.g., large expected savings, in Btu/year) measure (e.g., insulating all walls in a large house) is likely to be smaller than the absolute magnitude of the error or uncertainty in estimates for a less-influential measure (e.g., replacing one storm window). If we assume for simplicity that the magnitude of the uncertainty (as measured by its standard deviation) increases linearly with the magnitude of the savings estimates themselves, then this implies characterization of the uncertainties as percents or fractions of savings estimates, just as was done for the top-level uncertainties $J_{\overline{\Delta e}}$, J_N, $J_{\overline{C}}$ and $J_{\overline{n}}$ in the introduction. This in turn implies adoption of a multiplicative model of the influence of each uncertainty:

$$A = B * J_o \iff B = A/J_o \iff J_o = A/B \tag{16a}$$

$$B = C * J_{123} \iff C = B/J_{123} = A/(J_o * J_{123}) \iff J_{123} = B/C \tag{16b}$$

$$\vdots$$

$$E = F * J_6 \iff F = E/J_6 = \frac{A}{(J_o * J_{123} * J_4 * J_5 * J_6)}$$

$$\iff A = F * (J_o * J_{123} * J_4 * J_5 * J_6) = F * J_{\overline{\hat{\Delta e}(n)}} \tag{16c}$$

Note that in each case, the "actual" value is modeled as its point-estimate times the uncertainty in such point estimates, just as in the introduction. The product of a point estimate and the random variable which models its estimated uncertainty yields a quantity whose *pdf* can be used to derive confidence intervals for the actual values. The implication of this model is that the estimated *pdf* characterizing the total uncertainty in prototype+HDDM-based estimates of first-year weather-normalized energy savings is equal to the *pdf* of the product of the individual uncertainty terms (random variables). The *pdf* characterizing the uncertainty in $\overline{\hat{\Delta e(n)}}$ as an estimator of $\overline{\Delta e(n)}$ (where $\overline{\Delta e(n)}$ is also referred to as "$\overline{\Delta NAHC}$"), is then estimated to be

$$pdf\left[\overline{\Delta e(n)} \text{ (or "}\overline{\Delta NAHC}\text{")}\right] \Leftarrow MCS\left\{\overline{\hat{\Delta e(n)}} * J_{\overline{\hat{\Delta e(n)}}}\right\} \tag{17}$$

Note also that this multiplicative model of the influence of the separate uncertainties contributing to $J_{\overline{\hat{\Delta e(n)}}}$ enables expression of each contributing uncertainty as the ratio of an "actual" quantity to a "prediction" of that quantity. Empirical estimates of these uncertainties will then be provided by empirically-derived *pdf*s for each of these ratios of actual to predicted. Table 2.7 summarizes these relationships.

Measured Weather-Normalized Savings Uncertainty, J_0

The first component, J_0, is the uncertainty associated with measurement-based estimates of mean weather-normalized energy savings. Its consideration is necessitated because *true* mean weather-normalized energy savings are unobservable. Thus, while ample empirical data is available from weatherization studies to characterize the uncertainty in audit+HDDM-based predictions relative to *measurement-based estimates* of weather-normalized energy savings (and/or metered energy use before and after weatherization), neither of these types of measurements allows direct comparison of predictions with *true* weather-normalized energy savings. For this reason, our estimate of the uncertainty in audit+HDDM-based estimates of *true* weather-normalized energy savings (developed from empirical data below) must be multiplied by J_0 to derive the total uncertainty in predictions of actual mean (first-year) weather-normalized energy savings.

How can J_0 be estimated if true mean weather-normalized energy savings are unobservable? First, the method of estimating $\overline{\Delta NAHC}$ must be specified. The present analysis is based on the use of PRISM to estimate $\overline{\Delta NAHC}$, since it has been the dominant method for measuring weatherization savings to date. Two elements of uncertainty in PRISM estimates are discussed below: errors in PRISM prediction of $\overline{\Delta NAHC}$, and possible savings "takeback."[19]

A few studies have compared PRISM energy consumption estimates with metered savings estimates. (e.g., Hill et al. 1992; Fels et al. 1986) One consistent finding is that

[19]A fourth and major contributor to savings measurement uncertainty in the evaluation of weatherization programs relates to the estimation of *program-induced*, or *net* savings, as distinct from the *gross* savings observed among the sample of program participants (e.g., Train 1994; Buller and Miller 1992; EPRI 1991c, EPRI 1992; and Hirst and Reed 1991). A host of factors can cause gross savings to differ from the true savings which should be attributed to the program. Program-induced savings is an issue distinct from, and generally broader and more complex than, mean weatherization-induced savings among a sample of studied homes. The studies which compare measured and predicted energy savings (reported by Cohen et al. 1991 -- see below) all appear to compare predictions with *gross* measured savings.

PRISM estimates of space heating consumption typically overestimate sub-metered space heating consumption by 5-10% if the heating fuel is also used for other end-uses (such as water heating and cooking). This is due to seasonal variation in non-heating energy consumption (e.g., water heating and cooking), which PRISM models as part of the heating consumption. However, as long as seasonally-variable non-heating energy consumption is not appreciably reduced by weatherization, then this effect should not appreciably bias estimates of ΔNAHC upward. Fels (1986) reported that typical per-house standard errors (for the PRISM regression's prediction of observed consumption per billing period) are in the range of 3% of NAHC, when space heating is the only end-use for the heating fuel.[20] For groups of houses, PRISM consumption prediction is even better, since aggregate consumption data mask much of the month-to-month variability in individual-house consumption data which is not explained by HDDs. (Fels and Goldberg 1986) The very high capability of PRISM models to predict aggregate consumption using only observed HDDs per billing period (e.g., $R^2 > 0.995$ are typical) indicates *indirectly* that, aside from the possibility of a bias *if* weatherization alters seasonal non-heating consumption, uncertainty in PRISM-based estimates of $\overline{\Delta NAHC}$ appears small; unfortunately, PRISM cannot compute a statistic which quantifies this uncertainty directly.

Finally, savings observed in the fuel bills of weatherized houses may be affected by "takeback" or "rebound," which refers to the occupants' decision to "buy more heat" with some of the energy cost savings which were achieved by weatherization. In other words, if take back is significant, then measured savings estimates will miss the fraction of savings which was real but was used to purchase increased comfort. Potential examples of such behavior include raising average daily thermostat temperatures, or altering "zoning" behavior (shutting off un-occupied rooms). Several studies which have

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[20]Estimated standard errors for ΔNAHC may be derived from PRISM-estimated standard errors of NAHC as described in Appendix 3 of Fels 1986.

directly measured indoor temperatures before and after weatherization have found no evidence of take-back larger than a few (<5%) percent of space heating energy savings.[21]

Based upon the discussion above, the present study will conservatively assume that uncertainty in PRISM predictions of $\overline{\Delta NAHC}$ is small enough relative to other uncertainties (examined below) to be neglected. If many PRISM estimates have missed taken-back savings, this would contribute a downward bias of perhaps 1-5%. If weatherization measures appreciably reduce seasonal non-heating energy consumption on average, this would contribute an upward bias of similar magnitude.

Modeling and Parameterization Uncertainty, I_{123}

The discrepancies between measured energy savings and audit+HDDM-based predictions of energy savings in home weatherization (as well as measures addressing other end-uses) are notorious; among numerous examples, see Hirst et al. 1989, Hewett et al. 1986, Hirst and Goeltz 1983, etc., as well as a summary of this topic by Nadel and Keating (1991) and a summary of reported weatherization savings prediction errors in Cohen et al. 1991.

Empirical studies of energy savings for populations of retrofitted houses have found very wide variability in savings per home. (e.g., Schweitzer et al., 1989; Brown et al. 1993; and the references in the previous paragraph) Audit+HDDM-based predictions have consistently been very poor at explaining much of the observed variability in

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[21]Thermostat-related takeback behavior is measurable and has been studied repeatedly; only studies which measured indoor temperatures directly are described here. For example, a series of experiments by researchers at the Oak Ridge National Laboratories (e.g., Ternes and Stoval 1988; Ternes et al. 1991) has consistently found average changes in indoor temperature among weatherized houses to be nearly zero after weatherization, and nearly equal to the average changes observed in a control set of non-weatherized houses. They have concluded that "indoor temperature and its change does not contribute significantly to lower than expected savings observed in weatherization programs but does contribute to the variation in measured savings observed in individual homes" (Ternes et al. 1991, p.88). On the other hand, Dinan (1987) reported a mean indoor temperature increase of 0.6°F which indicated that 3.7% of predicted savings had been taken back.

energy savings per home. Evidently there is considerable variation among households in the factors which influence energy savings but which are not adequately modeled by audit+HDDM-based methods. Fortunately for analysts of conservation potential, study *mean* predictions have done a much better job at predicting *mean* measured savings than have their per-home counterparts, indicating that a significant portion of the effects of inadequately-modeled between-home variability averages out over a population of retrofitted homes. (Cohen et al. 1991)

HDDM-based energy savings predictions using a prototype represent a single calculation for a single house-description, but they are nevertheless a prediction of mean savings made for a population of houses, over which much of the un-modeled (or improperly measured, or improperly modeled) sources of variability in actual savings has been shown to average out. In fact, since aggregation error, sampling error, and discrepancies between prototype characteristics and sample mean characteristics are all dealt with by other uncertainty terms (J_4, J_5, and J_6 respectively) , J_{123} should reflect only the uncertainty remaining after it is assumed that the HDDM-based energy savings calculation for the prototype is equal to the mean of the audit+HDDM calculations which would have been obtained if every eligible home had been audited and modeled using HDD-based methods. That is, J_{123} **should be equivalent to the uncertainty introduced by using the *mean* of a population of audit+HDDM-based predictions as an estimator of the *mean* of a population of measured-savings results.**[22]

The uncertainty in mean audit+HDDM savings estimates as a predictor of mean measured savings is in fact well characterized by a sample of 24 separate studies

[22]Note that an additional assumption being made here is that the sample of housing characteristic data upon which prototypes are generally based reflects a level of measurement accuracy and detail equivalent to that obtained in audits which are designed to support HDDM calculations.

summarized by Cohen et al (1991).[23] The data in this 24-study summary reflect wide variation among reported mean prediction biases: per-study mean ratios of measured to predicted savings range from 0.14 to 2.08, with a standard deviation of 0.41 about their mean of 0.78 (see Figure 2.7). Should these summary statistics be taken at face value as a best estimate of the uncertainty in audit+HDDM prediction means as estimators of mean measured savings? Surely, some fraction of the large variation in study mean prediction errors is due to variation among the individual studies in factors such as data quality, installation quality, un-modeled characteristics influencing savings, etc. Nevertheless, unless some of this variability *can be explained* by variation in particular characteristics underlying the individual studies, all of the variability must be considered as indicative of the "universe" of possible instances of prediction mean error, when audit+HDDM prediction means are to be used as estimators for measured savings means.

Future research might attempt to "dig up" from the original reports or their authors more extensive data for each of these studies (and for studies completed since the 1991 summary report) such as per-study variances among predicted and measured savings, whether estimates were calibrated to pre-weatherization consumption levels, etc., in order to facilitate more rigorous synthesis of the study results using techniques of meta-analysis.[24] Such an analysis is beyond the scope of the present study. Nevertheless,

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[23]In addition to the 24 studies summarized by Cohen et al. which employed HDD-based methods to predict energy savings, the authors also presented summary results for 8 studies which utilized building energy simulation models that "attempt to account explicitly for solar and internal gains, utilize more sophisticated algorithms to model infiltration and ground-coupling, and are designed so that predicted energy use can be calibrated to actual utility bills" (p. 67). Since the level of input detail employed by such models is not realistically available for use in energy conservation potential studies, the use of sophisticated energy simulation models for such studies is not practical either, and the results of these eight studies should not be considered representative of the energy savings prediction uncertainty associated with energy conservation potential studies.

[24]Analysts of energy conservation programs have recently begun to explore the application of meta-analysis in order to synthesize the results of individual program evaluations; see, for example, Violette et al. 1992; Greene et al. 1993; Karr et al. 1993; Lagerberg et al. 1993, and Green and Violette 1994.

some of the major potential sources of variation among study results are considered briefly below, both in an attempt to make more careful use of the data in the present study, and to point out some of the major factors which may be important to consider in future meta-analytic studies of the topic. Three separate issues are examined briefly below:

1) there are two separate program types among the 24 studies: utility and R&D;
2) three program-based factors, which contribute an unknown fraction of the total prediction error observed among the *utility* studies, do not generally affect estimates of conservation potential; and,
3) study final report details were examined for the four extreme prediction error outliers reported by Cohen et al. It was found that data reported for one of the four outliers could not be confirmed by the original published reports, and that two other out-lying studies were not appropriately considered representative of audit+HDDM prediction accuracy.

Factors which vary by program type.

Within the 24 HDD-based studies, Cohen et al. "believe that it is important to analyze results separately for R&D studies and utility programs because of differences in input data quality and, in some cases, model sophistication." In particular, Cohen et al. judge that utility programs, but not R&D programs, are susceptible to three factors discussed in the next sub-section which contribute an unspecified amount of prediction error to the utility program results. Second, Sonnenblick (1993) cited several reasons why savings achieved by smaller-scale, higher-profile pilot programs are expected to be higher than those achieved by full scale utility programs.[25] Only one of the ten utility

[25]The factors cited included pilot program use of the most qualified personnel available, and the motivational benefits brought by the higher profile of pilot programs. Sonnenblick also noted additional differences which could either increase or decrease pilot-achieved savings relative to full scale programs.

programs in Cohen et al.'s dataset was a pilot, while all of the research studies could potentially benefit from the advantages of pilot programs. A third difference between the two types of programs is sample size, which ranged from 101 to 6289 among utility programs, and from 3 to 32 among R&D programs. Finally, the utility studies generally involved installation of multiple measures per household, for which individual prediction errors might partially cancel per house, while most of the R&D studies examined the effects of one measure only. In summary, the underlying differences between utility programs and R&D studies are mixed: two sets of factors contribute uncertainty to utility predictions relative to R&D studies, while two other factors should reduce utility mean prediction error relative to R&D studies. These factors are also mixed in their applicability to studies of conservation potential, as summarized in Table 2.8.

Program-based factors which should not affect conservation potential estimates.

In addition to inaccuracies inherent in characterizing houses with audit-based data and modeling annual energy consumption with HDD-based methods, there is an additional set of factors to which some of the authors of the individual studies attributed unspecified fractions of their mean prediction error, according to Cohen et al. These factors apply only to utility studies, and arguably do not influence the HDD-based predictions used in estimates of conservation potential:

a) a "small portion" of the prediction error was attributed to cases where not all recommended measures (upon which predictions were based) were actually installed in each house;

b) some of the earliest studies failed to account energy savings interactions among measures installed in the same house; (such interactions generally reduce the total savings actually achieved, and so would contribute to the observed over-prediction of savings); and,

c) not all studies calibrated their savings estimates to pre-weatherization consumption levels.

While these factors reportedly contributed to the total prediction error observed in Figure 2.7, energy conservation potential estimates can generally be considered unaffected by these sources of prediction error. First, incomplete installation bias (a) should clearly not affect estimates of conservation *potential.* Next, it is standard practice for potential studies to explicitly model the effects of measure interaction, whose neglect lead to bias (b). Finally, conservation potential analyses can (and should) calibrate their savings estimates to measured consumption data for the year of study, avoiding (or at least reducing) bias (c). Unfortunately, information is not available to enable assessment of what fraction of which studies' mean prediction error was caused by these factors. Thus, it can only be concluded that these factors jointly contribute to some of the prediction error observed among utility studies.

Outlier examination.

Four of the 24 HDD-based studies exhibit ratios of mean measured to mean predicted savings which are located noticeably far from the central cluster of twenty remaining studies. Available details for each of these "outliers" are examined briefly below. Note that the three data points located farthest from the 24-study mean are all R&D studies.

• Outlier #1: University of Illinois Wall and Ceiling Insulation Study.

The highest reported ratio of mean measured to mean predicted energy savings was 2.1, for a 12-home, 1978 University of Illinois Wall and Ceiling Insulation Study. (Hegan et al. 1982) Cohen et al. reported values of 20 and 42 MBtu/year for mean predicted and mean measured NAC savings, respectively (Table 12, p. 70), citing a paper in the Proceedings of the 1982 ACEEE Summer Study. The final peer-reviewed publication of the results of this Illinois study was (Herendeen et al. 1983). Both references were obtained by the present author, but neither provides data which aggress with the summary results reported by Cohen et al., indicating either reporting errors by Cohen et al., or the use by Cohen et al. of a different draft of the proceedings submission than the final one made available to the present author by ACEEE.[26]

Unfortunately, determining the mean measured and mean predicted savings from the study reports is not straightforward, since savings were measured three different ways and predicted two different ways. The standard calculation of measured (gross) NAC savings is as the difference between NAC measured for the last year before weatherization and the first year following weatherization. (e.g., Fels 1986) The study by Herendeen measured NAC for three years prior and three years following weatherization. Using this data, measured savings were calculated three different ways (average pre minus average post, last pre minus first post, and deviation from interpolated trend). The report's authors further selected what they considered to be the most reliable estimate from among the three as a final result per house, and reported the mean of these "final" measured savings as well. One set of savings predictions was generated by using standard heating degree-day methods. Another was calculated by multiplying the HDDM-based percent savings by the average measured NAC during the years prior to weatherization. The mean predicted and measured savings from each method are reported in Table 2.9 for data from both versions of the paper. None of the possible results matches the results published by Cohen et al. In fact, all of the possible results calculated yield ratios of mean actual to mean predicted savings well below 2.08; the results from the published paper indicate consistent *over-prediction* of savings, and

[26]Karen Olson was unable to locate a copy of the cited proceedings paper at LBL. Two of the paper's authors (Stiles and Harendeen) were contacted, but were only able to locate copies of the final 1983 published paper. ACEEE (John Morrill of the Washington, D.C. office) provided a copy of the final proceedings submission, but indicated that several drafts of most papers were submitted during the pre- and post-conference period.

indicate predictions which are considerably higher than those reported by the earlier conference paper.

One final attempt was made to reconcile the Cohen et al. and published results. The text of both the 1982 and 1983 papers explicitly noted that the highest over-prediction of savings occurred for a very complex house. It was checked whether dropping this home from the sample and re-calculating the results yielded numbers which matched, or even bracketed Cohen et al.'s. Unfortunately it did not (see Table 2.9).

To achieve consistency with the standard methods of predicting and measuring savings, the appropriate predicted-measured comparison is between the standard HDDM-based prediction and the "last pre minus first post" measured savings. Since the results reported by the most recent and peer-reviewed paper (Herendeen et al. 1983) are probably to be preferred over those reported in earlier conference papers, it is concluded that the ratio of mean measured to mean predicted savings for the Illinois study should be 0.950, not 2.1 as reported in Cohen et al.

- Outliers #3 and 4: Robinson Foundation Insulation Studies.

The two R&D programs with the lowest ratios of mean measured to mean predicted savings (0.14, and 0.20 respectively) both pertained strictly to a study of basement wall insulation retrofits. (Robinson et al. 1989; Hewett et al. 1991) Mechanisms governing basement-related whole-house heat loss are believed to include both conductive and convective interactions between basements and the rest of the house, are highly complex, poorly understood, and are known to be inadequately modeled by even highly detailed models of basement wall conductive effects. (Robinson et al. 1990; Hewett et al. 1991) For these reasons, HDD-based methods (as well as more detailed energy simulation models) are known to have *uncharacteristically poor* predictive accuracy for basement wall retrofits. These two data points confirm that engineering-based estimates of energy savings from foundation insulation retrofits are highly uncertain. However, the mean prediction error reported by these two studies should not be considered indicative of the prediction error associated with HDD-based models of weatherization measures in general.

• Outlier #4: Puget Power Weatherization Loan Program.

The one HDD-based "outlier" associated with a utility program was the 6289-home study of Puget Sound Power and Light Company's weatherization loan program. (Croft 1982) In this study, the ratio of mean measured to mean predicted savings was 1.57. Program evaluators attributed the excess (gross) electricity savings among the participating households (i.e., the greater-than-predicted average drop in weather-adjusted annual consumption after weatherization) to increased use of wood stoves or fireplace inserts along with "dramatic" increases in electric rates during the multi-year study period. (Cohen et al. 1991, vol. 2, p. 27)

Based on these details, it appears that the prediction error in Puget Power's HDD-based estimate of the mean change in *energy use* (distinct from *electricity* use) achieved by program weatherization measures was considerably smaller than indicated by this data point. However, the use of auxiliary fuels complicates fuel specific estimates of conservation potential as well as program performance prediction. In fact, unforeseen post-weatherization *reductions* in wood use have contributed to *over-prediction* of electricity savings in several other weatherization programs, both in the Pacific Northwest. (e.g., Hirst et al. 1989) and New England (Nadel and Keating 1991) While the details underlying the Puget Power results indicate that HDDM-based methods may have done a better than indicated job of predicting savings of *total* energy, the prediction error represented by this data point nevertheless reflects the impact of factors which *do* contribute uncertainty to predictions of fuel-specific conservation potential.

In summary, details from the individual studies' final reports indicate that the three outliers from the R&D dataset should not be considered representative of audit+HDDM-based prediction uncertainty; one data point appears to be a reporting error, while two others pertain to a particular measure for which prediction accuracy is atypical of HDD methods in general. The fourth (Puget Power) is an outlier due at least in part to the influence of a factor which *does* contribute to the uncertainty in HDDM-based estimates of conservation potential, and so should be retained in the data set. The three R&D study outliers were omitted from the dataset, and statistics recomputed (see Table 2.10). (It was found that nearly identical results were obtained if the University of Illinois study was modified to a mean of 0.95 rather than omitted.)

Recall that an examination of the factors related to program type indicated that the set of ratios of mean measured to mean predicted savings from *utility programs might over-estimate the uncertainty* in audit+HDDM-based estimates of first-year weather-normalized mean energy savings used in studies of conservation potential. Likewise, factors related to program type indicated that the set of ratios from *R&D studies might tend to underestimate this uncertainty.* After deleting the three outliers, the statistics of each sample are in line with this hypothesis (see Table 2.10), in that the variance among utility program prediction errors is larger than that of R&D studies. The statistics for the combined sample provide a mid-range estimate which will be used as a basis for inference in the present study.

All samples exhibit small positive skewness. Applying a natural log transformation reduced this skewness of the combined sample to near zero (Table 2.10). Thus, as a rough approximation of the prediction uncertainty in audit+HDDM-based predictions of mean measured savings, J_{123} is estimated to be distributed lognormally:

$$J_{123} \sim e^{Y}, \quad Y \sim N(-0.3,\ 0.3^2) \tag{18}$$

Future exploration of this complex topic using meta-analysis is recommended.

Aggregation Error Uncertainty, I_4

Aggregation error uncertainty, in the present study, refers to an unknown error introduced when the mean energy savings for a population of houses is estimated as the energy savings for the mean house. Space conditioning energy consumption is non-linearly dependent upon building characteristics. Aggregation error arises because of "the assumption of linearity built into any averaging scheme [used to define prototypes], and the contradiction to this assumption that characterizes actual building energy use." (Eto et al. 1990)

Mosleh and Bier (1992) provide a literature survey and a review of issues related to aggregation error in the estimation and analysis of uncertainty. Only one known study has examined the impact of aggregation error on predictions of mean energy consumption. For the commercial buildings sector, the impact of modeling energy use with a single prototype versus separate models of seven small (< 30,000 ft^2) office buildings was studied by Eto et al. (1990). Their finding of significant aggregation error in the prototype-based estimates of energy consumption led them "to suggest caution in the use of prototypes for energy demand forecasting and demand-side planning. While the use of prototypes is probably unavoidable, we believe the need for validation and calibration is significant." The researchers concluded that:

> It is not sufficient to ensure, as we have done in this study, that each individual physical and operating characteristic of a sample of buildings is carefully weighted and averaged in the creation of a prototype because the energy performance of the sample, much less a larger population, cannot be approximated by such a linear averaging of these characteristics. (p. 10.36)

Eto et al. tested two different building characteristic weighting schemes, and found prototype prediction errors for space heating, space cooling, and ventilating energy use which ranged from 8% to 26% of weighted modeled energy use in the population of 7 buildings. The mean of the prediction error percentages among the six separate predictions (two weighting schemes, three types of space-conditioning energy use) was

16%. There was little evidence of systematic positive or negative bias in prototype estimates, with equal numbers of over- and under-estimates. Despite the cause for concern indicated by Eto et al.'s results, a review of the literature and consultation with multiple researchers in the field has uncovered no studies which assess the importance of aggregation error for the residential sector. The present study will adopt a crude initial estimate of *J4* as normally distributed with mean 1.0 and standard deviation 0.15, based solely on Eto et al.'s results, which were for small commercial buildings. Clearly, prototype aggregation error and its effect upon uncertainty in conclusions about residential space conditioning conservation potential is an important topic for further research.

Sampling Error Uncertainty, *J5*

Factor 5 represents the uncertainty in energy savings estimates which is due to propagating through HDDM calculations the uncertainty in sample-based estimates of population means for each house characteristic required by the calculations. Uncertainty propagation through building energy simulation models is an active area of on-going research. (see, for example, Lomas and Eppel 1992) To date the focus of the research appears to have been propagation of *measurement uncertainty* for individual audited (or designed but not yet constructed) buildings (e.g., factor 2 in Table 6), rather than the uncertainty associated with sample means. Also, building energy simulation models and their input data are much more detailed than generally practical for studies of conservation potential.

The uncertainty in sample-based estimates of mean values for stock and climate characteristics ($\hat{\bar{\bar{s}}}_j$ and $\hat{\bar{\bar{k}}}_j$) for the population of houses eligible for measure j is related to the sample size, the sampling method, and the sample standard deviation. If the sample of audits is purely random and the sample size n is greater than 30, then the probability distribution for $\bar{\bar{s}}_j$ can be approximated by a normal distribution with mean equal to the sample mean, and standard deviation equal to the sample standard deviation divided by $\sqrt{n}$. For sampling strategies other than simple random sampling, other formulae or methods for estimating the underlying distribution must be used.[27]

As discussed in the section related to market size estimation, the single major survey of national and multi-state regional residential stock characteristics related to energy consumption is the EIA's RECS. Also mentioned earlier was the Lawrence Berkeley Laboratory's effort to combine the results of nearly 100 utilities' residential appliance saturation surveys ("RASSes") into a national database whose sample size is over 90 times that of RECS. The LBL RASS database has the potential to significantly improve the precision of market potential estimates, as compared with RECS-based estimates. However, since RASSes are typically administered by either phone or mail (rather than the in-home audits used by RECS), the LBL RASS database is not likely to contain much in the way of the quantitative *building characteristics* needed for prototype specification, such as floor area, wall area, window area, thickness of existing attic insulation, etc. States compiling databases of Residential Conservation Service-style audit results (also discussed in the section addressing market potential estimation) may have a viable alternative/supplement to RECS-based prototype estimation.

For the present study a crude estimate of J_5 is developed based upon the following considerations. The 1990 RECS survey reported the mean heated floorspace in single family homes for each of the nine census divisions with approximate relative standard

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[27]See, for example, Cochran 1977. EIA's triennial Residential Energy Consumption survey, the only comprehensive national source of residential energy-related building characteristics, employs a multistage area probability sample design of a complexity which precludes development of an analytic expression for the estimated sampling error variance. For this reason, EIA conducts balanced half-sample replication analysis in order to develop estimates of relative standard error for the cross tabulations published in the RECS summary reports. RSE's for variables used in estimating prototype characteristics, particularly if prototypes are to be specified based on measure-eligible sub-populations, would require additional half-sample replication analyses. Details of the RECS sample design are found in Appendix A of EIA 1992; details concerning the estimation of sampling error for RECS data are found in Appendix B of that reference.

errors (RSE's) which ranged from 3 to 6% of the estimates.[28] The sample sizes for sub-populations (e.g., gas-heated single-family homes lacking wall insulation) will be smaller (recall Table 5), making their RSE's larger; unfortunately, RSE's for such sub-populations were not calculated by EIA. A normal distribution with mean 1.0 and standard deviation 0.1 is used here as a crude estimate of J_5. This estimate is likely to significantly understate the true uncertainty caused by sampling error if RECS data is used to estimate mean characteristics of measure-eligible sub-populations within census divisions (as has been the case in the major national prototype development efforts to date. Also, J_5 (like the uncertainty in estimates of market potential) can be expected to very significantly by measure. Better quantification of this uncertainty is an important topic for future research, particularly as alternative databases of national and regional residential building characteristics become available.

"Errant Prototype" Uncertainty, J_6

Within the total population of houses in a study area there is a subset of N_j houses eligible for measure j; call this sub-population the "j-population." Note that the j-population for one measure will in general be a different set of houses than the j-populations for each of the other measures, although there is likely to be some overlap since many houses are eligible for more than one measure. Unless the j- populations for two measures are identical, then if separate prototypes are not specified for each measure, the estimated uncertainty introduced by simple sampling error described above will be an underestimates of the total uncertainty caused by using prototypes as point-estimates of the mean characteristics of each j-population.

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[28]Table 15, p. 48. The nine census divisions are New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific.

As it turns out, development of separate prototypes to describe the population of homes eligible for each measure may have *never been done* in practice. Indeed, prototype characteristics are often not even set equal to sample means at all. As Eto et al. (1990) observed: "Historically, prototype development has relied primarily on 'engineering judgment.' This practice often results in the development of 'representative' buildings (i.e., a building description largely based on an actual building, but 'modified' (often in an undocumented manner) to be more reflective of a larger population of buildings)."

The standard prototype development process does not document the differences between sample mean and prototype characteristics, much less investigate the impacts of such differences upon uncertainty in estimates of energy savings. The most rigorous efforts to develop residential prototypes for the US to date (e.g., Bluestein and DeLima 1985; Ritschard and Huang 1989; Ritschard et al. 1992) have combined statistical analysis of RECS data with engineering judgments in order to specify "representative" prototypes for several key age-classes of residential buildings in each census division. For the present study, given the absence of quantitative data from which to derive an estimate, a conservative approach appears to be to assume that its effects are on the order of those of sampling error, which has been estimated by J_5 as normally distributed with mean 1.0 and standard deviation 0.1. As with the bulk of the factors contributing to empirical input uncertainty described in this report, "errant prototype" error must be recommended as an important topic for future research.

Total Uncertainty in Estimates of Mean Weather-Normalized First-Year Energy Savings

Finally, the product

$$J_{\bar{e}_j(n)} = J_o * J_{123} * J_4 * J_5 * J_6 \tag{19}$$

provides an (obviously quite speculative) first-order estimate of a random variable whose *pdf* characterizes the uncertainty in prototype+HDDM-based estimates of the true mean of achievable savings per installation of measure j under the assumption of normal climate.

The results of a 200-sample Latin Hypercube simulation of equation (19) are presented in Figure 2.8. As the figure illustrates, the 90% confidence interval for $J_{\bar{e}_j(n)}$ is estimated to range from roughly 0.4 to 1.3, meaning that the 90% confidence interval for the actual value of $\Delta\bar{e}_j(n)$ (the population-mean, first-year, weather-normalized energy savings per measure) is estimated to range from roughly 40% to 130% of the standard-method-estimate (i.e., prototype+HDDM-based calculations) of this quantity.

Climate-Induced Variability in Annual Energy Savings

The annual heating degree-days (HDDs) which will occur each year during the lifetime of an energy conservation measure will certainly differ from the long-term climate averages used in energy savings predictions. In terms of the uncertainty in estimates of annual energy savings over a measure's lifetime, what matters is the deviation of the *average annual climate over the lifetime of the measure* from the long-term normal value used in energy savings estimates (30 years is the typical period over which heating degree-day normals are averaged). The climate-induced uncertainty in average annual energy savings over a measure's lifetime is thus related to the uncertainty introduced by using the most recent 30-year normal climate as a predictor of the average (future) annual climate throughout the measure's life. For weatherization measures, estimated lifetimes generally range from 5 to 30 years.

