A Quality-Adjusted Cost Index for Estimating Future Consumer Surplus from Innovation

David Austin
Molly Macauley

Discussion Paper 98-45

July 1998

RESOURCES FOR THE FUTURE
1616 P Street, NW
Washington, DC 20036
Telephone 202-328-5000
Fax 202-939-3460

A Quality-Adjusted Cost Index for Estimating Future Consumer Surplus from Innovation

David Austin and Molly Macauley

Abstract

This paper describes a model for estimating, in a probabilistic framework, expected future consumer surplus from planned new product innovations. The model has been applied to estimations of taxpayer benefits from NASA's New Millenium Program (NMP), which develops new technologies for space science, and to the digital data storage technologies being supported by the Department of Commerce's Advanced Technology Program (ATP). The model uses cost index methods based on consumers' estimated marginal valuation for quality improvements in the technology. Probabilistic values for performance increases are taken from the innovators' own expectations. The analysis reveals the sensitivity of welfare increases to these values, which are assumed to be biased upward. The cost index, when combined with an expected rate of adoption, estimates consumer benefits from the innovation, gross of its research and development costs. Benefits are estimated net of a dynamic baseline defined by the best available substitute technology, which is also assumed to improve over time. Findings are therefore expressed in terms of the economic value of the innovation to consumers, compared to advances that might occur in the absence of the NMP or ATP investments.

Illustrative results--estimated cost indices and 95% confidence bounds--are presented for technologies that are expected to improve consumer welfare and for those that, on a quality-adjusted cost basis, are likely to be outperformed by the selected baseline technology.

Key Words: quality-adjusted cost index, consumer surplus, innovation

JEL Classification Numbers: 032, H43, D60

Acknowledgments

We thank John Ledyard, Bronwyn Hall, and Rachel Griffith for comments on this work, as well as colleagues at the California Institute of Technology, the Jet Propulsion Laboratory, and participants in seminars and workshops at Resources for the Future and the National Bureau of Economic Research. We also appreciate comments received at the National Institute of Standards and Technology's international conference on The Economic Evaluation of Technological Change. Nancy Bergeron and Ron Lile provided excellent research assistance. Responsibility for errors and opinions rests with the authors.

Table of Contents

List of Tables and Figures

A QUALITY-ADJUSTED COST INDEX FOR ESTIMATING FUTURE CONSUMER SURPLUS FROM INNOVATION

David Austin and Molly Macauley*

I. INTRODUCTION

This paper describes a method for estimating future consumer surplus from planned new product innovations. We hope that the ability to make these calculations is useful to policy-makers and government agencies involved in supporting technology research and development (R&D), both in the private and public sectors.[1] We have used this model to estimate taxpayer benefits from NASA's New Millenium Program (NMP), which develops new technologies for space science,[2] and are now deploying the model in a study of digital data storage technologies supported by the Advanced Technology Program (ATP) of the Department of Commerce. The Advanced Technology Program seeks to generate benefits from innovations enabling new medical, communications, computing, and other services, as well as from the improved price-performance characteristics of those innovations for existing services.

The consumer benefits in existing services can be estimated using cost index methods, and are the focus of our analysis. For both NMP and ATP, as well as other programs that invest in R&D, identifying consumer benefits from these taxpayer-supported investments is a natural way to account for an important element of their performance.

Both NMP and ATP describe the new technologies as leapfrogging beyond current best practice, and we assess their benefits with respect to the baseline defined by existing, state-of-the-art technologies. The baseline is not a static reference point, as these technologies are themselves continually being improved. We express our findings in terms of the economic value to consumers of quality improvements, compared to advances that would have been expected to occur in the absence of the programs.

Our focus on input performance will not capture all of the potential consumer benefits from government-sponsored R&D. For example, these include new services enabled by ATP's advanced technology investments, which are an important motivating factor in the creation of that program. Such investments may also create unmeasured

---

* The authors are, respectively, Fellow, Quality of the Environment Division, Resources for the Future; and Senior Fellow, Energy and Natural Resources Division, Resources for the Future.

1 This method supports much of what the 1993 Government Performance and Results Act (GPRA) requires of government agencies**.**

2 The primary "consumers" of space science are actually space scientists, rather than ordinary taxpayers. Since NASA's agency ultimate responsibility is to taxpayers, however, the distinction is only apparent. The point is these are benefits enjoyed by *users* rather than producers of a technology.

private benefits, appropriated by the innovator or enjoyed by other firms in the form of knowledge spillovers. The public benefit from the new services is potentially large, and may result in increases in demand for the new technologies compared to existing ones. Prospective estimation of this benefit is problematic, however. More so than for improvements in price and input performance, forecasting the growth in demand due to quality improvements in the *outputs* (e.g., true video-on-demand, or virtual real-estate touring) is fraught with uncertainty. Measuring benefits of new services calls for predictions of the market's response to the new products, and the analyst is not always on very firm ground in doing this.[3]

All types of benefits, public and private, are of equal importance from an economic efficiency perspective. However, it may be sufficient to assess public benefits just from improvements in the delivery of existing services, through new technologies for space science or consumer services.[4] These benefits are an important goal of ATP and NMP, and may suffice to demonstrate favorable agency performance. In fact, were their investments to yield only private benefits, neither ATP nor NMP would succeed in producing market spillovers.[5] To account fully for *net* benefits, the development and opportunity costs of achieving the benefits should also be included. Full cost estimates are problematic, however, if the technology has already undergone significant initial development before NASA or the Department of Commerce began their involvement.[6] In any case, full cost estimation goes beyond the scope of this study. Our analysis provides a rigorous and defensible estimate of one important type of likely future benefits, those accruing directly to consumers in the form of increased service at lower cost.

Along with forecasts of demand changes resulting from quality changes, our approach requires estimates of shadow values, or consumer willingness to pay for those quality changes. We use hedonic econometric techniques to estimate values for improvements in the most important of a technology's "generic" performance dimensions. By way of example, for ATP's digital data storage program, we estimate the shadow values of new tape units' improved storage capacity, data rate, and file access time.[7] For our NMP study, we use

---

[3] By contrast, forecasting demand for new pharmaceuticals, for example, can be approximated using the size of the population affected by the condition addressed by the new drug.

[4] This formulation is intended to include even many new technologies sponsored by ATP. In the archetypical example of ATP's flat-panel display project, new display screens would be coupled with existing computing services, for example.

[5] It may produce knowledge spillovers, benefits enjoyed by other innovating firms.

[6] For example, development of some NMP technologies was funded at various stages by a host of government laboratories and agencies as well as by industry, and full cost accounting is next to impossible. Similarly, some ATP technologies have also received prior investment funding from a variety of government and private sources.

[7] We use recent market data, for digital data storage devices similar to the existing technology, to estimate consumer willingness to pay for improvements in product quality along these dimensions.

shadow values predicted by existing hedonic-like models of small spacecraft costs.[8] Hedonics involves explaining changes in price by examining changes in performance capabilities over time. Consumers' implicit willingness to pay for these quality changes are estimated as the relationship between each quality dimension and the product's market price.

As already noted, our approach seeks only to measure returns from individual projects, exclusive of R&D costs, although these could be included with some extensions to the model. For instance, a full accounting of performance would, in addition to taking such costs into account, examine the record of the agency program over a portfolio of investments. Because returns are an *ex post* measure, a finding of negative expected consumer surplus would not necessarily indicate unsatisfactory agency performance. All investments have, *ex ante,* a risk of failure or of under-performance. Indeed, some ATP and NMP investments have failed to reach fruition. It is only in the context of the collective returns to the program, and the market spillovers it has created, that the investment program can be judged.

In future research, we plan to extend our model to accommodate a portfolio approach to R&D investment. With slight modifications, our approach can be adapted for use in planning private R&D investment strategies as well. At the planning stage, this model can be used to assess the potential of proposed R&D investments before committing to them.

II. BACKGROUND

We employ a cost-index approach pioneered in Bresnahan (1986). Bresnahan estimated the consumer surplus from advances in general purpose, mainframe computers between 1958 and 1972. He demonstrated the applicability of a cost-index approach (Caves et al., 1982) to measuring consumer surplus using changes in quality-adjusted prices of new technologies. Under certain key assumptions this approach permits the estimation of the relevant area under the demand curve for the new technology, without having to estimate the demand curve itself. This obviates the need for econometric estimation and, in particular, makes it possible to perform the estimation in sectors for which output quantity and quality-adjusted output price are unobservable. As Bresnahan (1986) and Griliches (1979) point out, this unobservability tends to characterize sectors in which the benefits from important technological advances have been realized.[9]

---

[8] These models use both government and *commercial* spacecraft data (Sarsfield, 1998; Wertz and Larson, 1996). (Several of the NMP technologies, ion propulsion and solar arrays, will find ready application in telecommunications satellite markets.) These models feature cost curves for precisely the dimensions we require: mass, volume, and power. Interestingly, while the technology prices NASA faces are stipulated by contract or internal arrangement, internal markets have emerged recently for spacecraft payload requirements. Project teams can trade unused volume, mass, or power to other teams, transactions which do yield marginal cost data. We use some of these marginal cost data in our NMP research.

[9] These are, as Bresnahan (1986) notes, "the downstream sectors--such as services, government, health care, etc.--[which] lack sensible measures of real output." This is a particular problem for measuring digital data storage benefits of the high-end, high-capacity tape "library" systems that are our focus, and where the using sectors tend to produce outputs with unobservable quality.

