# Estimating Future Consumer Welfare Gains from Innovation: The Case of Digital Data Storage

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Discussion Paper 00-13

March 2000

RESOURCES
for the future

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## ABSTRACT

We develop a quality-adjusted cost index to estimate expected returns to investments in new technologies. The index addresses the problem of measuring social benefits from innovations in service sector inputs, where real output is not directly observable. We forecast welfare gains from two U.S. Advanced Technology Program innovations equaling 25%-50% of expected price, and aggregate consumer benefits of $1-$2 billion, relative to trends in existing technologies. Our model's probabilistic parameters reflect uncertainty about prospective outcomes and in our hedonic estimates of shadow values for selected product attributes. The index can be readily adopted by research and development (R&D) managers in industry and government.

*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 earlier versions of 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. Finally, we are grateful to Kent Rochford and Ron Goldfarb of NIST's Boulder, Colorado facility for providing detailed comments on our parameter assumptions. Don Crocker, Nancy Bergeron, and Ron Lile provided excellent research assistance. Responsibility for errors and opinions rests with the authors

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David Austin and Molly Macauley*

## INTRODUCTION

Measuring or forecasting consumer benefits is an important part of any research and development (R&D) program. In many cases, however, and particularly with high technology, the innovations are intermediate inputs in the provision of services. Final consumer demand for services, and thus derived demand for the innovation, depends on service quality, which is not readily observable and is difficult to measure quantitatively. This complicates efforts to estimate consumer welfare gains from the innovation.

Bresnahan (1986) solves this problem by developing a cost-of-living index that, under certain general assumptions, eliminates unobservable quantities from the welfare expression. The index compares the observed price and performance of an innovated product against a hypothetical, best-available price and performance had the technical advance not occurred. Since the prices of other goods and services in consumers' choice sets cancel out, the index is a function only of observed and hypothetical technology prices—adjusted for quality differences—and expenditures as a share of total personal consumption expenditures.

Our approach extends Bresnahan's methodology in two directions to make it useable for the important case of the R&D investment decision. Bresnahan retrospectively estimates consumer welfare gains from innovation. Our first extension is to adapt the cost index to a *prospective* setting. This permits the evaluation of expected consumer welfare gains from proposed R&D projects.[1] We allow for the gradual diffusion of the new technology, and we express the model's parameters as probability density functions to reflect uncertainties over future or estimated parameter values. A second extension is to use a hedonic analysis to adjust

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[1] This kind of analysis would satisfy, for a federal program, the 1993 Government Performance and Results Act.

for consumers' preferences for differentiated product characteristics—which produce benefits that may not be fully reflected in product prices.

The result is a theoretically grounded economic model of future consumer demand for a product, embedded within a cost-index simulation model with quality-adjusted prices and dynamically changing product characteristics. The model produces empirical probability density estimates of consumers' welfare gains from the introduction of a new technology and thus provides a rigorous, transparent approach to forecasting future benefits. The cost-index model can be used to assemble R&D portfolios from a selection of disparate, competing projects. Thus it has potential utility to both allocation of private-sector R&D resources and government R&D procurement.

We illustrate the model by estimating expected consumer welfare gains from a pair of private-sector innovations in digital data storage (DDS) that have received public support in the form of R&D grants from the federal Advanced Technology Program (ATP). These new technologies are expected to offer faster writing and retrieval of digital data, and one would offer a large increase in storage capacity as well. One innovation would pioneer the use of optical tape, and the other would replace helical with linear scanning of magnetic tape. Both technologies promise superior price/performance characteristics compared with existing tape drives. We estimate how much better off consumers will be than if either new technology is not introduced.[2]

Our analysis shows that these first generation technologies, if successfully introduced, should generate five-year discounted consumer welfare gains of approximately $2.2 billion (linear scanning) and $1.5 billion (optical tape), relative to the best existing technologies, even assuming they improve at faster than historical rates. These estimates are medians of probability distributions; corresponding 5$^{th}$-percentile estimates are $1.3B and $1.1B. On a per-unit basis, these values represent in excess of $2,400 in surplus value for each linear

[2] A long-standing rationale for public subsidies to support private research and development depends on the expectations that private returns from the innovation will be difficult to appropriate and that consumer benefits will be sufficiently large. The rationale also depends on a convincing demonstration of a market failure. We do not address these issues in this paper.

scanning device sold, and more than $20,800 per optical tape unit. With expected unit prices of $10,000 and $40,000, respectively, per-unit welfare gains would be considerable.[3]

We parameterize our model with information on expected new product characteristics, as provided by the innovators and others familiar with these technologies. The information includes expectations about likely ranges of price, performance, and rate of adoption. We estimate consumer shadow values for different product characteristics using recent data on prices and attributes (e.g., faster file access times) of digital tape data-storage devices. Given our data sources, we adopt conservative parameter assumptions with respect to the performance and price of the innovations, their rates of adoption, and the size of the market. We also base our qualitative conclusions on the model's 5$^{th}$ percentile forecasts. We are conservative to balance out any tendency for the innovators to be overly optimistic.

The cost index is defined relative to an aggressive baseline scenario where we assume that the best available performance, though in most dimensions lagging that of the would-be innovations, improves at the same rate after their introduction. We adjust nominal prices for anticipated quality differences in three key performance attributes of data-storage devices: capacity, data transfer rate, and file access time. The adjustments reflect our estimates of consumer valuations for these attributes, based on hedonic analysis of the retail prices of recent tape data-storage products. The index indicates the relative amount consumers would be willing to pay for the innovations in a counterfactual, no-ATP-investment world. Applied to total expenditures on DDS devices, the index estimates consumer welfare gains—net of purchase price but gross of the R&D subsidy—from the introduction of the new tape drives.

The model's estimates are surprisingly precise considering its many degrees of freedom and the dynamically increasing uncertainties of its parameters. Sensitivity analyses, in which we shift parameter locations, further demonstrate the robustness of the basic conclusions. Where greater precision is desirable, model simulations can reveal the most important sources of uncertainty in the final benefit estimates, suggesting where additional research on the true values of individual parameters might be most cost-effective.

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3 Two caveats in applying this approach to ATP investments are that (1) our findings are not an assessment of the ATP's entire portfolio of DDS investments, as several projects failed; and (2) we do not estimate future consumer benefits that may arise from knowledge spillovers to other innovators.

## 1. A COST-INDEX APPROACH TO WELFARE ESTIMATION

Bresnahan (1986) shows that a Törnqvist cost index (Caves, *et al.*(1982)), can be used to measure consumer surplus from innovation. Measuring the gain is straightforward if the demand curve can be econometrically estimated; however, this is difficult to do in service sectors, where real output is not readily observed (yet where much of the demand for high technology is located).[4] These considerations make the cost index approach attractive, because it does not require estimating a demand curve. To paraphrase Bresnahan, the method substitutes economic theory for (unobservable) data.

The validity of the cost index estimates depends on the assumption that the downstream (technology-buying) market is competitive. Demand for DDS arises largely from firms using it as an input to the production of services that require the storage of large amounts of data (e.g., the insurance, banking, and retail sectors; increasingly, local-area-networks at business facilities across the economic spectrum also rely on tape-based DDS for redundant storage). If these downstream markets are competitive, derived demand for DDS accurately reflects consumer demand, and the cost index will correctly estimate the welfare gain.[5] Although we do not believe downstream market power is a significant issue in our analysis, ignoring it is consistent with the conservative treatment we also accord the performance and price data.

Figure 1 illustrates the expected gain in consumer surplus from an outward shift in the supply curve (as from innovation). Period 0 supply $S_0^{DT}$ is the pre-innovation baseline, where only a *defender technology* (DT) is available. The ATP-sponsored innovation occurs at period 1, shifting the supply curve out to $S_1^{ATP}$ (see figure 1, graph on right) due to a combination of cost reductions and quality improvements. Continuous improvement in the defender technology means the baseline supply curve has shifted out to $S_1^{DT}$. The shaded area

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4 Government statistics treat inputs to production as proxies for real outputs in these sectors. Bresnahan (1986) and Griliches (1979) both point out that it is in service sectors that the benefits from technological advances (e.g., in computers and related equipment) tend to accrue.

represents the consumer welfare gain at a point in time, due to the innovation. It is measured with respect to the hypothetical, future $S_1^{DT}$ curve rather than the observed $S_0^{DT}$. As long as $S_1^{ATP}$ lies to the right of $S_1^{DT}$, the innovation offers an improvement over the defender technology. In this case the cost index is greater than unity, meaning costs are higher under the baseline scenario and consumers will be better off (gross of R&D costs) if the innovation occurs.

