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FROM MY PERSPECTIVE
Avoiding "The Big Mistake" in forecasting technology adoption☆

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1. Introduction

A common fallacy afflicting even sophisticated forecasters is that they seek immutable laws of human behavior, much like the physicist discovers physical laws through experiment. Such generalizations about human and economic systems often fail because these systems are adaptable in ways that physical systems are not. Policy choices affect how the future unfolds, and parameters that embody historical behavior are bound to lead us astray whenever a forecast relies on those parameters to project far into the future.

Heavy reliance on statistically derived historical parameters and outdated modeling assumptions is what I call "The Big Mistake." It is related, but not exactly equivalent, to what William Ascher [1] calls "assumption drag" in forecasting, and is an issue that afflicts both "top-down" macromodelers and "bottom-up" engineering modelers. Assuming that

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[1] Details Koomey's work visit ⟨http://enduse.lbl.gov⟩. Koomey is also author of the new book Turning Numbers Into Knowledge: Mastering the Art of Problem Solving ⟨http://www.numbersintoknowledge.com⟩.

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human behavior is immutable will inevitably lead to errors in forecasting the future, no matter which kind of modeling you do.

2. Physical laws vs. human behavior

Physicists conduct replicable experiments to uncover fixed physical laws. A scientist measuring the speed of light in a vacuum, for example, would find the velocity the same in the US or Tahiti. If another scientist conducted a similarly accurate experiment in Russia, the test would produce the same result.

On the other hand, relationships between cause and effect for individuals and human institutions are dependent on institutional, social, and economic context. Furthermore, these relationships change over time. A market researcher attempting to predict consumer acceptance for a new toothpaste would find that a market test in San Francisco would likely yield quite different results than in Tahiti, even though the speed of light remains the same in both places. In addition, if the same experiment had been conducted in the 1950s, the results would have presumably varied wildly from those of the current day.

This ostensibly obvious observation is oft-ignored. For example, in the mid-1970s and early 1980s, the conventional wisdom held that modern societies could not reduce energy use without also reducing gross domestic product (GDP) and harming their economies. Gordon Corey, vice-chairman of Chicago's Commonwealth Edison, stated in 1981 that, "there is an unbreakable tie between economic prosperity and energy use." Similarly, the Chase Manhattan Bank stated, in its 1976 *Energy Report* that

> there is no documented evidence that indicates the long-lasting, consistent relationship between energy use and GDP will change in the future. There is no sound, proven basis for believing a billion dollars of GDP can be generated with less energy in the future (quoted in Stobough et al. [2]).

Believers in an unbreakable link between energy use and GDP assigned the immutability of a physical law to this historical relationship, but found their belief shattered by events. From 1973 to 1986, US primary energy consumption stayed flat, but GDP rose 35% in real (inflation adjusted) terms. These believers had forgotten that people and institutions can adapt to new realities, and historically derived relationships (like the apparent link between energy use and GDP that held up for more than two decades in the post World War II period) can become invalid when events (like the 1973 oil embargo) overtake them.

3. This mistake as embodied in computer models and forecasts

Most economic computer models embody historical experience through relationships that are derived statistically, and then use those relationships to forecast the future. These models are often used to assess the potential effects of proposed changes in government policy or business strategy. The models embody history, but cannot give an accurate picture of a world in which the fundamental relationships upon which they depend are in flux. If the statistically derived relationships embedded in such a model are the very ones that would be affected by choices or events, then those relationships must be modified in the analysis; otherwise, the results are suspect.

For example, many economists trying to assess the costs of reducing carbon emissions assume that the only way to reduce these emissions is to impose a large carbon tax, which would raise the price of coal, oil, and natural gas in a way that has no historical precedent. They further compound this error by using models that embody historical relationships to do long-term forecasts without altering those relationships to reflect the unprecedented nature and size of these taxes, or the likely effects of other near-term policy choices.

Creating a world with vastly lower carbon emissions presupposes massive behavioral and institutional changes that render past relationships between energy use and economic activity largely irrelevant (just like after 1973). It also presupposes alterations in government policies. It is simply laughable to use computer models based on historical relationships for 100-year forecasts in the face of such changes. Instead, scenario analysis is the appropriate tool for exploring the key relationships and how the world might evolve if those relationships change (see below).

Engineering–economic modelers can also fall prey to The Big Mistake. In Autumn of 1997, the US Environmental Protection Agency and Department of Energy asked me and my team at Lawrence Berkeley National Laboratory to conduct analysis of the Clinton Administration's soon-to-be proposed tax credits for energy efficient equipment (For details on the calculations, download the analysis spreadsheets at http://enduse.lbl.gov/Projects/TaxCredits.html). Our first attempts to model the effects of the credits involved running two engineering–economic models with a reduced price for the more efficient appliances, but I soon realized that this approach was doomed to failure. Simply reducing the capital cost of more efficient equipment without changing the decision parameters affecting efficiency choices in the model was another form of The Big Mistake.