The ability of the cost-index approach to return an estimate of consumer surplus depends on the structure of the downstream market in which the technology is applied.[10] Demand for the kinds of new technologies sponsored by ATP typically has been mediated by producers using the innovations in their production processes. For our NMP study, demand is also mediated by space scientists acting as agents to carry out scientific endeavors for the public as a whole. It is this *derived* demand, in the satisfaction of demand for output services, that is the focus of the cost-index method.[11] As long as the downstream market is competitive, or is a government agency such as NASA or the Department of Defense, then the producer acts as an agent for consumers when it uses an upstream technology.[12] This agency aligns the downstream producer's profit maximization with consumer's expenditure minimization, which renders the area under the derived-demand curve, calculated by the cost-index method, a measure of consumer surplus.

If the using market is concentrated, the index would measure, as Bresnahan points out, what is being maximized by the producer, i.e., profit, rather than total (producer+consumer) surplus. When downstream producers have market power, the derived demand curve for the innovation is shifted inward relative to the competitive case. This is not a difficulty with the method, since the appropriate quantity to measure would be this consumer surplus given the producer's market power. In a concentrated market, integration of the area under the demand curve yields a measure that understates total surplus. Heuristically, since even monopoly producers typically cannot appropriate all consumer surplus, the resulting measure of profit undercounts total benefits.[13]

A similar point can be made about competition in the upstream, technology-producing market. Our analysis makes no assumptions about competition in the upstream market. To reiterate, it measures the welfare that is available given market conditions, rather than the maximum welfare that could be achieved under perfect competition. Significant innovations in the upstream market will create market power there, and rather than compromising the cost-index approach, they are the *sine qua non* of this analysis!

---

[10] The other "key assumption" necessary for this method's accuracy is that the price index is correct. No index perfectly satisfies all of the tenets of demand theory or conforms to all of the desirable properties of index numbers, such as transitivity, scalability, and so forth. The index formula selected by Bresnahan and used in this paper satisfies most of the more important properties (see Diewert and Nakamura, 1993). In the empirical section, we forecast the price index. Although Bresnahan has the benefit of price indexes constructed from actual experience, even so he is forced to rely on a pair of indexes that differ significantly from one another. He bounds his estimates on the high and low side using these indexes.

[11] The notion is that the innovation is an intermediate good, and the services it provides (refrigeration, space science, data storage) are the final good. Demand for the innovation is derived from the demand for final goods.

[12] Some political economy theories point out that government agency may only poorly embody consumers' tastes for space science, at least on the margin. Our results can be interpreted in light of whatever belief one holds about NASA's representation of consumer tastes.

[13] Note we--and Bresnahan--make no assumptions about potential gains from a competitive market structure in the *innovating* sector. The cost index approach measures only the expected *actual* gains.

Bresnahan applied this methodology to the financial services sector (FSS), one of the leading users of mainframe computers at that time. The final output, financial services, is not observable in terms of quantity and quality-adjusted price. That the FSS could be treated as highly competitive allowed it to be treated as an agent for the end consumer, particularly with respect to the purchase of computers. The derived demand for computers, as an intermediate good in the provision of financial services, is mediated through final demand for those services. The market for financial services was, at that time, a competitive one, which allows Bresnahan to treat the derived demand as if it was generated directly by consumers of those services. Therefore the area under the derived demand curve provides a measure of consumer surplus from the development of these computers.

Bresnahan's approach was *retrospective:* he applied his model to past innovations. Our contribution is to apply this methodology *prospective*ly, to innovations that have not yet reached the market. We developed our approach in our research on space technologies--propulsion, communication, solar energy, imaging, and navigation systems--selected for trial and flight validation under the auspices of NASA's New Millennium Program. NASA is both the consumer of these technologies--literally, and as agent for the taxpaying public--and the producer of the downstream product, space science. The downstream market in this case provides a public good, and the consumer "agency" requirement is satisfied, not by a competitive market structure but literally by NASA's being a government agency.

The technologies of the NMP are scheduled for imminent launch on the first mission of the program, Deep Space I, set for October, 1998. As such, their performance and quality-adjusted prices are already fairly well understood and provide a basis for predicting likely values and uncertainties several years beyond their initial use. The ATP technologies are not as far along, so our evaluation involves predicting consumer surplus *on the basis of what we currently know* about these technologies.

Our data comprise the stated expectations of engineers, product managers, technologists, and other persons familiar with the innovation. For each technology we elicit these experts' beliefs concerning the most likely values of current and near-future "off-the-shelf" prices,[14] performance--in each of several dimensions, the size of the market, and the rate of market acceptance. Our analysis compares these data against the same attributes of the best and most comparable of existing technologies. The change in consumer well-being resulting from each innovation is then captured by a price index that estimates consumers' hypothetical willingness to pay for them in a "counterfactual" world in which they were not invented.

We do not attempt a comprehensive accounting of consumer surplus in all markets in which the technology is to be used. Bresnahan focused on the major downstream market for mainframe computers, and our purpose is to identify the most important market or markets for our technologies. In this way we capture a representative, if not dominating, portion of total

[14] As already noted, these do not include development costs. Many of the space technologies and the ATP technologies have been under development in one form or another for many years, and a full accounting of their development costs over the years probably would be impossible to achieve.

consumer spillover, while avoiding details about the technologies' penetration in minor markets. For the NMP innovations, we have comprehensively estimated their near-term diffusion in space science but have not included the surplus from possible exploitation in commercial markets, such as communications satellites.

Because our data consist of expectations about the future, we explicitly incorporate uncertainty and conduct sensitivity tests of our specific parametric assumptions. Bresnahan used single-point values for expenditure shares and costs. Although those numbers are no doubt approximations and probably reflect some accounting error, his data do not support an analysis of uncertainty beyond a sensitivity analysis over a pair of divergent, quality-adjusted computer price indices. In this way Bresnahan bounds the estimates. By contrast, since our technologies have no record of performance at all, we are obtaining from our subjects both their point estimates of expected values and their associated uncertainties. We use these inputs to parameterize the probability densities that represent the likely price and performance of the innovations. This in turn goes into our implementation of the cost-index calculation in a decision-modeling framework. In this setting, analysis of the relative influence of each input, and of the joint implications of the many assumptions that inform the experts' forecasts, is straightforward.

The result is a flexible model which simulates the empirical probability density of consumer surplus outcomes implied by the input uncertainties. The structure of the model eases the tasks of isolating the inputs that most drive the uncertainty in the results, and analyzing the sensitivity of mean output values to fluctuations in the values of the inputs. As noted earlier, because it combines uncertainties and expected values across a range of performance attributes and adoption rates, this modeling framework may prove particularly valuable to R&D planners, public and private, whose analytical methods have to now been more piecemeal.[15]

The chief contribution of this prospective cost index approach is in demonstrating the implication for future benefits of disparate and uncertain input assumptions--about costs, performance, price, and sales--considered jointly. We thus broaden the use of cost indexes from retrospective estimation to project evaluation. This model provides a flexible, experimental platform upon which can be conducted "what if" sensitivity analyses to provide a fuller picture of the likelihoods of comparative successes and failures. By casting input parameters in probabilistic terms we can examine the importance of different levels of input uncertainty in determining the uncertainty of the output. Probabilistic returns may be commonplace for prospective innovators, but the unified framework of this cost index approach, where point estimates and uncertainties can be modeled simultaneously, may be an advance beyond what is commonly practiced in private firms' planning.

---

[15] In our analysis we perform, for each model input, a sensitivity analysis--the effects of changing input levels on mean consumer surplus. We also carry out an *importance* analysis for each input, or the effect of input uncertainty on uncertainty in the estimate of consumer surplus.

III. MODEL

The cost index indicates how much more expensive an equivalent level of services would have been in the absence of the new technology.[16] We use the index to compare utility in the *expected* world of services employing new innovations and a "defender-technology" (DT) world using best-available technologies. For instance, for ATP we compare a high-capacity, high-density linear scan tape library to a currently-available line of helical-scan-based technologies with lower-densities. The performance of the ATP technologies is intended to leapfrog conventional technology capabilities. We assume innovation continues over time in both technologies, but that DT innovations come at a slower pace because the technologies have been available for awhile.

The cost index, multiplied by the share of total expenditures devoted to the technology, gives the consumer surplus, in dollars, resulting from the outward shift in the technology supply curve. This shift represents increases in output that can be supplied at a given price, because the technology has reduced costs. The defender technology's supply curve will also shift outward over time. As long as the initial shift in the government-sponsored technology's supply curve is larger than that of the DT curve, the cost index will be greater than unity. Ignoring the cost of the R&D, the measured consumer surplus would indicate how much better off taxpayers are than in the absence of the government investment. Where the shift in the DT supply curve is greater, the index will be less than one and consumers will be worse off than if the government-sponsored technology had not been adopted.

Figure 1 illustrates the consumer surplus from the government-sponsored innovation, or consumers' willingness to pay to move from the defender technology to the expected innovation. The shift in the government-funded-technology supply curve can be due to a combination of cost reductions and quality improvements. The purpose of a quality-adjusted cost index is to account for both.

Assumptions

We make no assumptions about the market structure of the upstream sector where the technology is produced; if it is produced by a firm with significant market power--or if it is a sufficiently "drastic" innovation that it *bestows* market power on the innovator--less consumer surplus will be created than if the upstream sector is competitive. We measure available surplus, not potential surplus.

We also focus on downstream markets that can reasonably be described as competitive. Without this feature, the cost index approach will underestimate total surplus, for reasons we give elsewhere.