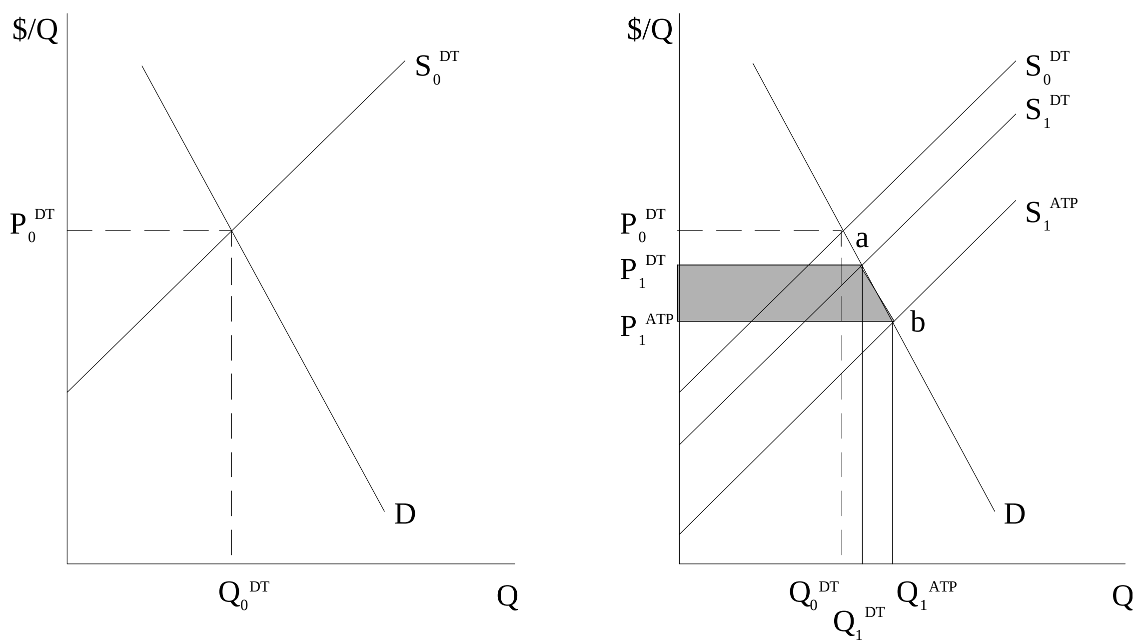


**Figure 1. Derived Demand for New Technologies: Illustration of Net Surplus Change**

[5] Following Bresnahan, no assumptions are needed concerning the structure of the DDS-producing market. If there is market power—or if the DDS innovations create market power—the gain in consumer welfare will be less than if the upstream market is competitive, and the cost index will be a lower bound on these gains.

## 2. MODEL

As Bresnahan points out, assuming the DDS-using markets are competitive allows us to treat the cost index as an index of consumers' cost of living and of producing DDS-using services.[6] The index is an estimate of the change in the cost of living (and of producing those services) under the innovation scenario, relative to the baseline. In our application, the index is a function of consumer demand for DDS over time, the market's rate of adoption of the innovation, and consumer preferences for improvements in DDS performance. Adjustments to the off-the-shelf prices of the devices reflect these preferences.

### Quality Adjustments

These adjustments to nominal unit prices reflect consumer tastes for faster data transfer rates, larger capacities, and faster file access times. We adjust prices in the following manner. Let $\dim_x(y)$ represent technology *y*'s performance on product dimension *x*, *y* Î *{defender technology (DT), Innovation (I)}*, and $\Delta\dim_x$ represent the difference in performance between innovation and defender, i.e.,

$$\Delta \dim_x \equiv \dim_x(I) - \dim_x(DT),$$

where *x* Î *{Capacity (CAP), Transfer Rate (TR), File Access Time (FAT)}*. We estimate shadow values $b_x$ in a hedonic regression,[7] adding $\left(b_x \cdot (\Delta \dim_x)\right)$ to the price of the technology that is inferior in dimension *x*. We assume that consumers prefer higher capacities and transfer rates and lower file access times. With $W^y$ standing for the quality-adjusted price of technology y, $p^y$ its expected—and bracketed terms being indicator variables—off-the-shelf (nominal) price, our quality adjustments to the defender *DT* and the innovation *I* are:[8]

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[6] Competition in these markets leads to the same level of services production—and demand for DDS—as if consumers were producing those services themselves, as without market power, production is at consumers' optimal level. Whence an index of consumers' cost of living and of producing DDS-using services.

[7] See appendix for a description of the hedonic data and analysis.

[8] See, for instance, Berndt, *et al.* (1995). A discussion of quality-adjustment methods employed by the Bureau of Labor Statistics in their construction of the consumer price index (CPI) can be found in Moulton & Moses, 1997. See in particular p. 332 under "direct quality adjustment," where the method we employ here is described.

$$W^{dt} = p^{dt} + b_{CAP}(\Delta CAP)\cdot[\Delta CAP > 0] + b_{TR}(\Delta TR)\cdot[\Delta TR > 0] - b_{FAT}(\Delta FAT)\cdot[\Delta FAT < 0]$$

$$W^{I} = p^{I} + b_{CAP}(\Delta CAP)\cdot[\Delta CAP < 0] + b_{TR}(\Delta TR)\cdot[\Delta TR < 0] - b_{FAT}(\Delta FAT)\cdot[\Delta FAT > 0].$$

We assume shadow values decline over time,[9] reflecting consumers' declining marginal utilities: an extra gigabyte of storage capacity is more valuable to consumers the greater a fraction of their total capacity it represents. Therefore the value of a given increase in capacity (or other attribute) will decline over time if performance improves over time.

In our application, it is almost always the defender technologies whose prices we adjust. Their (usually) lower capacities and transfer rates, and longer file access times, impose real user costs relative to the innovations. The price adjustments equal consumers' willingness to pay to achieve the superior performance of the innovations relative to the given baseline.

## Cost Index Formula

We construct a Törnqvist cost index to measure the change in the cost of services due to DDS innovations. The index is the geometric mean of a Laspeyres index—measuring consumer willingness to accept compensation to give up the gains from the innovation—and a Paasche index, measuring their willingness to pay to *receive* gains from innovation. Both are measured relative to the baseline, and neither is theoretically superior to the other. The Törnqvist index is an equally weighted average of the two.[10]

Following Caves et al., we assume that digital data-storage devices are separable from other consumption in the consumer's utility function,[11] so that the quality-adjusted prices $W$ in consumers' expenditure functions can be distinguished from the general prices $P$ of other goods and services. $C^{*dt}$ in expression (1) is then the minimum cost of achieving utility $u^{dt}$, which is optimal in the baseline scenario, relative to the cost of $u^{dt}$ given the ATP innovation.

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[9] Time subscripts have been suppressed in this expression.

[10] See Varian (1992) for details. 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).

[11] Marginal rates of substitution are unchanged at different levels of DDS consumption.

Similarly, $C^{*I}$ is the cost of achieving optimal utility $u^I$ under the innovation scenario with baseline prices $W^{dt}$ relative to the cost with post-innovation prices $W^A$:

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

Because we assume an innovation is adopted gradually, the quality-adjusted DDS prices faced by post-innovation consumers is not $W^I$, the price of the new technology. Instead, on average they pay $W^A = rW^I + (1-r)W^{dt}$, where $r$ is the adoption rate of the innovation.[12] Prices $P$ of other commodities can change over time, but we assume that they are unaffected by innovation in DDS: $P^{dt}=P^I$ at all times.

Figure 2 depicts the relationship between expenditure functions, utility, and the two Könus cost indexes. A welfare-enhancing innovation lowers consumers' costs of achieving a given level of utility, shifting the expenditure function downward from $E^*(u,W^{dt})$ to $E^*(u,W^A)$. The vertical distance between the two curves depends on DDS's share of total consumption expenditures; their ratio is given by the curve $C^*$. Given a welfare-enhancing innovation $I$, the consumer's optimal utility rises to $u^{*I} > u^{*dt}$. With separable utility and other prices unaffected, increased utility implies greater consumption of, in our application, DDS. That, in turn, means that the relative cost to achieve $u^{*I}$ with higher baseline prices $W^{dt}$ *versus* reduced, post-innovation prices $W^A$ exceeds the relative cost to achieve $u^{*dt}$. Here the Paasche willingness-to-pay index $C^{*I}$ exceeds the Laspayres willingness-to-accept measure $C^{*dt}$, which fixes DDS consumption at a lower level.

12 We suppress time subscripts in this formulation. Here our approach departs from Bresnahan (1986), where the innovation's market share is 100% (general-purpose computers constituting a new product category).

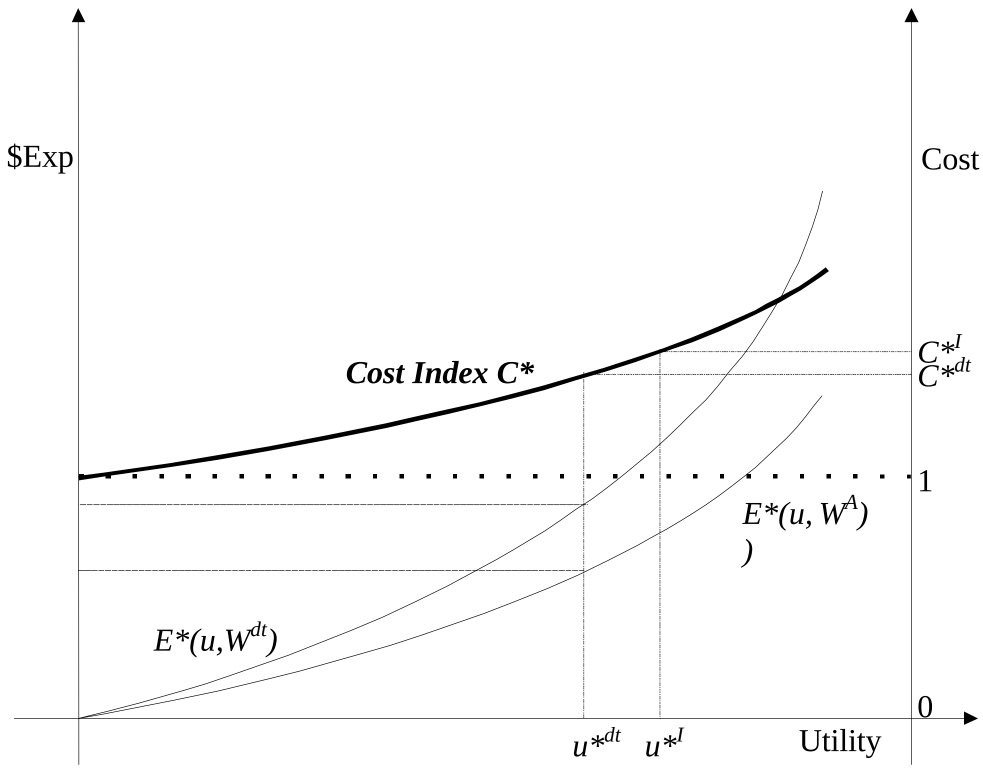


**Figure 2. Relationship between Expenditures, Cost Index** [13]

We assume, following Caves, et al. (1982), that the consumer expenditure function $E^*$ can be represented by a translog functional form. Thus, the Törnqvist index reduces to[14]:

$$\tfrac{1}{2}\ln\left(C^{*dt} \times C^{*I}\right) = \left(\tfrac{1}{2}(s^{dt} + s^{I}) \cdot \ln\left(\frac{W^{dt}}{W^{A}}\right)\right). \qquad (2)$$

The terms $s^{dt}$ and $s^{I}$ give, respectively, DDS expenditures as a share of personal consumption expenditures (PCE) under the baseline and innovation scenarios.[15] We forecast values for cost

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13 To simplify figure labeling, prices *P* have been omitted from the expenditure functions.