Annual recorded heating degree-days (HDDs) for a particular station or state exhibit significant serial autocorrelation. For this reason, the simple statistics (mean and variance) calculated for a sample of annual HDDs do not provide a sufficient basis for estimating HDD prediction error. That is, if it is simply assumed that annual heating degree days are distributed normally with an empirically-estimated mean and variance, then the resulting estimates of the variance of mean annual heating degree days over the lifetimes of conservation measures will be underestimates. Instead, empirical estimation of climate-induced uncertainty requires a historical climate record long enough to enable comparison of average annual heating degree days for measure lifetime periods (ranging from 5-30 years) with the 30-year normals which were observed just prior to the measure life periods.

The longest available historical records of state average heating degree days are provided by a series of 48 (one for each of the contiguous states) reports from the National Climate Data Center (NOAA 1983); heating and cooling degree-day data were obtained from 46 of these 48 reports for the present analysis (copies of the Washington and Oregon reports were not located by our search). These reports provide estimates of annual state-wide average heating and cooling degree days (to a base temperature of 65°F) for each year from 1895 through 1982. For the present study, historical HDD data for three different states are examined in detail: New Hampshire, New Jersey, and Tennessee. These three states were selected to provide examples from each of the three DOE climate regions (see, for example, Brown et al. 1993), in order to explore if and how warmer and colder climates differed in the uncertainty of 30-year normals as predictors of future annual HDDs. Following this detailed analysis for the three states, data from all 46 states are examined for consistent trends in climate-induced uncertainty as a function of severity of climate.

Figures 2.9 and 2.10 report the results of the three-state analysis. Clearly, period-mean HDDs become less variable as the length of the period (i.e., the measure life) increases. This trend is reflected in monotonically decreasing standard deviations for the samples of period means divided by the prior normals. Also evident in the figures is the fact that while *absolute* variation in annual HDDs from year to year is greater in the colder states, the *relative* variability (i.e., standard deviation divided by the mean) is greater in the milder states. Thus, the spread of period means divided by prior normals is larger for the milder states, increasing from roughly ± 5% in New Hampshire to roughly ± 10% in Tennessee.

Another feature of the results is that the serial autocorrelation in the past century's temperature record leads to consistent tendencies for the prior normals to either overestimate (as in New Hampshire and New Jersey) or underestimate (as in Tennessee) the subsequent-period means on average during the period. That is, for New Hampshire and New Jersey, an over-all warming trend from the beginning of the record through about 1955 caused prior normals to tend to over-estimate subsequent period-mean heating degree days, while a cooling trend in Tennessee after 1920 lead to the opposite tendency for that state. In fact, the data from all three states showed that thirty-year normals generally under-predicted subsequent 5-year means through the early 1950's, after which a more recent cooling trend in the records reversed this effect. The fact that the mean prediction error ("bias") increases steadily as the measure lifetime increases is actually an artifact of the sampling procedure.[29] Therefore, it does not appear justifiable to conclude that the relationship between measure life and climate prediction bias observed in the present results would persist if longer climate records became available and were sampled from. Nevertheless, it is worth noting that the existence of long-term "trends" (serial autocorrelation) in annual climate data leads to *serial autocorrelation in prediction error* as well.

The tendency of milder heating climates to experience increased (relative) climate-induced heating energy savings uncertainty was examined by checking for a correlation between mean heating degree-days (over the full 88-year record) and the coefficient of variation (standard deviation divided by the mean). The possibility for milder (cooler)

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[29]For the two colder states, the requirement for longer periods of "post prediction" data causes the samples for longer-lifetime predictions to end earlier during the climate record, omitting more of the later instances of under-prediction which occur during the more recent period of generally cooler winters. In Tennessee, a consistent trend of increasing HDDs following the first 30 years of data (which are used to generate the earliest 30-year normal) leads to persistent underestimation of future period means by prior normals.

cooling climates to experience greater climate-induced cooling savings uncertainty was also examined in a similar manner. The results are plotted in Figure 2.11. As shown in the plots, colder heating climates (and hotter cooling climates) exhibit generally less climate variability from year to year (in relative terms) than their milder counterparts. The curvilinear relationships between climate variability and climate severity mean that among the colder heating climates (HDD > 4000), climate variability is nearly independent of climate severity.

Most importantly for the present study, the uncertainty in lifetime average annual savings due to climate variability appears relatively small compared with some of the other sources of uncertainty studied in the present paper. For this analysis, the uncertainty, $J_{HDD}(y)$, will be approximated as a normal distribution with mean 1.0 and standard deviation 0.06, which is roughly the mean coefficient of variation for states with > 4000 HDDs annually (see Figure 2.11). Climate-induced uncertainty is inversely related to measure life, and is greater than indicated by the above estimate for $J_{HDD}(y)$ in states with milder heating climates.

Persistence: Variability in Annual Weather-Normalized Savings

Many factors can lead to variation in the annual weather-normalized energy savings attributable to energy conservation measures, relative to weather-normalized savings during the first year after weatherization. The question of importance here is how much uncertainty do these factors contribute collectively into estimates of technical and cost-effective conservation potential which rely on assumptions of perfect persistence. Differences between conservation measures' *program impact*s (in relation to which empirical persistence studies are generally conducted) and their *conservation potential* must be borne in mind, in the process of interpreting data on savings persistence in order to assess the persistence-related uncertainty in estimates of energy conservation potential.

It is possible to identify three distinct sets of factors which can lead to imperfect persistence of weatherization-induced weather-normalized energy savings:

1) Changes in Behavioral, Environmental, or Structural Influences of Heating Demand

   If the average winter thermostat setting is raised in later years, annual savings will increase; if the average winter thermostat setting is lowered in later years, annual savings will decrease. Addition or subtraction of occupants, appliances, and even nearby trees or buildings may influence the final demand for fuel-based heat. Finally, structural modifications which change the heated square footage of a home, such as building additions, conversion of garages, basements, and attics, can affect total heating energy use.

2) Physical Alteration or Degradation of Energy Conservation Measures

   The performance of some weatherization measures may degrade physically over time relative to first-year savings, particularly if maintenance is inadequate, or if installation quality was poor. Furnace performance under improper maintenance, the savings from a furnace clean-and-tune, or the air-sealing benefits of caulking and weather-stripping on heavily-used doors and windows are obvious examples. The performance of some longer-lived shell measures may also degrade with time; improperly-installed wall insulation can settle; attic or sub-floor insulation may be tampered with, or small portions may be damaged or removed, either of which can significantly reduce its energy conservation effectiveness.

3) Out-year Installation of Additional Efficiency Measures or Appliance Upgrades

   Heating energy consumption can be idealized as the product of three terms: the heat load H, the reciprocal of the heating appliance seasonal efficiency, $1/\eta_a$, and the reciprocal of the distribution system efficiency, $1/\eta_d$:

$$\text{annual energy consumption} \approx H * \left(\frac{1}{\eta_a} \right) * \left(\frac{1}{\eta_d} \right) \qquad (20)$$

To a first approximation, equation (20) describes the interactive relationships among space-heating conservation measures. Later installation of measures alters the conditions upon which earlier savings calculations were based. For example, when a new, more efficient furnace is purchased to replace a failed older furnace several years after walls were insulated, then the annual fuel savings achieved by wall insulation are reduced.

All three of the sets of factors listed above will collectively influence persistence data, which can make their separate influences difficult or impossible to isolate from billing analyses alone. However, while each clearly influences the persistence of weatherization-induced savings, their influence upon the uncertainty in estimates of conservation potential varies. Each is considered separately below.

Behavioral factors can be divided into *measure-induced* and *non-measure-induced* effects. Presumably, measure-induced effects (e.g., savings take-back) will impact savings from the first year onward, and as long as they are not expected to change systematically over time, should not appreciably contribute to uncertainty in first-year savings as a predictor of future annual savings. Regarding non-measure-induced effects, year-to-year variability in behavioral factors such as average thermostat settings is known to be significant for individual houses, but to tend to cancel out on average within aggregates of houses. (e.g., Ternes et al. 1991) In fact, the same relationship between per-home and population wide-variability is observed for the persistence of weather-normalized annual consumption generally (under the influence of all three factors listed above), in that per-home variation in annual weather-normalized consumption generally appears erratic, while aggregate variability exhibits generally smooth trends. (Fels and Goldberg 1986; Cohen et al. 1991: pp. 63-65)

Environmental and structural influences, on the other hand, probably do not have a measure-induced component. The magnitude of their influence is not separately observable in billing data, but might be better inferred from engineering analysis together with data on rates of residential remodeling. Upper bounds on the size of its influence might also be inferred by examining the magnitude of residual prediction errors in models such as REEPS or LBL/REM, which predict aggregate residential space-heating energy demand as a function of weather, price, and estimated stock turnover dynamics. Data such as that summarized by Cohen seems to show that much of persistence variability during the first three to six years of program is related to price dynamics.

Factor set (2), **physical degradation or alteration** of conservation measures, will contribute to imperfect persistence evidenced in billing data, and is also an effect which fully contributes to uncertainty in estimates of annual energy savings used in projections of conservation potential. A significant problem is how to isolate its effects using billing data. The standard approach is to compare post-weatherization consumption histories with those of comparison groups of households which were not weatherized, since "The use of a control group should control for behavioral, equipment, and structural changes [factor sets (1) and (3)] which are assumed to be the same between groups." (Degens 1992) Another complimentary approach would be long-term studies which incorporate periodic physical inspection of conservation measures. For many measures this should prove feasible (e.g., WCDSR 1992), but for some such as air sealing measures physical inspection will face serious challenges. (Bordner 1994)

Finally, there is factor set (3), the **out-year installation of additional efficiency measures or appliance upgrades**. Measures do interact; thus, the reduction in fuel consumption caused by wall insulation will be less for a house with a more efficient heating system. In studies of current conservation potential, measure interaction is taken into account, although influence is modeled as propagating from "earlier" measures (that is, most cost-effective) to "later" measures, rather than the reverse chronology described above (e.g., the furnace upgrade occurring after wall insulation saves less energy than if wall insulation had not been installed).

The important point is that estimates of total technical conservation potential include an attempt to correct for measure interactive effects. Estimates of cost-effective potential include interaction among all cost-effective measures. Only chance for missing actual interaction is if non-cost-effective measures are naturally implemented (will effectively reduce the savings achievable by the full set of cost-effective measures), or if new measures become technically feasible and are implemented (but invention/ commercialization of new measures expands the total technical energy savings potential more than their partial installation reduces the potential associated with the original set).

In summary, factor sets (1), (2) and (3) all impact weather-normalized energy consumption in weatherized homes, but only factors sets (1) and (2) contribute to persistence-related uncertainty in estimates of conservation potential, since measure interactive effects are explicitly accounted for when summing measure energy savings to derive estimates of total conservation potential -- with the one possible omission noted above, along with errors in modeling measure interaction. Next we turn to look at what empirical data on persistence is available.

As noted earlier, empirical studies of the persistence of weatherization-induced, weather-normalized annual energy savings generally attempt to quantify *program-induced* energy savings. For example, Train (1994) discusses how program-induced savings ("net savings") should be equal to the measure-induced savings among program participants ("gross savings"), minus those measure-induced savings which would have occurred in the absence of the program ("free ridership"), plus any additional energy savings caused by the existence of the program but not included among the participants' program-measure-induced savings ("spillover effects"). Train also discusses how program-induced savings, as defined above, are not properly measured by simply subtracting the savings among households not offered the program from the savings among program participants (because participants in voluntary programs may exhibit significant energy-related behavior differences relative to the wider population, which is represented by the population of households non offered the program). However, if differences among weatherized and non-weatherized homes can be minimized in the design of weatherization persistence studies, by making willingness-to-participate not a factor in separating weatherized from non-weatherized homes (as is generally attempted), then this calculation *is* the most logical one to perform when attempting to isolate the influence of factor set (2) upon persistence. This calculation is the basis for estimates of the persistence of "net" savings in weatherization persistence studies. Persistence of "gross" savings -- that is, of savings among weatherized homes, is also sometimes reported separately by persistence studies.

Let us summarize the relationships between factors sets (1), (2) and (3), measured data on persistence, and the needs of the present analysis. Only factor sets (1) and (2) contribute to persistence-related uncertainty in estimates of energy conservation potential. Measured persistence of *gross* savings is affected by factor sets (1), (2), and (3). In fact, operation of factor (3) (out-year investments in efficiency) should tend to *reduce* gross weather-normalized consumption relative to first-year consumption (all else being equal), effectively *increasing* the apparent persistence of weatherization-induced savings. The influence of factor set (3) on gross persistence should be minimal, however, since most persistence data comes from evaluations of *comprehensive* weatherization programs which should leave little near-term opportunities for further investment in cost-effective efficiency in the treated homes. Measurements of the persistence of *net* savings attempt to isolate the influence of factor set (2) upon persistence, by controlling for the effects of factor sets (1) and (3) observed in a comparison group of houses; however, comparison group specification is difficult, *and*, particularly for comprehensive weatherization programs, net savings estimates may penalize estimated weatherization-induced savings for out-year installation of the some of the same weatherization measures by members of the comparison group.

The summary above indicates that measurements of the persistence of gross savings, by including the effects of factor set (3), should provide a very slightly upwardly-biased estimate of the effects of (1) and (2) alone. Measurements of net savings, on the other hand, will miss the contribution of factor (1) to variability in annual weather-normalized energy savings, which data from two major persistence studies in the Pacific northwest indicates is significantly related to dynamics in the price of energy.[30] Measured persistence of net savings will also be reduced by the control group's out-year installation of weatherization measures. In the end, neither gross nor net persistence data provides an adequate characterization of the expected contribution of persistence-related effects to the total uncertainty in predictions of out-year weather-normalized energy savings. The best that can be hoped, based on the discussion above, is that the magnitudes of annual savings variability observed in gross and net persistence data may *bracket* the magnitude of persistence-related out-year savings uncertainty.

Empirical Data on the Persistence of Weather-normalized Weatherization Savings

Data on the persistence of residential weatherization savings comes primarily from three major studies. Six cohorts weatherized during various years of the Bonneville Power Administration's Residential Weatherization Program (BPA RWP) were studied for persistence of savings. (Horowitz et al. 1991, White and Brown 1990) Four of the

[30] A note on the potential for negative correlation between energy price and a component of persistence uncertainty: If demand is stimulated by falling energy prices, then energy savings increase while their monetary value per Btu is reduced. If demand is reduced by rising energy prices, then measure-induced savings are reduced but their monetary value per Btu is increased. Thus, assuming that price uncertainty and persistence uncertainty were independent could lead to over-estimating the uncertainty in measure cost-effectiveness. The present study is not considering uncertainty in energy price at all, since CCE is independent of energy price. Future studies, particularly those which may consider other indices of cost effectiveness which include the price of energy, such as net present value or benefit-cost ratio, should keep in mind the potential for negative correlation between energy price and one component of persistence uncertainty.

BPA RWP cohorts were evaluated for three years after weatherization, one for two years, and one for six years. Four different sets of non-participant cohorts were identified, corresponding to different versions of the RWP. Four cohorts from the Seattle City Light Home Energy Loan Program (SCL HELP) were evaluated for persistence of weatherization savings. (Sumi and Coates 1988, 1989) Post-retrofit data was available for periods ranging from 3 to 6 years total duration. The SCL study reported consumption for a single set of non-participants throughout the study period.

The results of the studies cited above were combined and analyzed in terms of the persistence of both gross and net first-year savings. Annual gross savings were simply calculated as the difference between mean annual weather-normalized consumption among the weatherized houses and the mean weather-normalized consumption during the last year prior to weatherization for that group. Annual net savings were calculated as annual gross savings minus the savings observed in the control group of houses. Then, this annual net savings result was compared with the net savings observed during the first year after weatherization.

As expected based upon the discussion in the preceding section, the variability observed in Figure 2.12 among persistence results for a given year is generally greater for gross savings than for net savings (recall that net savings excludes (more accurately, *attempts to correct for)* the effects of (mostly price-induced) behavioral variability in annual consumption); this difference is also documented by the standard deviations reported in Table 2.11. Second, recall that gross savings credits persistence with the effects of out-year investments in efficiency, which should not be included in the effects contributing to persistence-related uncertainty. Finally, note that net persistence is generally below gross persistence, presumably reflecting some of the control houses' out-year investments in some of the measures installed during weatherization of the treated houses.

What are the implications for the contribution of persistence-related effects (factors (1) and (2)) to uncertainty in estimates of annual weather-normalized energy savings? The isolated effects of only factors (1) and (2) are unfortunately not observable in the data. Persistence of gross savings is, on average, slightly greater than 100%, due presumably to contributions from factor (3); as a first-order approximation it will be assumed based on Figure 2.12 and Table 2.11 that absent factor (3), factors (1) and (2) combined do not yield an expected persistence effect for weatherization measures significantly different from 100% persistence. Second, there is no consistent trend in the means of study results for either net or gross persistence over time.

Third, neither is there a clear trend in the variability among study results for either gross or net persistence over time (see Table 2.11). Of course, the number of studies declines to zero past year six, so that in this sense uncertainty about longer-term weatherization savings persistence clearly grows after the sixth year following weatherization. But no clear trend of increasing sample standard deviations is observed during the first six years' data, even though the estimated standard deviation is influenced by the diminishing number of data points per year.[31]

The gross persistence data plotted in Figure 2.12 appears to exhibit significant serial autocorrelation. That is, cohorts whose gross savings increased in the second year after weatherization tended to maintain this higher-than-first-year gross savings into the third and fourth years, and vice versa. The presence of serial autocorrelation was checked for by regressing gross persistence in year "y+1" upon gross persistence in the previous year ("y"). The same was done for the net persistence data. The results are plotted in Figure 2.13, which clearly shows significant autocorrelation in gross persistence, but negligible autocorrelation in net persistence.

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[31]Note that the confidence intervals associated with the individual studies' data points generally grow with time, partially as a function of diminishing sample size caused by attrition (e.g., Horrowitz et al. 1991). This effect could be accounted for explicitly in a meta-analysis of persistence results, but is not observable in the present simpler approach to the data.

Based on the discussion in the preceding section, together with the results summarized in Figures 2.12 and 2.13, the present study will adopt a first-order estimate for $J_{persist}(y)$ which is based on the gross persistence results, and includes the observed serial autocorrelation. $J_{persist}(y)$ will be defined as identically equal to 1.0 for $y=1$ by default (since persistence relates to out-year deviations from first-year savings. In each of the out-years, based upon the results in Figure 2.13, $J_{persist}(y)$ will be defined as:

$$J_{persist}(y) = J_{persist}(y-1) + \text{Normal}(\mu=0,\ \text{std. dev.} = 0.2) \qquad (21)$$

The actual contribution of persistence-related effects to uncertainty in out-year predictions of weather-normalized energy savings should be studied in much more detail; the discussion and data presented above indicate that its magnitude may be quite significant, but also that the characterization in equation (21), based as it is directly upon gross persistence data, is not especially accurate. Another limitation is that empirical data beyond the sixth year following weatherization is non-existent.

Summary of Results and Conclusions

This chapter has suggested a taxonomy of the uncertainties affecting the empirical inputs to analysis of current weatherization potential, has reviewed the state of available data which can support estimates of these uncertainties, and has suggested initial estimates for these uncertainties, based upon empirical data wherever possible. The results of this effort are summarized in Table 2.13. In addition to the parameter-specific notes included below Table 2.13, a few broad conclusions may be offered.

First, empirical data to support characterization of the uncertainty in empirical inputs to analysis of weatherization potential are clearly lacking for many of the factors which contribute to final uncertainty in the four inputs. Of these four inputs, estimates of measure life and annual energy savings appear to be the most in need of an improved empirical basis for estimating their uncertainty.

Second, the taxonomy of factors has helped illustrate how the uncertainty in estimates of annual energy savings is by far the most complex input uncertainty to analyze, as it is influenced by at least seven individual sources of uncertainty.

Third, methods of meta-analysis may help refine and narrow the confidence intervals for some of the estimated input uncertainties. In the near term, if combined with updated attempts to gather program evaluation results, they might be fruitfully applied to factors such as the uncertainty in audit+HDDM-based predictions of first-year weather-normalized savings, the uncertainty contributed by persistence-related effects, and possibly the uncertainty in quote-based estimates of mean installed costs. Beyond these three areas, the effective near-term application of meta-analytic methods to refine estimates of the uncertainty in the empirical inputs to the analysis of weatherization potential is likely to be blocked by a lack of data.

Table 2.1: R. S. Means Regional Cost Multipliers for Selected Residential Retrofit Categories in New England

Location		Thermal and Moisture Protection (includes insulation/sealing)			Mechanical (includes heating system work)		
		Material	Installation	Total	Material	Installation	Total
CT	Bridgeport	100.1	109.9	103.2	103.5	93	98.3
	Hartford	101.1	93.1	98.6	101.4	90.2	95.8
	New Haven	88.2	107.2	94.3	101.9	92.5	97.2
	Stamford	88	109.8	95	101.4	99.6	100.5
	Waterbury	88.8	92.8	90.1	100.4	88.1	94.3
	CT mean	*93.24*	*102.56*	*96.24*	*101.72*	*92.68*	*97.22*
	CT std. dev.	*6.73*	*8.84*	*4.92*	*1.13*	*4.33*	*2.37*
ME	Lewiston	88.3	60.4	78.3	96.8	90.1	93.5
	Portland	96.8	90.1	93.4	96.8	90.1	93.4
MA	Boston	107	134.4	115.8	103.8	126.3	115
	Lawrence	98.8	131.8	109.4	98.9	109.2	104.1
	Lowell	99.4	131.8	109.8	98.6	99.2	98.9
	Springfield	97.8	108.4	101.2	97.8	98.8	98.3
	Worcester	99.7	120.9	106.5	101.1	84.5	92.8
	MA mean	*100.54*	*125.46*	*108.54*	*100.04*	*103.6*	*101.82*
	MA std. dev.	*3.68*	*10.86*	*5.32*	*2.43*	*15.44*	*8.38*
NH	Manchester	96.6	108.5	100.4	97.2	81.6	89.5
	Nashua	102.2	108.5	104.2	98.7	81.7	90.2
VT	Burlington	88	75.1	83.9	100.9	77.3	89.1
RI	Providence	106.2	102	104.8	99.9	91.3	95.6
	overall mean	***96.69***	***105.29***	***99.31***	***99.94***	***93.34***	***96.66***
	overall std. dev.	***6.51***	***20.07***	***9.84***	2.23	***11.87***	***6.38***

Table 2.2: Variability Among Residential Retrofit Measure Cost Quotes in a National Survey *

Com-ponent	Measure	Quoted Installed Cost (1989$/sqft)	Mean Quote by Measure	Quote/ Measure Mean	Variance & (Std. Dev.) Of Quotes By Measure	Variance & (Std. Dev.) Of Quotes by Component
Ceiling	add R19	0.49	0.45	1.09	0.047	0.037
		0.29		0.64	(0.217)	(0.192)
		0.39		0.87		
		0.54		1.20		
		0.52		1.16		
		0.39		0.87		
		0.55		1.22		
	add R30	0.64	0.65	0.98	0.040	
		0.43		0.66	(0.201)	
		0.61		0.94		
		0.73		1.12		
		0.65		1.00		
		0.61		0.94		
		0.86		1.32		
	add R38	0.73	0.93	0.78	0.049	
		1.12		1.20	(0.221)	
		0.77		0.83		
		1.09		1.17		
	add R49	1.38	1.26	1.10		
		1		0.79		
		1.41		1.12		
Walls	Blow in R11	0.54	0.79	0.68	0.060	0.060
		0.68		0.86	(0.245)	(0.245)
		0.65		0.82		
		0.66		0.84		
		0.75		0.95		
		0.8		1.01		
		1.1		1.39		
		0.66		0.84		
		1.02		1.29		
		1.03		1.30		
Sub-Floor	R11 Batts	0.8	0.65	1.23	0.024	0.060
		0.58		0.89	(0.154)	(0.244)
		0.62		0.95		
		0.61		0.94		
	R19 Batts	0.56	0.85	0.66	0.116	
		0.65		0.76	(0.340)	
		1.13		1.33		
		1.07		1.26		
			Mean(variances by meas)		0.056	
			Mean(std. dev's by meas)		(0.230)	
		Variance(total set of ratios)		0.045		
		Std.Dev.(total set of ratios)		(0.211)		

* Source: Boghosian and McMahon 1993. Costs were normalized to Boston using regional cost multipliers.

Table 2.3: Published Estimates of Residential Retrofit Measure Lifetimes

	Source:					Range of Estimates
	1	2	3	4	5	(min, max)
Shell						
Insulation (ceiling + floor)	20	30	20	25	25 (a)	20-30
Insulation (wall)	20	30	25	25	25 (a,e)	20-30
Caulking/weatherstripping	10	-	5	10	10 (a)	5-10
"House Doctor" air sealing	10	-	10	10	-	10
Storm Windows	15	-	15	15	-	15
Storm Doors	15	-	10	15	-	10-15
Replacement Windows	15	-	20	15	22 (e)	15-22
Replacement Doors	15	-	20	15	-	15-20
Heating System.						
clean and tune-up	2	-	-		-	2
set-back thermostat	-	15	-		-	15
component retrofits	10	-	10-15		-	10-15
filter replacement	-	-	-	-	1 (ea12) 5 (e)	1-5
furnace repair	-	-	-	-	15 (e)	15
appliance replacement	15	20	25	23	see next table	15-25

Sources: 1, 2, and 4 come from Table H.1, p. H.1.3, in Brown et al. 1993.

(1) Ternes et al. 1991

(2) Koomey et al., 1991

(3) Cohen et al., 1991

(4) *An Energy Efficiency Blueprint for California, Appendix A: Measurement Protocols for DSM Programs Eligible for Shareholder Incentives,* Report of the Statewide Collaborative, Jan. 1991.

Notes (a, e, etc., refer to type of reference cited in EMS report, as follows):

(a) = Based on measure life estimates from the California Collaborative Process;
(e) = "An engineering judgment based on experience with this technology";
(e3) = Article on remodeling in *Housing Economics,* July 1991;
(e12) = "Based on filter change at the end of each heating season (accounts for retention and performance factors)."

(5) EMS 1993

Table 2.4: Published Estimates of Residential Heating Appliance Lifetimes

	Source					Range of Estimates
Appliance Type	1 Appl. Mag.	2 Easton/GRI	3 LBL/REM	4 ASHRAE	5 EMS	(min, max)
Heat Pump	9 - 11 - 15	10 - 12 - 15	8 - 14 - 16	-	18 (a)	8-18
Gas Furnace	13 - 16 - 20	15 - 18 - 20	18 - 23 - 29	18	18 (a, e, e3) 22 (e) non-condensing	13-29
Oil Furnace	12 - 15 - 19	15 - 17 - 20	18 - 23 - 28	18		12-28
Electric Furnace	15 - 18 - 22	20 - 20 - 25	18 - 23 - 29	-		15-29
Gas Boiler	13 - 17 - 22	20 - 20 - 25	-	30		13-30
Oil Boiler	12 - 15 - 19	20 - 20 - 25	-	30		12-30

Sources: 1-4 come from Table 3.5, p. 24, of Hanford et al. 1994.

(1) Appliance Magazine (annual) -- first-owner lifetimes only

(2) Easton/GRI: Lewis, J. and A. Clarke, 1990. *Replacement Market for Selected Commercial Energy Service Equipment.* (Topical Report: Phase 1B - Commercial). Gas Research Institute. GRI-89/0204.02. June.

(3) LBL/REM: Lawrence Berkeley Laboratory's Residential Energy Model.

(4) ASHRAE: ASHRAE 1987 (HVAC Systems and Applications)

(5) EMS 1993

Table 2.5: Market Size for Selected Weatherization Measures in Regions of the US[1,2]

Million U.S. Single Family or Mobile Home Units which in 1990 lacked insulation in/of:	Northeast Census Region		Midwest Census Region	South Census Region		West Census Region	
	≥ 5500 Heating Degree-Days	< 5500 Heating Degree-Days	≥ 4000 Heating Degree-Days	< 2000 Heating Degree-Days	≥ 2000 Heating Degree-Days	≥ 4000 Heating Degree-Days	< 4000 Heating Degree-Days
Walls	1.1±12%	0.8±24%	1.7± 9%	2.0±15%	2.4±17%	0.7±17%	2.2±13%
Roof/Ceiling	1.0±14%	0.5±28%	1.3±10%	1.3±17%	1.5±20%	0.3±20%	1.2±16%
Floor[3]	2.5±10%	0.8±19%	4.2± 7%	4.8±12%	3.4±14%	1.6±14%	2.3±11%
Water Heater	6.1± 7%	2.7±14%	12.6± 5%	9.4±9%	8.3±10%	2.8±10%	5.1±8%
Units in region	8.7±6%	3.6±12%	17.6±4%	14.4±7%	11.2±8%	5.7±9%	8.3±7%

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[1]Derived from EIA 1992, pp. 147-148.

[2]For each cell, the point estimate is reported along with the approximate relative standard error (RSE).

[3]Includes only houses with basements or crawlspaces which are either un-heated or only partly heated.

Table 2.6 : Summary of Factors Leading to Uncertainty in Prototype+HDDM-Based Estimates of Population-Mean, First-Year, Weather-Normalized Energy Savings per Measure

Type of Error or Uncertainty	Instances which effect predictions of energy savings	Comments
Factor 1:	$k_i(n) \neq K_i(n)$	Not expected to be a major factor -- see text
Omitted Variables	$s_i(0) \neq S_i(0)$	Some of the un-modeled factors will
	$s_i(1) \neq S_i(1)$	be altered by weatherization, such as behavioral factors.
Factor 2:	$\tilde{k}_i(n_{past}) \neq k_i(n_{future})$	The standard deviation among 30-yr normals sampled from an 88-yr period of NH data was < 2%; see Table 5.
Measurement/ Reporting Error	$\tilde{s}_i(0) \neq s_i(0)$	Ex., mis-measuring or mis-reporting pre-weatherization characteristics.
	$\tilde{s}_i(1) \neq s_i(1)$	May include: • errors in $\tilde{s}_i(0)$ for characteristics assumed not to change from year 1 to 2; • mis-characterization of ideal or "perfect" measure installations; • actual incidences of poor quality or "imperfect" matls./installation; • mis-characterized or neglected behavior *within* set s_i.
Factor 3: Model Mis-specification	$\hat{e}(s_i, k_i) \neq e(s_i, k_i)$	Refers to model limitations (other than omission of variables) which would cause model predictions to be in error even if perfect input data $s_i(0)$ and $s_i(1)$ were available.
Factor 4: Aggregation Error	$\bar{e}_j \neq e(\bar{S}_j, \bar{K}_j)$.	Although total energy savings for measure j equals N_j*(mean savings), *it is not generally true that savings for the "mean house" equal mean savings.* While this idealized case is obviously impossible to test, it *can* be shown (e.g., Eto et al. 1990) that $\bar{\hat{e}}_j \neq \hat{e}(\bar{s}_j, \bar{k}_j)$.
Factor 5: Sampling Error	$\hat{\bar{k}}_j(n) \neq \bar{k}_j(n) = \frac{\sum_{i=1}^{N_j} k_{j,i}(n)}{N_j}$	Differences between heating degree-days observed at weather station(s) and the mean heating degree-days for the population of eligible houses.
	$\hat{\bar{s}}_j(y) \neq \bar{s}_j(y) = \frac{\sum_{i=1}^{N_j} s_{j,i}(y)}{N_j}$	For example, prototype wall area will not be equal to the mean wall area of all houses eligible for wall insulation.
Factor 6: "Errant Prototypes"	$\hat{\bar{s}} + \varepsilon \neq \hat{\bar{s}}$	For example, use of the same prototype to evaluate all measures; or use of judgement-based "typical" building characteristics rather than the mean characteristics of the sample of eligible homes.