---

[16] Bresnahan calculates a "cost of living and of providing financial services" index, based on computer expenditures for financial services as a share of the total personal consumption expenditures (PCE). If quality-adjustments and expenditures on digital data storage are too small a share of PCE, we would base the cost index on expenditures as a share of sector expenditures only. We do this for the space technologies to distinguish the cost index from unity. Since NASA serves the space science community as well as the public, an index of the "cost of providing space science and of making propulsion systems" is relevant.

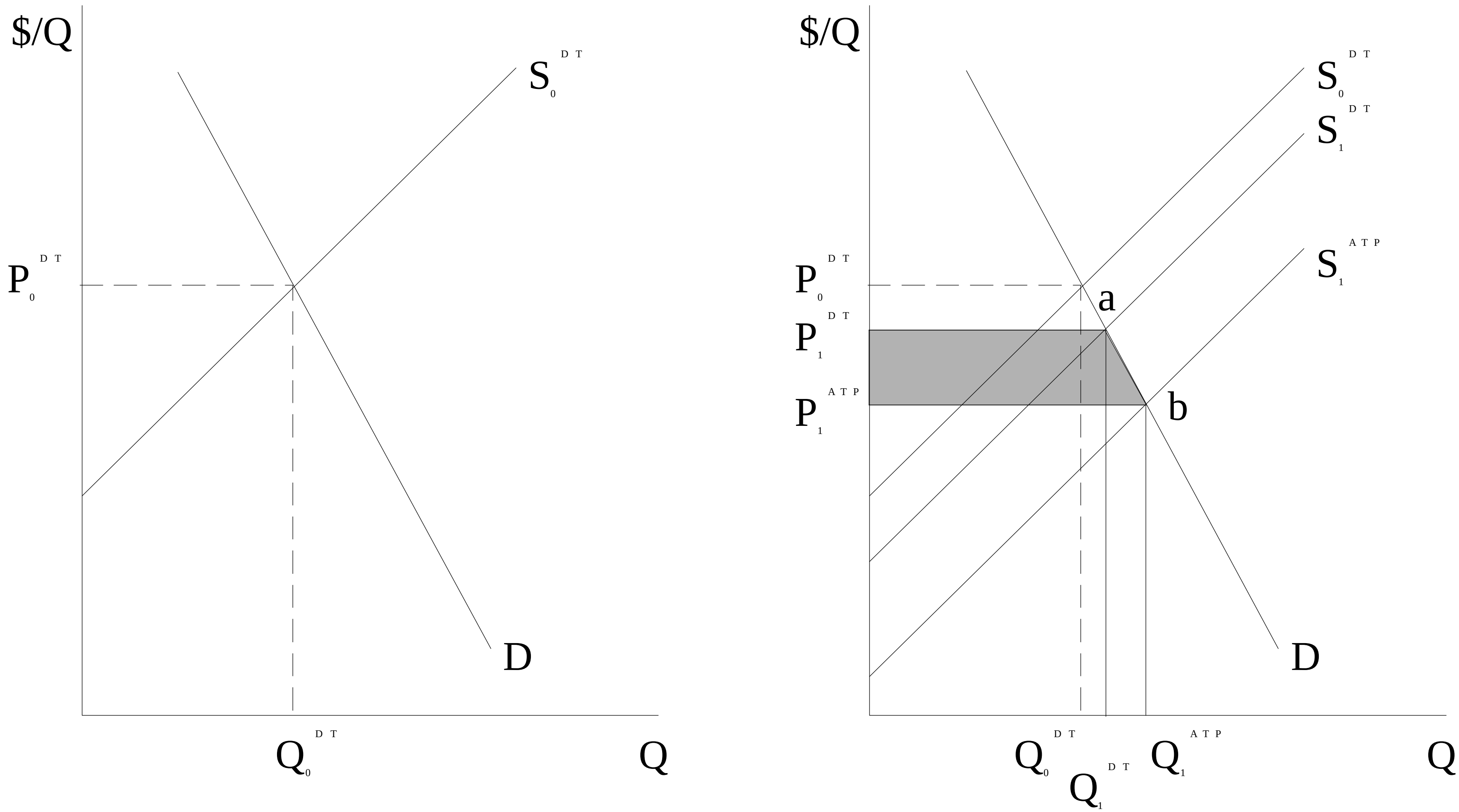


Figure 1. Derived Demand for New Technologies:
Illustration of Net Surplus Change

To calculate the cost index, we gather data on the expectations about unit sales and price of the innovation in its expected major market sector(s), along with expected trends in these figures. Independently, we also include total expenditures "for" consumers incurred by the relevant downstream sectors in providing services to those consumers. From this we calculate expected expenditure shares on the technology or its innovative substitute. Expenditure shares, one of the two components of the cost index formula, are simply

PRICE*UNITS / EXPENDITURES

In our model, prices are indexed by, and decrease over, time in a manner described by the technology experts we interview. We assume this trend is fueled by learning-by-doing and by continued R&D. We also assume that prices for the defender technology also decline over time, possibly at a slower rate, if learning economies have already been exploited. We provide formal details later in the paper.

The other significant component of the cost-index formula is the ratio of quality-adjusted prices for the defender technology and the innovation. We quality-adjust the expected price of the innovation relative to the defender in the following manner: we identify the most important quality dimensions of the particular technology (file access time, data transfer rate, and capacity for the digital data storage devices; mass, power requirement, and volume savings for the space technologies), and estimate consumer willingness to pay for incremental improvements in these quality dimensions, using hedonic econometric techniques.[17] We take the resulting shadow values and calculate a quality adjusted price, for a technology with quality dimensions dim1,…, dim3 as follows:

$$W^I = p^I - \beta_1(\Delta dim1) - \beta_2(\Delta dim2) - \beta_3(\Delta dim3)$$

Here p^I is the expected sales price of the innovation; Δdim_i expresses the difference in the performance of the innovation along this quality dimension, relative to the DT. Because the quality improvements are taken relative to the DT, and the innovation is always compared to what the DT is *expected to be* in the near future, it is obviously the case that $W_{dt}=p_{dt}$, and no quality-adjustment is necessary for the DT.

Finally, we assume that the rate of adoption of the new technology in preference to the defender DT is sensitive to the relative quality improvement of I over DT.

Our estimation is forward-looking. We have gathered information about expectations about 5 years into the future. In each future year we estimate the change in consumer surplus induced by innovation I relative to the DT *in that year*. The "benchmark" defender technology is assumed also to improve in quality over time, and it is this dynamic standard against which we compare the innovation. While the expected performance of both technologies is hypothetical because it is projected into the future, the "DT" regime in our discussion of the cost index is hypothetical in another sense as well: the cost index expresses

---

17 For a good description of the hedonic model, see Berndt (1991).

the average consumer willingness to pay to achieve innovation "I" *assuming it will not have occurred.*

Cost Index Formula

We use the Törnqvist cost index presented in Caves et al. (1982). This index measures the quality-adjusted change in the price of a technology, provided by an upstream sector, as an input in the production process of a downstream sector. The index is the geometric mean of two monetized measures of change in consumer utility. These measures, a pair of Könus cost indices, are ratios of "minimum expenditure functions" for achieving two given levels of consumer utility. In general, the expenditure function $E(u,p)$ is the least amount a consumer must spend to achieve utility u given prices p, or $E(u,p)=min\{p \cdot x : U(x) \geq u, x \geq 0\}$, where x is the consumer's consumption bundle and $U(x)$ reflects the consumer's preferences.

Following Caves et al., we separate quality-adjusted prices W from general prices p. For consumers facing quality-adjusted prices W^I or W^{dt} for the technology inputs[18] to production in the adopting sector (e.g., tape backup as an input to provision of information services), and aggregate prices $p^{\bullet}$ for everything else in their consumption bundle, C^{*dt} in the expression below is the cost of achieving utility u^{dt} in the non-government world, relative to what it would cost to achieve this level of utility given the innovation I. Similarly, C^{*I} gives the relative cost of achieving utility u^I given government-sponsored innovation I compared to what it would have cost to provide this level of utility with only the DT:

$$C^{*dt} = \frac{E^{*}(u^{dt}, p^{dt}, W^{dt})}{E^{*}(u^{dt}, p^{I}, W^{I})} \text{ and } C^{*I} = \frac{E^{*}(u^{I}, p^{dt}, W^{dt})}{E^{*}(u^{I}, p^{I}, W^{I})}. \qquad (1)$$