14 See Caves, et al. (1982) for derivation. The translog, a flexible functional form, well approximates many production and expenditure functions.

15 See appendix for description of terms in numerator of expenditure-share parameter. PCE data are from "Personal Income and Outlays," Bureau of Economic Analysis. We assume the additional DDS expenditures in

index (2) out to 2005, predicting PCE and DDS expenditures on the basis of past data, and making assumptions about the rate at which DDS prices will change over time. The monetary value to consumers of the innovation is just the product of their predicted PCE times the exponent of the cost index.[16] This corresponds to the area of the shaded rectangle in figure 1.

Unlike the familiar Consumer Price Index, expression (2) compares prices in a *single* period—expected, future prices given the innovation subsidy *versus* hypothetical future prices that might otherwise have occurred had there been no subsidy. Because prices and expenditure shares of non-DDS consumption, and prices of other inputs in the adopting sectors, are assumed to be unchanged by innovation in DDS, separability assures that these parameters cancel in expression (2).

Changes in relative DDS prices will affect the mix of inputs used in production. However, it is not necessary to make any assumptions about input substitutions because the translog places no restrictions on the elasticities of technical substitution between inputs.[17] The translog also does not restrict the income and price elasticities of demand for DDS-using services. While DDS innovation may affect equilibrium prices for these services, implying movement along their respective demand curves, translog expenditure functions even permit arbitrary shifts in those demand curves—say, due to innovation in complements to those services. As long as consumers' elasticities of substitution among all goods and services are unaffected by DDS innovation—and this is an implication of the separable utility assumption—the translog can accommodate taste-driven changes in demand for DDS, as for computer technologies generally.[18]

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the innovation scenario do not affect PCE (as DDS is a tiny fraction of PCE, there would be very little displaced consumption).

[16] Expression (2) actually is the percentage change in consumer surplus from DDS innovation, and takes values near zero because DDS is a very small portion of the cost of living. To calculate a cost index, (2) must be exponentiated. An *information-processing equipment* cost index can also be calculated, using DDS expenditures as a share of information processing and related equipment expenditures (National Income Product Account tables, U.S. Bureau of Economic Analysis).

[17] We introduced expenditure functions with respect to consumers. It is appropriate (and necessary) to extend the discussion to production of information services, because our assumption of a competitive market structure implies that producer profit maximization coincides with consumer expenditure minimization.

[18] These features of translogs are noted in Bresnahan (1986), p. 751.

The assumption on consumers' elasticities of substitution is really a restriction on changes in consumers' tastes for DDS-using services relative to other consumption. Because our forecasting window is relatively short, this assumption is not overly restrictive. If demand elasticities will be affected by DDS innovation, our forecasts for the later years should be discounted more heavily.

## 3. DATA AND ESTIMATION OF SHADOW VALUES

The cost index is a function of estimated total DDS expenditures as a fraction of total personal consumption expenditures (PCE); off-the-shelf DDS prices; differences in the technical attributes of the defender technologies and the innovations; marginal consumer valuations of those differences; quality-adjusted prices reflecting those valuations; and market conditions of DDS demand and adoption of the innovation. The index also incorporates expectations about the values of all of these inputs over the relevant time horizon, including forecasts of PCE.

The cost index itself is simply the ratio of quality-adjusted DDS prices, weighted by the shares of PCE devoted to DDS in the baseline and innovation scenarios. The price ratio indicates relative "real" prices of the competing technologies, while the expenditure shares adjust for levels of demand. A superior new DDS technology might generate a large quality-adjusted price ratio, but since DDS expenditures are small relative to PCE, consumers' cost of living will not be much affected. Per-unit benefits are large, however.

The index is calculated in a simulation model's containing 18 parameters, all but two of which are drawn from probability distributions. We directly observe current prices and performance of the defender technologies, but must forecast even their initial values because the innovations, as of late 1999, had not yet been introduced.[19] The model's price and performance forecasts for the new products reflect the innovators' targets, at introduction and two to five years ahead. We assume these forecasts reflect some "pioneer project bias"—a tendency for innovators to be overoptimistic about their projects.[20] We make allowances for this by putting extra weight on "disappointing" outcomes. The affected parameters are expected growth in market size, adoption rates, prices, and performance of the innovations.

Lognormal density functions have long upper tails and can model this pioneer bias. Since we have only one or two data points per product, however—from interviews with the

[19] The model's initial period is keyed to the introduction of a new product.

innovators—there is no empirical basis for choosing one family of curves over another. We therefore use triangular functions to model these asymmetries: they are easy to work with because their tails can be read directly from the specifications of the curves.

In contrast to this conservative treatment of the innovations, we use symmetric functions to model the distributions of parameters for the existing products. We make our forecasts of these parameters on the basis of recent trends in leading DDS devices. We assume, conservatively, that prices of the existing products will decline—and their performances improve—at the same rate as for the innovations.[21]

The only parameters for which we have distributional data are the consumer shadow values. We estimate the shadow values by hedonic regression analysis of recent retail prices and performance characteristics. These regressions also produce estimated standard errors, which we insert into the initial-period probability distributions. For the remaining parameters, we must use ad hoc rules of thumb for the uncertainties. In each period we assume standard deviations ranging from 5% to 30% of the means, or modes in the case of the triangular distributions. We assume less uncertainty for the existing-product parameters than for innovations, even in later years. We reserve the 30% standard deviations for the upper tails of the asymmetric distributions of the innovations.

The randomness in the model's parameters has three primary sources: variability in manufacturing and market conditions, imperfectly observed data, and, most significantly, uncertainty about future outcomes. As with all of the model's parameters, we assume that uncertainty increases over time. While the use of some arbitrary assumptions is unavoidable given the data, the resulting model is very transparent, and alternative assumptions can easily

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[20] See Quirk and Terasawa (1986). A more careful approach to assessing a pioneer-project bias might be based on how well the innovators satisfied their price/performance targets on earlier products. Such data are not readily available.

[21] These are conservative assumptions because it is likely that easy economies (learning by doing, product performance improvement) are exploited earliest in a product's life, and that for the existing technologies many of these already will have been achieved.

be explored. Sensitivity tests reveal the extent to which it is necessary to explore alternatives, and allow us to bound the expected benefits in a meaningful way.[22]

Because price and performance are functionally equivalent here, we can model the effect of innovation on consumer welfare either by fixing prices and continually improving the performance parameters, or by holding performance constant and modeling prices as continually declining. In our model, it is easier to change one price than it is to manipulate three performance parameters, so we hold performance fixed and model technological change by having prices decline over time. To the extent that the actual rate of innovation outpaces the rate of price decline in our model, our forecasts of consumer welfare gains will be conservative.

In the appendix (also available from the authors and online at *www.rff.org*), we report specific details about our data sources and parameter assumptions.

[22] In addition to making conservative forecasts, our analysis ignores benefits from second-generation products, and any private benefits accruing to the innovator or to other manufacturers, via knowledge spillovers. Potential to create knowledge spillovers is one of ATP's key selection criteria.

## 4. RESULTS

We calculate a pair of indexes to compare costs at a single point in time, with and without the DDS innovations. Since DDS expenditures constitute a tiny fraction of total consumption expenditures, the indexes are only slightly greater than one. On a per-unit basis, though, the innovations would both generate significant consumer benefits.[23] The performance specifications for the new technologies are clearly superior to those of existing products, and their target prices are similar, and welfare gains are the unsurprising result. The purpose of this analysis has been to estimate their magnitude, and to see how uncertainties propagate through the model.

In present-value terms, we find that median consumer welfare gains over five years would be $2.2 billion from the digital, linear scanning (DLS) technology, and $1.5 billion for optical tape, discounting at a 5% annual rate. Compared with current DDS trends, the innovations would create approximately $2,400 in additional consumer welfare per DLS device sold—about 23% of the expected unit price—and $20,800 per optical tape device—about 50% of the unit price.[24] These relative gains reflect marked downward trends in consumer shadow values and steadily declining prices for *all* DDS devices.

Initial per-unit gains should be higher still, but total welfare gains will be lower initially due to minimal early market penetration. By the 5th year, we assume rates of adoption for DLS and optical tape devices will reach 40% and 30% of new medium- and high-capacity unit sales, respectively. Knowledge spillovers and follow-on improvements may eventually affect every sale. Although we explicitly estimate only the gains from first-generation products, such ancillary benefits are implicitly captured in the results. Our assumptions about adoption rates are not intended to reflect knowledge spillovers; if they occur, our benefit

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[23] Our estimates are gross of R&D costs; benefits are likely to dominate those costs, however. Note that our estimates also depend on the assumption that the prices of other goods and services in consumers' market basket are unaffected by DDS innovation. This seems innocuous because digital data storage constitutes a very small part of the economy.