After this realization, we went back to the best empirical data on responses to rebates, which was created by Kenneth Train at UC Berkeley [3], and used it to create a spreadsheet embodying those responses. We identified two effects of a rebate from the Train data. The first is the "Direct Price Effect" on the market share of the more efficient product, which was what we first attempted to model. The second is the effect of a rebate that is independent of the size of the rebate (Train's analysis showed a change in market share for a rebate of zero), which we dubbed "The Announcement Effect." The very fact of a rebate's existence lends institutional credibility to a particular technology that it did not necessarily have before. In addition, the people selling the product change their marketing strategy to use the existence of the rebate in their promotions, modifying markups and pricing to reflect the new strategy.

Because it was based on data from one (large) utility service territory, Train's analysis did not account for a third important effect relevant for national tax credits, that of learning associated with increased production experience with a particular technology. As cumulative production experience for a product doubles, costs typically decline by 10–20% on a per unit basis [4,5]. Many high-efficiency technologies are niche products with small sales, so it is easy to double cumulative production experience many times in the early stages of market acceptance. Cost reductions associated with increasing production experience are critically important for such technologies; they represent a lasting effect of the policy and are not easily reversed.

Fig. 1 shows the results of our analysis for two products, high-efficiency Central Air Conditioners (CACs) and Heat Pump Water Heaters (HPWHs). The graph shows the percentage of all high-efficiency units purchased over the analysis period attributable to the direct price effect, the announcement effect, and the cost reduction effect of increased production experience. The last effect is the biggest, accounting for two-fifths to two-thirds of all efficient CACs and HPWHs promoted by the tax credits. The announcement effect is also important in both cases.

Our naive initial attempt to change capital costs in the engineering–economic models only addressed the direct price effect, which in our more sophisticated spreadsheet calculations

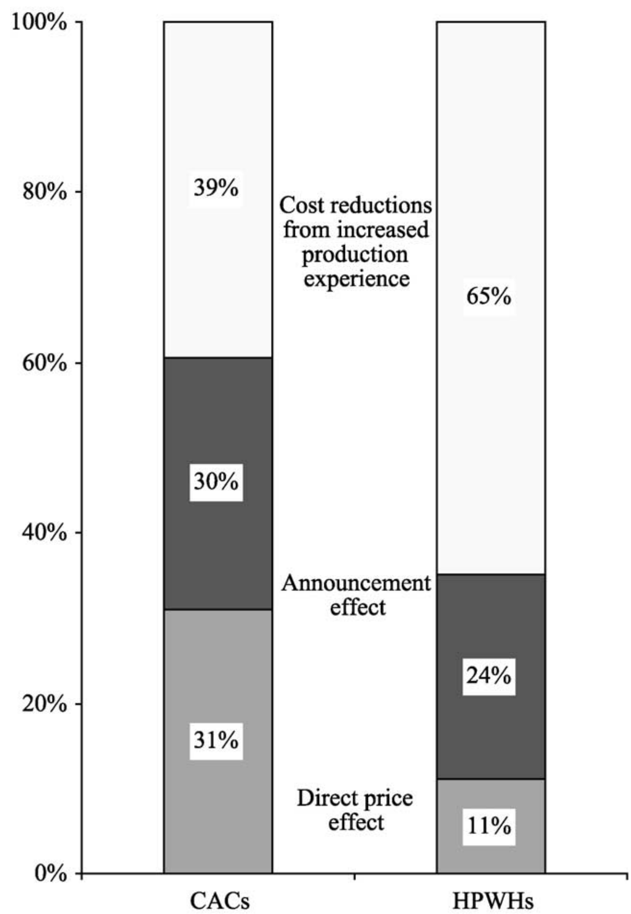

Fig. 1. Percentage of all high-efficiency CACs and HPWHs projected to be purchased as a result of tax credits from 2000 to 2015, attributed to direct price effect, announcement effect, and increased production experience effect. CACs = Central Air Conditioners. HPWHs = Heat Pump Water Heaters.

accounted for only 10–30% of the total effect of the tax credits for HPWHs and CACs, respectively. Had we not examined the data more carefully, we might have missed out on the lion's share of the potential effects of the tax credits.

Another more subtle form of The Big Mistake occurs when forecasters conduct an analysis with an incomplete technology portfolio. For example, many large-scale models of the costs of reducing climate change contain relatively detailed representations of conventional electricity supply-side technologies, but have little or no representation of efficiency technologies for end-users. Even on the supply side, these models typically omit the technologies of the most interest from a long-term perspective (like fuel cells, cogeneration, and renewables) because of data limitations, ideological precommitments, or lack of familiarity with these technologies by the model's designers. Yet, these technologies are exactly the ones most likely to have costs reduced by policy action and to make a large difference in greenhouse gas emissions over the medium to longer term.

The decision to omit key technologies from analyses that claim to be comprehensive is a pernicious one, and it implicitly reflects a view that only historically successful and familiar technologies (or those with characteristics that are tractable from a modeling perspective) are relevant to how the future will unfold. In other words, it embodies the historical success of certain technologies and shackles a forecast to that historical precedent in the same way that statistically derived elasticities do.