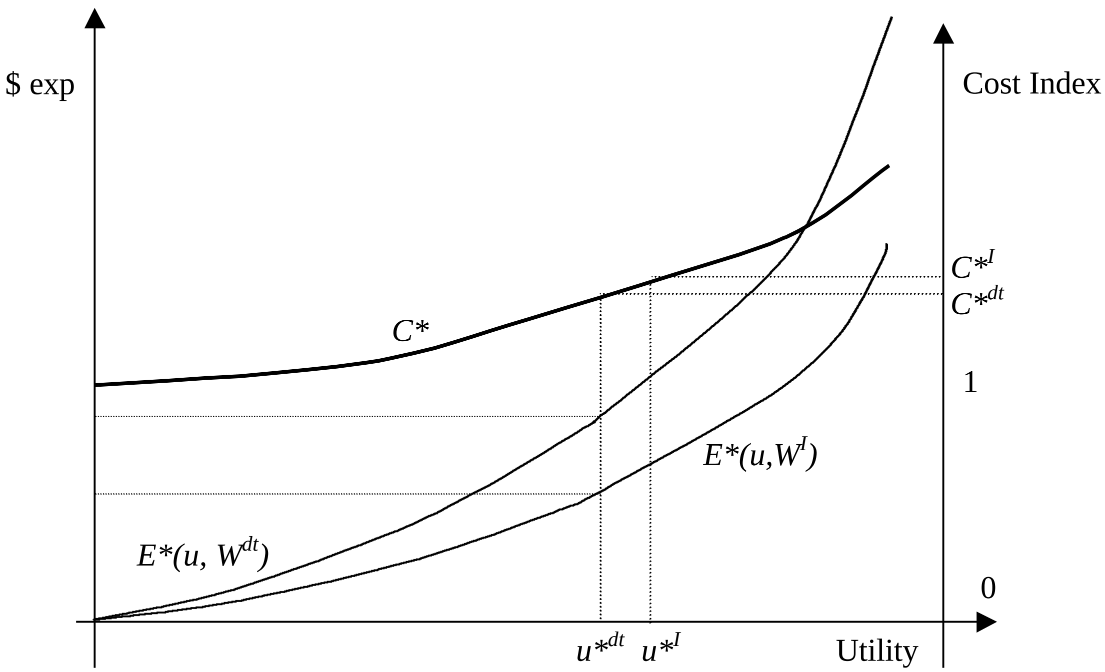
Utility u^{dt} and u^I are the best an optimizing consumer will achieve in a world in which, respectively, either the DT or the government-funded technology is the state of the art. Quality adjustments to prices W are expressed relative to the initial baseline quality of the defender technology. Prices p of all other commodities a consumer buys are allowed to change over time, but we assume them to be the same under both regimes (*i.e.,* $p^{dt}=p^I$) at all times.[19] As we show in an appendix, this simplifies the problem considerably. Both C^{*dt} and C^{*I} will be less than unity if the government-funded innovation is inferior, on a quality-adjusted price basis, to what will be available at the same time from the DT technology. The indices will be greater than one if the government-supported technology is superior.

Figure 2 is a graphical representation of the ratios in expression (1). Assuming the innovation I performs better than the defender technology DT, and so is welfare-enhancing, it will cost a consumer less to achieve any given level of utility with quality-adjusted prices W^I

18 Expenditure functions normally take output prices as arguments. Here, the assumption of perfect competition or agency allows substitution of input prices for output prices.

19 This assumption implies that general prices p are unaffected by the substitution of *I* for *dt*.

Figure 2. Relationship Between Expenditures, Cost Index



than with the higher W^{dt}.[20] (Here general prices p have been omitted to simplify the figure labeling.) In the no-innovation case DT, technology prices will be W^{dt}; the consumer's optimal utility level for these prices is labeled u^{*dt}. At this point the cost index is C^{*dt} with its value indicated on the right vertical axis. Given welfare-enhancing innovation I, the consumer's optimal utility will be $u^{*I} > u^{*dt}$, at which level it would be comparatively more expensive under the no-innovation regime than it is to provide utility u^{*dt}, so $C^{*I} > C^{*dt}$.

Both cost indexes are measures of consumer surplus. Both C^{*I} and C^{*dt} have advantages and disadvantages, and neither is ideal for all applications.[21] The Törnqvist index is a composite of both of these cost indexes, and gives each equal weight. The Törnqvist index is the geometric mean of the two indexes (see expression (2), below). As is well known from the theory of index numbers, no single index satisfies all "desirable" properties or tests (e.g., tests related to scalability, transitivity, symmetry, proportionality). The Törnqvist index satisfies many of the tests (see Diewert and Nakamura,1993).

We assume, following Caves, et al. and Bresnahan, that consumer expenditures E^* can be represented by a translog functional form.[22] In an appendix, we give details about the translog formula and show that when the expenditure function $E^*$is translog, the Törnqvist index takes the simple form:

$$\tfrac{1}{2}\ln\left(C^{*dt} \times C^{*I}\right) = \left(\tfrac{1}{2}(s_{dt} + s_I)\cdot \ln\left(\frac{W_{dt}}{W_I}\right)\right). \qquad (2)$$

The ***s*.** denote factor expenditure shares for the defender technology *dt* or innovation *I*, as a fraction of total personal consumption expenditures. For NMP, we used the U.S. space science budget as our denominator, for reasons already described. Beyond swapping observable input price and quality for unobservable output price and quantity, an additional advantage of this approach is that, because the two "time periods" are contemporaneous, prices and expenditure shares for "other" goods, and quality-adjusted prices for other inputs in the adopting sector, are unchanging and cancel out of the equation.

Changes in relative prices can lead to changes in the mix of input factors in production of final output, and in the demand for that final output. The translog functional form places no restrictions on elasticities of substitution between the new technology and other factors, or on the income or price elasticities of demand for the final good. Moreover, the translog allows for arbitrary shifts in demand, say, (for space exploration) due to technical progress in unrelated computer technologies, or from taste-driven changes, not attributable to ATP, in the budget for computer technologies, as long as elasticities of substitution are unaffected.[23] We do not

---

20 As we later explain, the vertical distance between the two expenditure functions depends on the importance of this technology in the total consumption bundle.

21 See Varian (1992) for details.

22 The translog, aside from having desirable properties exploited by this procedure, is a flexible functional form that is able to approximate well many production and expenditure functions.

23 This paragraph paraphrases remarks in Bresnahan (1986) p. 751.

believe this latter difficulty impinges on our analysis of ATP case studies in the near term. We restrict our attention to the short- to medium-term future of 5-8 years. To the extent this issue is a concern, later years should be increasingly discounted.

The cost index describes how much higher (or possibly lower) costs would have been in the absence of the innovation. For any relative price W_{dt}/W_I the index will be closer to unity the smaller the share of the total budget (or of total private consumption expenditures) is spent on the technology. The index for an innovation that offers only small savings over the defender technology, but which is a significant share of total expenditure, would be larger.

Inputs and Output

The inputs to the model include the elements of the cost indices--quality-adjusted prices and expenditure shares; expectations about changes in prices and expenditure shares over time; and the expected rates at which the innovations will replace the defender technologies. Most parameter values are represented as uncertainties in our model, according to processes we present in the following sections. We discount all of the future price expectations to present-value terms.

Expected benefits reflect off-the-shelf prices (and quality adjustments). We present expected consumer surplus of the innovation *net* of that generated by the defender technology, but *gross* of the R&D costs. The shape of the empirical probability density function for consumer surplus is a function of our assumptions about uncertainties.

We simulate the model a large number of times (N=100 for figures given in this paper) to form the empirical density function. In each iteration of the model, we sample independently from each input distribution, and combine the values according to the cost-index expression (2). The final density function summarizes the outcomes of the individual simulations.

Finally, in a future version of this paper we will report the results of sensitivity analyses for each of the input parameters. We will also report the outcome of an "importance analysis," which reveals which uncertainties in the input parameters are most responsible for uncertainty in the consumer surplus density function.

Market Size and Expenditure Share

In the application of our model to the ATP case studies, the expenditure shares $s_{\bullet}$ in the cost index formula refer to the total outlay on digital data storage devices *by sectors using those devices to produce final outputs*. To calculate these numbers it is necessary to know both the expected sales, in dollars, of digital data storage devices--for the defender and the innovator--and the size of the downstream industry, information services, buying the devices.

Digital data storage devices are purchased to produce data storage services, as part of a larger set of computer network services. Since this sector is also relatively competitive, it is reasonable to treat the information sector as purchasing digital data storage devices, and providing information services, "for" consumers. In other words, because market-power distortions may be small in this sector, it is fair to think of competitive firms acting as "agents" for consumers. If the reality is otherwise, the result would understate consumer surplus.

The calculation thus produces a "cost of living and of making digital data storage devices" (COLAMDDSD). In our NMP calculations, we adopt an approximation to this cost index that avoids using the very large PCE in the denominator of the calculation. The annual space science budget is a miniscule part of the economy, and we were concerned the difference between the innovation and the defender technology would disappear into rounding error, and the index would calculate to unity. To avoid this, we developed a very close approximation to the cost index that avoids the PCE term.[24] We use this for the digital data storage technologies as well, the result being a "cost of providing information services and of making digital data storage devices" index. The dollar value of the surplus (or deficit), from applying this index to total information services expenditures, is very close to COLAMDDSD*PCE.

Dynamic Trends in Prices and Adoption of New Technology

The model's quality adjustments and parameter uncertainties take place in a dynamic setting. Information about the expected timing and planned characteristics of a new technology introduction have been provided by the technology's experts. However, we are also concerned with how parameter values are expected to change over the following several years. Past experience shows technology prices, for a given level of quality, can decline markedly. The further into the future a forecast is made, the more uncertainty there would have to be about all values, including the possibility of as yet unforeseen new technologies. We restrict ourselves, therefore, to forecasting out about five years.

We institute dynamic elements into the model by putting time trends on some of the parameter values in the model. For instance, we expect prices to decline over time, both from learning by doing and from continued R&D. These processes are assumed to occur for both the innovation and the DT. Although we assume prices should decline--from both causes--more quickly for the innovation than for the defender technology (the easier cost-saving opportunities will already have been exploited for the DT), we have required compelling evidence that they will do so in selecting actual price paths. Our default assumption is that prices decline at identical rates for both versions of a technology.