[24] The model forecasts that mean unit sales in QIV-2004 will be approximately 133,790 linear scanning devices, and 10,670 optical tape units. Innovators of the linear-scanning technology reported cost *and* price expectations; based on this, their producer surplus in the 5th year would be approximately 30% of expected price.

estimates may be low. If, on the other hand, disk drive arrays continue to make inroads into traditional tape storage markets, actual benefits will be lower than expected. The uncertainty in our estimates implicitly allows for these possibilities, provided our assumptions about market shares and changes in price—our model's equivalent, recall, of technological improvements—are accurate.

Table 1, and figures 3 and 4, report our basic set of benefits estimates. As our sensitivity analysis will show, these results are robust to large changes in assumptions. Even with generous allowances for uncertainty and biases in our data, $5^{th}$ percentile benefits are driven to zero only by large changes in specific parameter assumptions.

### TABLE 1: EXPECTED NET PRESENT VALUE OF CONSUMER WELFARE GAINS, PAIR OF DDS INNOVATIONS, THROUGH FIVE YEARS

| Percentile | LINEAR SCANNING | OPTICAL TAPE |
|---|---|---|
| 5th | 1.25 | 1.05 |
| 25th | 1.79 | 1.30 |
| Median | 2.16 | 1.45 |
| 75th | 2.53 | 1.62 |
| 95th | 3.17 | 1.88 |

*($ billions, 2000; N=1000 iterations)*

Figures 3 and 4 show how gains are expected to accumulate over time. The shapes of these curves are determined principally by our assumptions about rates of adoption, growth in demand for DDS devices, and changes in price. Our five-year forecasting window is a compromise between forecasting ahead indefinitely—as if the ATP would be putting DDS technology on a permanently higher plane—and making no forecast at all, as if the innovations would have been achieved on schedule even without assistance. As with other assumptions in our model, the truth must lie somewhere in between.

**Figure 3. Expected Quarterly Consumer Benefit Given Successful Introduction: Digital, Linear Scanning Innovation vs. Defending Products**

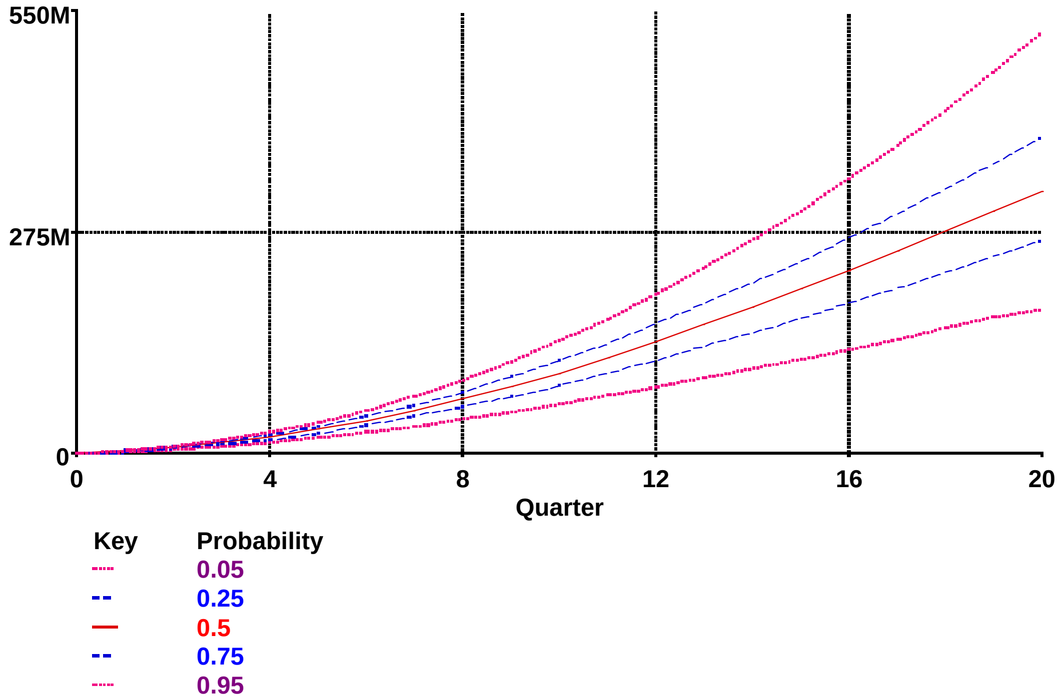
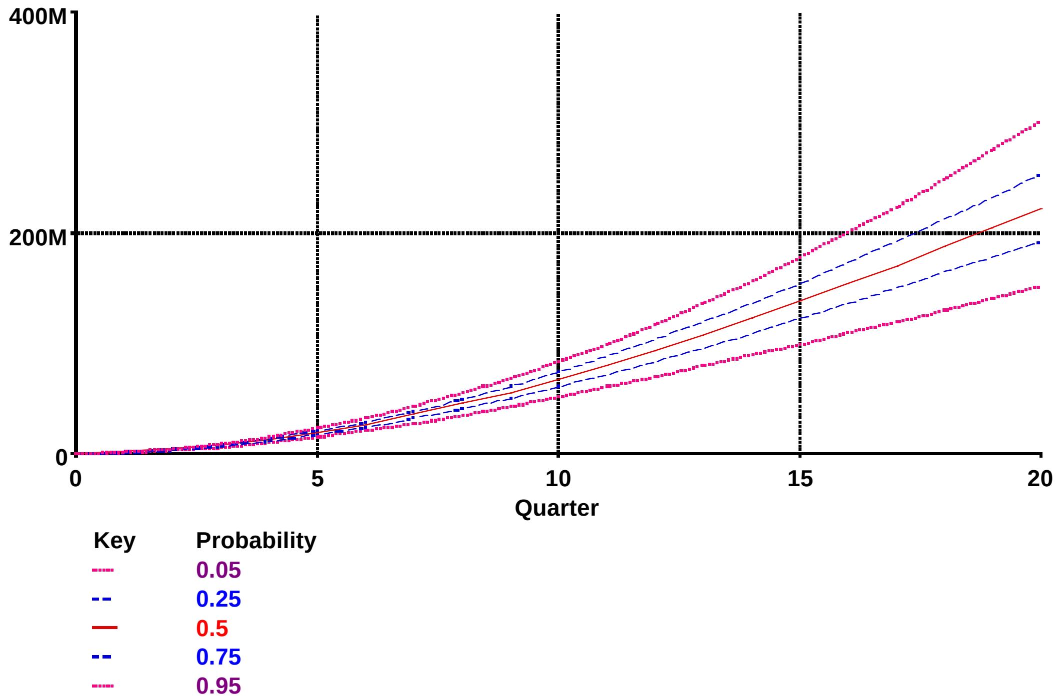


**Figure 4. Expected Quarterly Consumer Benefit: Optical Tape Innovation versus. Defending Products**




## Sensitivity Analyses

We perform three types of sensitivity analysis. First, we ask how sensitive our results are to parameters whose values are informed by the innovators. We shift by +/-50% our assumptions about performance, rates of adoption, and price, while making proportional changes in uncertainties. Second, we consider the effects of parameters affecting both defender and innovation. Here, we focus on shadow values and market size. It is important to test shadow value sensitivities, because in the model we are applying estimates of *marginal* valuations to large changes in quality. Finally, aside from parameters that affect the level of benefits, we also identify the drivers of uncertainty in the forecasts. We ask which parameter uncertainties are most highly correlated with variation in benefits.

As we show in the appendix, benefits estimates are relatively insensitive to the performance parameters; price and rate of adoption are more influential, particularly the latter. The elasticity of benefits with respect to the adoption rate is slightly greater than one. Raising the prices of the innovations—and lowering their rates of adoption and change in price—by 50% reduces forecasted benefits by fully 80%. However, such large changes are well outside the expected range for these parameters, especially for the two price parameters. In particular, innovation prices should drop *faster*, not more slowly, than the defender prices.

The market-condition parameters, including consumer preferences, affect both innovation and defender alike. We find that the shadow values are not very influential, in part because innovation price uncertainty swamps the effects of variation in the shadow values. For the same reason, total benefits are not very sensitive to the technological performance parameters of the devices. For the current model configuration, then, applying marginal shadow valuations to large changes in performance does not pose problems. Among the market-condition parameters, the key is market size. The elasticity of benefits is roughly unity with respect to this parameter, because it factors out of the cost index and acts as a scaling factor. The market growth parameter contributes much less to benefits; if both the market size and market growth assumptions were lowered by 50%, forecasted innovation benefits to consumers would decrease by 54%.

Uncertainty in these two market parameters is the most highly correlated with uncertainty in the benefits forecast of any other parameter. Thus, the most efficient way to reduce uncertainty in the forecast is to acquire more precise data on market size and past growth rates. Obviously, though, market growth forecasts resulting from the new data may prove no more accurate than what is already in the model.

In the context of our model, the size of the market for DDS storage on tape and the adoption rates of the innovations are therefore the most important scaling factors for estimated consumer benefits.[25] Lowering both parameters simultaneously by 50% reduces estimated benefits by 75-77%. To drive 5$^{th}$-percentile benefits to zero, parameters affecting the relative benefits of the innovations must be changed. For instance, shadow values must be reduced 85-90%, or innovation prices must be fixed at introductory levels while defender prices drop as originally assumed (linear-scanning), or twice as fast as assumed (optical tape).

[25] Of course, these market parameters are partially endogenous to the performance characteristics of the innovations, though we do not model that process. Recall that neither of the market parameters affects the sign of the benefits estimates, which are driven solely by the relative performances and prices of the innovations.

Details of our approach are in the Appendix.

## 5. CONCLUSIONS

Our analysis has shown that consumer welfare gains from ATP investments in digital data storage are likely to be substantial. Median expected benefits of innovation, given successful completion of these projects, are equivalent to approximately 23% of the target price of the digital, linear-scanning device, and 50% of the price for the optical tape drive. We compare the anticipated innovations to a counterfactual scenario that assumes current technological trajectories continue as before. The estimated welfare gains are relative to consumer surplus already produced by those baseline tape-drive technologies; with the innovations, total consumer surplus, which we do not estimate, would be the sum of existing and incremental benefits. If the new technologies achieve expected sales, the total, median consumer welfare gains from these innovations will be several billion dollars each.