Table 2.7: Components of Total Uncertainty in Prototype+HDDM-Based Estimates of Population-Mean, First-Year, Weather-Normalized Energy Savings per Measure

	J_0	J_{123}	J_4	J_5	J_6
Error Type:	Measurement	Audit+HDDM	Aggregation	Sampling	Errant Prototype
Nature of the Uncertainty:	How well does the mean measurement-based estimate predict the mean actual ΔNAHC?	How well does the mean audit+HDDM-based estimate predict the mean measurement-based estimate?	How well does the savings for the mean house predict the mean savings for the population of houses?	How well do the savings for the sample-based estimate of the mean house predict the savings for the true mean house?	How well do the prototype characteristics match the sample-based estimate of the mean characteristics of the eligible population?
Table 1 Factors Contributing to Uncertainty:	n/a	1, 2, and 3	4	5	6
Definition (notation)	$\overline{\Delta NAHC_j} \big/ \overline{\Delta \widehat{NAHC}_j}$	$\overline{\Delta \widehat{NAHC}_j} \big/ \overline{\Delta\hat{e}_j[\tilde{s}(0,1),\tilde{k}(n)]}$	$\overline{\Delta\hat{e}_j[\tilde{s},\tilde{k}]} \big/ \Delta\hat{e}_j[\bar{\tilde{s}},\bar{\tilde{k}}]$	$\dfrac{\Delta\hat{e}_j[\bar{\tilde{s}},\bar{\tilde{k}}]}{\Delta\hat{e}_j[\hat{\bar{\tilde{s}}},\hat{\bar{\tilde{k}}}]}$	$\dfrac{\Delta\hat{e}_j[\hat{\bar{\tilde{s}}},\hat{\bar{\tilde{k}}}]}{\Delta\hat{e}_j[\hat{\bar{\tilde{s}}}+\varepsilon,\hat{\bar{\tilde{k}}}+\nu]}$
Definition (words)	mean actual weather-norm'd energy savings / mean measurement-based estimate of energy savings	mean measurement-based estimate of energy savings / mean audit+HDDM-based prediction of energy savings	mean energy savings prediction / energy savings prediction for mean house	energy savings prediction for mean house / energy savings prediction for sample-based estimate of mean house	energy savings prediction for sample-based estimate of mean house / energy savings prediction based on prototype
Estimated Distribution	= 1.0	~ e^Y, Y ~ N(-0.3, 0.3^2)	~ N(1.0, 0.15^2)	~ N(1.0, 0.1^2)	~ N(1.0, 0.1^2)

Table 2.8: Summary of Factors Influencing Observed Mean First-Year Energy Savings Prediction Error Which Vary by Program Type

Factor(s)	Incomplete Installation, Mis-modeled Interaction, and Lack of Calibration	Pilot Study Effects	Very Small Sample Size	Multiple Conservation Measures per Prediction
Influence Observed in:	Utility Programs only	R&D Studies only	R&D Studies only	Utility Programs only
Nature of Influence	Generally contributes to observed prediction error by increasing tendency to over-predict savings	Generally mitigates prediction error by reducing tendency to underachieve predicted savings	Widens confidence intervals associated with each data point	Within-study RMS error among per-home predictions may be smaller than that expected for per-measure predictions.
Summary	This factor will increase the prediction error (bias and variance) observed in utility studies relative to that expected for conservation potential studies: **The set of utility study ratios may over-estimate the uncertainty in conservation potential predictions.**	This factor will reduce the prediction bias observed in R&D studies relative to that expected for conservation potential studies: **The set of R&D study ratios may under-estimate uncertainty in conservation potential predictions.**	This factor will reduce the weights applied to R&D study individual data points in a meta-analysis; **No clear effect on the set of R&D study ratios as an estimator of the uncertainty in conservation potential predictions.**	This factor may increase the weights applied to utility study data points in a meta analysis, but may need to be corrected for if inferring uncertainty of per-measure predictions. **No clear effect on the set of Utility study ratios as an estimator...etc.**

Table 2.9: Derivation of Energy Savings Mean Predicted and Mean Measured Savings Results Based on Data from Two Published Reports

	Measurement Method				Prediction Method	
	Avgerage *Pre* minus Average *Post*	Last *Pre* minus Last *Post*	Deviation from Estimated Trend	Measurement selected by paper authors	Basic HDDM-based prediction	HDDM-based, scaled by prior consumption
Results for Original Set of 12 Houses						
Herendeen et al 1983: En. Savings, MBtu/yr	41.6	**33.0**	29.4	35.8	53.0	43.2
μ measured/ μ basic prediction	0.785	**0.622**	0.555	0.676	1.000	0.815
μ measured/ μ calibrated prediction	0.963	**0.764**	0.681	0.830	1.227	1.000
Hegan et al. 1982: En. Savings, Mbtu/yr	41.6	**33.7**	32.7	36.6	35.5	30.0
μ measured/ μ basic prediction	1.171	**0.950**	0.921	1.031	1.000	0.843
μ measured/ μ calibrated prediction	1.388	**1.127**	1.093	1.223	1.186	1.000
Results for Set of 11 Houses ("Complex House" Removed)						
Herendeen et al 1983: En. Savings, MBtu/yr	40.3	**34.2**	27.7	34.6	44.4	36.9
μ measured/ μ basic prediction	0.907	**0.769**	0.623	0.778	1.000	0.831
μ measured/ μ calibrated prediction	1.092	**0.925**	0.749	0.936	1.203	1.000
Hegan et al. 1982: En. Savings, Mbtu/yr	40.3	**34.1**	30.0	35.3	29.8	25.8
μ measured/ μ basic prediction	1.353	**1.146**	1.008	1.186	1.000	0.866
μ measured/ μ calibrated prediction	1.563	**1.323**	1.165	1.371	1.155	1.000

Table 2.10: Statistics for Ratios of Mean Measured to Mean Predicted Energy Savings

Study Type Included	Statistic Reported	Characteristics of the Sample		
		All Observations Reported by Cohen et al (1991) Included	Three Outliers Removed from Sample	Statistics for Natural Logs of Ratios, with Three Outliers Removed
Utility Studies	Minimum	0.443	N/A	N/A
	Maximum	1.574		
	Count	10		
	Mean	0.774		
	Median	0.673		
	Std. Dev.	0.358		
	Variance	0.128		
	Skewness	1.088		
	Kurtosis	0.396		
R&D Studies	Minimum	0.118	0.488	N/A
	Maximum	2.1	1.143	
	Count	14	11	
	Mean	0.792	0.790	
	Median	0.777	0.792	
	Std. Dev.	0.469	0.182	
	Variance	0.220	0.033	
	Skewness	1.329	0.264	
	Kurtosis	2.623	-0.180	
Utility and R&D Studies Com-bined	Minimum	0.118	0.444	-0.813
	Maximum	2.1	1.574	0.454
	Count	24	21	21
	Mean	0.785	0.782	-0.299
	Median	0.752	0.763	-0.271
	Std. Dev.	0.418	0.273	0.333
	Variance	0.175	0.074	0.111
	Skewness	1.323	1.061	0.181
	Kurtosis	2.622	1.433	-0.449

Table 2.11: Persistance of First-Year Gross and Net Energy Savings from Two Sets of Weatherization Studies

Annual Gross Savings as Percent of First-Year Gross Savings

	First Year	Year 2	Year 3	Year 4	Year 5	Year 6
BPA1	100%	117%	119%			
BPA2	100%	98%	102%			
BPA3	100%	107%				
BPA4	100%	100%	110%			
BPA5	100%	82%	55%			
BPA6	100%	100%	116%	92%	88%	60%
SCL1	100%	102%	138%	145%	117%	105%
SCL2	100%	144%	151%	128%	126%	
SCL3	100%	105%	76%	59%		
SCL4	100%	67%	41%			
	mean:	102%	101%	106%	110%	82%
	std. dev.:	20%	37%	38%	20%	32%

Annual Net Savings as Percent of First-Year Net Savings

	First Year	Year 2	Year 3	Year 4	Year 5	Year 6
BPA1	100%	85%	61%			
BPA2	100%	89%	67%			
BPA3	100%	92%				
BPA4	100%	95%	100%			
BPA5	100%	79%	69%			
BPA6	100%	95%	60%	85%	85%	75%
SCL1	100%	107%	104%	85%	81%	96%
SCL2	100%	105%	81%	90%	129%	
SCL3	100%	73%	73%	86%		
SCL4	100%	80%	64%			
	mean:	90%	75%	87%	98%	86%
	std. dev.:	11%	16%	3%	26%	15%

Table 2.12: Summary of Results for Contributors to Uncertainty in Inputs to Analysis of Current Weatherization Potential

Uncertainty	J_N Market Size	J_C Installed Cost	J_n Useful Lifetime	J_o Savings Meas. Er.	J_{123} audit+ HDDM	J_4 Aggreg. Error	J_5 Sampling Error	J_6 Errant Prototype	J_{HDD} Climate Variability	$J_{persist}$ Persistence Uncert.
Availability of data to characterize uncertainty:	O.K.	O.K./ Poor	Poor	Good	O.K./ Poor	O.K. but needs analysis	O.K. but needs analysis	N/A needs analysis	Good	O.K./ Poor $J_{per}(1)=1.0$
Estimated Uncertainty (μ, std.dev)	N(1, 0.14)	N(1, 0.2)	N(1, 0.25)	1.0	e^Y, Y= N(-0.3, -0.3)	N(1, 0.15)	N(1, 0.1)	N(1, 0.1)	$J_{HDD}(y)=$ N(1, 0.06)	$J_{per}(y>1)=$ $J_{per}(y-1)$ + N(0, 0.2)
Notes:	1	2	3	4	5	6	7	8	9	10

1. Uncertainty is very measure- and study-specific. Coming RASS compilations should reduce uncertainties considerably for sub-national studies. Otherwise, estimates (using RECS data) are very uncertain below the census region level.

2. Few studies have been done to compare mean installed cost per measure with quote-based estimates; also, several studies have relied on cost data which was quite old and/or representative of other regions.

3. Lifetime uncertainty's influence is greatest for shorter-lived measures (such as tune-up); these should be studied empirically.

4. Has benefited from a standardized method (PRISM) which has been widely used and documented. Uncertainty appears relatively small.

5. Needed are: a) a standardized method for calculating savings per measure, particularly for calibrating savings estimates to prior consumption; and b) a series of empirical tests of this method, applied to populations within full-scale programs rather than pilot programs. Absent these new initiatives, an exhaustive search for additional results might be coupled with meta-analysis techniques.

6. This source of error has never been analyzed for the residential sector; only once for the commercial sector.

7. This source of error should be analyzed next time RECS-based prototypes are updated, and the methods clearly documented. Sampling error suffers from same small-sample problem as estimates of market size; however, RASS compilations are not likely to help much here.

8. This error is completely study-specific. It has never been documented; in fact, it has rarely if ever been calculated, since mean characteristics for each measure-eligible population are rarely calculated themselves. This uncertainty may be understated by this estimate.

9. For measures with lives well under 5 years (ex., tune-ups) this uncertainty may be significant. Not for longer-lived measures.

10. This uncertainty needs more careful study. First, existing data should be further analyzed to determine whether net, gross, or some function of the two best represent the contribution of persistence-related effects to uncertainty in predictions of energy savings potential and measure cost-effectiveness. This analysis might clarify data needs to inform future empirical studies of persistence.

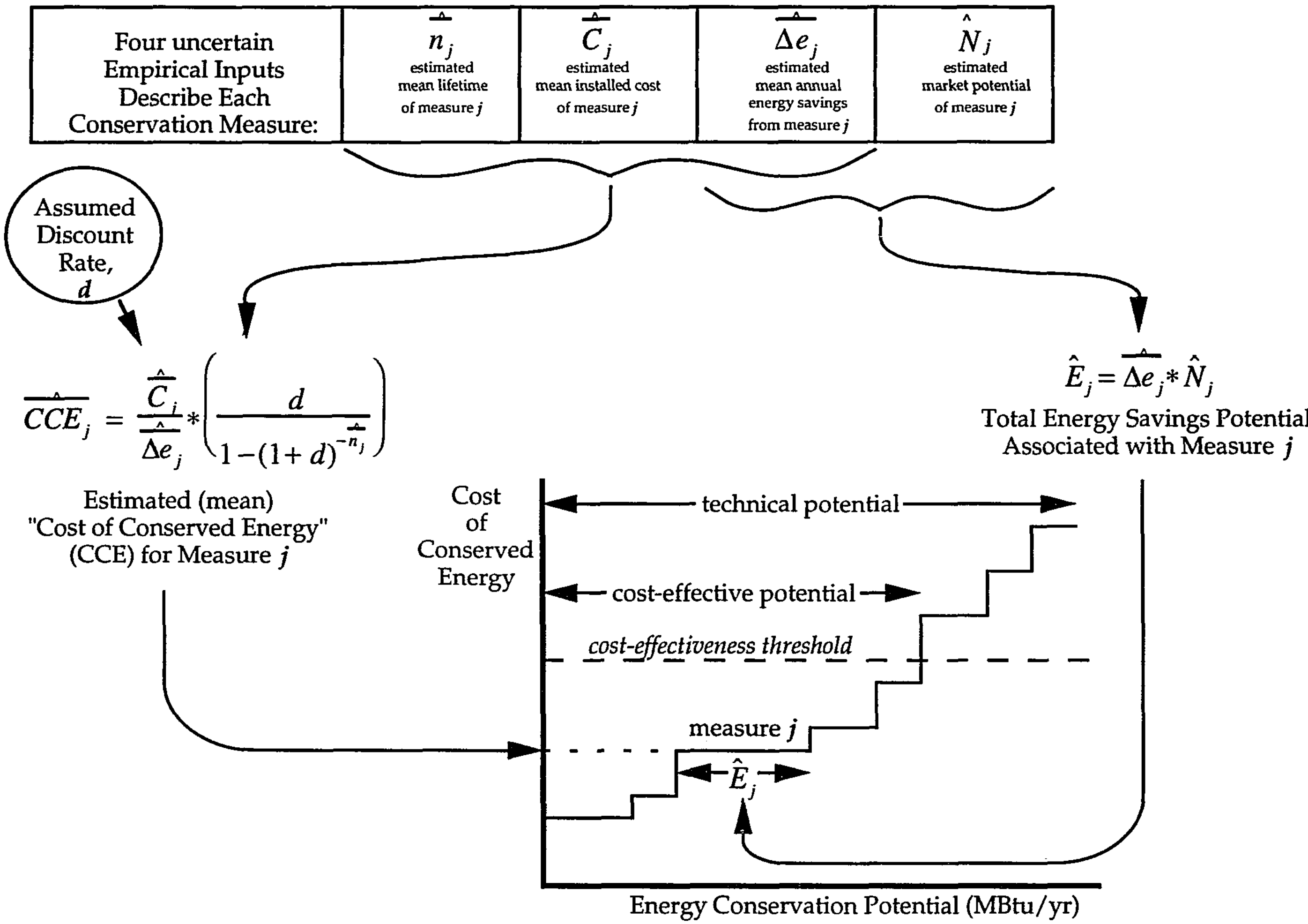


Figure 2.1: Usage of Uncertain Empirical Inputs in the Analysis of Energy Conservation Potential

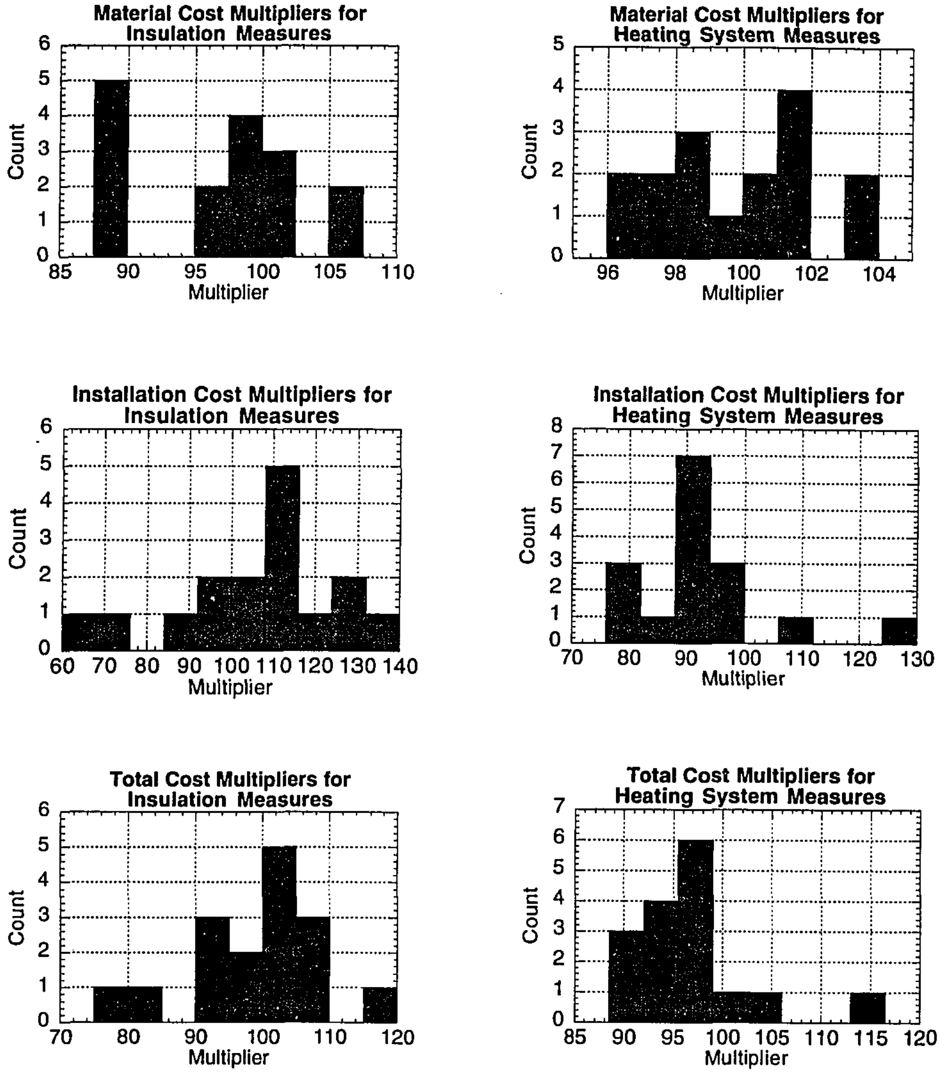
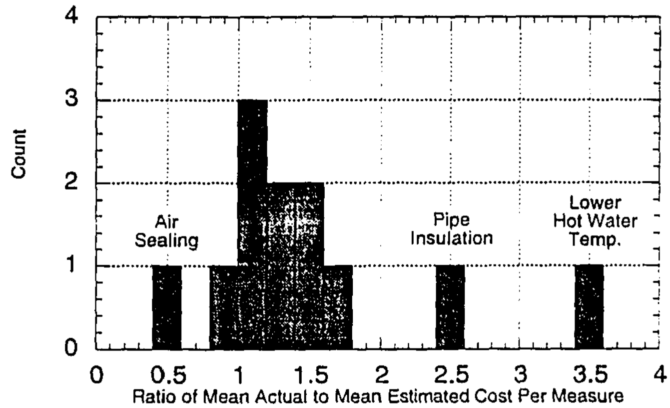


Figure 2.2: Histograms of R.S. Means Regional Multipliers for New England

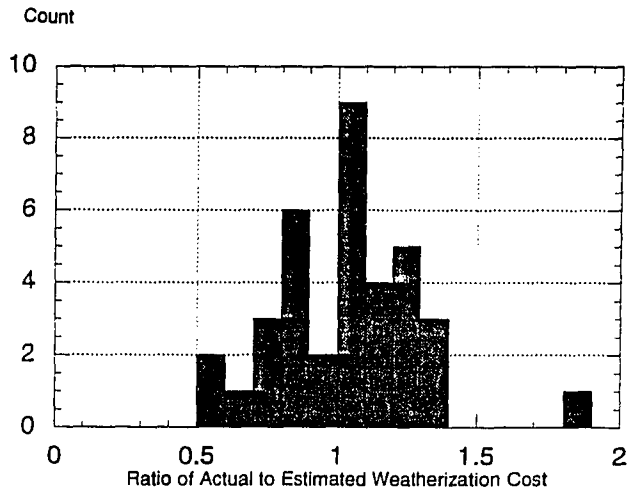


Source: Temes et al. 1991

Statistics for Ratios of Mean Actual to Mean Estimated Installed Cost per Measure	
Minimum	0.400
Maximum	3.5
Points	12
Mean	1.485
Median	1.289
Std Deviation	0.806
Variance	0.649
Skewness	1.342
Kurtosis	1.445

Statistics for Ratios of Mean Actual to Mean Estimated Installed Cost per Measure *With 3 Outliers Removed*	
Minimum	0.924
Maximum	1.765
Points	9
Mean	1.275
Median	1.276
Std Deviation	0.272
Variance	0.074
Skewness	0.459
Kurtosis	-0.857

Figure 2.3: Ratios of Mean Actual to Mean Predicted Cost per Residential Retrofit Measure



Source: Ternes et al. 1991

Statistics for Ratios of Actual to Estimated Total Weatherization Cost Per Home

Minimum	0.549
Maximum	1.803
Points	36
Mean	1.027
Median	1.029
Std Deviation	0.250
Variance	0.062
Skewness	0.507
Kurtosis	1.043

Figure 2.4: Ratios of Actual to Estimated Weatherization Cost per Home

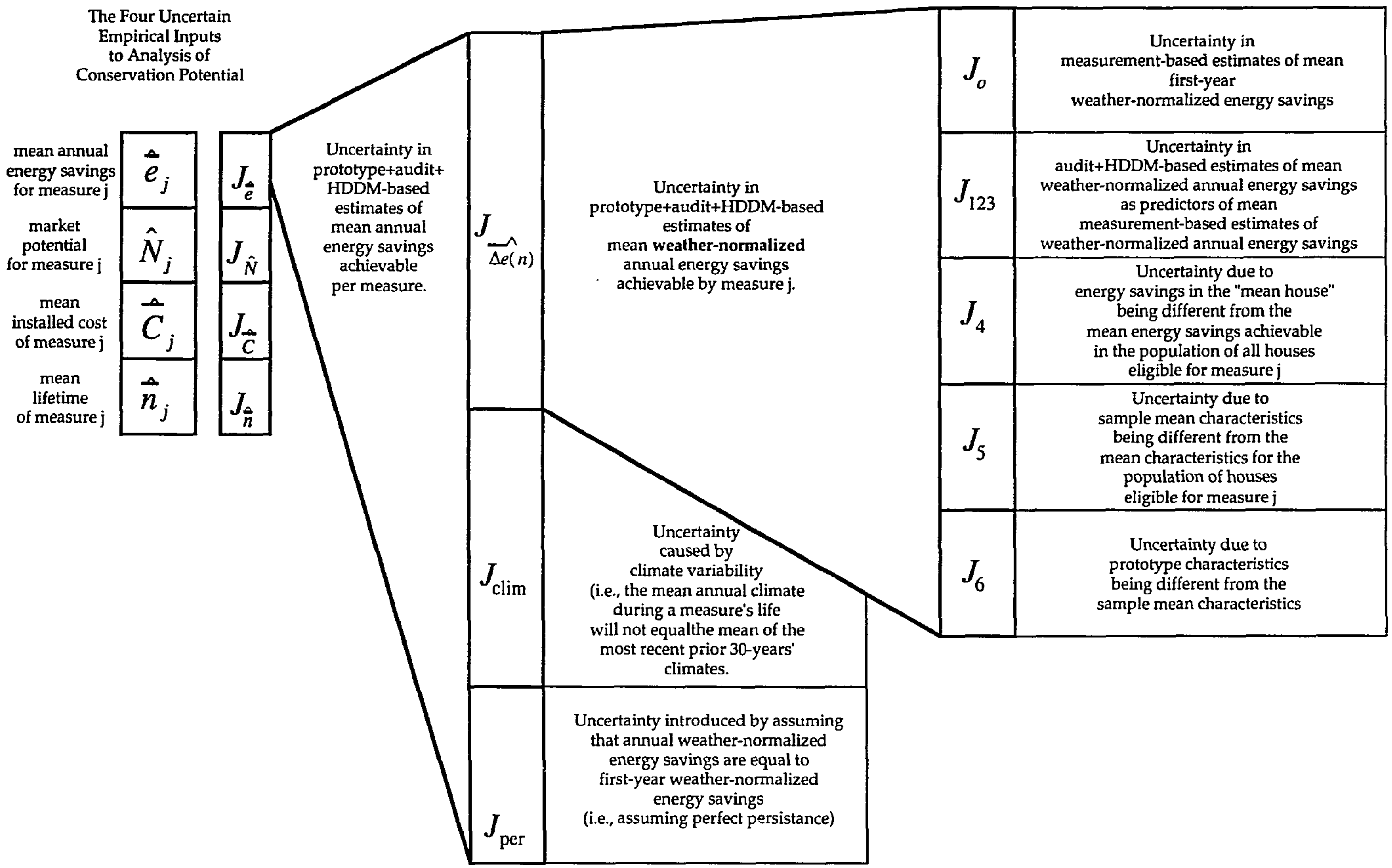


Figure 2.5: Decomposition of the Uncertainty in Annual Energy Savings Into Its Constituents

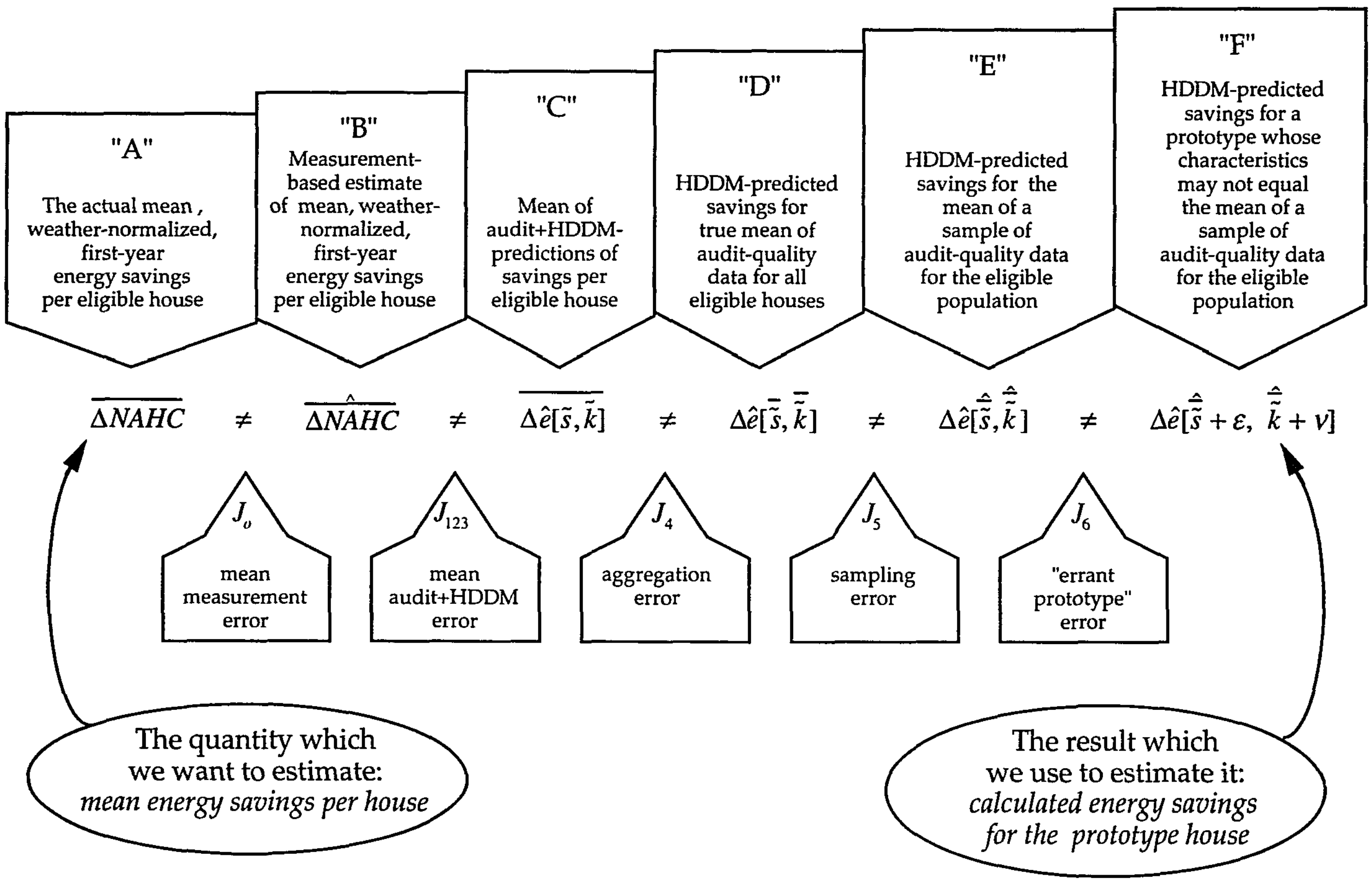
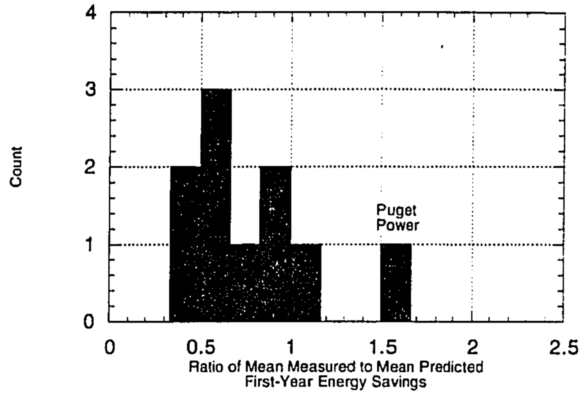


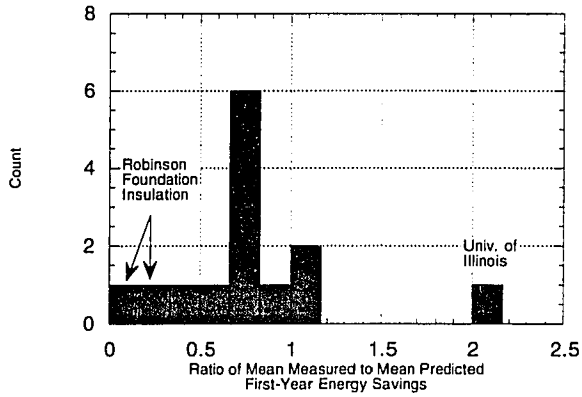
Figure 2.6: The "Chain of Inequalities" Illustrating the Individual Sources of Uncertainty In Estimates of First-Year, Weather-Normalized, Mean Energy Savings

Figure 7a: Histogram of Reported Ratios of Mean Measured to Mean Predicted Energy Savings For Utility Programs



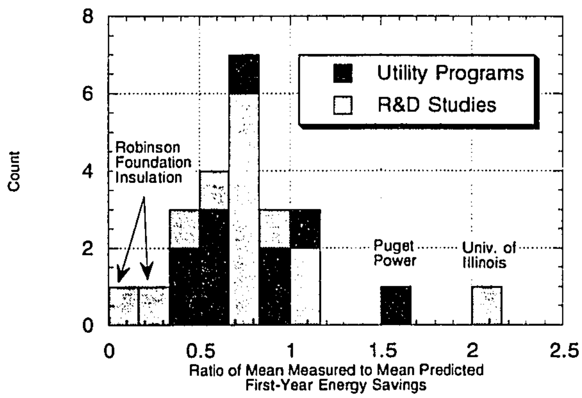
Ratios of Mean Measured to Mean Predicted Energy Savings for Utility Programs	
Minimum	0.443
Maximum	1.574
Points	10
Mean	0.774
Median	0.673
Std Deviation	0.358
Variance	0.128
Skewness	1.088
Kurtosis	0.396

Figure 7b: Histogram of Reported Ratios of Mean Measured to Mean Predicted Energy Savings For R&D Studies