In the model, prices are expected to decline according to:

$$p_t = p_0 * (1-q)^t,$$

[24] To avoid rounding error in working with very small parts of the economy, we can approximate consumer surplus by using as the expenditure share the fraction of total downstream sector expenses devoted to the technology. Given the data for PCE and expenses in our downstream sectors--and given our quality adjustments and technology expenditures--this approximation is extremely good for the short term. Letting Ω_X stand for the right side of expression (2), the *correct* calculation is $(\exp(\Omega_{PCE})-1)$*PCE. Our approximation is Ω_{SECTOR}*SECTOR, which with our data errs by about 10^{-4}-10^{-2}%, outperforming the more natural $(\exp(\Omega_{SECTOR})-1)$*SECTOR. The accuracy of the approximation depends on the size of the downstream sector remaining relatively stable as a share of PCE, reasonable in our short time horizons.

where p_0 is the price in the initial forecast period, *t* is time in years, and q is a normal random variable with a mean value that depends on the technology.

We assume that adoption of the innovation in preference to the defender technology occurs as a monotonically increasing function of time. Specifically, we project that the innovation will be substituted for the DT according to a monotonic function taking values between 0 (no adoption) and 1 (complete market penetration), according to the following process:

$$l\ t^{g})$$

Here the adoption rate F(t) is the cumulative Weibull distribution function, an S-shaped function where time *t* is in years, λ is the scale parameter of the distribution, $0<\lambda<1$, and $\gamma>0$ is a shape parameter for the distribution. λ has the interpretation of a hazard rate,[25] the probability the innovation will be adopted in the next increment of time at *t*, given it has not yet been adopted. We intend making the rate of adoption, via the two Weibull parameters, a function of the quality-adjusted price difference between the two technologies, but have not yet implemented this in the model. Figures 3 and 4 depict two possible adoption rates. The flatter curve, Figure 3, depicting a more protracted period of adoption, is the more conservative assumption.

Uncertainty

Our approach to modeling uncertainties is based on Bayesian "subjective " probabilities. This approach rejects the notion that probability necessarily derives from frequencies that would be realized from an idealized "infinite sequence" of repeated outcomes. This "frequentist" paradigm is appropriate for making statements such as the odds of "heads" from an unbiased coin-flip is 50%. However, this formulation is not well suited to non-repeatable events, such as probable future costs or adoption rates. In our model, for example, uncertainty about prices stems more from what is not yet known about the technology than from randomness in the underlying conditions determining prices.[26]

Our model must combine the subjective beliefs of technology experts with our own beliefs about the likely biases of these experts. We have experimented with, and performed sensitivity analysis on, a number of ways of handling these disparate sources of uncertainty. Because no one method is *a priori* superior to any other, we have adopted the most conservative of what we judged to be "reasonable" treatments of the technology expectations data.

We do not take the engineering guesses or technology expectations a at face value. Instead, we assume that these persons, as closely associated with the technologies as they are, are over-optimistic. There is a small literature on expectations bias in "pioneering" technologies, on which we base this approach.[27]

---

[25] *f(adoption)/(1-F(adoption)),* where *f(•)* is a continuous probability density function (Weibull in our application), and *F(•)* is the associated cumulative distribution function

[26] This is a subtle but important distinction. Some of the uncertainty in expert opinion does arise from randomness in real manufacturing costs over time.

[27] See Quirk and Terasawa (1986).

Figure 3. Simulated Adoption Rate

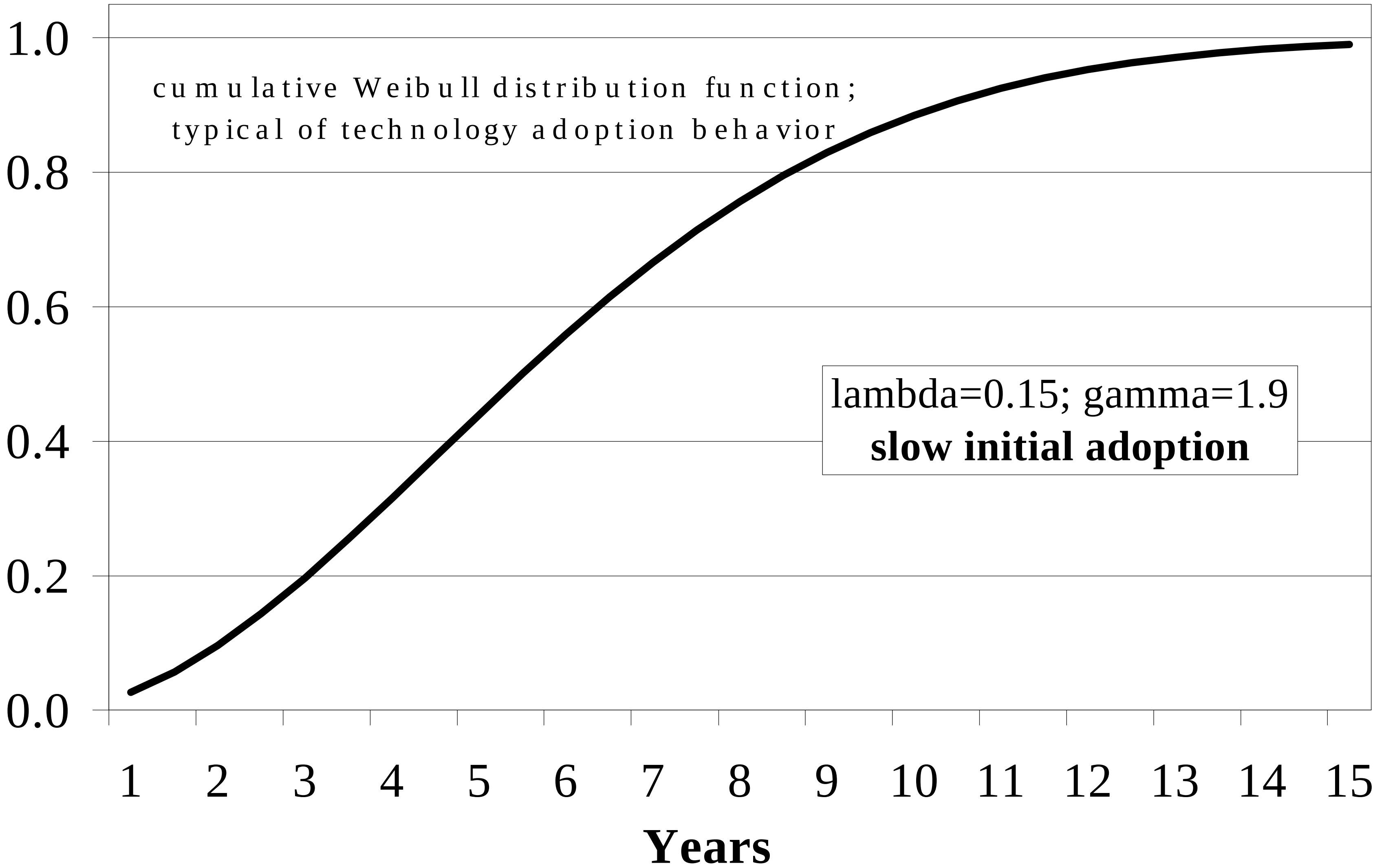
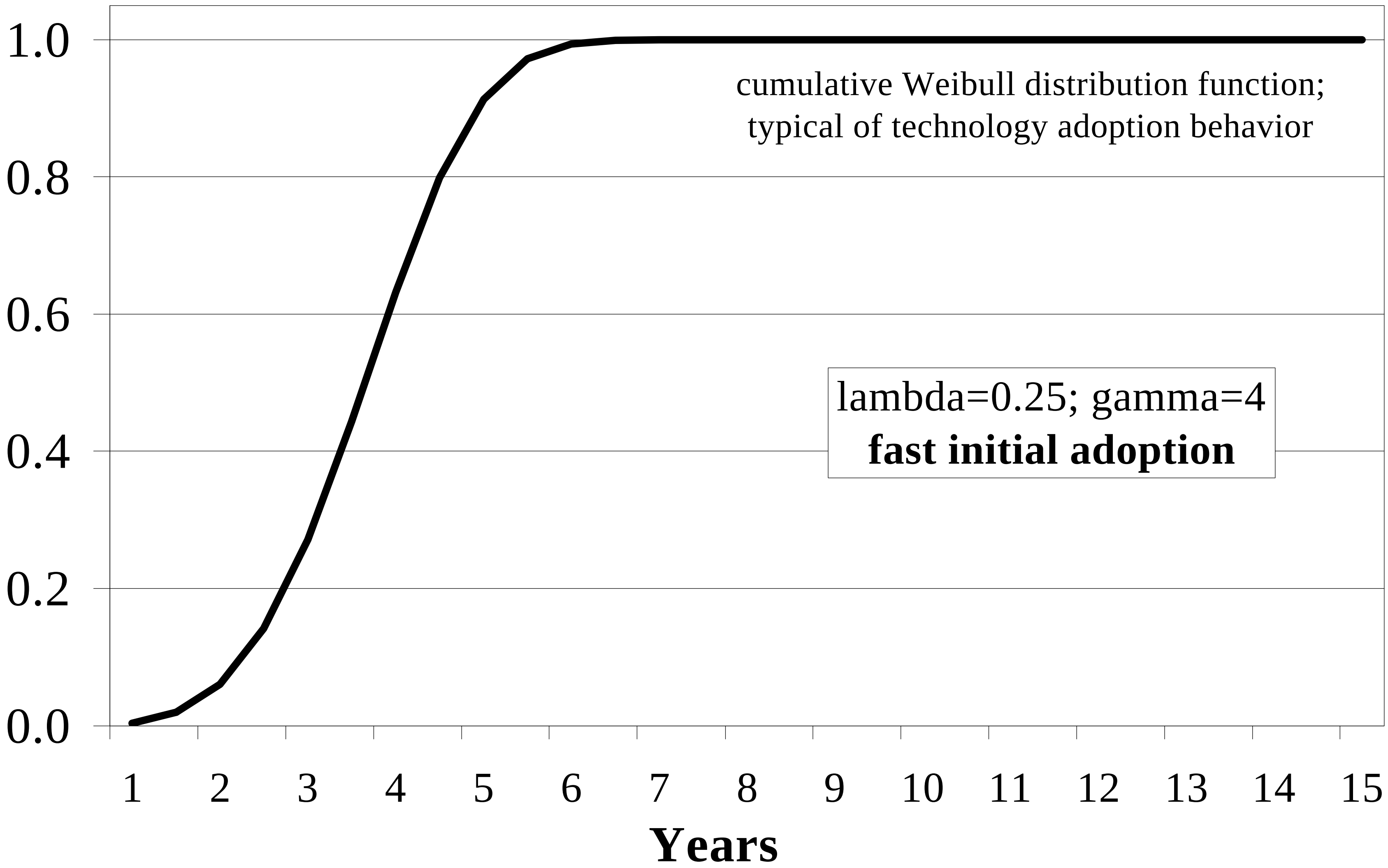