The ATP explicitly assumes that, without their support, these innovations would not be currently pursued. By design, the “generic” technologies ATP seeks to support are too technically risky to attract private capital, and insufficiently appropriable because they promise to create significant knowledge spillovers for other, future innovators. To attribute the welfare gains estimated in this paper to ATP investments, it is necessary to assume that these ATP investments correct a market failure, or that their screening criteria do apply to these innovations.

The consumer welfare gains are not, by themselves, sufficient argument for public subsidies to private R&D. A full assessment of the ATP’s DDS investments, for instance, would also consider other, failed DDS investments the ATP has made, as well as the opportunity costs of all of these investments. Just one success on the scale of the two forecast in this paper would far outweigh the ATP’s total annual investments in all areas of technology, however. With a few documented successes, the case for the ATP could come down to whether they are correcting market failures in R&D. Consideration of these issues is, of course, beyond the scope of this project.

The "total" welfare gains we estimate of course depend on the choice of the appropriate simulation window. We chose five years to match the innovators' apparent time horizons. Our results, as illustrated in figures 3 and 4, suggest that the incremental benefits from ATP's investments would continue to grow beyond five years. This begs the issue of whether the ATP has put the DDS trajectory on a permanently higher plane, or merely sped up developments that would have occurred eventually. We do not address that issue, though we clearly assume that the new DDS technologies would not have been developed within five years without ATP assistance. Accommodating a differing view would simply mean shortening the window to some other agreed-upon length.

The results are clearly no stronger than the assumptions underlying the model. The probabilistic parameters allow for unforeseen technological developments, however, and one of the model's strengths is that it incorporates all relevant information and varies all of the parameters simultaneously. The implications of changes to any subset of parameter assumptions can be explored within a unified framework. As a result, we have been able to show that significant welfare gains from two highlighted investments in DDS technologies are very likely, and that this qualitative conclusion is robust to very large changes in the assumptions of the model. Finally, while our paper discusses the intricacies of the model in its application to one new technology, we think this cost-index approach is a straightforward and potentially useful resource allocation tool for R&D managers in both the private and public sectors.

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## APPENDIX

### Data

Our data on the innovations—and on the identities of the technologies they consider their future competition—come from structured interviews we conducted in the spring of 1998 with the leaders of the innovating teams.[26] The interviews concerned specific details about the proposed technologies and the market conditions they are expected to face. Having examined the innovators' funding proposals, we asked respondents to compare their actual progress to date against the project's original goals. We sought information not only on current projected transfer rates, capacities, and access times, but also about advances in competing technologies.[27] In addition to items relating to price and performance, we also elicited their forecasts of market conditions, particularly the expected rate of adoption of their innovation, and the size of the market.[28] Using the innovators' responses about the identities, price, and performance of competing products, we collected precise data directly from the manufacturers of those products for use in the simulation model. Finally, we subjected our fully specified model to a careful review by several engineers familiar with data storage theory and practice.[29]

As table A-1 indicates, the interviews elicit beliefs about "most likely" outcomes (assuming successful innovation). The latter responses inform some of the parameter uncertainties in our model, in ways we make precise below. Although there are in principle three sources of uncertainty that can affect the parameters of the model—variability in

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[26] Our access to project leaders and their information was gained through the assistance of the Advanced Technology Program. The ATP's interest in our research was that, while the R&D it sponsors may yield large benefits in future, the program must report annually to Congress as stipulated by the Government Performance and Results Act (GPRA). The forecasts produced by the model we present here are one kind of information the ATP may wish to report in fulfillment of the GPRA.

[27] Although we asked about other performance characteristics, the interview subjects were unanimous in identifying capacity, transfer rate, and access time as the relevant dimensions.

[28] The DDS market is apparently segmented according to capacity. We divide the market into expensive, high-capacity drives and more affordable, low-capacity drives. The two matches we have assigned to the optical innovation come from the former segment, and for the digital-linear scanning technology from the latter segment.

[29] The outside reviewers are both employees of the National Institute of Standards and Technology, which is the ATP's home institution. The reviewers suggested a number of changes in our assumptions, which we implemented.

manufacturing and market conditions, imperfectly observed data, uncertainty about future outcomes—the third source must dominate. We assume uncertainty increases over time.

## Shadow Values

Compared with existing products, the DDS innovations promise improved performance at comparable prices. If they are successfully introduced, it is thus very likely the innovations will enhance consumer welfare, making the interesting question not *whether*, but *by how much* welfare would increase. We measure this by estimating consumers' willingness to pay for improvements in the data transfer rate, storage capacity, and file access time of a tape-based data-storage device.

We compare new and existing devices on the basis of differences in their performance attributes. We translate these differences into monetary terms using our willingness-to-pay estimates, and adjust the list prices of the machines accordingly. These quality-adjusted prices reflect relative differences in the values consumers will realize from the devices. As we explain below, we make upward adjustments to the prices of *inferior* technologies, reflecting the relative "user costs" that their slower speeds and smaller capacities effectively impose.

## Table A-1—Structured Interview

| | |
|---|---|
| **I. TECHNOLOGY** | |
| | 1. What are the most important technical innovations (attributes or characteristics) of your project? |
| | 2. According to ATP documents, at the start of your project, your goals were to achieve [X, Y, Z among the key characteristics]. Can you confirm or update these capabilities? |
| | i. Optical tape: *100 megabytes per second*; *1 terabyte capacity; 8 meters/sec tape speed* |
| | ii. Digital linear scanning: |
| | 3. At the start of your project, the best available technologies were capable of: |
| | i. **File access time**: *44 secs.* Your project was initially expected to achieve *XX secs*, a YY% gain in average access time over the then current best available technology (BAT). Is this information still correct? What is now the best *currently available* file access time? |
| | ii. **Storage capacity:** *35 gigabytes*. Your project was expected to achieve *XX gigabytes*, a YY% gain in capacity over the current BAT. Is this still correct? What is now the best *currently available* capacity? |
| | iii. **Data transfer rate:** *0.21 MB/sec.* Your project was expected to achieve *XX MB/sec*, a YY% improvement over the then-current BAT. Is this still correct? What is now the best *currently available* transfer rate? |
| | 4. Has the pace of your own R&D achievements been as expected in these dimensions? In other dimensions? |
| | 5. Have R&D developments among your competitors been as expected? *(list specific dimensions of product performance)* |
| | 6. Have we failed to ask you about any important dimensions of your new product's performance? What units are they measured in, and what improvements do they promise with respect to the BAT? |
| **II. MARKET** | |
| | 1. What is the innovation's primary market, or markets? |
| | 2. What is the expected size of this market, in terms of units shipped? |
| | 3. When do you expect to reach market? |
| | 4. What is your expected adoption rate over 2-5 years (with uncertainty bounds)? |
| | 5. At what price do you expect to sell the product embodying the new technology? |
| | 6. How do you expect this price to trend over the first two years? Five years? (as driven by continued R&D or learning-by-doing, as well as anticipated market dynamics.) |
| | 7. What are your most important market-related hurdles?<br>• Is it critical to be first to market?<br>• How likely is it that improvements in the defender technology would render yours uncompetitive?<br>• Does the success of your innovation depend on new applications arising for digital data storage?<br>• Will it be necessary for users to adopt complementary technologies to take advantage of yours? |
| | 8. What is the "off-the-shelf" price of the defender technology? *[This item probes respondent's familiarity with or identification of its competitors. The model uses manufacturer data]* |
| | 9. What rates of change in defender price and performance do you expect over the next 2 years, 5 years? |
| | 10. Do you expect the defender to compete on price with your innovation? |
| | 11. What is the going market price for a unit of capacity (per MB), access time (per second), transfer rate (KB per second)? *[This item sought innovator opinion on shadow values; especially for the latter two. The typical responses were sharply at odds with market data; with our hedonic analysis; and with opinions from disinterested experts. We concluded that the innovators do not have a clear idea of how much consumer surplus they may generate; as our results suggest, their pricing will not extract much of the consumer surplus their innovations will create.]* |
| | 12. Do you expect your innovation will drastically change any of these [shadow prices]? |
| | 13. Have we omitted any important market issues? |

We estimate consumers' marginal valuations of DDS quality changes using a hedonic regression model of DDS drive attributes. We estimate a simple, linear model to explain variation in DDS retail prices, using product attributes and other control variables as independent variables. The data for this procedure come from current manufacturers' web sites, and from "Dirt Cheap Drives" advertisements in issues of *Computer Shopper*[30] dating from 1994 to 1998.

The model we estimate is:

$$p^t = a + b_1(\text{data rate}) + b_2(\text{access time}) + b_3(\text{capacity}) + b_4(\text{time}) + \text{squared terms} + \text{interactions} + \text{dummies} + e,$$

where the intercept term $a$ and the coefficients $b_x$ are parameters to be estimated, and $e$ is a mean-zero, normally distributed error term. The fitted coefficients $\hat{b}_x$ are estimates of consumers' shadow values, the amount they are willing to pay for marginal changes in the corresponding attributes. *Data rate* is measured in megabytes/sec, *capacity* in gigabytes, *access time* in seconds,[31] and *time* in quarters since QI-1994. We use indicator variables to control for the identities of the leading manufacturers; whether the tape medium is 4mm (the size of DAT cassettes); whether the product is a (multi-drive) library system; and whether it is an internal drive. We interact the quality attributes with the time variable to estimate how consumers' marginal utilities change over time. Finally, we include squared terms to capture non-linear aspects of consumer valuations.