This particular analytical error is difficult to unearth, but its effect is the same as that of the other forms of The Big Mistake: It makes deviations from the business-as-usual future appear to be more expensive and difficult in a forecast than they are likely to be in reality. In their study of the differences between ex ante and ex post estimates of the costs of regulations, for example, Harrington et al. [6] found "numerous instances in the case studies where actual compliance costs are lower than predicted costs because of unanticipated use of new technology." Correcting for this error can be quite difficult, because of the unpredictable nature of technological innovation and adoption, a process that is at best only imperfectly understood.

Of course, not all analysts make The Big Mistake. Krause et al. [7], for example, account for the effects of policy choices on technology costs, on fuel prices, and on resource availability in assessing the costs of reducing carbon emissions for Europe. Their studies rely on empirical data to ground the scenario exercises in real-world experience. This work is also exemplary because of its detailed and complete technology portfolio, which reflects years of work by those authors to characterize both demand- and supply-side technologies (conventional and advanced).

4. Defend against this mistake

If you are confronted by results of computer-generated forecasts, always ask whether the analysts changed the key historical relationships to reflect the possibility that those relationships will be affected by policy choices or other developments. If not, then you have identified a key failing of the analysis, and the results are suspect.

Never rely on just one forecast. Instead, use a set of forecasts (i.e., scenarios) to explore the future, as described by Schwartz [8]. Schwartz builds on the work of Pierre Wack, a planner in the London Offices of Royal Dutch/Shell whose own scenario analysis helped that company respond quickly and successfully to the Arab oil embargo following the Yom Kippur war in 1973 [9,10]. As Schwartz and Wack recommend, vary key factors and investigate which of them to ignore and which to dissect further. All forecasts are wrong in some respect, but if the process of designing them teaches you something about the world and how events may unfold, creating them will have been worth the effort.

Most of Schwartz's examples of scenario analysis have only a small quantitative component, but many other futurists are obsessed with numbers and computer models. Most explorations of the future with which I am directly familiar err by focusing too much on the mechanics of forecasting and quantitative analysis (e.g., on particular modeling tools and techniques) and far too little on careful scenario development. Quantitative analysis can lend coherence and credence to scenario exercises by elaborating on consequences of future events, but modeling tools should support that process and not drive it, as is so often the case.

In my 15 years of involvement with development of national energy policy, I have been most struck by how few resources are devoted to sensible scenario development and associated data, and how much to the development of different modeling tools to assess such policies. Computer tools are sexy and appealing (at least to the funding agencies). Data and scenario analysis, upon which the results generally hinge, are virtually always given short shrift.

Millions of dollars are spent every year on models whose capabilities are redundant with others, usually because a particular agency with money wants its own "in-house" modeling capability and is unwilling because of institutional rivalry or personal biases to adopt one of the preexisting frameworks. The policy makers fail to realize that models are *all* unable to predict the future in an accurate way, and that small improvements in modeling methodology are made irrelevant by inadequate scenario development.

The importance of clear and complete documentation to successful scenario design cannot be overestimated. Instead of burying analytical assumptions in "black box" models, as is so often done, it is essential that all assumptions be recorded in a form that can be evaluated, reproduced, and used by others. The uncertainties in predicting the future are vast, and making assumptions for the most uncertain variables is often the best we can do. Unless those assumptions are explicit, however, others cannot evaluate their reasonableness, and we cannot claim to be doing anything akin to science. It is for this reason that simpler and more transparent models are often superior in accuracy and usefulness to large and complex ones, since the simpler models are more amenable to peer review of underlying data and assumptions.

Finally, it is important to identify and adopt strategies that are robust in the face of those inevitably imperfect and uncertain forecasts. For example, several computer companies have moved to "build-to-order" manufacturing, which allows them to assemble computers as requested by customers. This strategy reduces dependence on forecasts, but introduces other challenges in manufacturing (which are surmountable using current technology). This same lesson applies equally well to other such decisions: If the key variables are difficult or impossible to foresee, then use scenario analysis to evaluate the possible outcomes [11], assess the situation from multiple perspectives [12], analyze the uncertainties using statistical techniques [13], and adopt strategies that are less dependent on forecasts.

5. Conclusions

I have found that many physical scientists, computer modelers, and economists are susceptible to "The Big Mistake." I am not certain why forecasters from these disciplines fall prey to this pitfall, but I have noticed it often. It may be what my social science-oriented friends call "physics envy," or it may be that most analyses are conducted in a mechanical way without significant reflection. In any case, once forewarned you need not let them get away with it.

Our choices affect how the future unfolds. For analyses of the costs of reducing carbon emissions, actions taken now to promote the development and adoption of advanced efficiency and renewable power technologies can stimulate the learning and economies of scale effects that will make these technologies more cost effective in the future. The world in which technology adoption takes place is one governed by increasing returns to scale and path dependence [14,15]. In such a world, policy choices matter, and analyses that do not account for the dynamic nature of human behavior and technology adoption are bound to mislead and confound.

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