Figure 4. Simulated Adoption Rate



We solicited, from scientists and managers familiar with the technologies, opinions about the "most likely" cost outcomes, as well as about the full range ("worst case" and "best case," in the language of our survey instrument) of possible values, based on their perceptions of uncertainties and their experiences with past outcomes. To properly answer questions about uncertainties, the experts must have in mind their own personal subjective probability distribution from which their expectations are drawn. Our interview is structured to elicit this type of information.

We operationalize our assumption about optimism by embedding the expert expectations in a probability distribution that is skewed to the left. We assume that the actual costs will be distributed asymmetrically about their expected mean value, with a greater than 50% chance that costs will exceed expectations. We use the high-low ranges--usually one or two per technology--as expressions of the experts' uncertainty, with which we adjust their "most likely" values to account for "pioneer bias." For each technology, we assume that the *true* median cost is the expert's expressed median plus half of their range. To capture the non-negativity of the cost expectations, and our assumption of pioneer bias, we assume that true costs are distributed lognormally.[28]

Besides the location parameter, which we select using all of our survey information, the second parameter of the lognormal is a scale parameter, the geometric standard deviation. After some experimentation, we set this at 1.5 for all technologies. This value best reflects our desire to treat the expectations data conservatively.[29]

For the ATP analysis, there was less uncertainty over market price (used here instead of the off-the-shelf production costs we used in the non-marketed space case) than over the timing of the introduction and the performance of the innovation. Firms felt their technologies would fit into particular niches at certain fixed prices, and their uncertainties concerned what performance levels they would ultimately achieve in a reasonable time, and the length of time it would take for their technologies to be embodied in marketed products. The model is flexible and required no special changes to accommodate these differences.

Figure 5 contrasts this type of distribution function with the one we employ for experts' forecasts concerning the *defender* technology. For the DT, experience and direct observation inform the responses, so we assume actual costs will by symmetric about the expected level, and with less uncertainty than for the innovation. We assume the experts' subjective prior probability distributions for the DT are normally distributed.

---

[28] The production-cost literature offers little guidance on the form our prior probability density functions should take. We use the lognormal family to model "pioneer" project cost overruns because it is skewed in the desired direction, and because their family of curves has a simple parametric representation.

[29] This is obviously *ad hoc*. The geometric standard deviation (GSD) yields a degenerate distribution for GSD=1.0, and a symmetric distribution for slightly larger values. Values much greater than 1.5 yield unrealistically high cost expectations. We tried a less conservative method of placing expert expectations at the 30th percentile of a lognormal, and their "worst case" outcome at the 90th percentile. Among the distributions we examined, estimated net benefits are fairly insensitive to our actual choice.

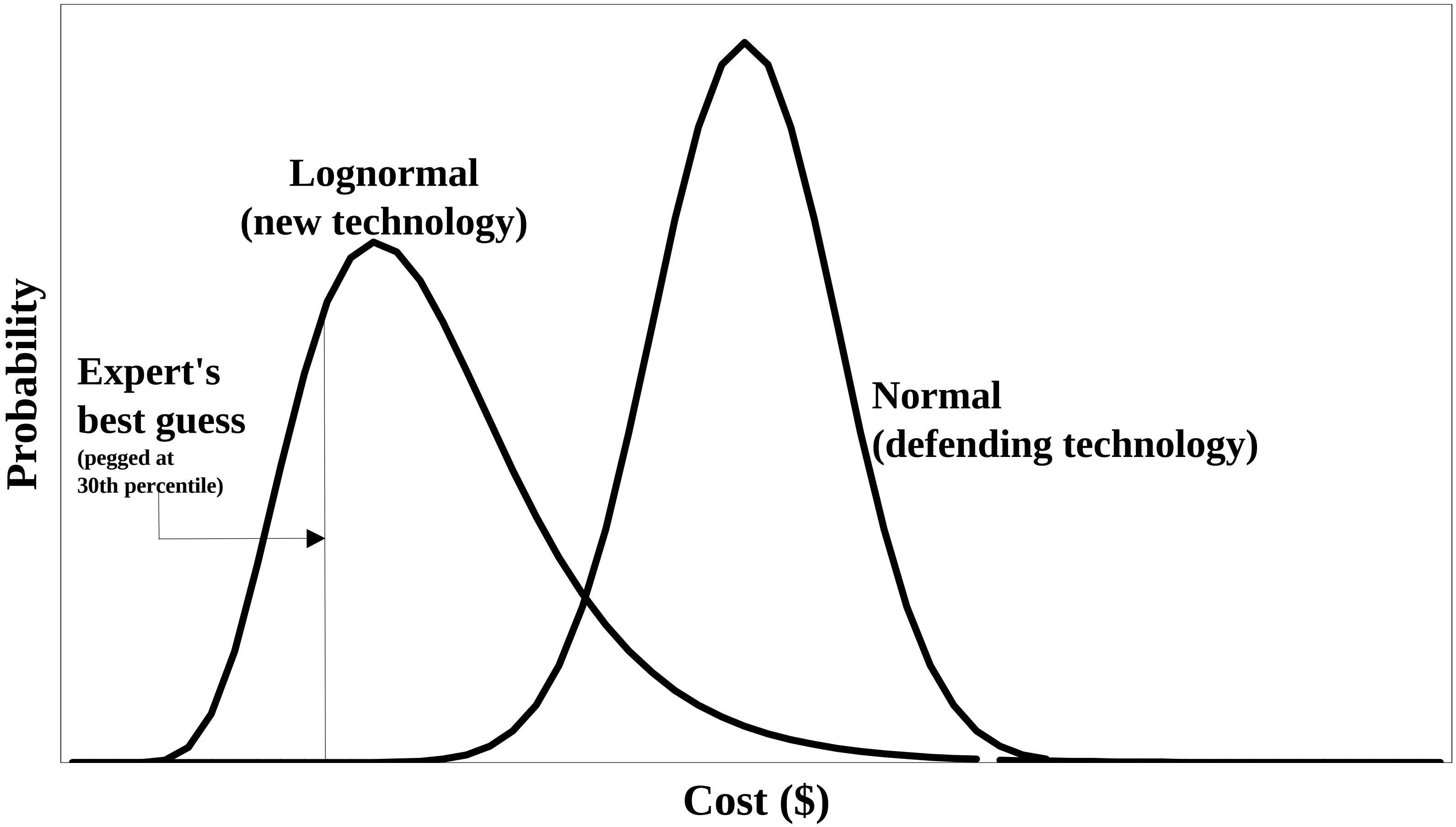


Figure 5. Illustration of Cost Under-Estimation

Figure 5 contrasts sample cost density functions for the DT and for the innovation. If the experts are less over-optimistic than we assume, so that the lognormal distribution is less skewed than we make it, we will underestimate consumer surplus. Given the prospective nature of our analysis, it is appropriate to make conservative assumptions so as to minimize concerns, if we find greatly increased consumer surplus from innovation, that the result was driven by best-case assumptions.

Quality Adjustment

Prices of the innovation technology and the defender may differ because of different quality characteristics of these technologies. To put expected prices of the DT and the innovation on a comparable footing, we account for these quality differences by estimating consumer willingness to pay on the margin, and adjusting the prices accordingly. For digital data storage devices, we control for quality differences in file access time, data transfer rate, and storage capacity. For the space study, we account for differences in the volume, power consumption, and mass of the new technologies. In both cases, these dimensions are not the only potential sources of quality change, but they are widely agreed to be the most important.

Consumers are generally willing to pay more for higher performance, but it is not immediately obvious how *much* more they are willing to pay. To estimate this, we perform a hedonic statistical analysis to explain the contribution to market price of each relevant quality characteristic. That is, for a collection of price and quality characteristics data on similar products, we regress market price against the characteristics, and other controls such as time. The coefficients of the independent variables (the characteristics), estimated by ordinary least squares, have the interpretation of shadow values, or consumer willingness to pay for incremental changes in quality in that dimension.

These shadow values are valid over small changes in quality. For more drastic improvements the marginal willingness to pay should decline, in accordance with standard economic utility theory. We address this by including non-linear terms in the hedonic regressions, but in some cases the projected innovation will probably go significantly beyond the range of our market data.[30] In this case we will make a conservative assumption about the appropriate value to use. In all cases we will incorporate the uncertainties in our estimates of shadow values into our model.