Our results contain no big surprises. The signs of the coefficients on the quality terms are positive, meaning consumers are willing to pay more for better performance.[32] The interaction terms indicate that the marginal utility of additional quality declines over time—as a result, no doubt, of the rising level of quality in DDS devices that is captured in the data. The value of an extra gigabyte of storage is greater when average device capacity is closer to

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30 Ziff-Davis

31 The average time required to queue up a file on a tape is measured by a device's spool speed multiplied by half the length of the tape.

32 There is one exception: the coefficient on *Access Time* is negative, obviously for the same reason.

1 GB than when it is 100GB.[33] The squared terms, which allow for curvature in the rates of decline, are small and not statistically significant.

Table A-1 reports our estimates of the initial shadow values in the simulation model. These have dropped considerably over time—our regression equation estimates they were 2-3 times higher in 1995 than they will be in 2000. As might be expected, the current cost of a gigabyte of storage on *disk*, about $100 in 1999, is higher than our estimated shadow value of tape storage capacity, though the cost of disk storage is dropping by up to 40% per year.[34] Our estimate's relative similarity to this value is reassuring; as with our other assumptions, however, we check the sensitivity of our results to changes of +/-50% in the shadow values.

**Table A-2: Shadow Value Forecasts**[35]

| Attribute | Shadow Value (std. dev.) Estimate: 2000 | Forecast: 2005 |
|---|---|---|
| Data Transfer Rate | **$791** /MB/sec ($208) | **$433** /MB/sec |
| Storage Capacity | **$39** /GB ($9.88) | **$13** /GB |
| File Access Time[36] | **$49** /sec ($12.25) | **$40** /sec |

These values should apply only to marginal improvements in quality. As the innovations may introduce quite large changes, these initial shadow values may overestimate the resulting welfare gains. In our model, however, the shadow values decline over time and, as sales of the innovations *increase* over time, most of the large quality differences that are expected will be valued at significantly lower levels than suggested by the figures in table A-2. By the last period of the simulation, we estimate that the shadow values for the attributes will have declined by 50%, 75%, and 20%, respectively, as we describe.

33 As a possible exception, the marginal utility of faster file access times may increase over some range, as that second saved on the margin represents an increasing fraction of total remaining access time.

34 Kent Rochford, NIST, personal communication.

35 Our interview subjects suggested marginal valuations that are sharply at odds with our estimates. These included $5,000/MB/second for data rate, $4,300/GB of capacity, and $1,000/second file access time. While these guesses appear quite optimistic, given their price targets the manufacturers clearly have no intention of extracting this supposed consumer surplus. The third guess is somewhat more plausible, as we will discuss.

36 Estimated shadow value of *reduction* in access time, the outcome of a heuristic process. Hedonic methods did not work well for this attribute, as we explain below.

The data do not yet support the derivation of a statistically significant shadow value estimate for file access time in a hedonic regression. Until only very recently, slow file access times have not been considered a significant constraint on the utility of DDS drives. As a result, shadow values for differences in file access times have apparently been small. The relative past unimportance of access times may be because DDS storage capacities and transfer rates have only recently reached levels at which file access times are a significant bottleneck in DDS performance. Larger capacities are probably correlated with slower access times, and with transfer rates increasing, the slower access may have only recently become a nuisance. The position of data-storage experts is that, whereas capacity and transfer rate have each been, in turn, the most significant performance bottleneck for DDS performance, access times are now the most important constraints—particularly as new, data-intensive applications continue to develop and the demand for new forms of storage—for instance in "near-line" storage to relieve congestion in network hard-drive storage systems—continues to grow.[37] See figure A-1.

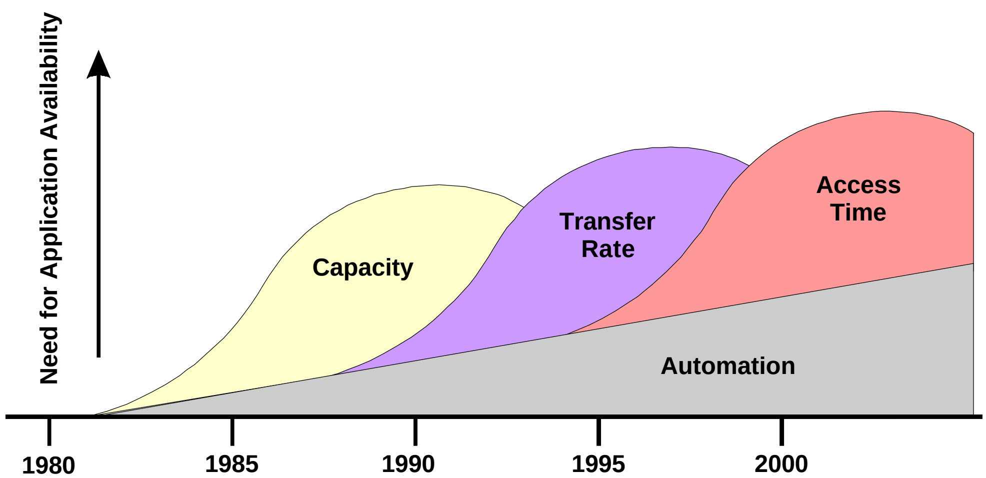


**Figure A-1: Technological Constraints in Digital Data Storage**[38]

[37] See "Tape Opportunities for the '90s and Beyond", Michael Peterson, Strategic Research Corporation; February, 1997. Large arrays of hard drives can successfully compete with tape for some applications, and offer extremely fast file access times. However, we believe a consistent market for tapes exists where a permanent, portable record is required—as with archival functions—and file access times are expected to become an important limiting factor in the utility of those systems.

[38] Figure taken from "Tape Opportunities for the '90s and Beyond," op. cit.

To estimate the shadow value of file access time, we perform a simple calculation based on heuristic arguments that depend on conservative assumptions about a machine's average service life, intensity of usage, and the average value of users' time on the job. We then calculate what a consuming firm should be willing to pay for each second of file access time saved per file request relative to the slower technology. This value is given by:

(file requests/day)*(service days/year)*(years of service life)*(value of worker time/second)

We assume a DDS device will receive read/write requests 235 days per year, the equivalent of 47 work weeks per year, and will have a useful service life of five years. We estimate the value of worker time at $15 per hour, the approximate national hourly wage in 2000.[39] Finally, we assume the device will receive 10 read/write requests per working day.

The first two assumptions are intended to be a little conservative; for white-collar professionals, who are the typical users of DDS, $15 may be a very conservative estimate of the value of their time, unless they are productive at other tasks while they wait for a file. Our assumption about the number of file requests is arbitrary; table A-3 shows the shadow values that would be implied by other levels of usage. In the model we assume 10 requests because it is on the low side of what we believe are reasonable levels of usage to expect in the face of data-storage demands sufficient to induce the purchase of a DDS device. We conservatively assume that average usage of a device does not grow over time.

At 10 file transfers per day, an average DDS purchaser would be willing to pay an extra $49 *for each second* of reduction in file access time. If one device queues up a file an average of 30 seconds faster than another device, the additional value would be $1,470 (=30•$49) over the life of the machine.

[39] This figure is based on the Bureau of Labor Statistics estimate for 1999. The 2000 estimate will be somewhat higher, another reason to believe ours is a conservative estimate.

**Table A-3: File Access Shadow Values by Expected Intensity of Use**

| Anticipated Daily Requests | Shadow Value of 1 second Faster Avg. Access Time |
|---:|---|
| 1 | $5 |
| 10 | $49 |
| 50 | $245 |
| 500 | $2,448 |

*Rates of Change in Consumer Valuations*

The time-interaction terms in the hedonic analysis yield linear estimates of the rates of change in capacity and transfer rate shadow values as 5.6% and 3.0%, respectively, per quarter. As we explain below, we also assume access-time shadow values will decline at a 1% rate. As we have noted, it is necessary to assume the rates decline exponentially, to avoid forecasting negative shadow values by 2005. We assume these shadow values decline according to:

$$b_{x,t} = b_{x,0} \cdot e^{(r_x \cdot t)},$$

where $b_{x,0}$ is the estimated shadow value for quality attribute $x$ in the initial period, $r_x$ is the estimated coefficient of interaction term $(x*t)$ in the hedonic regression, and $t$ is time in quarters, from (QI,2000) to (QI,2005). These functions yield rates of decline that appear nearly linear in the initial years, and that begin to level out toward 2004.

As with the shadow values themselves, the hedonic regression does not usefully estimate a rate of decline for access-time shadow values. If access time is increasingly to become a bottleneck for DDS, as industry experts believe, shadow values should initially *increase*. We conservatively assume they will not increase, but will decline at a slower rate than for the shadow values of capacity and transfer rate.

The simulation model's probability distributions for shadow values and their rates of decrease are tabulated in the appendix.

## PARAMETER ASSUMPTIONS

For expositional simplicity, rather than compare the new technologies against each of several leading, existing products, we instead average the characteristics of the two strongest defending technologies (constituting, in both the high- and medium-capacity segments of the DDS market, significant fractions of total sales) and compare the new technologies against these "virtual" defenders. We calculate weighted averages of the prices and performance of each pair of defenders, using as weights each defender's estimated share of the total unit sales between them, immediately prior to the expected introduction of the innovations. Simulations based on individual product comparisons produce qualitatively similar results.

We compare the digital-linear scanning technology against the Sony GY2120 and the Quantum DLT 7000 tape drives, both of which employ conventional helical scanning technology. In the market for these medium-capacity tape storage units, the DLT 7000 is the most popular drive by a fairly wide margin, though the GY2120 currently commands a significant share of that market as well.