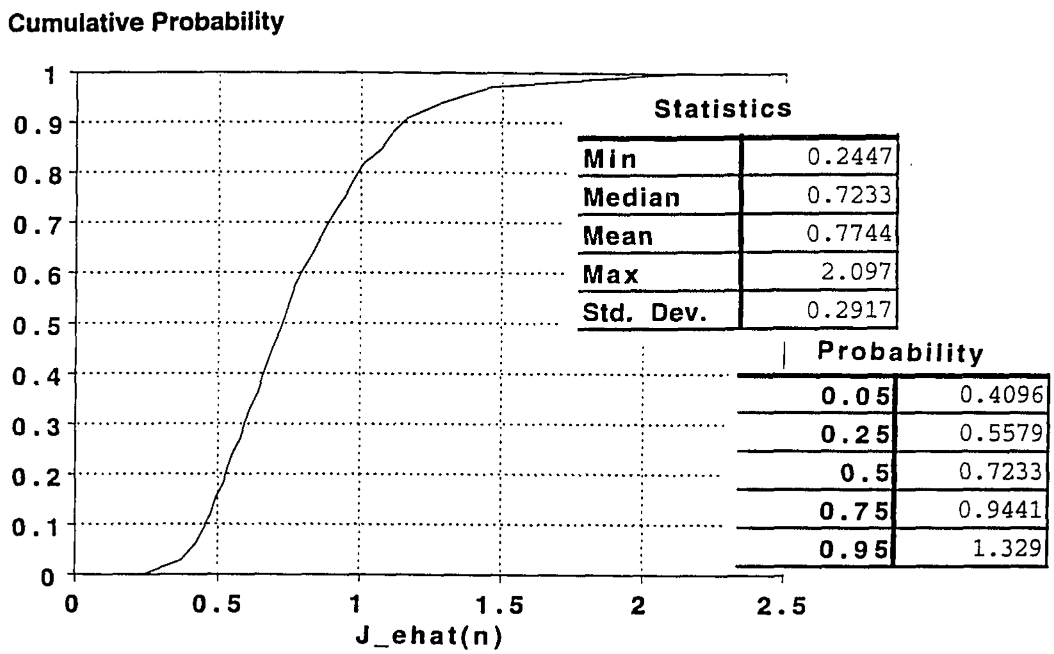
Statistics for the Ratios of Mean Measured to Mean Predicted Energy Savings for R&D Studies	
Minimum	0.118
Maximum	2.100
Points	14
Mean	0.792
Median	0.777
Std Deviation	0.469
Variance	0.220
Skewness	1.329
Kurtosis	2.623

Figure 7c: Histogram of Reported Ratios of Mean Measured to Mean Predicted Energy Savings For Both Utility Programs and R&D Studies



Statistics for the Ratios of Mean Measured to Mean Predicted Energy Savings for R&D Studies and Utility Programs Combined	
Minimum	0.118
Maximum	2.100
Points	24
Mean	0.785
Median	0.752
Std Deviation	0.418
Variance	0.175
Skewness	1.323
Kurtosis	2.622

Figure 2.7: Variability Among Ratios of Mean Measured to Mean Predicted Annual Energy Savings



Statistics

Min	0.2447
Median	0.7233
Mean	0.7744
Max	2.097
Std. Dev.	0.2917

Probability	
0.05	0.4096
0.25	0.5579
0.5	0.7233
0.75	0.9441
0.95	1.329

Figure 2.8: Statistics and Cumulative Probability of $J_{\overline{\Delta\epsilon}(n)}$

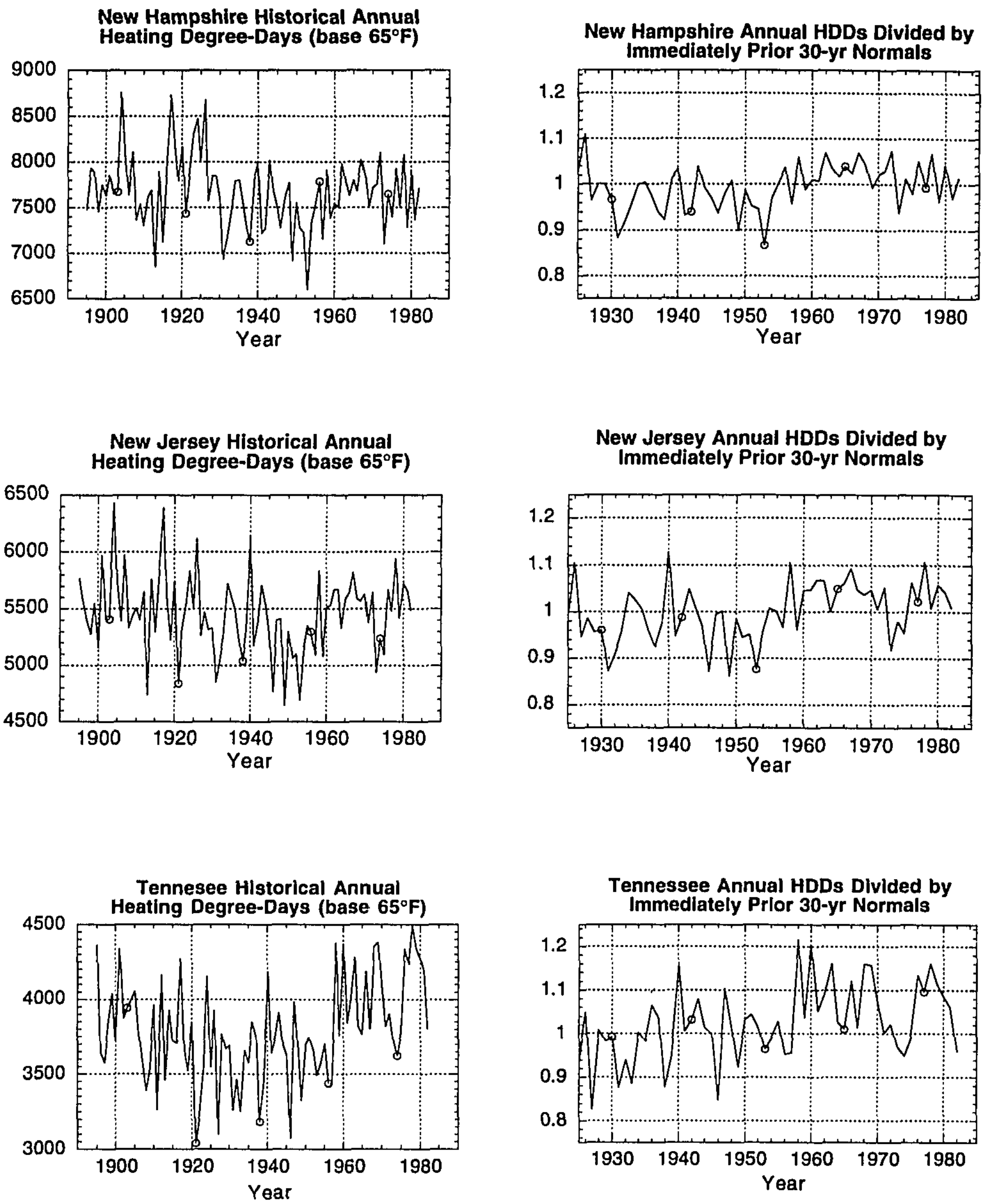


Figure 2.9: Historical Annual Heating Degree Days and Their Predictability by the Prior 30-year Normal for Three States in the US

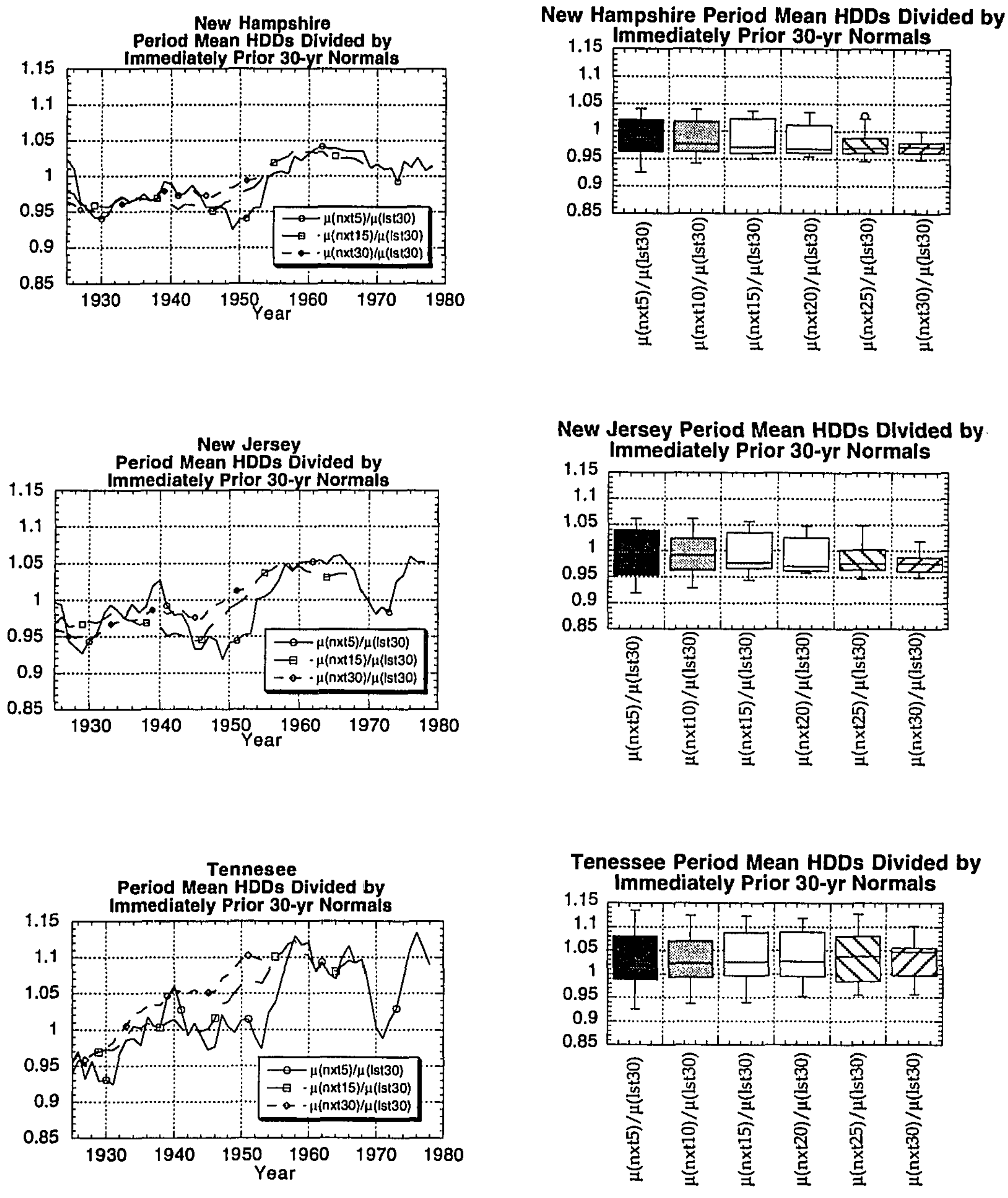
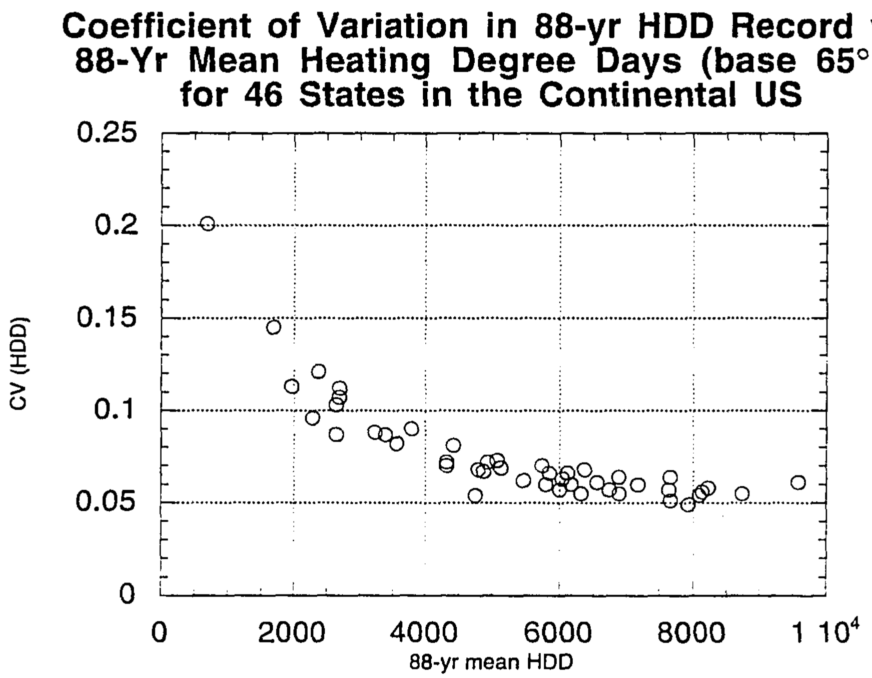


Figure 2.10: Period-Mean Heating Degree-Days Divided by Immediately-Prior 30-Year Normals for Three US States



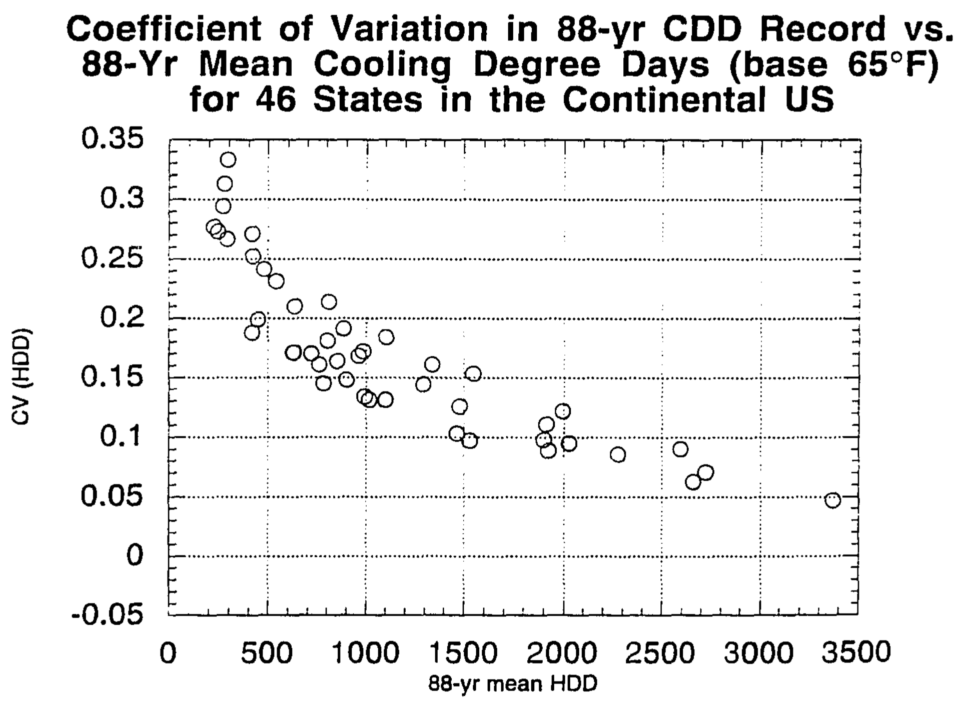
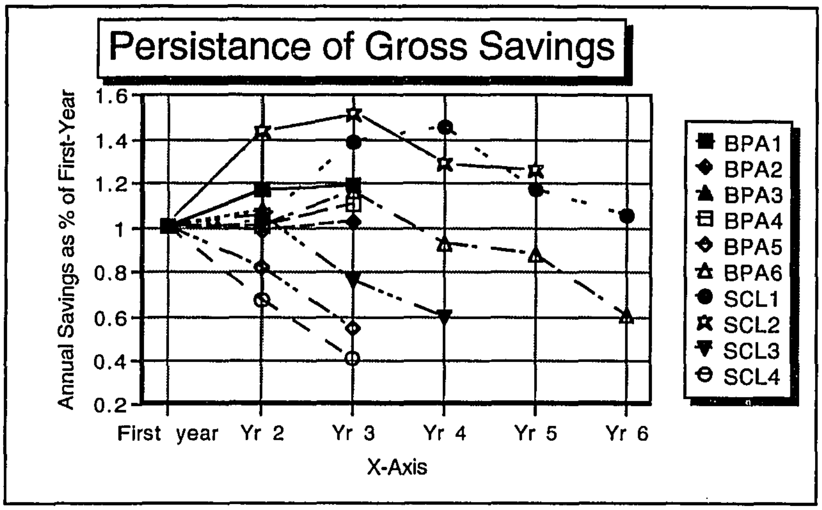


Figure 2.11: Climate Variability in Relation to Climate Severity



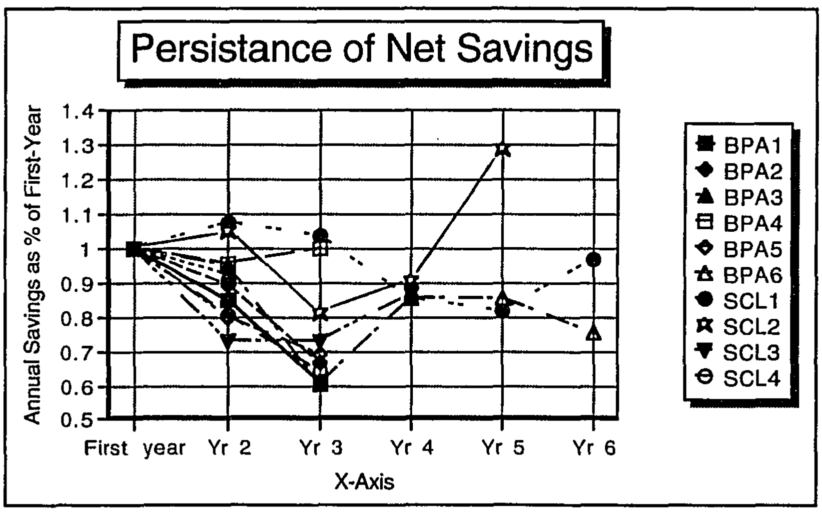
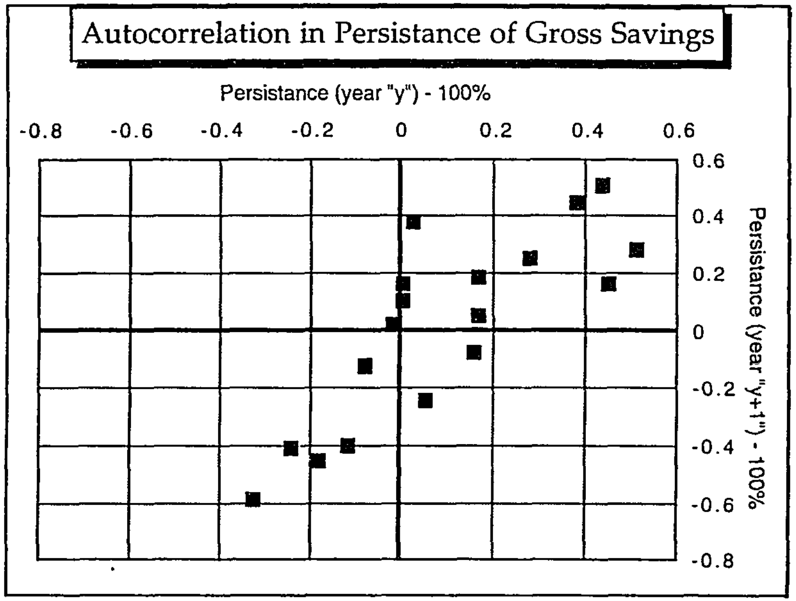
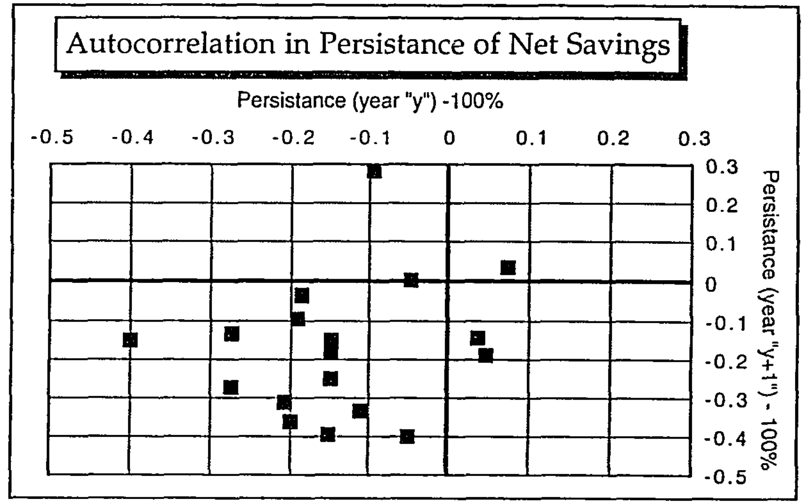


Figure 2.12: Persistance of Gross and Net First-Year Energy Savings





Regression Results for Gross Savings:
Model: Persistance(y+1)= a + b•Persistance(y)

Constant (a):	-0.085
Std Err of Y Estimate:	0.195
Coefficient (b):	1.081
Std Err of Coefficient:	0.192
R^2	0.665
# of Observations:	18
Degrees of Freedom:	16

Regression Results for Net Savings:
Model: Persistance(y+1)= a + b•Persistance(y)

Constant (a):	-0.131
Std Err of Y Estimate:	0.174
Coefficient (b):	0.296
Std Err of Coefficient:	0.350
R^2	0.043
# of Observations:	18
Degrees of Freedom:	16

Figure 2.13: Autocorrelation in Persistance of Gross and Net Savings

CHAPTER 3

PROBABILISTIC ANALYSIS OF CONSERVATION POTENTIAL

Introduction

Chapter 1 examined the sensitivity of the principal cost-effectiveness indices to variations in the inputs to conservation potential analysis. Chapter 2 developed probabilistic estimates of the uncertainty in each of these inputs. The present chapter effectively combines these two strands into a third and new one: probabilistic analysis of energy conservation potential.

The chapter begins with a review of the terminology and the standard (deterministic) methods of conservation potential analysis. Next, an application of the methods of *uncertainty propagation* (e.g., Iman and Helton 1988, Morgan and Henrion 1990) to conservation potential analysis is illustrated. That is, the probabilistic descriptions of the uncertainty in the inputs which were developed in Chapter 3 are here used in, or "propagated through," the constitutive equations of energy conservation potential analysis, in order to characterize their effects, singly and jointly, upon the uncertainty in the results of such analyses. Finally, extensions to the conservation supply curve framework are introduced which allow reporting of the results of probabilistic conservation potential analysis. A numerical example illustrates the methods and results.

Methods and Terminology of Conservation Potential Analysis

This section provides an overview of existing approaches to conservation potential analysis. The variety of perspectives, time frames, definitions of conservation potential, and classes of conservation potential studies are illustrated in Figure 3.1. An outline of the basic steps and iterative process at the heart of measure-level analyses (which are the focus of the present study) is provided in Figure 3.2.

Some Basic Terminology

Analyses of energy conservation potential attempt to develop quantitative estimates of the potential for using energy more efficiently through investments in available technologies. Energy provides *energy services* (e.g., warm homes, cold beer, well-lit stores) in numerous *end-uses* (e.g., space heating, water heating, refrigeration, lighting). An *energy conservation measure* is an investment in a particular technology which allows the same level of energy services to be provided using less energy input. For most end-uses a host of individual conservation measures are technologically feasible; in addition, measures addressing one end-use may influence the energy consumption in another end-use (as when high-efficiency lighting may increase space heating requirements and reduce space cooling requirements). Measures can be divided into two broad classes: *retrofits*, which upgrade the efficiency of existing capital stocks (examples include adding insulation to existing buildings, replacing light bulbs or appliances before wear-out with higher-efficiency alternatives, or cleaning and tuning a furnace), and *new purchases*, which upgrade the efficiency of newly added capital stocks at their time of purchase or construction (examples include appliance or building standards which set minimum efficiency levels for suppliers, or purchaser selection of higher-efficiency alternatives).

Supply curve analyses generate several different types of conservation potential estimates. The cumulative energy savings attributed to the entire set of technically feasible, non-mutually measures, regardless of their cost-effectiveness, is the estimate of *technical potential.* The cumulative energy savings attributed to all technically feasible, non-mutually exclusive measures which also satisfy a chosen cost-effectiveness criterion constitutes the estimate of *cost-effective conservation potential.* A few studies (Brown 1993, Nadel and Tress 1990, Krause et al. 1987) have further estimated the *achievable* cost-effective conservation potential -- that fraction of the estimated cost-effective potential which is considered to be realizable by programs and policies having prior precedent, in light of such programs' demonstrated levels of participation and effectiveness.

A conservation supply curve is generally a "snapshot" of a relationship between available technology and either the current energy-using capital stock, or the forecast state of the capital stock in some future year, assuming no new policies are initiated (other than those already scheduled to take effect). Supply curves of *current potential* are usually based on currently available measures and on the most recent building and equipment stock data available (which is in fact usually a few years old). Estimates of *future potential* require descriptions of current building stocks *and* forecasts of how those stocks will evolve, including expected rates and characteristics of new construction, expected rates of demolition, *and* "a detailed baseline forecast of typical future technologies that will be installed in the absence of policy action, including the number of devices, their cost, and their expected energy consumption." (Koomey et al. 1991) Estimates of future potential may be based on presently available measures only, or may employ forecasts of future commercial availability and/or cost reductions for measures which are presently at a research stage or not yet economically viable. Finally, estimates of future *achievable* potential must explicitly account for the fact that measures cannot be adopted overnight. These studies make use of estimated measure adoption rates based on the performance of prior programs and on natural rates of capital stock wearout and replacement.

Not all analytical perspectives on energy conservation potential explicitly consider individual measures or even end-uses. The so-called "top-down" economic modeling perspective considers technologies in a highly aggregate fashion, using parameters such as the elasticity of price-induced substitution between capital-labor and energy, and the autonomous rate of energy efficiency improvement. In contrast, the "bottom-up" or "technology costing" perspective seeks to generate estimates of total energy conservation potential by aggregating the estimated savings from specific technologies applied to each end-use under consideration. These two approaches to modeling the potential for energy efficiency improvements are compared in, for example, Komor and Moyad 1992, and Howarth and Monahan 1992. The present research is directed at the methods and results of technology costing studies.

Classes of Technology Costing Studies

Within the class of technology costing studies there is wide variety in levels of regional, stock-descriptive, and technological detail. It is possible to identify three broad classes of "bottom-up" conservation potential studies: (1) those which build aggregate results from an *end-use* level of detail; (2) studies which build from the more detailed level of individual measures; and (3) studies which incorporate *program* characteristics but do not attempt to treat either end-uses or measures in exhaustive fashion. Each class of study is described briefly below. Of course it must be acknowledged that within these three categories, actual studies vary considerably in both detail and methodology.

Several recent analyses (e.g., EIA 1990, Carlsmith et al. 1990, EPRI 1990, OTA 1991, OTA 1992) have identified sets of efficiency improvement options at an end-use level of detail. Individual energy conservation options in these studies are of the sort: "increase space heating efficiency of existing residential housing", "increase new-purchase water-heating efficiency," etc. For each end-use option, cost and energy savings estimates are identified. Energy savings estimates for these options are frequently expressed as a percent of current or projected "business as usual" energy consumption for the given end-use, and tend to draw upon results of other more detailed measure-level studies and/or summaries of actual measured savings results, rather than conducting detailed engineering analyses of their own.

Measure-level studies identify cost and savings estimates for host of individual conservation measures addressing each end-use. Results for separate measures are synthesized and aggregated using supply curve analysis (see below). Studies of this type have been done at national, state, and utility service area scales. Recent examples for the US residential sector include Boghosian and McMahon 1993 and Koomey et al. 1991, as well as UCS 1991 and NAS 1991 which were not restricted to the residential sector. Recent state or regional residential supply curve studies include WCDSR 1994, XENERGY 1990, NPPC 1989, Miller et al. 1989, NEEPC 1987, Lovins 1987, Krause et al. 1987, Geller et al. 1986, and Hunn et al. 1986. Most of these studies have addressed only electricity-using end-uses, but even so, the number of individual measures examined per study exceeds 100 in the more detailed studies.

The third class of supply curve studies in addition to end-use and measure-level analyses is *program-based* supply curve studies of demand-side management (DSM) resources, which are used in utility least-cost integrated resource planning. Introductions to methods associated with this class of supply curves are found in EPRI 1991a and Krause and Eto 1988, for example. The studies are "program based" in that they account for the influences of program design upon total costs, technology choice, and size of market potential. In addition to material and installation costs associated with each measure, these studies account for the administrative, marketing, and evaluation costs of utility programs designed to achieve measure implementation. Not only are more cost elements included, but there are also a number of different perspectives from which DSM program costs and resources must be evaluated (e.g., total resource cost, societal cost, utility cost, rate payer impact measure, etc.), each of which can lead to a particular rank-ordering of the alternatives. Finally, the full set of costs *avoided* by the potential conservation program may go well beyond simple avoided energy costs, and may be a function of both the magnitude and timing of load reductions. (Krause and Eto 1988, EPRI 1991a, EPRI 1991b, Chernick et al. 1993)

Measure-level analysis provides an initial assessment of the availability of DSM measures, which may motivate and provide a basis for subsequent program-level studies. In order to provide at least a rough accounting for program-related expenses even at this earlier stage of analysis, several authors (e.g., Berry 1989, Krause et al. 1987, Nadel 1990, Koomey et al. 1991) have recommended and/or applied a "rule of thumb" that the "societal" cost of conserved energy should be increased by 10 to 20% to reflect utility "program costs." However, Koomey et al. caution that "Program costs for particular end-uses may be lower or higher than these crude averages; individual programs for specific end-uses may differ from these overall averages" (p.4). A survey of utility-reported program administrative costs as a fraction of direct measure costs by Joskow and Marron (1992) bears this out, reporting values ranging from 11% to 261% for residential programs.

In summary, it should be clear that each of the three classes of studies differ both in terms of the inputs used in the analysis and in terms of their objectives -- that is, the types of decisions they are designed to support. End-use-based studies are generally designed to inform policy deliberations in rather broad terms. Since they are usually assembled from the results of measure-specific studies for other regions, climates, and capital stocks, they are mainly useful when qualitative conclusions about the energy savings potential for all sectors and fuels are of interest. Program-based studies are at the other end of the spectrum, in that they are tools used in energy planning and/or initial program design, are region- and fuel-specific, do not attempt to characterize the potential associated with all technically feasible measures, but do include program characteristics among the inputs to the analysis. Measure-level studies are intermediate between these other two study classes, in that they are more detailed and complex than end-use level summaries, but still omit consideration of program characteristic data used in program-based studies. They are used, for instance, to support federal and state policy makers by providing detailed engineering-economic estimates of the costs of reducing carbon emissions (Koomey et al. 1991), and provide a basis for the other two types of studies. Uncertainty analysis for measure-specific studies is the focus of the present research.

Overview of Measure-Level Supply Curve Analysis Methods

Methods for generating measure-level supply curves of energy conservation potential have been developed and elaborated by authors including Meier (1982), Krause et al. (1987), and Vine and Harris (1990), and have been applied widely, as indicated by the citations in the previous section. Supply curve analysis specifies a procedure for systematically accounting for measure energy savings interaction when aggregating the effects of multiple measures. Supply curves also provide a standardized way of graphically summarizing the results of conservation potential analysis. Four elements of measure-level supply curve analysis are: (1) an iterative framework; (2) estimation of per-measure savings; (3) rank-ordering measures using a cost-effectiveness criterion; and, (4) plotting final results together with a cost-effectiveness threshold.

An iterative framework.

The iterative process of conservation supply curve development is summarized in Figure 3.2. Conservation measures are considered to be implemented one at a time. At each iteration, the set of not-yet-implemented measures is ranked using a cost-effectiveness criterion, and the most cost-effective measure from this set is selected for implementation. Following each new measure's implementation, the energy-using capital stock must be re-defined to reflect the measure's impacts on energy consumption in each end-use it effects (directly and indirectly), and also to preclude later implementation of measures which are mutually exclusive with previously-implemented measures. Measure interaction is modeled explicitly to avoid double-counting energy savings.

Estimating per-measure energy savings.