To illustrate our hedonic regressions for digital data storage devices take the form:

$$p^t = \alpha + \beta_1(\text{data rate}) + \beta_2(\text{access time}) + \beta_3(\text{capacity}) + \beta_4(t) + \text{squared terms} + \text{interactions} + \varepsilon$$

P is price, *t* is time in months from January, 1995, and α is an intercept term. The β coefficients are the OLS estimated shadow prices, which we use to quality-adjust the price of the innovation.

30 We have not completed our data collection as of this writing, so our hedonic results are preliminary.

All quality adjustments are done relative to the expected capabilities of the DT at any point in time, so it is not necessary to quality-adjust the price of the defender technology.

As we noted earlier in the paper, quality-adjusted prices W are given by:

$$W^{dt,t} = p^{dt,t}$$

$$W^{I,t} = p^{I,t} - b_1(\Delta dim1) - b_2(\Delta dim2) - b_3(\Delta dim3),$$

where for the space technologies dim1, dim2, dim3 are mass, power, and volume, and for digital data storage, they correspond to data transfer rate, file access time, and storage capacity.

The log of the ratio of these quality-adjusted prices is one of the two terms in the cost index for providing a service (data storage; space exploration) and making the technology. Where the new technologies represent a *substantial* gain over DT, beyond that observed in the data used in the hedonic regression, we subject our estimates to sensitivity analysis.

Finally, new technologies do not necessarily improve in all dimensions. Our model does not preclude a defender technology's having a smaller real unit price *W* than the real price W_I. Where the new technology is adopted it would, in this case, produce negative consumer surplus relative to that available for the DT. Presumably the market would reject the innovation in this case.

IV. RESULTS

Figure 6 illustrates schematically the relationships between the key model input steps described in this paper. Example outputs of the model are presented in Tables 1 and 2, and Figure 7.

Approximate uncertainties for these tables can be inferred from Figure 6

Table 1. "Cost-of-Performing-Space-Science-and-of-Producing-New-Technology" Index

Year	New technology #1	New technology #2
0	1	1
1	1.01335	1
2	1.01271	1
3	1.02638	0.99959
4	1.02674	0.99955
5	1.02709	0.99950

Table 2. Benefit of Using the NMP Technology, Relative to Defending Technology (U.S. dollars)

Year	New technology #1	New technology #2
0	0	0
1	27,040,000	0
2	27,400,000	0
3	58,550,000	-900,500
4	59,360,000	-1,002,000
5	60,140,000	-1,101,000

The tables contain example cost indices and dollar values of consumer surplus for a pair of generic innovations.[31] Technologies with index values greater than one will increase consumer surplus, while those with index numbers less than one would reduce consumer surplus if adopted. The dollar values for these contributions are given in Table 2.

We also estimate a "bottom line" in both studies. This is an estimate of total expected surplus over time. In the space study this is expressed as an "effective augmentation" of the public space science budget (since net cost savings on the space technologies can be used elsewhere in the space science program). Figure 7 shows how surplus grows over time. The shape of the curve depends on the rate of "market penetration" (or adoption, for space technologies), and on the budget for space missions requiring either the innovation or the DT. The figure also depicts uncertainty as growing over time, a natural result of the model's parameters.

V. SUMMARY

Our model provides a sound empirical basis for assessing returns to investment in new technologies. By taking explicit account of alternative technologies and the fact that innovation proceeds apace in *their* development--not just in the new technologies--and by accounting for uncertainties in the timing and quality of innovation, we derive defensible estimates of expected consumer surplus.

Our approach also represents a first formalization of the tendency towards cost-estimation bias in new technologies. We think the explicit treatment of uncertainty and the modeling of defender technologies, together with cost-estimation bias accounting, render our model a useful tool for government agencies that support private R&D, as well as for private firms to use in assessing their internal funding of new technologies.

---

[31] Careful readers may have noted that one must actually exponentiate expression (2) to get cost indices such as given in Tables 1 and 2. The index described in the text produces "percent change in surplus", which take values close to zero. Virtually the same result can be achieved by first exponentiating the index and subtracting 1. This is the correct calculation, and is what we actually do. We avoided this discussion earlier in the paper for expository reasons.

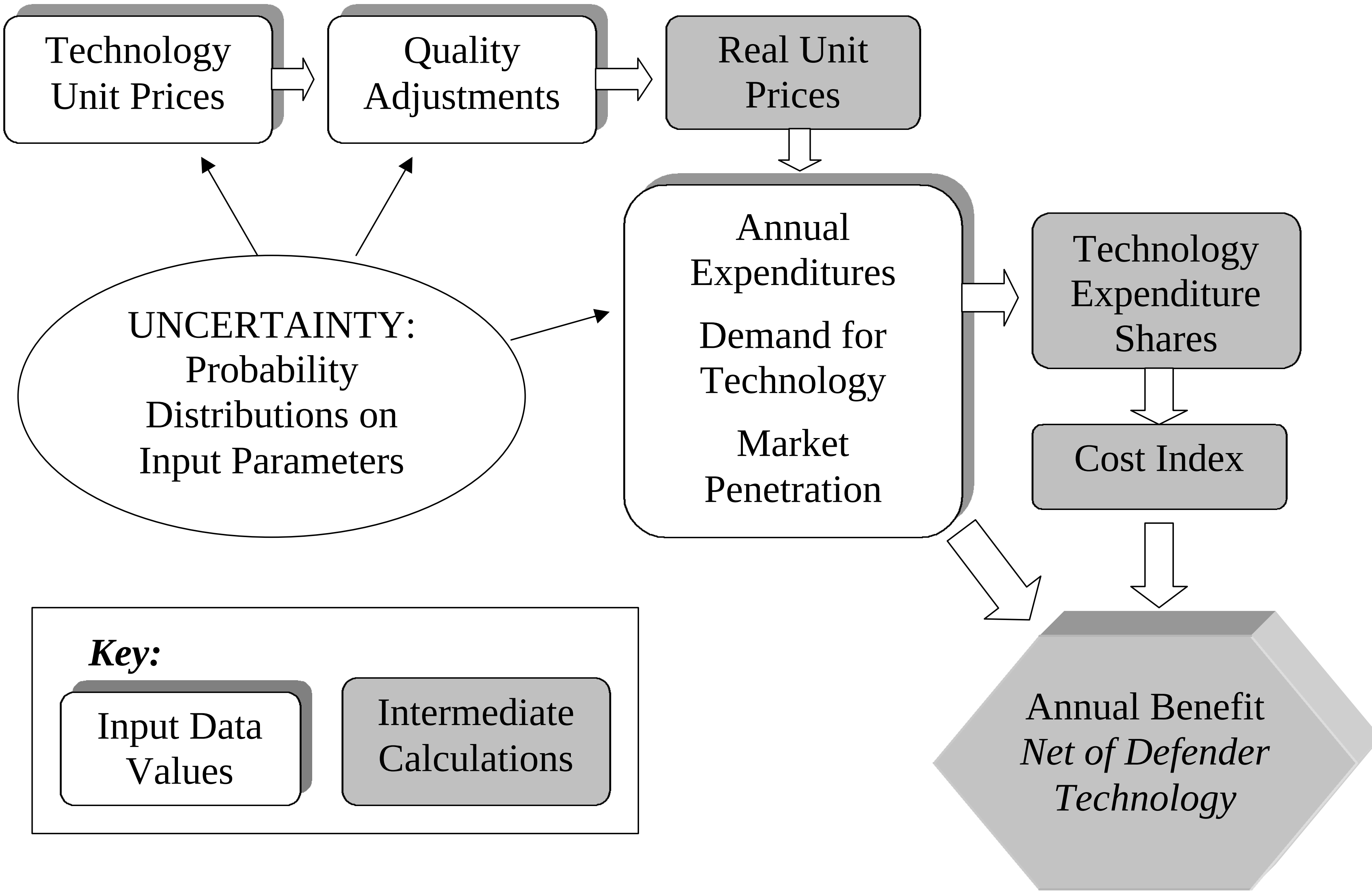
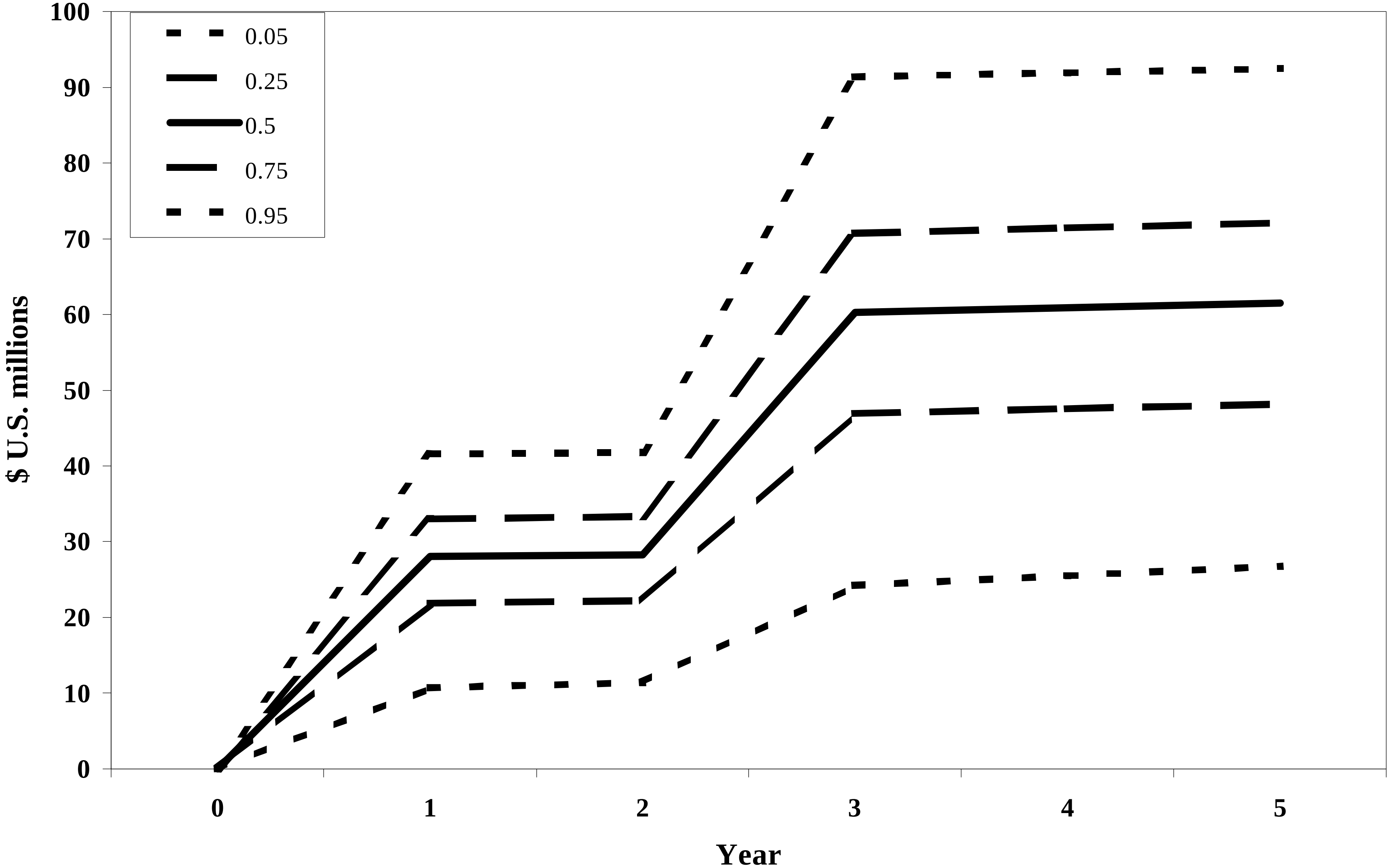