The optical tape technology is compared against the Ampex DST 412 and IBM 3590 high-capacity storage units, both of which employ conventional, magnetic tape technology. The Ampex is truly a niche product, albeit one with an enormous storage capacity. The IBM drive is by far the most popular in the high-capacity segment of the tape-storage market, and in what follows, the "optical defenders" distributions are therefore quite similar to those for the 3590 drive alone.[40]

The following parameters are discussed here:

- Off-the-shelf (nominal) prices
- Quarterly rates of change in nominal prices
- Quality differences (data transfer rates, storage capacities, file access times)
- Market sizes
- Adoption rates
- Personal Consumption Expenditures (PCE)
- Shadow values and rates of decline

[40] Quantum markets a high-capacity unit based on the DLT7000 drive, the PowerStor L500. However, this unit simply adds robotics and tape cartridges to the basic drive. We exclude that product on the grounds that the optical drive could also be paired with robotics.

*Off-the-Shelf Unit Prices*

| Drive | Nominal Price, $000 | Notes |
|---|---|---|
| **Digital, Linear** Scanning Innovation | Triangular (9,10,12) | Two respondents agree: $10k price target. No price range offered. We assume (–10%,+20%) dispersion |
| Virtual **Defender** (helical scanning) | Normal (6.9, 0.2) | Quantum ($5.7k), Sony ($31k). Prices as of Autumn 1998. We assume prices fall over time (see later table). By May '99, Quantum's price was $4.8k, but this is similar to our model's projection for that time. We assume 2.5% std. deviation |
| **Optical Tape** Innovation | Tri (38,40,48) | Two respondents differ, one offering range of $40-45k for target price. Thus assume (-5%,+20%) dispersion |
| Virtual **Defender** (magnetic tape) | N(63.3, 1.6) | IBM ($47.3k), Ampex ($115k), 2.5% std. deviation. IBM price includes 10 1Gb tape cartridges @ $80each. |

These assumptions yield the empirical densities depicted in figure A-2.

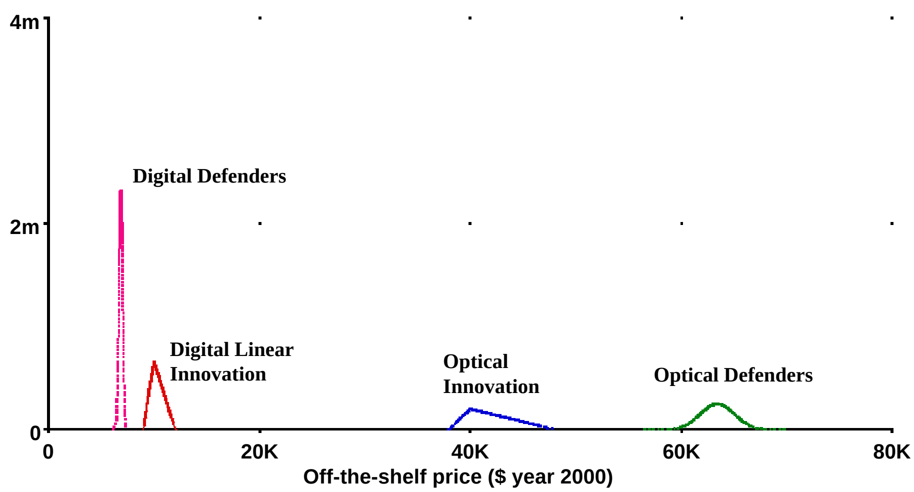


**Figure A-2: Nominal Price Distributions for Defender Technologies and Innovations**

*Quarterly Rate of Change in Nominal Prices*

We assume that nominal prices decay exponentially according to $p_t = p_0 \cdot e^{rt}$, where $p_0$ is the initial off-the-shelf price and $r$ is the rate of decline per quarter $t$. For each innovation, we solve for the rate $r$ such that the expected price for the 20th quarter equals the innovator's year-5 forecast. For all of these products, the resulting $r$ becomes the mode of a triangular distribution, with bounds determined as noted below. We conservatively assume the defender prices will drop as quickly as for the innovators, though the defender should already have exploited the more accessible learning-by-doing and scale economies. We implicitly assume innovators and defenders invest in R&D to continually improve all of their products.

| Drive | Quarterly Price Trend | Notes |
|---|---|---|
| **Digital, Linear** Scanning Innovation | Tri (-0.06,-0.0578,-0.018) | Innovators expect initial price of \$10k, \$5k after two years. Upper tail of this distribution is consistent with price of \$7k after *five* years. Lower tail gives nominally faster decline. |
| Virtual **Defender** (helical scanning) | Tri (-0.06,-0.0578,-0.018) | Matches paired innovation. |
| **Optical Tape** Innovation | Tri (-0.03,-0.024,-0.014) | Innovators expect initial price of \$40k, \$25k by year 5. Upper tail yields \$30k by year 5, lower tail a nominally lower \$22k. |
| Virtual **Defender** (magnetic tape) | Tri (-0.03,-0.024,-0.014) | Matches paired innovation. One respondent explicitly expects IBM 3590 price to keep pace with optical tape price. |

Figure A-3 illustrates our assumptions about rates of price decline $r$. We assume a much wider and more skewed distribution for the digital linear-scanning device to accommodate both its proponents expectation of faster decreases in price than for the optical tape drive, and our conservative assumption that its price may decline no faster than for the other technology.

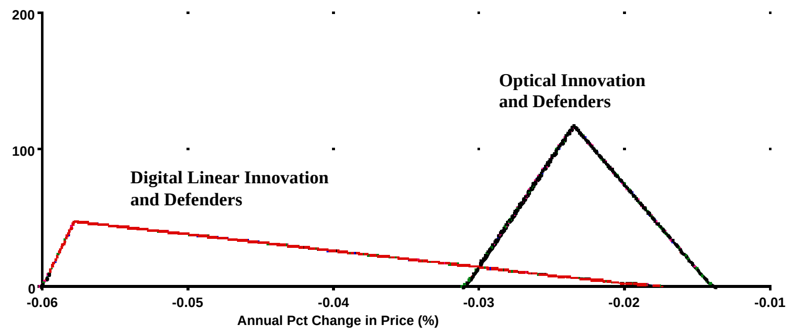


**Figure A-3: Rates of Exponential Price Decay**

We introduce a modest error into the price forecast, so that uncertainty grows over time. The error is normally distributed with mean zero, standard deviation 0.015, meaning that half of the density lies between -1.0% and +1.0%, and nine-tenths of the density lies between -2.46% and +2.46%. Prices are perturbed according to $P_{err}(t)=P(t)*(1+perturbation*t)$, where t is time in quarters.

*Quality Differences*

*Data transfer rate* is the maximum sustained rate at which data can be written to the tape.

| Drive | Transfer Rate (MB/sec) | Notes |
|---|---|---|
| **Digital, Linear** Scanning Innovation | Tri(18, 25, 30) | Mode of 25 MB/sec comes from interview responses of “20-30 MB/sec”; lower bound reduced additional 10% to be conservative. Though we hold quality fixed (changing price only), innovators reported expectation of faster rates by 2000. |
| Virtual **Defender** (helical scanning) | N(5.8, 0.145) | 2.5% standard deviations. Wgtd mkt average transfer rate. |
| **Optical Tape** Innovation | Tri (23, 25, 26) | Respondents agreed on 25 MB/sec. We assume dispersions of –10%, +5%. |
| Virtual **Defender** (magnetic tape) | N(14.3, 0.3575) | 2.5% standard deviations, Wgtd mkt average transfer rate. Best current transfer rate is 15 MB/sec (Ampex DST312) |

These assumptions yield the density functions in figure A-4 for the simulation model:

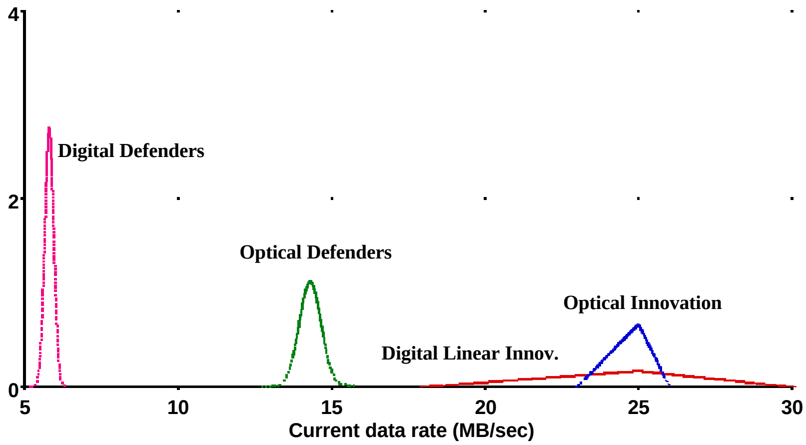


**Figure A-4: Current Transfer Rate: Innovations and Defender Technologies**

*Capacity* is the maximum quantity of data that can be stored on the unit as configured.

| Drive | Capacity (Gigabytes) | Notes |
|---|---|---|
| **Digital, Linear** Scanning Innovation | Tri(14.7,16,16.66) | Respondents confident of achieving 16 GB. Uncertainty arises because product does not yet exist. Asymmetric distribution has upper and lower bounds simulating, respectively, 5$^{th}$ percentile of a N(16,8) and 95$^{th}$ percentile of a N(16,4) dist'n. |
| Virtual **Defender** (helical scanning) | N(36, 0.90) | Mean reflects figures reported in current product literature. Std. Deviation is 2.5% of mean. |
| **Optical Tape** Innovation | Tri(918,1000,1041) | Respondents confident of 1000 GB target. Bounds set as above, using 5$^{th}$ percentile of N(1000,50) for lower bound, 95$^{th}$ of N(1000,25) for upper. |
| Virtual **Defender** (magnetic tape) | N(233.5, 5.84) | Mean reflects figures reported in current product literature. Std. Deviation is 2.5% of mean. |

The implications of these assumptions are depicted in figure A-5.