Methods for estimating the energy savings of energy conservation measures in buildings range widely in complexity, from simple percent-savings methods to the use of sophisticated hourly building energy simulation models.

Percent-savings methods characterize each measure in terms of the fraction or percentage by which it will reduce baseline per-end-use annual energy consumption. The analysis starts with estimates of baseline energy use per end-use, and measure interaction is modeled simply by reducing end-use energy consumption for each prior measure; more details and example calculations are provided in EPRI 1991a. While percent savings methods can be adequate for estimating residential energy conservation potential in end-uses such as lighting, electrical appliances, and perhaps water-heating, they are generally not adequate for space-conditioning measures. This is because the percentage of baseline energy saved per measure is strongly influenced by building and climate characteristics (which are typically heterogeneous within study areas), and because the interaction of space heating measures is not well-represented using the percent-savings approach.

Heating-degree-day methods for analysis of space-heating conservation measures (and the analogous use of cooling-degree days to address space cooling energy consumption) make use of data such as pre- and post-retrofit shell and glazing R-values, floor area, envelope surface and window areas, foundation type, and estimated infiltration rates, together with basic climate data, in order to estimate annual consumption for a given building.[1] Studies of residential conservation potential generally make use one or a few prototypical single-family and multi-family building specifications and climate descriptions intended to be representative of either typical or mean characteristics of the population. Commercial sector studies generally require a larger number of buildings prototypes than residential studies due to greater diversity in the commercial stock.

[1]Another method similar to heating-degree day methods in terms of data requirements and computational complexity is component loads analysis (see, for example, Huang et al. 1987a and 1987b, and Hanford et al. 1994.

Building energy simulation models require and make use of the basic prototype characteristic data listed above, together with much more detailed building information including solar orientation and shading, thermal mass properties, foundation geometry, etc. Since such detailed information is not realistically available for use in energy conservation potential studies, the use of sophisticated energy simulation models for such studies is not practical either.

Ranking measures by cost of conserved energy.

The standard cost-effectiveness index which has been used in virtually all conservation supply curve analyses to date is the cost of conserved energy (CCE), defined as:

$$\text{Cost of Conserved Energy (CCE)} \quad = \quad \frac{C*crf}{E} = \left(\frac{C}{E}\right)\left(\frac{d}{1-(1+d)^{-n}}\right) \qquad (1)$$

where ***E*** is the assumed constant annual energy savings due to the measure (e.g., in MBtu/year), ***C*** is the measure installed cost ($), ***n*** is the measure lifetime (years), and ***d*** is the selected real annual discount rate (% per year). The term *crf* is the "cost recovery factor." Multiplying the measure cost ***C*** by *crf* yields the effective value of equal annual payments to be made ***n*** times over the life of the conservation measure. Discounting accounts for the opportunity cost of purchasing the conservation measure, since the effective annual payments could (at least in principle) have instead been invested in its year of payment at a fixed rate of return ***d*** until the year ***t=n***.[2]

Other cost-effectiveness indices which could be used to rank measures in supply curve analysis include the cost-benefit ratio (CBR), which is equal to the CCE divided by the fuel price and is unitless; benefit-cost ratio (BCR) which is simply the inverse of CBR; or net present value (NPV), which subtracts costs from benefits rather than dividing

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[2]An equivalent view is that the conservation measure is paid for by borrowing the amount ***C*** at an interest rate ***d***; ***C*crf*** is the annual loan payment to be made each year during the measure life.

them by benefits.[3] The primary benefit of CCE relative to these other indices is its independence from assumptions (or altered forecasts) about the fuel prices, which may vary regionally as well as temporally. On the other hand, since they are ratio-based indices, CCE, BCR and CBR have the disadvantage that they do not indicate the magnitude of the energy savings or benefits. Given a budget constraint (spending limit), the use of ratio-based indices (BCR, CBR, or CCE) is generally recommended for screening or ranking competing investments (e.g., ASTM 1992). However, others have argued that when ranking *competing and cost-effective* conservation measures or conservation programs in energy planning, NPV should be used, since the budget constraint does not properly apply in this context. (e.g., Chernick et al. 1993)

Further discussion and citations related to the choice of a cost-effectiveness index is provided in the references noted above. There are two summary points worth noting here. First, an estimate of cost-effective energy conservation potential from a supply curve analysis which ranks measures based on NPV may differ from the corresponding estimate based on the use of CCE (or CBR or BCR). Second, neither estimate may strictly represent the best estimate of the *maximum possible energy savings achievable by measures which are all cost-effective when applied together.* This last estimate could be identified at least in principal by evaluating all possible measure-sequences, which seems computationally prohibitive for the larger studies; it might also be found by ranking measures iteratively in terms of ascending "benefits if the measure is cost-effective" (BICE). It is recommended that future studies of conservation potential explore the sensitivity of their results to the use of NPV vs. CCE, and explore the possible usefulness of BICE as a ranking index as well.

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[3]The use of these and other cost-effectiveness indices in energy investment decision-making is described in, for example, (Ruegg and Petersen 1987) and (ASTM 1992).

Plotting the supply curve and the cost-effectiveness threshold.

The measures are plotted as steps in a supply curve of energy savings versus incremental cost per Btu, as illustrated in Figure 3.3. The width of each step is equal to that measure's annual energy savings potential, and its height is equal to its CCE. The cost of conserved energy for a particular measure (in $/MBtu) can be directly compared with the real price of displaced energy P (e.g., in $/MBtu) to determine its cost-effectiveness: measures whose CCE is less than the cost of the energy they displace are cost-effective. A line indicating the "cost-effectiveness cut-off price" is often drawn on the supply curve at CCE=P to indicate the threshold of cost-effectiveness. As mentioned above, when measures are ranked by CCE the supply curve is independent of fuel price assumptions, so that these analyses need not be re-done every time fuel price forecasts change.

A common simplifying assumption in supply curve analysis is that the real price of displaced energy P will remain constant over the measure life; this assumption is not required, however. If real energy prices are forecast to escalate ahead of inflation at a constant rate r, starting from a current price P_o, the use of a levelized price $P_{levelized}$ as the cost-effectiveness threshold has been recommended (Meier 1982), where the levelized price is the arithmetic average real price over the measure lifetime, T:

$$P_{levelized} = P_o * \left(\frac{e^{rT} - 1}{rT} \right) \tag{2}$$

In fact, by taking the arithmetic average, the levelized price fails to adequately discount the value of energy cost savings occurring later in the measure life relative to those occurring earlier in the measure life (when fuel prices are lower). Therefore, equation (2) will slightly over-estimate the *full-discounting* cost-effectiveness threshold, P_{cutoff}, which is given by:

$$P_{cutoff} = P_o * \left(\frac{d\left[1-(1+d-r)^{-n}\right]}{(d-r)\left[1-(1+d)^{-n}\right]} \right) \tag{3}$$

In practice, for measure lives below 20 years, discount rates at or below 5% and annual fuel price escalation rates below 5% real, $P_{levelized}$ will overestimate P_{cutoff} by less than 20%. It must also be kept in mind that the forecast real escalation rate r and therefore the cost-effectiveness thresholds $P_{levelized}$ and P_{cutoff} are all uncertain estimates in any case.

Uncertainty in Estimates of Mean Savings, Total Potential, and Cost of Conserved Energy

Recall from Chapter 2 the following formulae. The temporal mean of the population mean energy savings for measure j, denoted $\overline{\overline{\Delta e}}_j$, is defined as

$$\overline{\overline{\Delta e}}_j = \frac{1}{n}\sum_{y=1}^{n}\overline{\Delta e}_j(y) \tag{4}$$

where n is the measure life in years, and $\overline{\Delta e}_j(y)$ is the population-mean energy savings in year y achieved by measure j. The total (temporal mean) potential for annual energy savings achievable by the jth measure is related to the market potential for that measure, N_j:

$$\overline{E}_j = \overline{\overline{\Delta e}}_j * N_j \tag{5}$$

Lastly, the mean "cost of conserved energy" (CCE) of measure j can be written as:

$$\overline{CCE_j} = \frac{\overline{C}_j}{\text{present - valued energy savings}} = \frac{\overline{C}_j}{\sum_{y=1}^{n_j} PV\left(\overline{\Delta e}_j(y)\right)} = \frac{\overline{C}_j}{\sum_{y=1}^{n_j}\left(\overline{\Delta e}_j(y) * e^{-yd}\right)} \tag{6}$$

Recall also from Chapter 2 that the uncertainty in estimates of these three quantities will be characterized through the use of uncertainty propagation analysis employing Monte Carlo simulations ("*MCS*") of the expressions in equations (4), (5), and (6).[4] These

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[4]For compactness of notation, the functional notation "*MCS*{ . . .}" will be used to represent the estimated *pdf* which results from a set of Monte Carlo simulations.

simulations will make use of the probability density functions ("*pdf*s") for the random variables $J_{\overline{\Delta e}}$, $J_{\bar{n}}$, $J_{\overline{C}}$ and J_N, which were developed to characterize the uncertainty in point estimates for the empirical inputs $\overline{\Delta e}$, $\bar{n}$, $\overline{C}_j$ and N, respectively. Thus, it is suggested that the uncertainty associated with measure-specific point estimates for $\overline{CCE}_j$. $\overline{\overline{\Delta e}}_j$, and $\overline{E}_j$ which are used in studies of current weatherization potential be estimated as indicated by equations (7), (8), and (9).

$$pdf\left[\overline{\overline{\Delta e}}_j\right] \Leftarrow MCS\left\{\left(\frac{1}{\hat{\bar{n}}*J_n}\right)*\sum_{y=1}^{\hat{\bar{n}}*J_n}\hat{\overline{\Delta e}}_j(n)*\left(J_{\overline{\Delta e}(n)}\right)\left(J_{HDD}(y)\right)\left(J_{persist}(y)\right)\right\} \tag{7}$$

$$pdf\left[\overline{E}_j\right] \Leftarrow MCS\left\{\hat{N}_j*J_N*\left(\frac{1}{\hat{\bar{n}}*J_n}\right)*\sum_{y=1}^{\hat{\bar{n}}*J_n}\hat{\overline{\Delta e}}_j(n)*\left(J_{\overline{\Delta e}(n)}\right)\left(J_{HDD}(y)\right)\left(J_{persist}(y)\right)\right\} \tag{8}$$

$$pdf\left[\overline{CCE}_j\right] \Leftarrow MCS\left\{\frac{\hat{\overline{C}}_j*J_C}{\sum_{y=1}^{\hat{\bar{n}}*J_n}\hat{\overline{\Delta e}}_j(n)*\left(J_{\overline{\Delta e}(n)}\right)\left(J_{HDD}(y)\right)\left(J_{persist}(y)\right)*e^{-yd}}\right\} \tag{9}$$

The (estimated) uncertainty in estimates of the three outputs $\overline{\overline{\Delta e}}_j$, $\overline{E}_j$, and $\overline{CCE}_j$ can be characterized in more general terms using the estimate of the *pdf* of the ratio of the true quantity to its point estimate. The result is a "normalized *pdf*" for each of the three outputs of interest.

$$pdf\left[J_{\overline{\overline{\Delta e}}}\right] = est'd\ pdf\left[\frac{\overline{\overline{\Delta e}}_j}{\hat{\overline{\overline{\Delta e}}}_j}\right] \Leftarrow MCS\left\{\left(\frac{J_{\overline{\Delta e}(n)}}{\hat{\bar{n}}J_n}\right)\sum_{y=1}^{\hat{\bar{n}}J_n}J_{HDD}(y)J_{persist}(y)\right\} \tag{10}$$

$$pdf\left[J_{\overline{E}}\right] = est'd\ pdf\left[\frac{\overline{E}_j}{\hat{\overline{E}}_j}\right] \Leftarrow MCS\left\{\left(\frac{J_N J_{\overline{\Delta e}(n)}}{\hat{\bar{n}}J_n}\right)\sum_{y=1}^{\hat{\bar{n}}J_n}J_{HDD}(y)J_{persist}(y)\right\} = MCS\left\{J_N J_{\overline{\overline{\Delta e}}}\right\} \tag{11}$$

$$pdf\left[J_{\overline{CCE}}\right] = est'd\ pdf\left[\frac{\overline{CCE}_j}{\hat{\overline{CCE}}_j}\right] \Leftarrow MCS\left\{\left(\frac{J_{\overline{C}}}{J_{\overline{\Delta e}(n)}}\right)\left(\frac{\sum_{y=1}^{\hat{\bar{n}}J_n}e^{-yd}}{\sum_{y=1}^{\hat{\bar{n}}J_n}J_{HDD}(y)J_{persist}(y)e^{-yd}}\right)\right\} \tag{12}$$

These normalized *pdfs* have the advantage that they are not functions of the point estimates for the input parameters $\hat{\Delta e}_{j(n)}$, $\hat{\overline{\overline{\Delta e}}}_j$ (which equals $\hat{\Delta e}_{j(n)}$), $\hat{\overline{C}}_j$, and $\hat{N}_j$, although they *are* all functions of $\hat{\overline{n}}_j$, and $J_{\overline{CCE}}$ is a function of the discount rate d as well.[5] Figures 3.3, 3.4 and 3.5 present the cumulative distributions and confidence intervals corresponding to each of these normalized *pdfs* , derived from the expressions above, using the *pdfs* estimated to characterize the input uncertainties which were developed in Chapter 2, and employing 200-sample Latin Hypercube simulations for each.[6]

Note from Figures 3.3-3.5 that all three outputs are influenced by an important result from Chapter 2: namely that audit+prototype-based estimates of mean energy savings per measure have tended to *over-estimate* mean measured savings by approximately 25% on average. Thus, the results of Chapter 2 lead to the conclusion that "best-estimates", or estimated expected values for $\overline{\overline{\Delta e}}_j$ and $\overline{E}_j$, are approximately 0.78 times the point estimates for these quantities developed by "typical" analyses of residential weatherization potential, whose methods and data sources were described in Chapter 2 and earlier in the present chapter. Likewise, the "best-estimate" for the mean CCE of a weatherization measure is found to be on the order of 1.7 times the typical point estimate. Ninety percent confidence intervals for actual population mean temporal mean annual energy savings per measure appear to range from roughly 35% to 160% of "typical" point estimates, while ninety percent confidence intervals for population mean cost of conserved energy are estimated to range from roughly 60% to nearly 400% of typical point estimates developed as described in Chapter 2.

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[5]The described independence of the normalized *pdfs* from the input parameters relies on the simplifying assumption made in Chapter 2 that the "J's" are not functions of the input parameters. This in turn relies on the simplifying assumption that the coefficient of variation characterizing the estimated uncertainty in a given input parameter is invariant across different measures.

[6]The simulations employed the Median Latin Hypercube sampling method (e.g., Morgan and Henrion 1990); the model was constructed using the DEMOS probabilistic analysis software, available from Lumina Decision Systems, Inc., Palo Alto, CA.

Figures 3.3 through 3.5 illustrate that neither $J_{\overline{\overline{\Delta e}}}$, $J_{\overline{E}}$, nor $J_{\overline{CCE}}$ are particularly sensitive to estimated measure life. Confidence intervals for each tend to widen slightly for longer-lived measures, but this effect is small relative to the overall uncertainty. Only $J_{\overline{CCE}}$ is mathematically a function of the discount rate, and Figure 3.3 shows that for discount rates at or below 10%, the actual influence of discount rate variation upon *the uncertainty in* predictions of $\overline{CCE}$ appears to be negligible. The virtual independence of $J_{\overline{\overline{\Delta e}}}$, $J_{\overline{E}}$, and $J_{\overline{CCE}}$ from measure life, (and of $J_{\overline{CCE}}$ from d as well) derives primarily from the much larger uncertainty in first-year weather-normalized savings (relative to measure-life uncertainty) and from the assumed time-invariance of the expected values and variances of $J_{persist}(y)$ and $J_{HDD}(y)$, as will become more clear below.

Finally, comparison of Figures 3.4 and 3.5 shows that J_N does not contribute appreciably to $J_{\overline{E}}$ (which = $J_N * J_{\overline{\overline{\Delta e}}}$). Based on the tentative estimates for input uncertainties developed in Chapter 2, the lion's share of the uncertainty in predictions of total (population-wide) weatherization potential per measure is contributed by the uncertainty in predictions of mean savings per measure. Although 90% confidence intervals for N_j were estimated to be on the order of ± 40% of $\hat{N}_j$, the confidence intervals for $J_{\overline{E}}$ are virtually indistinguishable from those of $J_{\overline{\overline{\Delta e}}}$. For this reason, along with the simplicity of the relationship between $J_{\overline{E}}$ and $J_{\overline{\overline{\Delta e}}}$, (equation (11)) only the results for $J_{\overline{\overline{\Delta e}}}$ (and $J_{\overline{CCE}}$) will be plotted in the remainder of the paper.

Comparative Influence of Separate Input Uncertainties

The functional forms and relative magnitudes of the influence of each input uncertainty upon the two output uncertainties $J_{\overline{CCE}}$ and $J_{\overline{\overline{\Delta e}}}$ are examined in this section. The appearance of an uncertain term (J_n) in the summation operators in equations (10) and (11) dictates that neither the variance of $J_{\overline{\overline{\Delta e}}}$ nor of $J_{\overline{CCE}}$ is simply decomposable as a sum or product of the variances of the inputs. Instead, the approach taken herein is to characterize the influence of each uncertain input independently, conditional upon the uncertainties in the other inputs all being negligible. For each of these scenarios, expressions for $J_{\overline{CCE}}$ and $J_{\overline{\overline{\Delta e}}}$ are presented in Table 3.1. Numerical simulations of these scenarios using the input uncertainty *pdfs* which were developed in Chapter 2 are presented in Figures 3.6 and 3.7.

Figures 3.6 and 3.7 clearly illustrate that for weatherization measures, based upon the results of Chapter 2, the most influential input uncertainty *by far* among the three which contribute to the total uncertainty in predictions of CCE_j and $\overline{\overline{\Delta e}}_j$ is the uncertainty in predictions of $\overline{\Delta e}_{j(y)}$. Comparison of Figure 3.6 with Figure 3.3, and Figure 3.4 with Figure 3.7, indicates that even if the uncertainties in estimates of both $\overline{C}$ and $\overline{n}$ were reduced to zero, this would not appreciably reduce the width of the estimated confidence intervals for either $\overline{CCE}_j$ or $\overline{\overline{\Delta e}}_j$ (or $\overline{E}_j$), given the estimated uncertainty in estimates of $\overline{\Delta e}_{j(y)}$ which was derived in Chapter 2. Figure 3.6b shows that the influence of energy savings uncertainty upon $\overline{CCE}_j$ uncertainty diminishes very slightly at higher discount rates. Figures 3.6a and 3.7 indicate that the influence of energy savings uncertainty upon both $J_{\overline{CCE}}$ and $J_{\overline{\overline{\Delta e}}}$ grows somewhat with measure life.

In relative terms, the uncertainty in estimates of mean installed cost per measure ($\overline{C}$) is found to be least significant (see Figure 3.6). This low significance is due to the much smaller *uncertainty* in estimates of $\overline{C}$ than in those of $\overline{\Delta e}_{j(y)}$; recall that the *sensitivity* of CCE to both energy savings and installed cost were equal to unity. Uncertainty in $\overline{C}$ affects only the cost of conserved energy, and its influence is not a function of either measure life or discount rate.

The influence of lifetime uncertainty (in isolation) is roughly equivalent to that of installed cost uncertainty for very-long estimated lifetimes (e.g., 30 years) and high discount rates (> 10%), but grows appreciably for shorter measure lifetimes and lower discount rates. Energy savings discounting is the reason that the influence of measure life uncertainty lessens for longer estimated lifetimes; this is illustrated by Figure 3.8, which plots the boundaries of the 90% confidence interval for $\overline{CCE}_j$ as a function of measure life and discount rate, assuming that mean measure life is the only uncertain input parameter. Finally, it should be noted that measure life uncertainty *does* influence the *total* uncertainty in estimates of mean annual energy savings $\overline{\overline{\Delta e}}_j$, its entry in Table 3.1 notwithstanding. It does so through its *interaction with* the product of climate and persistence uncertainties (see equation (10)). The *independent* influence of measure life uncertainty, as well as the independent influences of each of the input uncertainties which are characterized in Table 3.1, are based upon the restrictive assumption that the other input uncertainties are negligible.

Probabilistic Supply Curves

The results obtained in the previous section relate to estimates of CCE and energy savings potential for an isolated measure. On the other hand, analyses of energy conservation potential generally examine and aggregate the savings potential associated with a host of measures. The present section explores how such multi-measure analyses might utilize probabilistic characterizations of the input parameters, and how probabilistic estimates of the size and cost of energy conservation potential could thereby be generated. This section also presents a suggested generalization of the method of plotting conservation supply curves, which accommodates and portrays the results of probabilistic analysis.

Deterministic Base-Case Analysis

To provide a basis for the numerical examples presented in this chapter, use is made of an example pertaining to weatherization of a "hypothetical house," which was presented in detail in the original exposition of the methods of deterministic conservation supply curve analysis (Meier 1982). In the present example it is assumed that the "hypothetical house" defined below represents the prototype for a population of houses, each of which is eligible for all seven conservation measures analyzed. Results are presented in terms of estimated mean cost of conserved energy and estimated mean savings potential per house.

A summary of the assumptions underlying Meier's single-house example is provided in Table 3.2, together with the point estimates for installed cost, measure life, and energy savings for seven weatherization measures. As in the original reference, energy savings interaction among these measures is modeled by the following equation,

$$e = \frac{H}{\eta_{furn} * \eta_{ducts}} + p \tag{13}$$

where

H is the heat load, equal to the sum of the annual heat loss through attic, walls, windows, and via air leakage: $H = H_{attic} + H_{walls} + H_{windows} + H_{air}$;

η_{furn} and η_{ducts} are the furnace and duct efficiency, respectively; and

p is the furnace pilot loss.

The measures are ranked in terms of ascending cost of conserved energy, and energy savings are evaluated using equation (13) in an iterative fashion, as was described in Figure 3.2. The results are plotted in Figure 3.9, which will serve as a "prototypical" deterministic conservation supply curve for current weatherization potential. The width of each step in the supply curve is equal to the point estimate of the mean energy savings potential for the given measure, while the location of each step vertically is equal to the point-estimated mean cost of conserved energy for that measure. This figure provides the point of departure for the development of probabilistic supply curves.

Incorporating Uncertainty in Measure Mean Installed Cost

First, consider only the uncertainty in final results caused by uncertainty in estimates of mean installed cost per measure. The influence is strictly upon the estimated mean cost of conserved energy per measure; mean energy savings per measure is unaffected by measure cost uncertainty. Thus, the width of the steps in the deterministic supply curve remain deterministic, while the vertical location of each step is now uncertain. The influence of installed cost uncertainty upon a single step in the conservation supply curve is represented in the key to Figure 3.10. That key shows how steps may be replaced by bars of finite vertical thickness, and illustrates how such bars can be shaded to convey estimated confidence intervals for the mean cost of conserved energy per measure.

Figure 3.10 also shows how the single-step example can be extended to generate multi-measure, probabilistic supply curves. An important issue arising in probabilistic supply curve analysis is one of *ordering* of measures. Generally, the sooner a measure is implemented, the more energy it will save (because of energy savings interaction -- recall equation (13)), and the lower will be its cost of conserved energy. Measure ordering in turn can influence conclusions about the size of cost-effective conservation potential. In deterministic supply curves the ordering of measures is unambiguous; measures with lower point-estimated CCEs are implemented earlier than those with higher point-estimated CCEs. But what should be the basis for measure ordering in probabilistic analyses?

Two broad styles of probabilistic supply curve analysis appear possible: single-curve and multi-curve analysis. The single-curve approach is illustrated in Figure 3.10. In this approach (as in deterministic supply curve analysis), use of a single parameter to rank-order measures leads to a unique measure order and thus a unique supply curve. In Figure 3.10 measures have been ranked by the expected value of their individual CCEs at each iteration in the development of the curve, which happen to equal their point-estimated CCEs since cost estimates are assumed to be unbiased (based on Chapter 2). The advantages of deterministic ordering are its computational simplicity and its preservation of clearly discernible results for each individual measure. Each point-estimate step is "transformed" by the results of probabilistic analysis (Figures 3.3 through 3.7) from a step into a bar, and the bars are plotted to construct the supply curve. For deterministic measure-ordering, the iterative ranking and measure-interaction analysis must only be performed once, just as in deterministic supply curve analyses. Note that this "once" will still consist of as many re-evaluations of the rankings as there are measures, since the CCEs of not-yet-implemented measures are altered with the implementation of each measure, and this alteration can change the CCE-rankings among not-yet-implemented measures.

In multi-curve analysis, the entire supply curve plotting process would be performed many times, where each supply curve is based upon a sampled value obtained for the each of the uncertain input parameters for each measure. Thus, in this simplest case where only installed costs are uncertain, the *set* of supply curves would be derived as follows. A cost estimate for each measure would be drawn by random sampling from the distribution for each measures' cost, which (for the jth measure) is given by $\hat{C}_j * J_C$. Then, given this set of cost estimates, a supply curve analysis would be performed in deterministic fashion. Next, another set of cost estimates would be obtained by sampling, and the process repeated. After a sufficient number of repetitions, confidence intervals for the total curve could be estimated from the aggregate results.

The advantage of multi-curve analysis is that it would enable direct evaluation of the effects of input uncertainties upon conclusions related to the *supply curve as a whole*. The disadvantages are that it obscures measure-specific results, is quite computation-intensive, and requires explicit specification of any statistical dependence among different measures' input uncertainties in order to generate accurate confidence intervals for the curve as a whole (as will be discussed later). Table 3.3 suggests a summary of the sorts of results which could be obtained using each analysis method. It appears that the two separate approaches are complimentary, each serving different decision-making perspectives and providing a different view of the implications of input uncertainties. Ideally the results of *both* approaches would be available to consumers of conservation potential analyses. For the remainder of the present analysis, only the results of the simpler single-curve approach will be illustrated.

Adding Uncertainty in Measure Lifetime Estimates

The joint effects of weatherization measure mean installed cost uncertainty and mean measure lifetime uncertainty upon the estimated mean cost of conserved energy are shown in Figure 3.11, based upon a 200-sample Latin Hypercube simulation and the input uncertainty descriptions developed in Chapter 2. As with the influence of measure lifetime uncertainty alone, confidence intervals for $\overline{CCE}_j$ widen for shorter estimated lifetimes. The *expected value* of $\overline{CCE}_j$ is also slightly sensitive to the estimated mean measure life (see Figure 3.11), but as this dependence is small relative to the width of the confidence intervals, it will be neglected in the present analysis. The results in the lower plot in Figure 3.11 were used together with the original deterministic supply curve results (Table 3.2 and Figure 3.9), and measures were rank-ordered by expected value of $\overline{CCE}_j$ during each iteration as described above, in order to generate a probabilistic supply curve reflecting the joint influence of cost and lifetime uncertainties. As with the case examining cost uncertainty alone, only $\overline{CCE}_j$ is influenced by the input uncertainties, not energy savings per measure. The results are shown in Figure 3.12.

Adding Uncertainty in Annual Energy Savings

Uncertainty in predictions of population mean annual energy savings contributes uncertainty to estimates of both the mean cost of conserved energy per measure and the energy savings potential per measure. Thus, while the cost and lifetime uncertainties considered earlier contributed strictly a vertical dimension of uncertainty to the steps in a supply curve (uncertainty in $\overline{CCE_j}$), energy savings uncertainty contributes uncertainty in both the vertical and horizontal dimensions. The other notable characteristic of energy savings uncertainty is that (at least for weatherization measures, based upon the results of Chapter 2) energy savings uncertainty is the dominant contributor to total uncertainty in predictions of the mean cost of conserved energy per measure (recall Figure 3.6).

To see how the supply curve framework might be extended to accommodate uncertainty in two dimensions, first consider the functional relationship between annual energy savings and the cost of conserved energy for a given measure. As indicated by equation (6) earlier, CCE is inversely related to the sum of the present values of population mean annual energy savings. Under the conventional assumption of constant (deterministic) annual energy savings Δe, the equation for CCE takes the simple form:

$$CCE = \frac{C}{\Delta e}\left(\frac{d}{1-(1+d)^{-n}}\right) \tag{14}$$

The dependence of CCE upon Δe in equation (14) has been plotted in Figure 3.13, reflecting the confidence intervals for predictions of mean first-year weather-normalized energy savings ("$\overline{\Delta e}(n)$") developed in Chapter 2. That is, the influence of the sources of *dynamic* uncertainty in predictions of annual energy savings, which are persistence uncertainty and climate uncertainty, do not contribute to the confidence intervals portrayed in Figure 3.13. The figure illustrates how the nonlinear relationship between CCE and Δe, together with the upward bias in point estimates of $\overline{\Delta e}(n)$, jointly cause the upper confidence intervals for CCE to be considerably higher than the value of CCE obtained using the point estimate for $\overline{\Delta e}(n)$; the CCE based upon the estimated 95th percentile of $\overline{\Delta e}(n)$ is 2.5 times the nominal value of CEE obtained using the standard point estimate for $\overline{\Delta e}(n)$ in equation (14).

Finally, Figure 3.13 also introduces the concept of a "confidence shoe" -- that is, a shoe-shaped graphical object analogous to the "bars" which were plotted in the probabilistic supply curves earlier (Figures 3.10 and 3.12), which portrays the uncertainty in estimates of energy savings as well as the uncertainty in CCE induced by the energy savings uncertainty. It is proposed that probabilistic conservation supply curves (in single-curve analyses) be constructed out of such "confidence shoes" when attempting to represent the uncertainties in predictions of both the conservation potential per measure and the mean cost of conserved energy per measure.

The vertical extent of each "shoe" indicates the uncertainty in mean CCE, while the horizontal distance from the top right corner to the "toe" of each shoe indicates the uncertainty in predicted savings potential for each measure. The top of the shoe is a step plotted vertically at the 95th percentile for $\overline{CCE}_j$, and its horizontal width is equal to the estimated 5th percentile for $\overline{\overline{\Delta e}}_j$. The base of the shoe is a step plotted vertically at the 5th percentile for $\overline{CCE}_j$, and its horizontal width is equal to the estimated 95th percentile for $\overline{\overline{\Delta e}}_j$. Note that confidence shoes are only applicable in single-curve analysis, since multi-curve analysis generates families of curves and prevents rendering of measure-specific probabilities. A logical choice for the measure ordering parameter seems to be the expected values of $\overline{CCE}_j$, as was used before in the Figures 3.10 and 3.12.

The last issue to be resolved is how to horizontally locate all shoes besides the first (whose left edge is located at zero cumulative energy savings by default). Energy savings from multiple measures are represented as cumulative in supply curves; but *which estimates for energy savings should be accumulated?* A logical choice seems to be the expected values of $\overline{\overline{\Delta e}}_j$. Note that this *plotting* question mirrors an underlying *analytical* question: how (if at all) should uncertainty in prior-measure savings be propagated through the calculations of measure savings interactions? For example, since the mean energy savings achieved by the first measure are uncertain, then the starting point of the savings calculation for the second measure is affected by this uncertainty, in addition to the uncertainties in specification of the original prototype and the conservation measure. It seems that the multi-curve approach is the more appropriate framework for explicit analysis of probabilistic measure interaction. It is recommended that in single-curve analysis, the starting point for each subsequent savings calculation be based on the *expected values* for the influence of all prior measures.

A probabilistic conservation supply curve built out of confidence shoes for each of the seven measures of the present numerical example is portrayed in Figure 3.14. The uncertainties in both $\overline{CCE}_j$ and $\overline{\overline{\Delta e}}_j$ reflect the joint influence of all the input uncertainties, as those uncertainties were characterized in Chapter 2. Also displayed in Figure 3.14 is the original deterministic step curve of point estimates. The shoes themselves are effectively plotted astride a new curve of "best estimate" steps (shown as dashed in Figure 3.14), whose widths are equal to the expected values of $\overline{\overline{\Delta e}}_j$ and whose vertical heights are equal to the expected values of $\overline{CCE}_j$.