Figure 6: Model Inputs, Intermediate Calculations, and Outputs

Figure 7. Net Benefit of New Space Technology



We envision several extensions of our model in future research. It can be applied to private sector investments in new technologies, where estimation and valuation of quality improvements can be helpful in predicting the likelihood of a new technology's succeeding in the marketplace. The model can also be adapted to the estimation of *private* returns. With some modification, the model can be used to identify the investment rate and technology selections most likely to yield the highest returns among alternatives. In other words, the model can help designate investment portfolio strategies. Such an extension of the model would include the "drawing board" phase of the innovation process, where agencies and private firms consider optimal investment strategies given competing opportunities for use of the R&D capital.

Another extension we are planning is to consider technologies that generate externalities, such as ones that confer marginal social benefits on top of private benefits (for instance, "environmentally friendly" technologies). For this application, we would include shadow values of social benefits among a technology's "quality" adjustments.

VI. APPENDIX

Following Caves, *et al.* (1982), we assume consumer expenditure functions $E^*(u,p^{dt},W^{dt})$, which give the minimum expenditure necessary to achieve a given level of utility u given prices p^{dt} and quality-adjusted innovation price W^{dt}, can be represented by a translog functional form. Generically, and with prices (p^{dt}, W^{dt}) represented by w, and with utility (and individuals' characteristics) given by y, the translog is given by

$$\ln E^*(y,w) \equiv \alpha_0 + \sum_{n=1}^{N} \beta_n \ln w_n + \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N} \beta_{nm} \ln w_n \ln w_m + \sum_{i=1}^{I} \alpha_i y_i + \frac{1}{2}\sum_{i=1}^{I}\sum_{j=1}^{I} \alpha_{ij} \ln y_i \ln y_j + \sum_{i=1}^{I}\sum_{n=1}^{N} \gamma_{in}^{2} \ln y_i \ln w_n$$

where consumption goods are indexed by $n,m=1,\ldots,N$ and individuals by $i,j=1,\ldots,I$. Here $\beta_{nm}=\beta_{mn}$ for all n, m, and $\alpha_{ij}=\alpha_{ji}$ for all i,j.

Caves, *et al.,* show that, as long as innovation does not affect the second-order commodity terms β_{nm}, (*i.e.,* $\beta_{nm}^{dt} = \beta_{nm}^{I}$) or the second-order consumer taste coefficients α_{ij} (so that demand for any inputs, or tastes for any outputs, are permitted to change, but the elasticities of substitution are not), then the geometric mean of the two cost indexes, given in the text by equation (2), simplifies according to:

$$\tfrac{1}{2} \ln\left(C^{*dt} \times C^{*I}\right) = \frac{1}{2}\left(\sum_{n=1}^{N-1}(r_{n,dt} + r_{n,I})\ln\left(\frac{p_{n,dt}}{p_{n,I}}\right) + (s_{dt} + s_I)\cdot \ln\left(\frac{W_{dt}}{W_I}\right)\right).$$

Here there are N commodities in the economy; the N^th^ is the innovated technology, on which a fraction s_{dt} (s_I) of total expenditures are made, s_{dt} in the hypothetical "defender-technology" (no innovation) case or s_I in the expected innovation case. Aside from the innovated technology, individuals may also consume N-1 other goods, a set which is identical in either the DT or the innovation case. Expenditure shares on the other N-1 consumption goods are given by $r_{n,dt}$ ($r_{n,I}$) and prices by $p_{n,dt}$ ($p_{n,I}$). Only the price of the innovated technology is affected by the innovation, as a result of a change in quality. Thus $p_{n,dt}=p_{n,I}$ and $\ln(p_{n,dt}/p_{n,I})=0$ and this expression simplifies to expression (2) given in the text.[32]

---

[32] Bresnahan (1986, p. 747) divides the economy into an "advancing sector", a "downstream sector" and "other" goods. His treatment of this material allows K "other" goods, for which, in our notation, $p_{k,dt}=p_{k,I}$, as here. However, in his notation he makes a distinction we do not, between N1 innovated technologies in the upstream, advancing sector--for which quality-adjusted prices decline--and the remaining (N-N1) outputs of the downstream sector, for which they do not. The result is the same--quality-adjusted downstream prices are unchanged ($W_{d,dt}=W_{d,I}$, taking *"d"* for downstream) and drop out of the equation, and only the advancing sector appears in the Bresnahan equivalent of our (2), as here.

VII. REFERENCES

Berndt, Ernst R. 1991. *The Practice of Econometrics: Classic and Contemporary,* (Reading, Mass.: Addison-Wesley Publishing Company).

Bresnahan, Tim. 1986. "Measuring the Spillovers from Technical Advance: Mainframe Computers in Financial Services," *American Economic Review* vol. 76, no. 4 (September), pp. 742-755.

Caves, Douglas W., Laurits R. Christensen, and W. Erwin Diewert. 1982. "The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity," *Econometrica*, vol. 50, no. 6 (November), pp. 1393-1414.

Chambers, Robert G. 1988. *Applied Production Analysis: The Dual Approach* (Cambridge, UK: Cambridge University Press).

Diewert, W. Erwin and Alice O. Nakamura, eds. 1993. *Essays in Index Number Theory,* Volume 1 (Amsterdam: North-Holland).

Gordon, Robert J. 1990. *The Measurement of Durable Goods Prices* (Chicago: University of Chicago Press).

Griliches, Zvi. 1979. "Issues in Assessing the Contribution of R&D to Productivity Growth," *Bell Journal of Economics* vol. 10 (Spring), pp. 92-116.

Hausman, Jerry. 1997. "Cellular Telephone, New Products and the CPI," NBER Working Paper 5982, National Bureau of Economic Research, Cambridge, Mass., March.

Quirk, James and Katsuaki Terasawa. 1982. "Divergent Expectations and R&D Expenditures," in James Quirk, Katsuaki Terasawa, and David Whipple, eds., *Coal Models and Their Use in Government Planning* (New York: Praeger).

Quirk, James and Katsuaki Terasawa. 1986. "Sample Selection and Cost Underestimation Bias in Pioneer Projects," *Land Economics*, vol. 62, no. 2 (May), pp. 192-200.

Sarsfield, Liam. 1998. "The Cosmos on a Shoestring," RAND Critical Technologies Institute, Washington, D.C.

Terasawa, Katsuaki, James Quirk, and Keith Womer. 1989. "Turbulence, Cost Escalation and Capital Intensity Bias in Defense Contracting," in Institute of Cost Analysis, National Conference, *Cost Analysis Applications of Economics and Operations Research* (Springer-Verlag).

Trajtenberg, Manuel. 1990. *Economic Analysis of Product Innovation: The Case of CT Scanners* (Cambridge, Mass.: Harvard University Press).

Wertz, James R. and Wiley J. Larson, eds. 1996. "Reducing Space Mission Cost," (Torrance, Calif.: Microcosm Press).

Varian, Hal R. 1992. *Microeconomic Analysis* (New York, N.Y.: W.W. Norton & Company).