The important messages to be read from Figure 3.14 derive from the relative location and shapes of the deterministic and probabilistic results' curves. For this reason, the physical units for the two axes are not indicated on the figure. As the figure illustrates, both the mean cost of conserved energy and the mean energy savings per house appear to be highly uncertain for residential weatherization measures. Also, because Chapter 2 found that standard techniques of conservation potential analysis have tended to overestimate savings and underestimate the cost of conserved energy for weatherization measures, the probabilistic approach's curve of "best estimates" lies above and to the left of the original point-estimate curve.

Probabilistic Conclusions for the Supply Curve as a Whole

The results of this measure-specific, single-curve probabilistic analysis can be used to infer some first-order estimates about confidence intervals for the supply curve as a whole. First, it was already mentioned that the curve of expected value steps provides an estimate for the "true" curve as a whole. But can boundaries be drawn such that we have some estimated level of confidence that the "true" curve lies within those boundaries?

The sets of percentile steps from each confidence shoe were spliced together to form four additional curves as shown in Figure 3.15. Two observations can be made about these spliced curves. First, they all reflect the same measure-ordering, which was based upon the expected mean CCEs for all not-yet-implemented measures at each iteration in the analysis. Second, the interpretation of these spliced curves depends heavily upon our judgments about the degree and nature of any statistical dependence among the input uncertainties' effects upon multiple measures. That is, it was already assumed in Chapter 2 that each of the separate input uncertainties were statistically independent of *each other* -- that is, measure cost uncertainty is assumed to be independent of persistence uncertainty, etc. However, what about the possibility for correlation among the effects of the same input uncertainty upon two or more measures?

At one extreme, we might hold that there is near-perfect (positive) correlation among the effects of a given uncertainty upon the set of individual measures. For example, the influence of climate upon energy savings is roughly equivalent among all weatherization measures; a series of warmer-than-normal winters will effectively reduce the average annual savings for all weatherization measures by an equal percentage. Another example might be the influence of sampling error upon estimates of prototype characteristics. Since homes with greater floor area tend to have greater wall areas, window areas, etc., then sample-induced over-estimates of mean floor area will be positively correlated with sample-induced over-estimates of mean wall area, etc. If virtually all input uncertainties were characterized by such tendencies for strong correlations in their influence upon the savings and/or costs for the set of measures, then perfect correlation of uncertainties among measures might be adopted as a reasonable approximation. In this case, the spliced curve of 95th percentile steps would then provide a boundary below which one could be an estimated 95% confident that the entire true curve was located. Likewise, the spliced curve of 5th percentiles would bound the true curve from below with 95% confidence, etc.

At the other extreme, we might determine that there is a virtual lack of evidence for any significant correlation among the influences of input uncertainties among measures. An example is hard to cite, since there appears to be a possibility for at least partial correlation in *each* uncertainties' influence upon multiple measures. But *if* each input uncertainty was considered to have a statistically independent influence from measure to measure, then the probabilities of true curves lying *either fully outside or fully inside* the spliced-percentile boundaries would *both* be significantly reduced, to a degree which is directly related to the total number of measures included in the analysis. Another way to express the situation is to note that the possibility that the true curve intersects our spliced-percentile curves would increase greatly if the influence of the uncertainties upon separate measures were statistically independent.

For instance, in our example containing seven measures, the probability of the true curve lying entirely above the curve of 95th percentiles (crossing the spliced curve at no point) would be on the order of $(0.05)^7 = 7.8 \times 10^{-10} \approx 0$. Indeed, the probability of the true curve lying entirely above the curve of 75th percentiles would be $(0.25)^7 = 0.00006$; the algebra is similar for lower boundaries. On the other hand, the probability of the true curve lying entirely *below* the curve of 95th percentiles would be diminished as well (relative to the case of fully correlated influences), from 95% to $(0.95)^7 = 70\%$. These few numerical examples illustrate the principles involved.

Summary of Results and Conclusions

This chapter has introduced some basic concepts and methods related to the probabilistic analysis of conservation potential. In doing so, it has only scratched the surface of an area of investigation ripe for further elaboration and research. The preliminary results in the present chapter indicate that such further research is warranted. Specific recommendations for further research are deferred to the final chapter of the dissertation.

The first conclusion to be drawn from the analyses in this chapter is that probabilistic analysis of current weatherization potential, employing the tentative characterizations of input uncertainties generated in Chapter 2, indicates that deterministic estimates of current weatherization potential are highly uncertain. This is particularly true for the estimated mean cost of conserved energy for measures. Ninety percent confidence intervals for population mean cost of conserved energy per measure are estimated to range from roughly 60% to nearly 400% of typical point estimates. Ninety percent confidence intervals for population mean annual energy savings per measure are not as wide but still significant, ranging from roughly 35% to 160% of "typical" point estimates.

The dominant input uncertainties effecting estimates of current weatherization potential were found to be those influencing estimates of annual energy savings. Recall from Chapter 2 that among these influential factors, uncertainty in predictions of first-year savings and in the persistence of such savings are more important than climate uncertainty. The final effect of measure lifetime uncertainty in isolation upon the estimated mean cost of conserved energy for a given measure grows appreciably for shorter estimated lifetimes and at lower discount rates. It is consistently greater than the influence of installed cost uncertainty upon the estimated mean CCE, and consistently much smaller than the influence of energy savings uncertainty.

Conservation supply curves can be plotted to represent the uncertainty in both the cost-effectiveness and the energy savings potential associated with each individual measure. The results of such an analysis can also be used to develop first-order estimates about the confidence in the aggregate results. However, it was found that more precise probabilistic conclusions about the supply curve as a whole, as well as confidence intervals for such summary results as the total technical potential and the total cost-effective conservation potential given a threshold price, all require specification of the statistical dependence of each uncertainty's influence upon separate measures.

Table 3.1: Expressions for Independent Influence of Input Uncertainties upon Outputs of Energy Conservation Potential Analyses

Output: Input:	$\overline{CEE}_j$ Mean Cost of Conserved Energy	$\overline{\overline{\Delta e}}_j$ Mean Annual Energy Savings
$\overline{C}_j$	$J_{\overline{CCE}}\Big\vert_{\text{only } \overline{C} \text{ uncertain}} = J_C$	no relationship
$\overline{n}_j$	$J_{\overline{CCE}}\Big\vert_{\text{only } \overline{n} \text{ uncertain}} = \dfrac{\sum_{y=1}^{\hat{\bar{n}}} e^{-yd}}{\sum_{y=1}^{\hat{\bar{n}} J_n} e^{-yd}}$	$J_{\overline{\overline{\Delta e}}}\Big\vert_{\text{only } \overline{n} \text{ uncertain}} = 1.0$
$\overline{\Delta e}_{j(y)}$	$J_{\overline{CCE}}\Big\vert_{\text{only } \overline{\Delta e}(y) \text{ uncertain}} = \left(\dfrac{1}{J_{\overline{\Delta e}(n)}}\right)\left(\dfrac{\sum_{y=1}^{\hat{\bar{n}}} e^{-yd}}{\sum_{y=1}^{\hat{\bar{n}}} J_{HDD}(y) J_{persist}(y) e^{-yd}}\right)$	$J_{\overline{\overline{\Delta e}}}\Big\vert_{\text{only } \overline{\Delta e}(y) \text{ uncertain}} = \left(\dfrac{J_{\overline{\Delta e}(n)}}{\hat{\bar{n}}}\right) \sum_{y=1}^{\hat{\bar{n}}} J_{HDD}(y) J_{persist}(y)$

Table 3.2: Weatherization Measure Parameter Point Estimates for a "Hypothetical House," Derived from (Meier 1982)

Measure	Parameter Before Measure[a]	Parameter After Measure[a]	Measure Lifetime[c] (years)	Measure Installed Cost[c] ($)	En. Savings without measure interaction[b] (GJ/yr)	CCE without measure interaction ($/GJ)	En. Savings *with* measure interaction (GJ/yr)	CCE *with* measure interaction ($/GJ)
Insulate Ducts	η_{ducts} = 0.87 %	η_{ducts} = 0.96 %	10	300	13	1.6	13	1.6
Insulate Walls	H_{walls}= 35 GJ/yr	H_{walls}= 14 GJ/yr	30	900	35	1.7	32	1.8
Insulate Attic	H_{attic} = 20 GJ/yr	H_{attic} = 4 GJ/yr	30	700	27	1.7	24	1.9
Reduce Pilot Losses[d]	p= 7 GJ/yr	p= 0 GJ/yr	25	150	7	2.8	7	2.8
Tune Up Furnace	η_{furn} = 0.69 %	η_{furn} = 0.75 %	3	65	11	2.2	6	4.0
Weather-strip	H_{air}= 18 GJ/yr	H_{air}= 12 GJ/yr	10	300	11	3.5	8	4.7
Install Storm Windows	H_{window}= 13 GJ/yr	H_{window}= 3.5 GJ/yr	20	800	16	4.0	13	4.9
Total Energy Consumption:	e = 150 GJ/yr		**Total Savings w/o Measure Interaction:**		120	**Total Svgs. w/ Interact.:**	104	

[a] Values derived from information on pp. 20-22 of Meier 1982.
[c] From Table 5-2, p. 61 of Meier 1982.
[b] Cross-checked with p. 62 of Meier 1982.
[d] Install Intermittant Ignition Device

Table 3.3: Comparison of Single-Curve and Multi-Curve Probabalistic Analysis

	Single-Curve Analysis	Multi-Curve Analysis
Graphical Products	• single curve of measure-specific "confidence shoes"; and • curves of spliced measure-specific percentiles.	• Family of curves, with confidence intervals for the supply curve as a whole.
Examples of Questions Addressed	• which measures are highly uncertain in terms of energy savings and cost-effectiveness, and which are most reliable? • what are the 90% confidence intervals for the CCE of a particular measure? • is there evidence that once source of uncertainty is dominant for most measures? • does the best-estimate measure order appear to be robust or highly uncertain?	• what are the 90% confidence intervals for the supply curve as a whole? • what is the expected value of the cost-effective conservation potential, and what are the confidence intervals for this estimate? • what is the effect of the uncertainty in measure-order upon confidence intervals for the supply curve?
Advantages	• computational simplicity • measure-specific probabalistic results	• confidence intervals for the supply curve as a whole
Disadvantages	• single assumed measure order	• obscures measure-specific results • computation-intensive • requires explicit characterization of the statistical dependence among different measures' input uncertainties

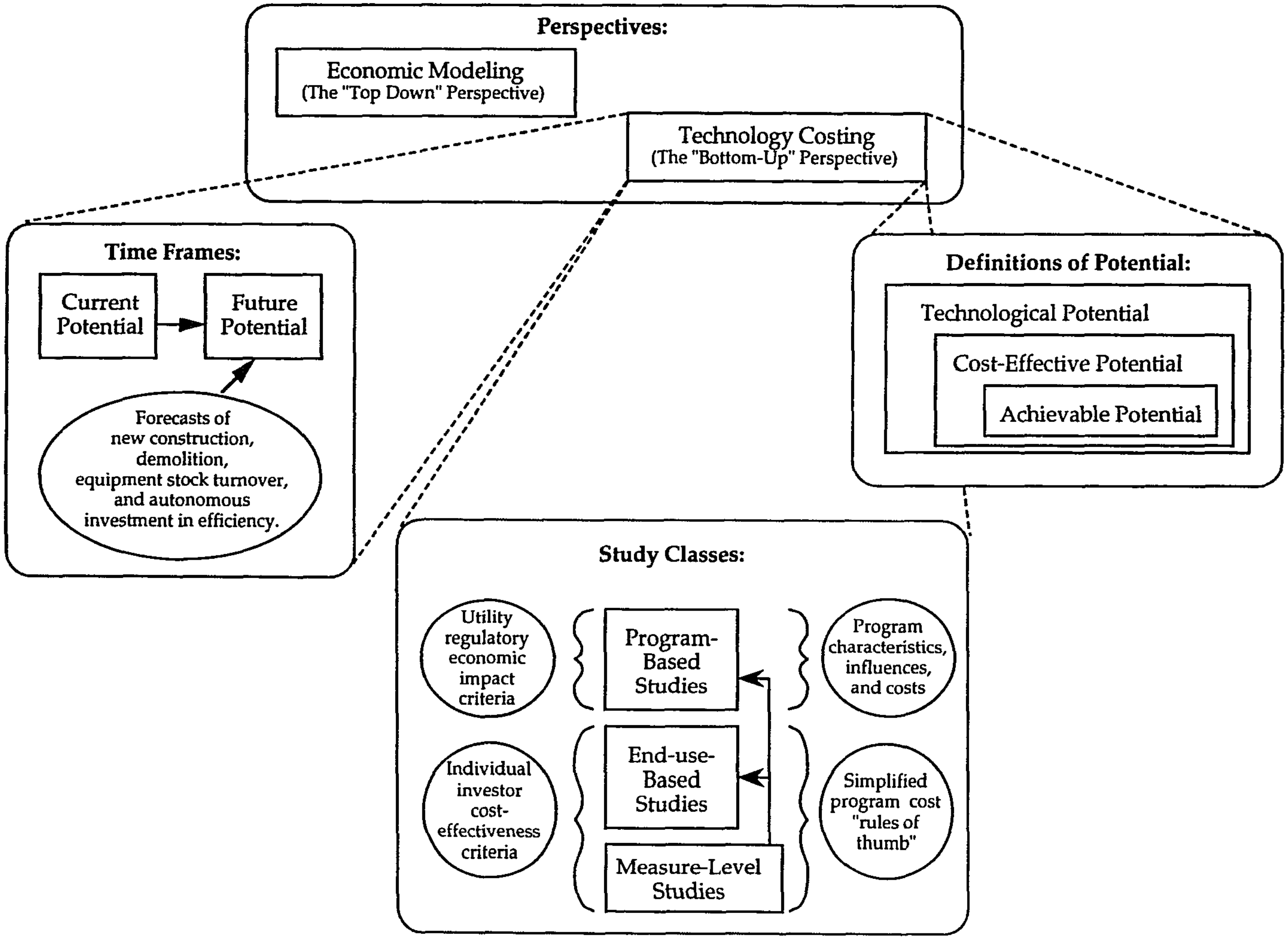


Figure 3.1: Perspectives, Time Frames, Study Classes, and Definitions of Energy Conservation Potential

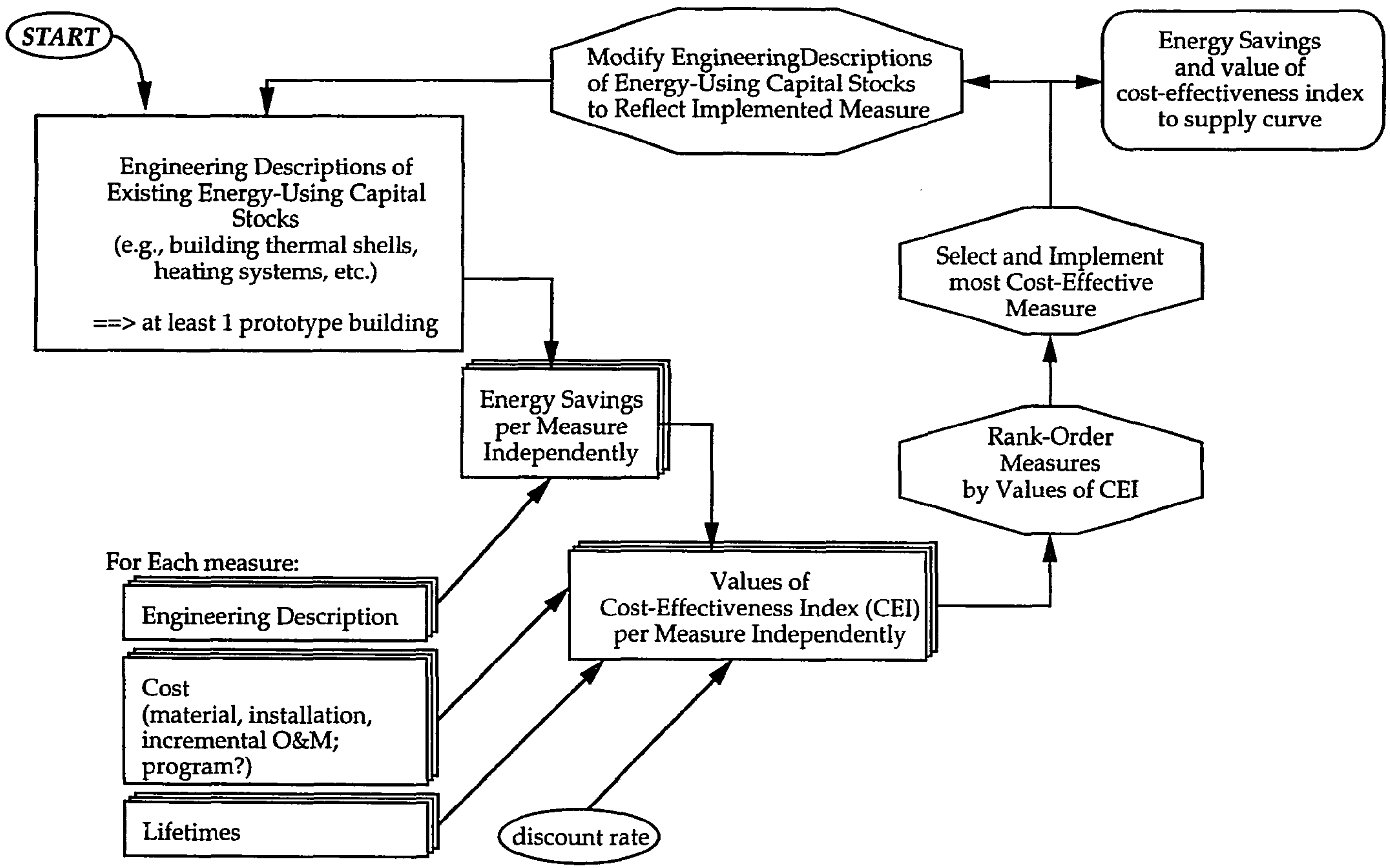


Figure 3.2: The Iterative Process of Conservation Supply Curve Development

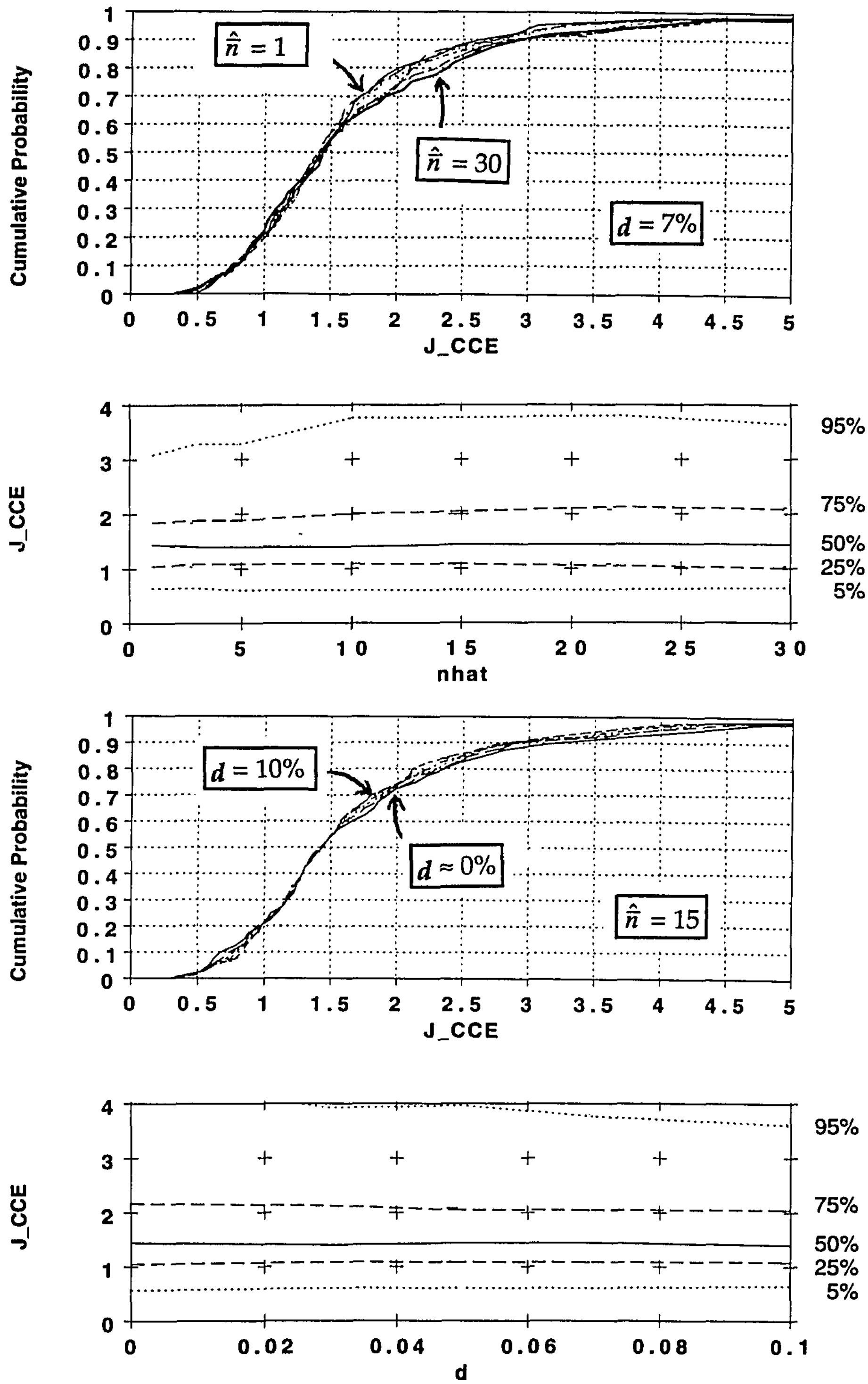
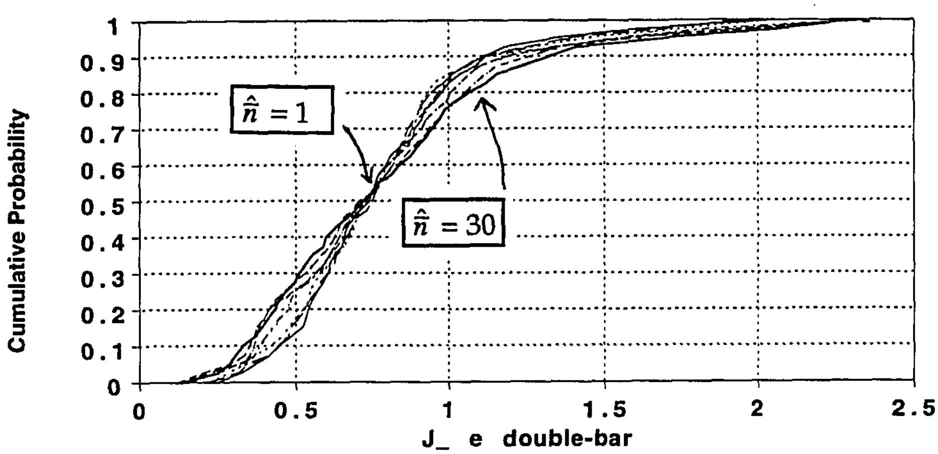


Figure 3.3: Uncertainty in Predictions of Cost of Conserved Energy Due to Uncertainty in Measure Lifetime, Cost, and Annual Energy Savings: Cumulative Distributions and Plots of Confidence Intervals



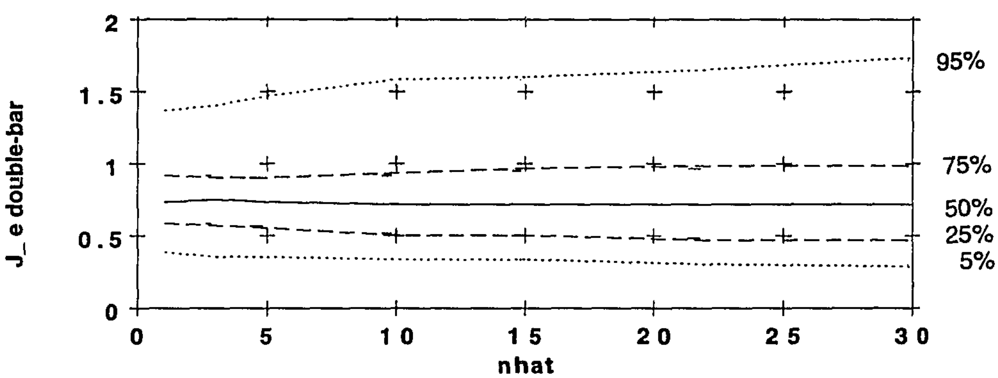
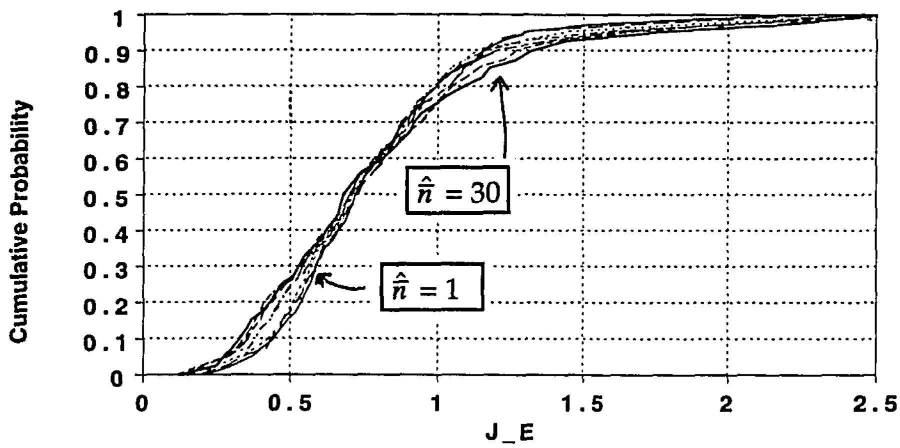


Figure 3.4: Uncertainty in Predictions of Mean Energy Savings Due to Uncertainty in Measure Lifetime, Cost, and Annual Energy Savings: Cumulative Distributions and Plots of Confidence Intervals



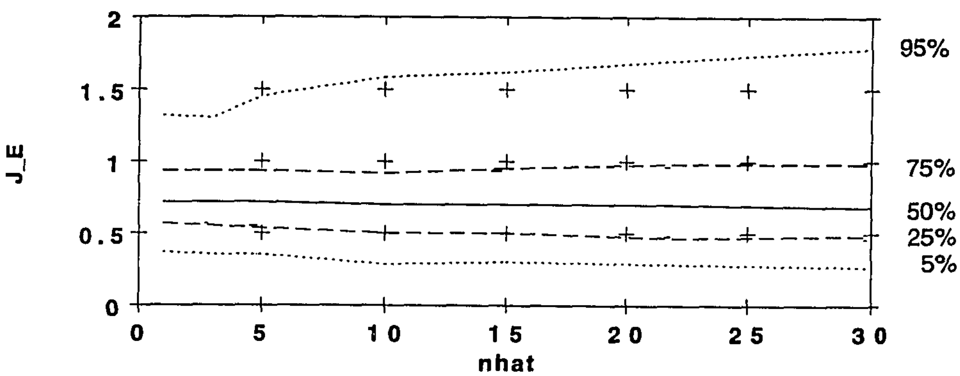


Figure 3.5: Uncertainty in Predictions of Total Savings Potential Due to Uncertainty in Measure Lifetime, Cost, and Annual Energy Savings: Cumulative Distributions and Plots of Confidence Intervals

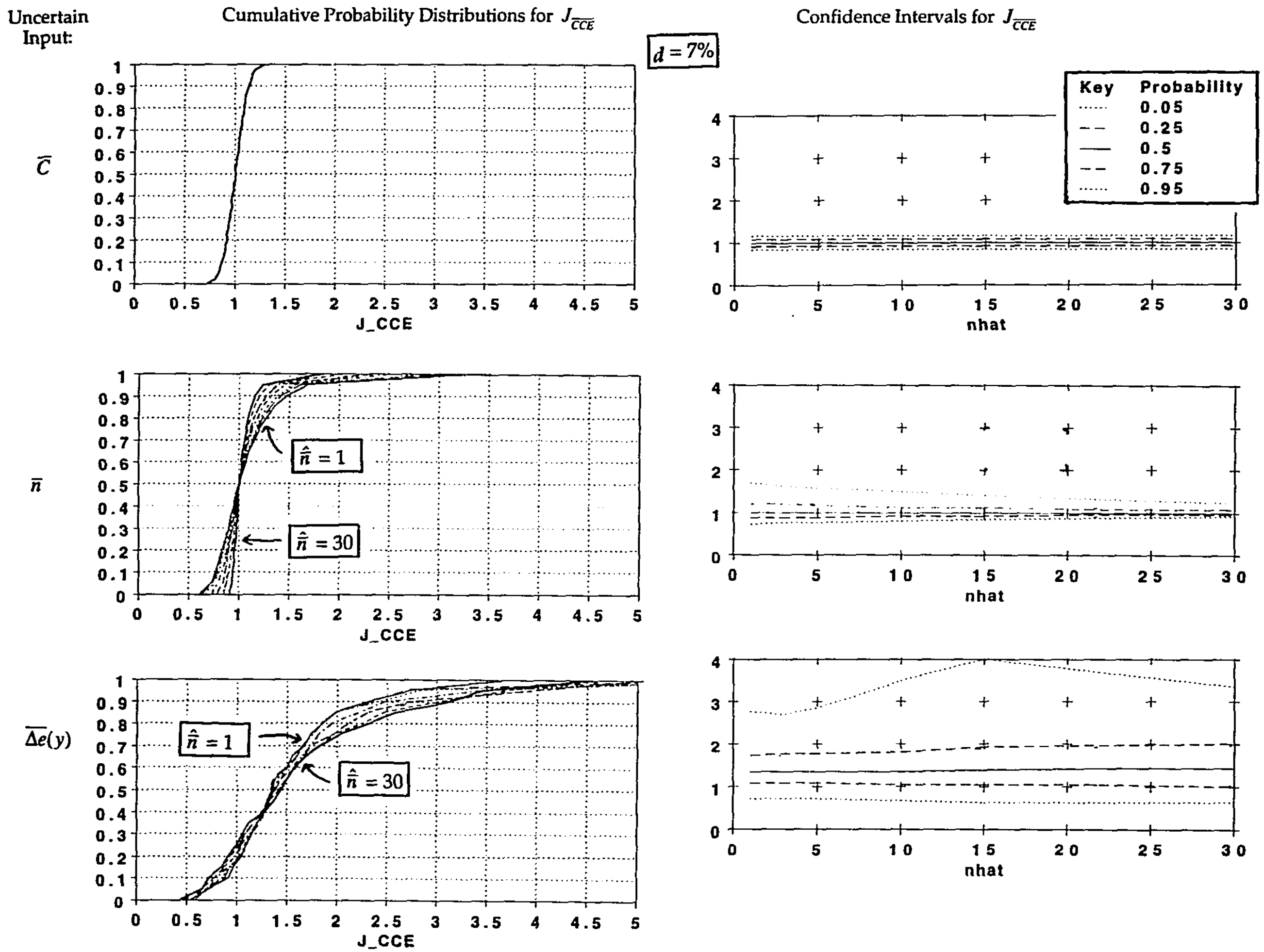


Figure 3.6a: Separate Influence of Input Uncertainties Upon Estimates of Mean Cost of Conserved Energy, As a Function of Estimated Measure Life

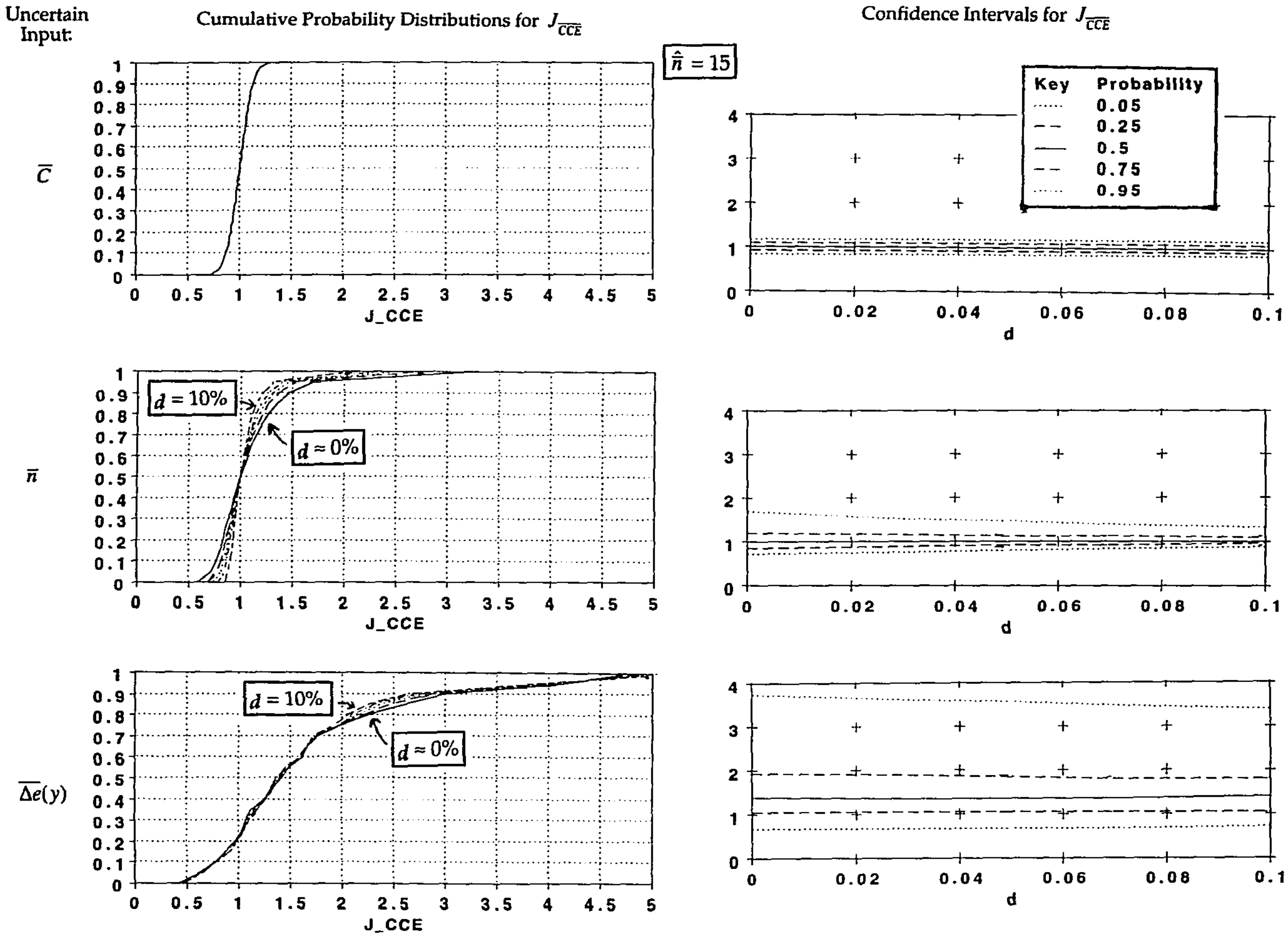


Figure 3.6b: Separate Influence of Input Uncertainties Upon Estimates of Mean Cost of Conserved Energy, As a Function of Assumed Discount Rate

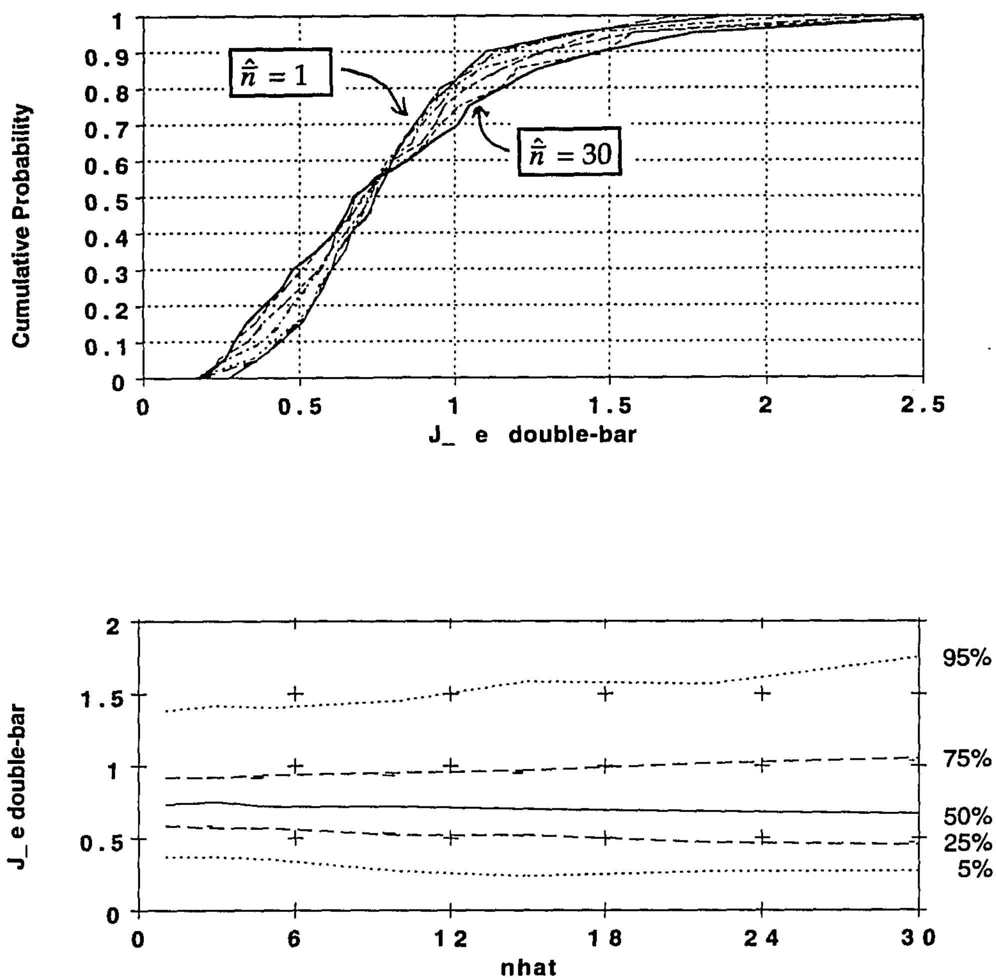


Figure 3.7: Uncertainty in Temporal Mean Annual Savings ($\overline{\overline{\Delta e}}$) Due Only to Uncertainty in Mean Yearly Energy Savings ($\overline{\Delta e}(y)$)

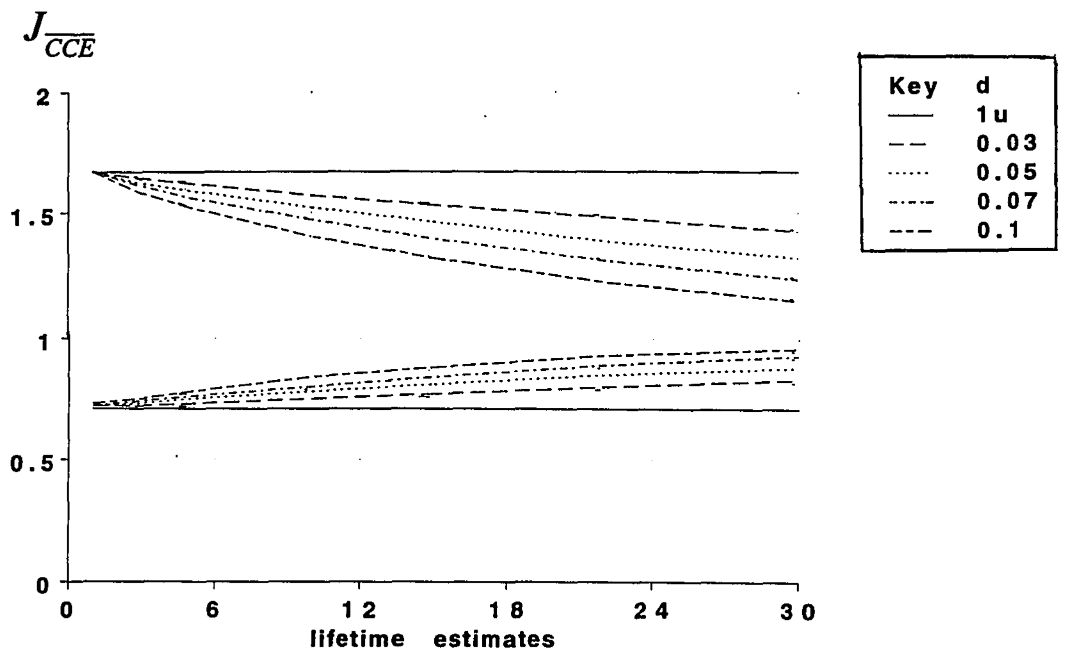


Figure 3.8: Dependence of 90% Confidence Intervals for Mean Cost of Conserved Energy Upon Estimated Measure Life and Discount Rate, When Mean Measure Life is the Only Uncertain Input

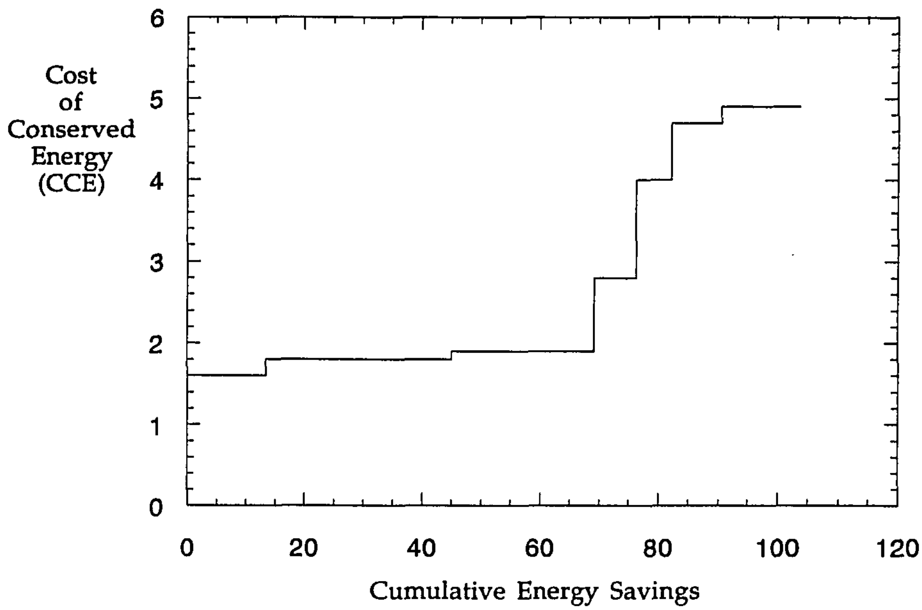


Figure 3.9: Baseline Deterministic Conservation Supply Curve

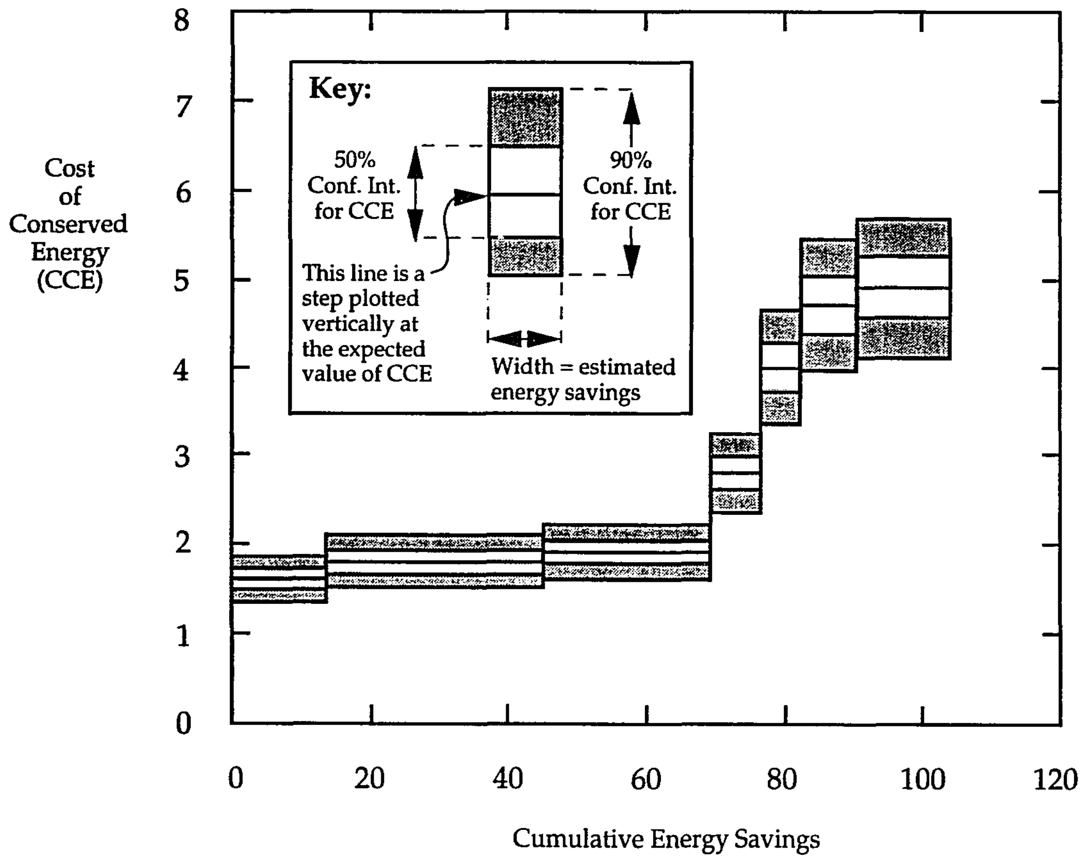


Figure 3.10: Probabilistic Conservation Supply Curve
for Current Weatherization Potential
with Installed Costs the Only Uncertain Input

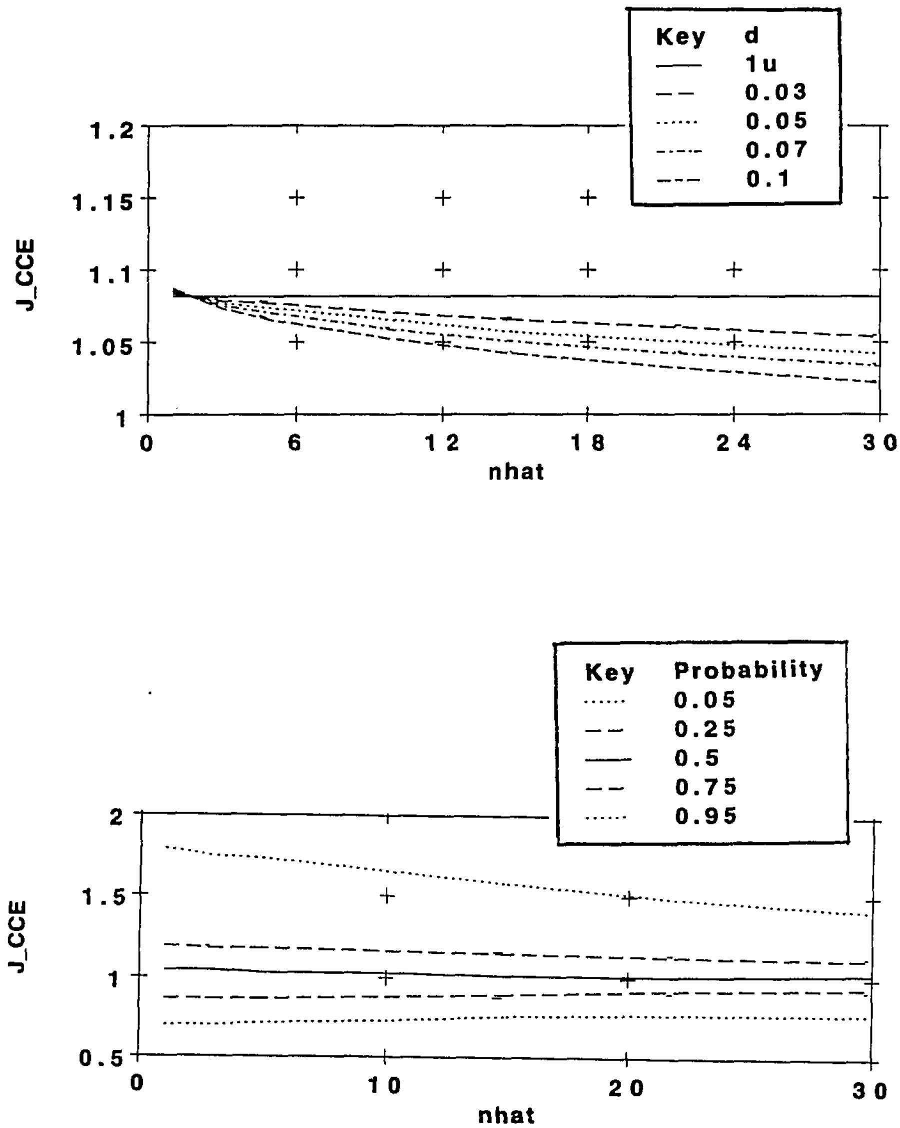


Figure 3.11: Expected Value and Confidence Intervals for Mean Cost of Conserved Energy as a Function of Estimated Measure Life, When Only Mean Installed Cost and Mean Measure Life are Uncertain

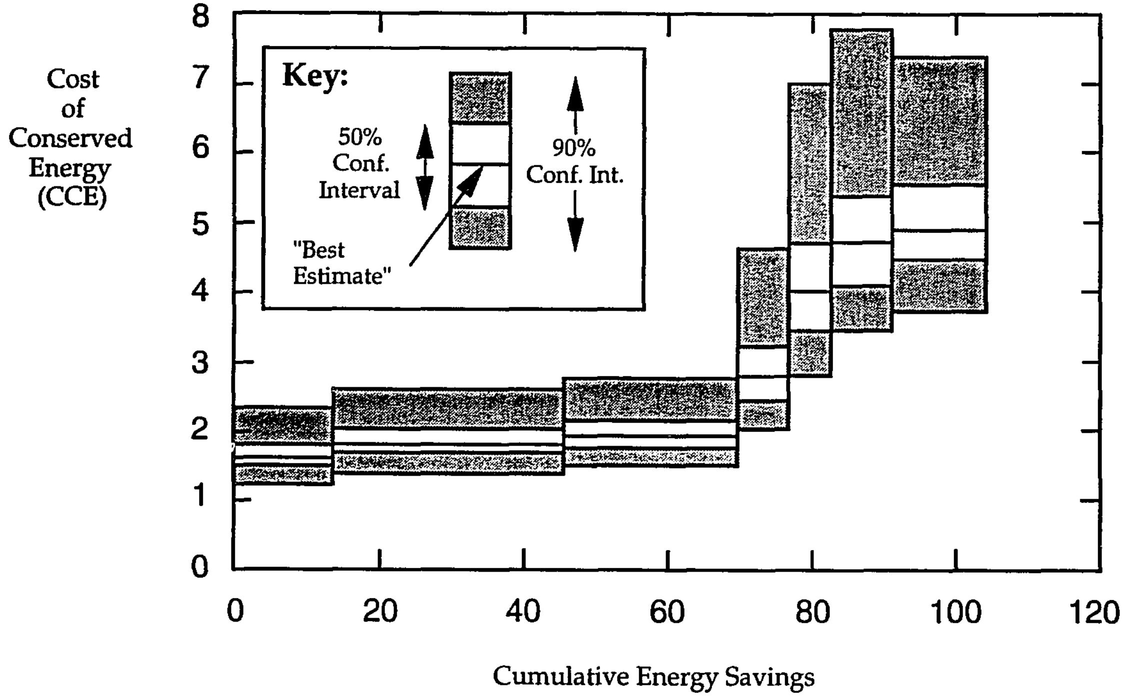


Figure 3.12: Probabalistic Conservation Supply Curve
for Current Weatherization Potential
with Both Measure Lifetimes and Installed Costs Uncertain

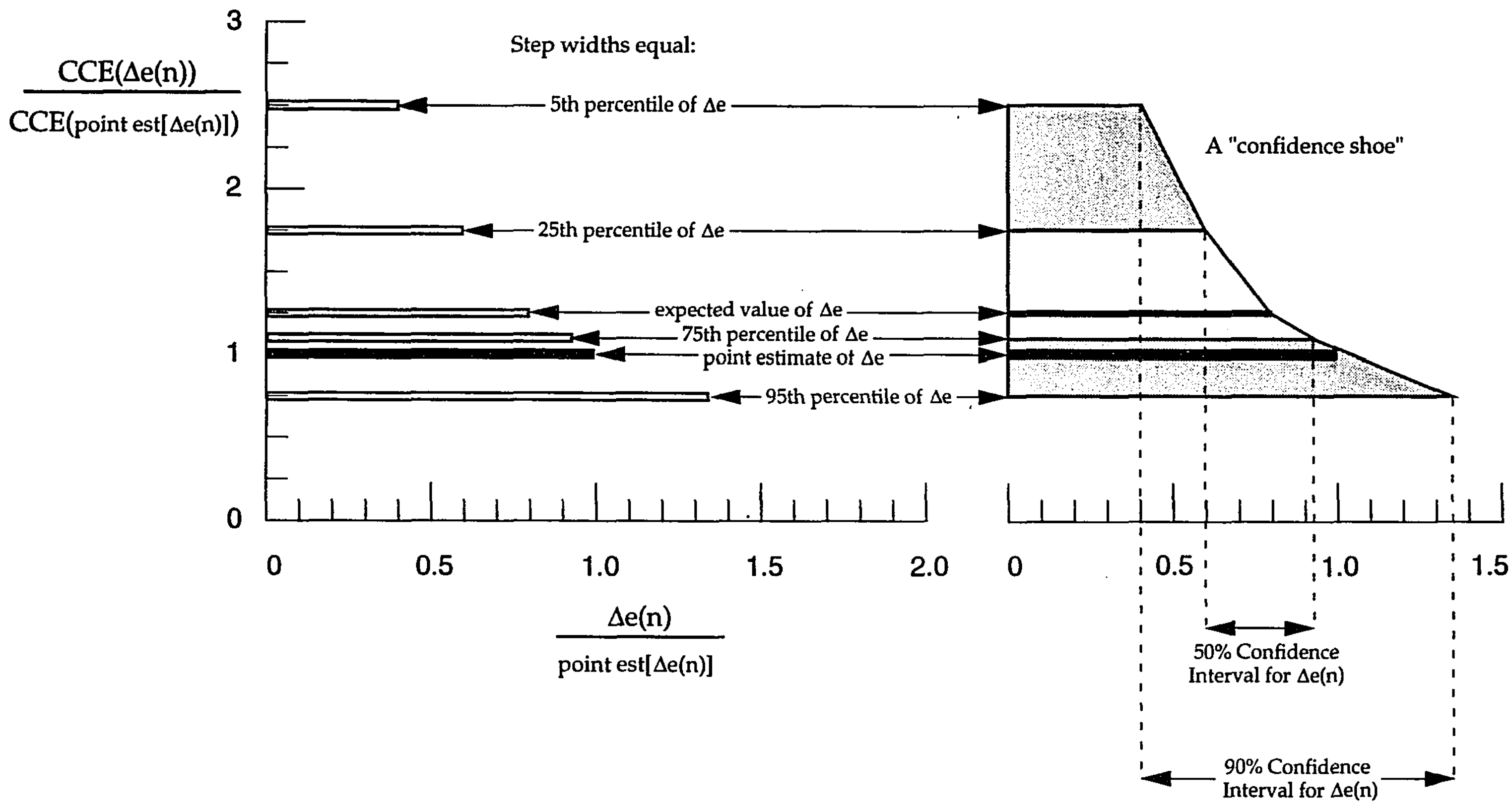


Figure 3.13: Cost of Conserved Energy (CCE) as a Function of Uncertainty in Mean First-Year Weather-Normalized Energy Savings (Δe(n)) for Residential Weatherization Measures

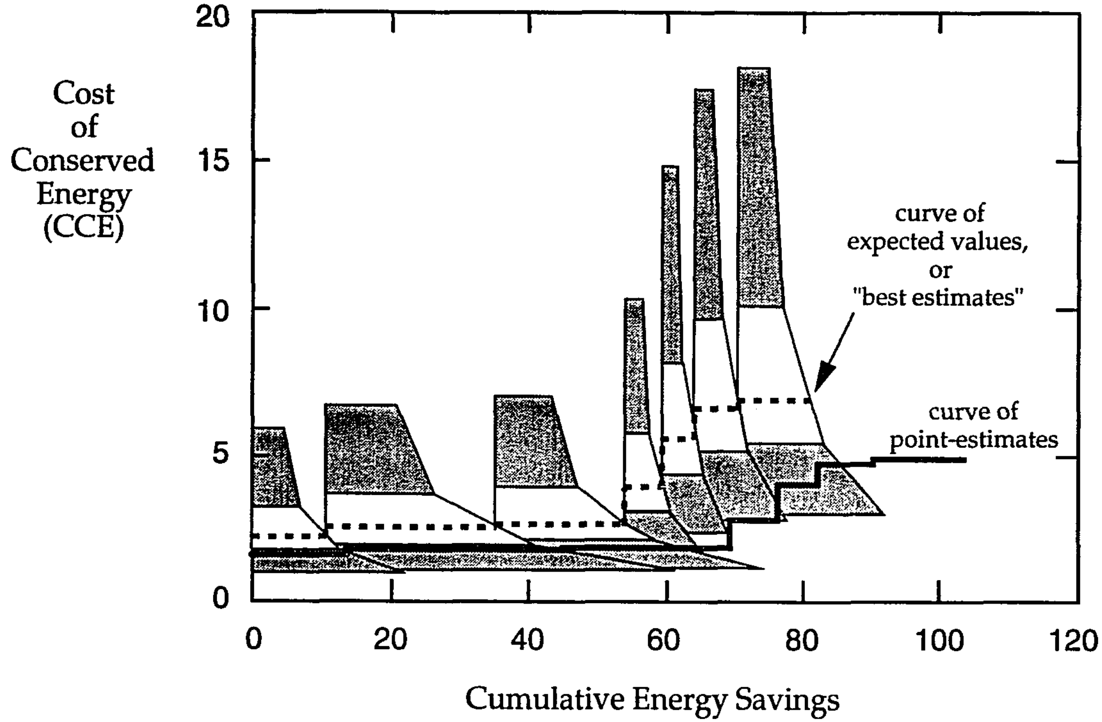


Figure 3.14: Summary Plot of "Confidence Shoes"
Depicting the Results of a
Single-Curve Probabilistic Analysis of Current Weatherization Potential

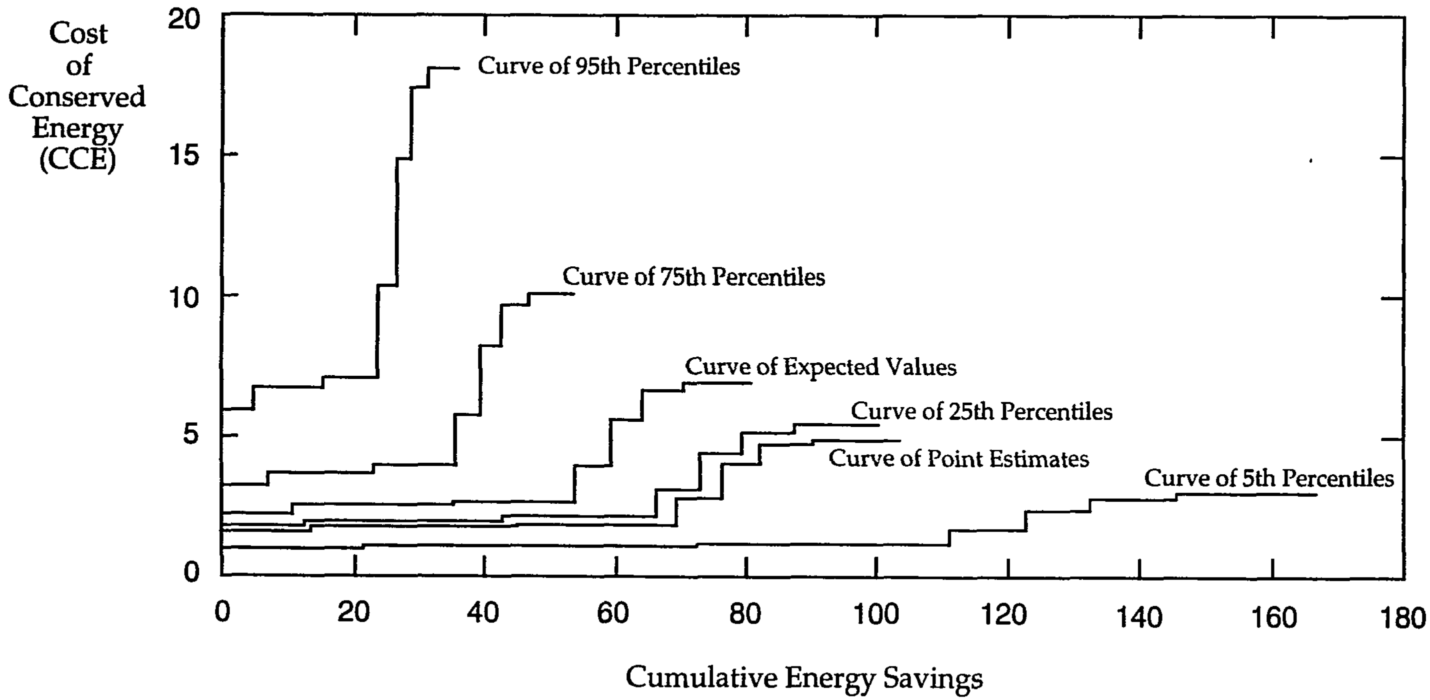


Figure 3.15: Step Curves Derived from the Probabilistic Single-Curve Analysis

CHAPTER 4

SUMMARY OF CONCLUSIONS AND SUGGESTIONS FOR FURTHER RESEARCH

Individual chapters have each offered conclusions based on the results of the individual chapter itself. When the results of the three chapters are viewed as a whole, their synthesis leads to additional conclusions and recommendations for further investigation. The present chapter first provides a brief summary of the individual conclusions from each of the preceding chapters. Then, conclusions and recommendations are offered which derive from the results of the dissertation as a whole.

Summary of Conclusions

Chapter 1 found that conclusions about cost-effective energy conservation potential are not as sensitive to variations in the discount rate as they are to variations in empirical inputs, contrary to claims which have appeared previously in the literature. This result cast doubt on the sufficiency of discount rate scenario analysis as a proxy for multi-variate uncertainty analysis of conservation potential estimates, and motivated a careful examination of the levels of uncertainty in each of the inputs to calculations of conservation potential.

Chapter 2 undertook such an examination for the inputs to analyses of current weatherization potential. It was found that the empirical basis for characterizing the uncertainty in the inputs was generally slim, and in a few cases was totally absent. Estimates of annual energy savings were found to be the most uncertain input to the analysis of current weatherization potential. This input's uncertainty was also shown to be significantly more complex to analyze and characterize than that of either installed cost or measure lifetime (for weatherization measures), because of the number of separate factors contributing to it.

Chapter 3 demonstrated how uncertainties in each of the empirical input estimates per measure can be translated into probabilistic measure-specific results, which in turn may be aggregated and plotted in a modified version of the conservation supply curve. Ninety percent confidence intervals for population mean cost of conserved energy per weatherization measure are estimated to range from roughly 60% to nearly 400% of typical point estimates. Ninety percent confidence intervals for population mean annual energy savings per weatherization measure are estimated to be not as wide but still significant, ranging from roughly 35% to 160% of "typical" point estimates. The most significant contributor to uncertainty in both of these output variables was the uncertainty in estimates of annual energy savings per measure per installation. Finally, it was found that probabilistic conclusions about the supply curve as a whole, as well as confidence intervals for such summary results as the total technical potential and the total cost-effective conservation potential given a threshold price, all require specification of the statistical dependence of each uncertainty's influence upon separate measures.

Suggestions for Further Research

The conclusions summarized above come from an investigation which *just began* to explore the complex topic of energy conservation potential uncertainty analysis. The methods and results which have been introduced and demonstrated require both further development and expanded application before they can make a central contribution to decision-making and to standard analytical practice related to energy efficiency potential. To this end, it is suggested that further research proceed along four complimentary fronts:

1) further examining and attempting to narrow the input uncertainties studied;
2) extending the scope of application in order to clarify which uncertainties are most influential;
3) expanding the applicability and utility of the analytical methods; and
4) learning from the consumers of conservation potential analyses which information needs are the most pressing

Examining and Narrowing the Uncertainties in the Inputs Investigated

This initial effort to characterize the uncertainties in empirical inputs to the analysis of current weatherization potential has found them to be significant, and to lead to considerably wide confidence intervals on projections of total cost-effective potential as well as per-measure cost-effectiveness. It is essential that these characterizations receive critical review and critique from members of the demand-side management research community.

For measure lifetimes and for several of the factors contributing to the final uncertainty in estimates of annual energy savings, the probability density functions ("*pdf*s") developed in Chapter 2 to characterize the input uncertainties were subjective rather than objective. Clearly, broad evaluation and critique of the subjective distributions is essential. A systematic approach following the methods for expert elicitation outlined and referenced in, for example, (EPRI 1991b) and (Morgan and Henrion 1990) would be especially valuable. In addition, important assumptions were made in development of several of the "objective" *pdf*s. These, too should receive critical review. An immediate priority along these lines should be the interpretation of persistence data; this uncertainty was found to be quite significant, yet Chapter 2's mapping from empirical data to the *pdf* was particularly tenuous for this factor.

The empirical basis for estimates of the input uncertainties should be upgraded. First, a search for additional un-published program evaluation results should be conducted, particularly for estimates of mean first-year weather-normalized savings per measure. This search could require considerable resources, however, especially if study details required to support the use of meta-analytic techniques are sought. (e.g., Green and Violette 1994, Lagerberg et al. 1993) In any case, the study reporting requirements which are determined by the data needs of meta-analysic characterization of input uncertainties should be specified and publicized immediately.

Three priorities are identified relating to the acquisition of new empirical data to support weatherization potential uncertainty analysis. First, experimental measure lifetime studies being initiated should estimate not only the mean but also the variability and the estimate uncertainty, particularly for the shorter-lived measures such as tune-ups and perhaps air-sealing. Second, even short-term (2-4 years) persistence studies would be highly beneficial if they included efforts to characterize the underlying determinants of variability in annual weather-normalized out-year savings. For example, surveys as well as audit evaluations of measure performance and repair could help separate the contributions of measure performance degradation, behavioral changes affecting total consumption, and out-year investments in efficiency. This information would greatly assist and improve the interpretation of persistence results for characterizing the persistence-related contributions to energy savings prediction uncertainty.

A third empirical priority should be the identification and testing of a standardized method and set of assumptions for calculating first-year weather-normalized mean energy savings. Such standardization could remove a considerable fraction of the total variability observed in savings estimate evaluations (as in the data reported by Cohen et al. 1991), and might help identify a standardized bias-correction procedure as well. Both developments would greatly improve the reliability of projections of weatherization potential.

Finally, analyses directed at the three factors related to prototype uncertainty (sampling error, aggregation error, and errant prototype specification) would clarify the estimates of these uncertainties and might significantly reduce them at modest cost as well. These uncertainties have not been systematically analyzed to date. The first two could be quantified through statistical analysis of existing data-sets which are used to specify prototypes. Also, analysts of conservation potential should clearly document the data sources and assumptions used in prototype specification, which would help characterization of all three uncertainties. Finally, the next project which updates the national residential prototypes should include statistical analyses which help subsequent users of the prototypes to quantify the uncertainty in conservation potential analyses which make use of these prototypes.

Extending the Scope in Order to Clarify Which Uncertainties are Most Influential

The focus of the present study has been necessarily narrow, limited to uncertainties affecting estimate of *current* potential in *weatherization* of the *residential* sector. Application of the present methods to other end-uses and sectors could yield significantly different conclusions about the degree of input and output uncertainties and the relative importance of different empirical input uncertainties. The results for current weatherization potential do not apply "as is" to these other end-uses and sectors.

For one thing, it appears likely that the empirical inputs to estimates of weatherization potential are more uncertain than those for some other types of residential energy conservation measures. For example, the per-home energy savings associated with refrigerator replacements *may* be less variable than savings typical for weatherization measures; the energy-use characteristics of the stock of existing refrigerators may be less heterogeneous than the stock of houses, and the mean cost of replacement is likely to be better-specified than the mean cost of per-home wall insulation, for instance.[1] Another important extension is to the commercial sector, where, for instance, measure lifetime uncertainty may prove to be as or more important than energy savings uncertainty for measures such as lighting.

A second important dimension along which to extend the scope of the present study relates to the realm of the uncertainties themselves. Estimates of current potential neglect potentially major uncertainties associated with evolution of the capital stocks and rates of autonomous investments in efficiency; these uncertainties affect estimates of *future* potential. Estimates of technical and cost-effective potential neglect uncertainties in estimates of the costs and performance of actual programs; these uncertainties affect estimates of *achievable* potential. Finally, uncertainty in future energy costs contribute uncertainty to projections of cost-effectiveness, and are strongly related to projections of base-case efficiency investments.

The other application area to which the methods of the present study should be soon applied is the study of the effects of *variability* in stock characteristics upon the conclusions of mean-based estimates of conservation potential. Aspects of this topic were raised in the introduction to Chapter 2; they relate to the use of binning in estimating mean cost-effectiveness and total potential per measure, and are closely tied to the analysis of prototype-based uncertainty mentioned above.

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[1] Summaries of research on variability in refrigerator energy consumption and energy savings from refrigerator replacement programs are found, for example, in (Heinemeier 1988) and the January/February special issue of *Home Energy* (volume 10, number 1).

Expanding the Applicability and Utility of the Analytical Methods

The most important methodological advance relates to deriving and then applying estimates of the correlation in each uncertainty's influence across measures. An important conclusion of Chapter 3 was that the statistical dependence of each uncertainty's influence across multiple measures needs to be characterized before useful estimates of the uncertainty in aggregate conclusions can be derived. Initially, the results of (Smith et al. 1992) should be used in an effort to assess which statistical dependencies are important to characterize and which can be safely neglected with little loss of precision. Then, once the necessary dependencies have been estimated, they should be applied to the specification of confidence intervals for supply curves as a whole. This result will clarify the quantitative interpretation of the families of curves developed at the close of Chapter 3. Specifying the statistical dependence will also make feasible the methods of multi-curve analysis outlined in Chapter 3.

Another potentially valuable contribution would be facilitating widespread availability of tools for exploring the implications of input uncertainties upon conservation potential conclusions. Software to enable both the calculations and plotting required by single-curve probabilistic analysis could be refined and made widely available for testing and "what if" analysis by the community of energy conservation potential researchers. A similar call for "flexible, public-domain software" to enable widespread (deterministic) supply curve analysis was made nearly ten years ago by Meier and Usibelli (1986), but does not appear to have been fulfilled. Widespread independent testing and exploration of single-curve probabilistic analysis should accelerate refinement of the tools and methods, and could in turn assist subsequent efforts aimed at the much more complex problem of multi-curve probabilistic analysis.

Learning From the Consumers of Conservation Potential Analysis

Finally, now that the "ice has been broken" regarding quantitative estimates of the uncertainties affecting estimates of energy conservation potential, it would be particularly helpful to investigate the views of energy planners and energy policy decision-makers about what sorts of questions and answers related to conservation potential estimates are most pressing, or are expected to become so in the future. Such inputs would help guide the further development of methods for energy conservation potential uncertainty analysis in directions most beneficial to the cause of effective energy policy-making and planning.

LIST OF REFERENCES

ASHRAE, American Society of Heating, Refrigerating and Air Conditioning Engineers, 1987. . *1987 HVAC Systems and Applications.* Atlanta.

ASTM, American Society for Testing and Materials, 1992. *ASTM Standards on Building Economics.* Philadelphia. March.

Beachy, William, 1994. Virginia Division of Housing. Personal communication. May.

Berry, L., 1989. *The Administrative Costs of Energy Conservation Programs.* Oak Ridge National Laboratory. ORNL/CON-294. November.

Berry, L. and E. Hirst, 1990. "The U.S. DOE Least-Cost Utility Planning Program." *Energy* 15(12) 1107-1117. December.

Bluestein, J. and H. DeLima, 1985. *Regional Characteristics and Heating/Cooling Requirements for Single-family Detached Houses.* Topical Report GRI-85/164, Gas Research Institute, Chicago, IL.

Bodlund, B., E. Mills, T. Karlsson and T. Johansson, 1989. "The Callenge of Choices: Technology Options for the Swedish Electricity Sector". In *Electricity: Efficient End-Use and New Generation Technologies, and Their Planning Implications.* Edited by T. Johansson, B. Bodlund, and R. Williams. Lund, Sweden: Lund University Press.

Boghosian, Stan, and James McMahon, 1993. *Shell Thermal Characteristics of US Single Family Residences -- Draft.* Lawrence Berkeley Laboratory. LBL-29417. Berkeley, CA.

Bordner, Robert, 1994. Synergic Resources Corporation, Avon, CT. Personal communication. May.

Boston Gas, 1990. *Conservation and Load Management Technical Potential in Boston Gas Service Territory.* Boston. May.

Brown, M., L. Berry, R. Balzer, and E. Faby, 1993. *National Impacts of the Weatherization Assistance Program in Single-Family and Small Multifamily Dwellings.* ORNL/CON-326. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Brown, Richard, 1993. *Estimates of the Achievable Potential for Electricity Efficiency Improvements in US Residences.* Energy and Resources Group, University of California, Berkeley, CA.

Buller, S. and W. Miller, 1992. "How Should We Treat Factors Contributing to Uncertainty in Measurement and Evaluation of DSM?" In: *Proceedings of the 1992 ACEEE Summer Study on Energy Efficiency in Buildings.* ACEEE, Washington, D.C.

Carl, Margot, and Richard Scheer, 1987. *Energy Conservation Potential: A Review of Eight Studies".* Energetics, Inc. Columbia, MD. September.

Carlsmith, R.S., Chandler, W., McMahon, J., and D. Santini, 1990. *Energy Efficiency: How Far Can We Go?* Oak Ridge National Laboratory, ORNL/TM-11441. Oak Ridge, TN. January.

CEC, California Energy Commission, 1993. "Completion of Appendix F in Protocols." Memo dated July 21, from Monica Rudman and Michael Messenger. In: EMS, Energy Management Services, 1993. *DSM Measure Life Project - Master Tables of Measure Life Estimates and Final Report.* Prepared for: CADMAC Persistence Subcommittee, Pacific Gas and Electric Company. September.

Chapman, Alan, 1994. Minnesota Department of Jobs and Training. Personal communication. May.

Chernick, P., et al., 1993. *From Here To Efficiency.* Resource Insight, Inc. Boston. Prepared for: Pennsylvania Energy Office, Harrisburg, PA.

Cochran, William, 1977. *Sampling Techniques.* New York: John Wiley and Sons.

Cohen, S.D., C.A. Goldman, and J.P. Harris, 1991. *Mearured Energy Savings and Economics of Retrofitting Existing Single-Family Homes: An Update of the BECA-B Database.* Lawrence Berkeley Laboratory. LBL-28147, Vol. 1. February 1991.

Costello, Patrick, 1994. New York Department of State. Personal communication. May.

Degens, Phillip, 1992. "Stability and Persistence of Savings in Residential Homes." n: *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings,* ACEEE, Washington, D.C.

Dinan, Terry, 1987. *An Analysis of the Impact of Residential Retrofits on Indoor Temperature Choice.* Oak Ridge national Laboratory, ORNL/CON-236. Oak Ridge, TN. October.

EIA, Energy Information Administration, 1990. *Energy Consumption and Conservation Potential: Supporting Analysis for the National Energy Strategy,* SR/NES/90-02. Washington, D.C. December.

EIA, Energy Information Administration, 1992. *Housing Characteristics 1990.* DOE/EIA-0314(90). Washington, D.C. May.

EIA, Energy Information Administration, 1993a. *Annual Energy Review 1992.* DOE/EIA-0384(92). Washington, D.C. June.

EIA, Energy Information Administration, 1993b. *Household Energy Consumption and Expenditures 1990.* DOE/EIA-0321(90). Washington, D.C. February.

EIA, Energy Information Administration, 1993c. *Household Energy Consumption and Expenditures 1990 - Supplement: Regional.* DOE/EIA-0321(90)/S. Washington, D.C. February.

EMR, Energy, Mines and Resources Canada, 1991. *The Economically Attractive Potential for Energy Efficiency Gains in Canada, Case Study #1 - Residential Space Heating.* Ottawa, Ontario. May.

EMS, Energy Management Services, 1993. *DSM Measure Life Project - Master Tables of Measure Life Estimates and Final Report.* Prepared for: CADMAC Persistence Subcommittee, Pacific Gas and Electric Company. September.

EPRI, Electric Power Research Institute, 1990. *Efficient Electricity Use: Estimates of Maximum Energy Savings.* EPRI CU-6746. Palo Alto. March.

EPRI, Electric Power Research Institute, 1991a. *End-Use Technical Assessment Guide - Volume 4: Fundamentals and Methods.* EPRI # CU-7222, v4. April.

EPRI, Electric Power Research Institute, 1991b. *TAG - Technical Assessment Guide: Fundamentals and Methods, Electricity Supply.* EPRI # TR-100281. December.

EPRI, Electric Power Research Institute, 1991c. *Impact Evaluation of Demand-Side Management Programs, Volume 1: A Guide to Current Practice,* EPRI CU-7179, prepared by RCG/Hagler-Bailly, Inc. Palo Alto, CA. September.

EPRI, Electric Power Research Institute, 1992. *Impact Evaluation of Demand-Side Management Programs, Volume 2: Case Studies and Applications,* EPRI CU-7179, prepared by RCG/Hagler-Bailly, Inc. Palo Alto, CA. September.

Eto, Joeseph, I. Turiel, H. Akbari, B. Lebot, and K. Heinemeier, 1990. "An Investigation of the Use of Prototypes for Commercial Sector EUI Analysis". In: *Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings,* ACEEE, Washington, D.C.

Fels et al., 1986. "Seasonality of Non-Heating Consumption and Its Effect on PRISM Results". *Energy and Buildings* 9:139-148.

Fels, M., 1986. "PRISM: An Introduction". *Energy and Buildings* 9:5-18.

Fels, M., and M. Goldberg, 1986. "Using the Scorekeeping Approach to Monitor Aggregate Energy Conservation". *Energy and Buildings* 9:161-168.

Ford, A. and J. Geinzer, 1990. "Adding Uncertainty to Least-Cost Planning: A Case Study of Efficiency Standards in the Northwest". *Energy Policy 18(4),* 331-339.

Geller, H., et al., 1986. *Residential Power Plant Study: Phase 1 - Technical Potential.* Pacific Gas and Electric Company. February.

Gordon, F., M. McRae, M. Rufo, and D. Baylon, 1988. "Use of Commercial Energy Efficiency Measure Service Life Estimates in Program and Resource Planning." In: *Proceedings of the ACEEE 1988 Summer Study on Energy Efficiency in Buildings,* ACEEE, Washington, D.C.

Granda, C., 1992. "A Statistically Based Impact Evaluation of a Direct Install Compact Flourescent Distribution Program." In: *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings,* ACEEE, Washington, D.C.

Greene, P. and D. Violette, 1994. *The Process and Results of a Meta-Analysis of Commercial and Industrial Lighting Programs.* RCG/Hagler Bailly, Boulder, CO.

Greene, P., et al., 1993. "A Meta-Analysis of Commercial and Industrial Lighting Programs." In: *Proceedings of the 1993 Chicago Conference on Program Evaluation.*

Hanford, J., J. Koomey, L. Stewart, M. Lecar, F. Johnson, R. Hwang, and L. Price, 1994. *Baseline Data for the Residential Sector and Development of a Residential Forecasting Database -- Draft Report.* Lawrence Berkeley Laboratory. LBL-33717. Berkeley, CA. May.

Hegan, N., R. Herendeen, and L. Stiles, 1982. "Measuring Energy Savings Using Personal Trend Data: 12 Retrofits in Champaign-Urbana, Illinois." In: *Proceedings of the ACEEE 1982 Summer Study on Energy Efficiency in Buildings*, ACEEE, Washington, D.C.

Heinemeier, Kirstin, 1988. "Your Mileage May Vary." *Home Energy* 5(5):12-14.

Henrion, Max, 1982. *The Value of Knowing How Little You Know: The Advantages of a Probabilistic Treatment of Uncertainty in Policy Analysis.* Ph.D. diss., Carnegie Mellon University, Pittsburgh.

Henrion, Max, 1989. *The Value of Knowing How Little You Know: Part I.* Manuscript, Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh.

Herendeen, R., N. Hegan and L. Stiles, 1983. "Measuring Energy Savings Using Personal Trend Data." *Energy and Buildings*, 5:289-296.

Hewett, M. et al., 1991. *Monitoring and Evaluation of Foundation Insulation Retrofits in Single-Family Detached Houses in St. Paul and Minneapolis, Minnesota.* Oak Ridge National Laboratory. ORNL/SUB/86-SA711/V. Oak Ridge, TN. March.

Hewett, M., et al., 1986. "Measured Versus Predicted Savings from Single Retrofits: A Sample Study". *Energy and Buildings* 9:65-76.

Hicks, Elizabeth, 1994. New England Electric System. Personal communication with author.

Hill, W., M. Blasnik, K. Greeley, J. Randolph, 1992. "Short-Term Metering for Measuring Residential Energy Savings". In: *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings*, ACEEE, Washington, D.C.

Hirst, Eric, 1992a. *Effects of Utility DSM Programs on Risk.* Oak Ridge National Laboratory, ORNL/CON-346. May.

Hirst, Eric, 1992b. *A Good Integrated Resource Plan: Guidelines for Electric Utilities and Their Regulators.* ORNL/CON-354. Oak Ridge National Laboratory, Oak Ridge, TN. December.

Hirst, E. and M. Schweitzer, 1990. "Electric Utility Resource Planning and Decision-Making: The Importance of Uncertainty". *Risk Analysis 10(1),* 137-146.

Hirst, E. and R Goeltz, 1985. "Estimating Energy Savings Due to Conservation Programs". *Energy Economics* 7: 20-28.

Hirst, E. C. Goldman and M.E. Hopkins, 1991. "Integrated Resource Planning: Electric and Gas Utilities in the USA." *Utilities Policy* (1(2), 172-186. January.

Hirst, E., and J. Reed, eds., 1991. *Handbook of Evaluation of Utility DSM Programs.* ORNL/CON-336. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Hirst, Eric, Richard Goeltz, and David Trumble, 1989. "Effects of the Hood River Conservation Project on Electricity Use". *Energy and Buildings* 13:19-30.

Hobbs, B.F. and P. Maheshwari, 1990. "A Decision Analysis of the Effect of Uncertaity upon Electric Utility Planning". *Energy 15(9),* 785-801.

Horowitz, M., L. Ecker, and P. Degens, 1991. *Long-Term Impacts of the Interim Residential Weatherization Program on Household Energy Savings.* ERCE/DSM-65. ERC Environmental and Energy Services, Portland, OR.

Howarth, R. and P. Monahan, 1992. *Economics, Ethics, and Climate Policy.* LBL-33230. Lawrence Berkeley Laboratory, Berkeley, CA.

Huang, Y.J., R. Ritschard, and J. Bull, 1987b. *Technical Documentation for a Residential Energy Use Data Base Developed in Support of ASHRAE Special Project 53.* Lawrence Berkeley Laboratory. LBL-24306. Berkeley, CA. November.

Huang, Y.J., R. Ritschard, J. Bull, S. Byrne, I. Turiel, D. Wilson, C. Hsui and D. Foley, 1987a. *Methodology and Assumptions for Evaluating Heating and Cooling Energy Requirements in New Single-Family Residential Buildings.* Lawrence Berkeley Laboratory. LBL-19128. Berkeley, CA. January.

Hunn, B. et al., 1986. *Technical Potential for Electrical Energy Conservation and Peak Demand Reduction in Texas Buildings.* Public Utility Commission of Texas. February.

Iman, R. and J. Helton, 1988. "An Investigation of Uncertainty and Sensitivity Analysis Techniques for Computer Models". *Risk Analysis* 8:71-90.

Joskow, P., and D. Marron, 1992. "What Does a Negawatt Really Cost? Evidence from Utility Conservation Programs". *The Energy Journal* 13:41-73.

Kahn, Alfred, 1991. "An Economically Rational Approach to Least Cost Planning". *The Electricity Journal 4(5): 11-22.*

Karr, A., K. Hamilton and J. McCray, 1993. "Synthesis of Findings from Two Independent Impact Studies of a C&I Retrofit Program." In: *Proceedings of the 1993 Chicago Conference on Program Evaluation.*

Komor, P., and A. Moyad, 1992. "How Large is the Cost-Effective Energy Savings Potential in U.S. Buildings?" In: *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings,* ACEEE, Washington, D.C.

Koomey, J., Atkinson, Meier, McMahon, Boghosian, Atkinson, Turiel, Levine, Nordman, and Chan, 1991.*The Potential for Electricity Efficiency Improvements in the US Residential Sector.* Lawrence Berkeley Laboratory. LBL-30477. July.

Krause, et al., 1987. *Analysis of Michigan's Demand Side Resources.* Lawrence Berkeley Laboratory. LBL-23025. Berkeley, CA.

Krause, F. and J. Eto, 1988. *Least-Cost Utility Planning Handbook for Public Utility Commissioners, Volume 2 - The Demand Side: Conceptual and Methodological Issues.*

National Association of Regulatory Utility Commissioners, Washington, DC. December.

Lagerberg, B., V. Schueler and P. Leistner, 1993. "A Meta-Analytic Approach to Estimating Natural Gas Conservation Savings -- Preliminary Weatherization Program Findings." In: *Proceedings of the 1993 Chicago Conference on Program Evaluation.*

LBL/EED, Lawrence Berkeley Laboratory, Energy and Environment Division, 1993. *Energy Analysis Program 1992 Annual Report.* LBL-33441. Berkeley, CA. June.

Lenahan, Tim, 1994. New Hampshire Governor's Office of Energy and Community Services. Personal communication. May.

Lesser, J., 1990. "Application of Stochastic Dominance Tests to Utility Resource Planning Under Uncertainty." *Energy* 15(11), 949-961.

Lomas, K. and H. Eppel, 1992. "Sensitivity Analysis Techniques for Building Thermal Simulation Programs." *Energy and Buildings,* 19:21-44.

Lovins Amory, 1987. *Advanced Electricity Saving Technologies and the South Texas Project.* Report to the City of Austin's Electricity Utility Department. Pursuant to Contract # 86-S300-FW. May.

Lovins et al., 1986. *Competitek.* Rocky Mountain Institute, Snowmass, CO.

Marshall, Harold, 1988. *Techniques for Treating Uncertainty and Risk in Economic Evaluation of Building Investments.* U.S. Department of Commerce, National Institute of Standards and Technology, NIST SP-757.

Marshall, Harold, 1991. *Economic Methods and Risk Analysis Techniques for Evaluating Building Investments--A Survey.* International Council for Building Research Studies and Documentation, CIB-136. Rotterdam, Netherlands.

Means, 1993. *Means Repair and Remodeling Cost Data 1993.* R. S. Means, Co. Kingston, MA.

Meier, Alan, 1982. *Supply Curves of Conserved Energy.* Ph.D. diss., University of California, Berkeley.

Meier, A., and A. Usibelli, 1986. *Supply Curves of Conserved Energy: A Tool for Least-Cost Energy Analysis.* Lawrence Berkeley Laboratory, LBL-20894, Berkeley, CA.

Meier, A., J. Wright, A. Rosenfeld, 1983. *Supplying Energy Through Greater Efficiency.* University of California Press, Berkeley, CA.

Messenger, Michael, 1994. California Energy Commission, Sacramento, CA. Personal communication. May.

Miller, P., J. Eto and H. Geller, 1989. *The Potential for Electricity Conservation in New York State.* New York State Energy Research and Development Authority. September.

Morgan, Granger, and Max Henrion, 1990. *Uncertainty.* Cambridge University Press. New York.

Mosleh, A. and V. Bier, 1992. "On Decomposition and Aggregation Error in Estimation: Some Basic Principles and Examples." *Risk Analysis* 12(2):203-214.

Nadel, Steven, 1990. *Lessons Learned: A Review of Utility Experience with Conservation and Load Management Programs for Commercial and Industrial Customers.* New York State Energy Research and Development Authority. March.

Nadel, Steven M. and Kenneth M. Keating, 1991. *Engineering Estimates vs. Impact Evaluation Results: How do They Compare and Why?* American Council for an Energy Efficient Economy. Washington, D.C.

Nadel, Steven, and H. Tress, 1990. *The Achievable Conservation Potential in New York State from Utility Demand-Sice Management Programs.* New York State Energy Research and Development Authority.

NAS, National Academy of Sciences, 1991. *Policy Implications of Greenhouse Warming.* National Academy Press, Washington, D.C.

NEEPC, New England Energy Policy Council, 1987. *Power to Spare: A Plan for Increasing New England's Competitiveness Through Energy Efficiency.* Boston. July.

NOAA, National Oceanic and Atmospheric Administration, 1983. *Statewide Average Climatic History: 1895-1982, (various states).* U.S. Department of Commerce, Washington, D.C.

NPCC., Northwest Power Planning Council,1986. *Northwest Conservation and Electric Power Plan.* Volumes 1 and 2.

NPCC, Northwest Power Planning Council, 1989. *Technical Appencis to Conservation Supply for the 1990 Power Plan.* 89-47A. November 21, 1989.

Ontario Hydro, 1990. *The Energy Efficiency Potential of the Existing Electrically-Heated Housing Stock in Ontario: Final Report.* Ontario. June.

OTA, Office of Technology Assessment, 1991. *Changing by Degrees: Steps to Reduce Greenhouse Gases.* OTA-O-482. Washington, DC: U.S. Government Printing Office. February.

OTA, Office of Technology Assessment, 1992. *Building Energy Efficiency.* U.S. Govt. Printing Office, Washington, D.C.

Randolph, J., et al., 1991. *Evaluation of the Virginia Weatherization Program.* Virginia Center for Coal and Energy Research, Virginia Tech, Blacksburgh, VA.

Ritschard, R.L, and Y.J. Huang, 1989. *Multifamily heating and Cooling Requirements: Assumptions, Methods, and Summary Results.* Topical Report GRI-88/0239, Gas Research Institute, Chicago, IL.

Ritschard, R.L., J.W. Hanford, and A.O.Sezgen, 1992. *Single-Family Heating and Cooling Requirements: Assumptions, Methods, and Summary Results.* Topical Report GRI-91/0236, Gas Research Institute, Chicago, IL.

Robinson, J., et al., 1989. *Monitoring and Evaluation of Foundation Insulation Retrofits in Twenty Minnesota Houses.* Robinson Technical Services, St. Paul, MN. December.

Robinson, J., et al., 1990. "Cold Climate Foundation Insulation Retrofit Performance." *ASHRAE Transactions 1990.* 96(2)

Rosenfeld, A., et. al., 1993. *Conserved Energy Supply Curves for U.S. Buildings. Contemporary Policy Issues* XI:45-68.

Rubin, E., et al., 1992. "Realistic Mitigation Options for Global Warming." *Science* 257: 148-149, 261-266. 10 July.

Schlegel, J. and S. Pigg, 1989. "Toward a Common Method of Reporting and Comparing Results from Evaluations of Residential Conservation Programs." In: *Proceedings of the 1989 Chicago Conference on Program Evaluation.*

Schweitzer, M., M. A. Brown, and D. L. White, 1989. *Electricity Savings One and Two Years After Weatherization: A Study of 1986 Participants in Bonneviille's Residential Weatherization Program.* ORNL/CON-289. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

SERI, Solar Energy Research Institute, 1980. *A New Prosperity: Building a Sustainable Energy Future.* Brickhouse Publishing, Andover, Mass.

Skumatz, L., et al., 1991. *Bonneville Measure Life Study: Effect of Building Changes on Energy Using Equipment.* Synergic Resources Corporation. Seattle.

Smith, A., P. Ryan, and J. Evans, 1992. "The Effect of Neglecting Correlations When Propagating Uncertainty and Estimating the Population Distribution of Risk." *Risk Analysis* 12(4):467-474.

Sonnenblick, R., 1993. *Evaluation of Energy Efficiency Programs.* Working Paper, Energy Analysis Program, Lawrence Berkeley Laboratory, Berkeley, CA. January.

SPNEC, St. Paul Neighborhood Energy Consortium, 1993. *Project Insulate Standards and Prices.* St. Paul, MN.

SRC, Synergic Resources Corporation, 1992. *Effective Measure Life and Other Persistence Issues in DSM Programs: Literature Review, Outstanding Issues and Implications for Further Work, and Retrospective Sampling.* Oakland, CA.

Sumi, D. and B. Coates, 1988. "A Longitudinal Analysis of Energy Savings from Seattle City Light's Home Energy Loan Program." In: *Proceedings of the ACEEE 1988 Summer Study on Energy Efficiency in Buildings*, ACEEE, Washington, D.C.

Ternes, M. and T. Stovall, 1988. "The Effect of House Indoor Temperature on Measured and Predicted Savings". In: *Proceedings of the ACEEE 1988 Summer Study on Energy Efficiency in Buildings*, ACEEE, Washington, D.C.

Ternes, M.P., P. Hu, L. Williams, and P. Goewey, 1991. *The National Fuel End-Use Efficiency Tield Test.* ORNL/CON-303. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Ternes, Mark, 1994. Oak Ridge National Laboratory. Personal communication. June.

Train, Kenneth, 1994. "Estimation of Net Savings from Energy Conservation Programs." *Energy* 9(4):423-441.

UCS, Union of Concerned Scientists, 1991. *America's Energy Choices.* Vols. 1 and 2. Cambridge, MA.

Usibelli, A., B. Gardiner, W. Luhrsen and A. Meier, 1983. *A Residential Conservation Database for the Pacific Northwest.* LBL-17055. Lawrence Berkeley Laboratory, Berkeley, CA. November.

Vine, E., and J. Harris, 1990. "Evaluating Energy and Non-Energy Impacts of Energy Conservation Programs: A Supply Curve Framework of Analysis". *Energy* 15:11-21.

Vine, Ed, 1992. "Persistence of Energy Savings: What Do We Know and How Can It Be Ensured?" In: *Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings,* ACEEE, Washington, D.C.

Violette, D., P. Greene, S. Feldman, and P. Hanser, 1992. "Applications of Meta-Analysis to Methods of DSM Research." In: *Proceedings of the 1992 ACEEE Summer Study on Energy Efficiency in Buildings.* ACEEE, Washington, D.C.

WCDSR, Wisconsin Center for Demand-Side Research, 1992. *Information Gaps in Marketing and Implementation of Wisconsin DSM Programs.* Madison, WI.

WCDSR, Wisconsin Center for Demand-Side Research, 1994. *Wisconsin's Statewide Technical and Economic Potential.* WCDSR-119-1. Madison, WI.

White, Dennis, and M. Brown, 1990. *Electricity Savings Among Participants Three Years After Weatherization in Bonneville's 1986 Residential Weatherization Program.* ORNL/CON-305. Oak Ridge National Laboratory, Oak Ridge, Tennessee.

Wiggens, D. and B. Boutwell, 1991. "Residential Lighting Program Customer Evaluation." In: *Proceedings of the 1991 Chicago Conference on Program Evaluation.*

Xenergy, 1990. *An Assessment of the Potential for Electrical Energy-Efficiency Improvements in the SMUD Service Territory.* Prepared for the Sacramento Municipal Utility District. July.