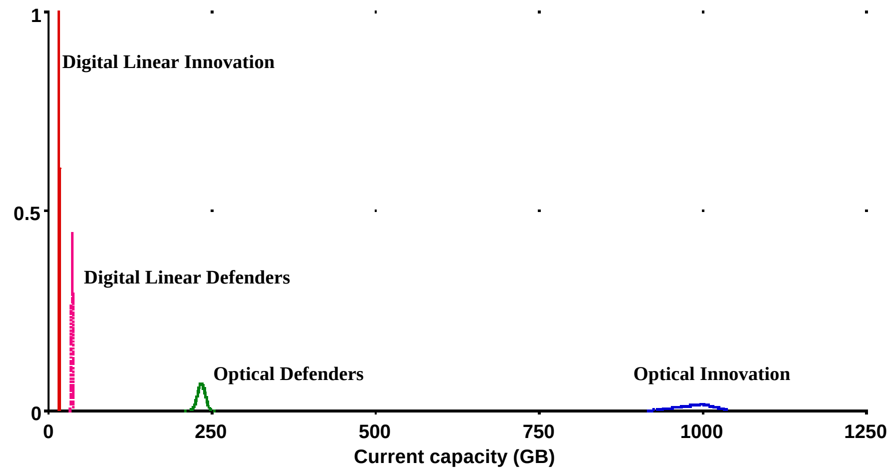


**Figure A-5: Storage Capacities: Innovations and Defender Technologies**

*File access time* is the time required to spool to the beginning of the average file, measured as spool speed times half the length of the tape. Although tape length might easily be adjustable, the innovators have indicated the length they intend choosing as their standard.

| Drive | Access Time (seconds) | Notes |
|---|---|---|
| **Digital, Linear** Scanning Innovation | Tri (7.2, 7.5, 10) | Respondents indicated 10-second access time as of 1997, expecting 7.5 by 2000. Lower bound analogous to optical lower bound (below); upper assumes no progress after 1997. |
| Virtual **Defender** (helical scanning) | N(61.2, 1.53) | Mean reflects figures reported in current product literature. Standard deviation assumed to be 2.5% of mean. |
| **Optical Tape** Innovation | Tri (11.5, 12, 13.25) | Respondents indicated “20 sec” and “20-25 sec” spool time. We assume 24 seconds +2.5 / -1.0; access time is half this. |
| Virtual **Defender** (magnetic tape) | N(38.6, 0.965) | Mean reflects figures reported in current product literature. Ampex offers access time comparable to innovation’s. IBM’s plans to introduce longer tape some time in 1999 are not reflected here. 2.5% std. deviation assumed. |

Figures A-6 illustrates these assumptions.

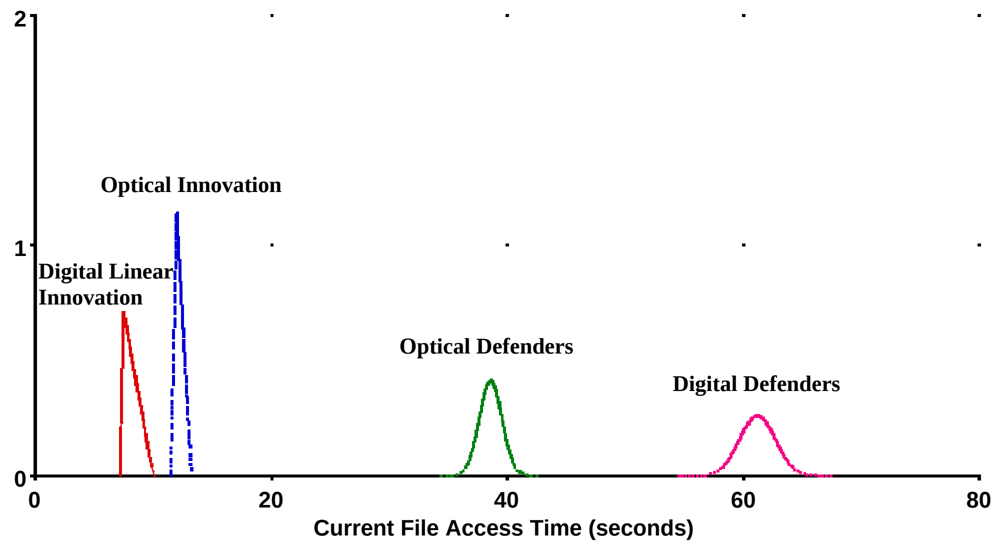


**Figure A-6: File Access Times for Innovators and Defenders**

*Market Size*

| Market Segment | Unit Sales (000s) | Notes |
|---|---|---|
| **Medium-capacity drives** (Digital, Linear Scanning Innovation & Defenders) | Uniform (198.05, 267.95) | *Interview subjects supplied the following information:* About 150,000 DLT 7000 drives sold in 1997 @ $5650. About 400,000 units were said to ship in $3500 range. As described below, we predict year-2000 sales of approx. 27,000 units of Sony GY2120 @$31,000, 206,000 units of DLT 7000. Total is 233,000, medium-capacity segment, year 2000. Bounds reflect 15% variation around this value. |
| **High-capacity drives** (Optical Tape Innovation & Defenders) | Uniform (20.71, 28.03) | *Interview subjects supplied the following information:* About 35,000 IBM 3590 drives shipped per year. A second opinion was “20,000+” units. Our model (described below) predicts sales of approx. 18,600 units of IBM 3590 @ $42,500, 5,700 units of Ampex DST 412 @ $115,000. Total is 24,300, hi-capacity segment, yr 2000. 15% bounds assumed. |

We intend these estimates to be somewhat conservative. We ignore smaller manufacturers, though because we believe that the defender technologies have substantial shares of their market segments, our data probably represent a large fraction of total sales. We derive our admittedly crude estimates by fitting a straight line through the price/quantity pairs (in logarithms) expressed in the interviews. This method yields a linear inverse-demand curve of log(Q)=22.5-1.2*log(P), which seems to fit the data quite well ($R^2$ = 0.93). We use this formula as the basis for predicting quantities sold in 2000 as a function of expected price. The ratio of the standard error to the coefficient of the log(P) term is about 1/6 in this regression. This provides our rationale—albeit not a strong one—for choosing 15% bounds on the market size parameters.

Future DDS demand may be affected by the innovations' potential stimulation of the development of new, storage-intensive services such as in medical imaging or virtual real-estate marketing applications. However, there is a countervailing risk that some of this demand growth will be satisfied by large hard-drive arrays or other competing technologies, as some expect their prices and performance may eventually overshadow current developments in tape technologies.[41] We have attempted to model neither possibility, about which we are agnostic. We note that our model can easily accommodate a wide variety of assumptions about market size or any other parameter.

*Expected Growth in Market Size*

| Scenario | Quarterly Growth Rate | Notes |
|---|---|---|
| **Baseline** (no subsidy for DDS innovation) | N (1.5%, 0.225) | Linear growth assumed: Mkt-Size(t)=Mkt-Size(t-1)*(1+(t*Growth Rate). See text. |
| **Innovation** (Public-sector subsidy results in Digital-Linear and Optical innovations) | N (1.8%, 0.540) | Exponential growth assumed: Mkt-Size(t)=Mkt-Size(t-1)*Exp(t*Growth Rate) See text. |

The U.S. Bureau of Economic Analysis expects growth in "information services and products, less telephonics" to be linear at a rate of 1.5% per quarter.[42] As we expect growth in

41 Kent Rochford, NIST. Personal communication.

42 National Income and Product Accounts tables. U.S. Bureau of Economic Analysis, Department of Commerce. Recent purchases of "Computers and Peripheral Equipment" have grown at approximately 2.5% per quarter (Survey of Current Business NIPA table 5.8 (August, 1998) for years 1994-1997). This series may be less relevant to forecasting demand in DDS, which we believe is closely associated with the demand for information services. It is also consistent with our overall approach to use the smaller, information services forecast.

the demand for medium- and high-capacity DDS drives more or less to keep pace with growth in information services, we use the BEA's forecast as the mean growth level in our baseline (no innovation) simulation scenario. We assume growth is normally distributed with standard deviation equal to 15% of the mean.

If either innovation is successful, we assume it will stimulate additional demand beyond the BEA's linear forecast. To reflect our expectation that demand growth may be slightly faster with public-sector subsidies, for the innovation scenario we assume that growth will be exponential with a quarterly rate of 1.8% and standard deviation equal to 30% of this amount, normally distributed.

Initially, the average innovation-scenario prediction is similar to the baseline market size forecast; after about the 8$^{th}$ quarter, however, the two predictions begin to diverge significantly, until in the 20$^{th}$ quarter the innovation scenario predicts 10% greater sales on average than in the baseline scenario.

In the upper tails of the growth-rate probability densities, the innovation scenario yields significantly faster growth rates. In the innovation scenario, the 95$^{th}$-percentile growth rate is 2.7%, which still lags our interviewees' much more optimistic expectations. One respondent expects sales of the IBM 3590 to increase roughly threefold by 2005, which implies a quarterly exponential growth rate of 3.3%. The same person expects total installed capacity to increase from 80 petabytes in 1997 to 500 PB in 2001, an 11.5% quarterly growth rate. We address these expectations in our sensitivity analysis.

*Adoption Rates*

| Innovation | Adoption Rate | Notes |
|---|---|---|
| **Digital, Linear Scanning** | $\lambda$=0.035, $\gamma$=2.2 | Lambda and gamma assumed constant. See text for interpretation. |
| **Optical** | $\lambda$=0.03, $\gamma$=2.2 | Lambda and gamma assumed constant. |

We assume that the innovation will partially displace sales of defender technologies and partially expand the market. In the model, innovation market shares increase monotonically with time according to the following Weibull process:

$$F(t) = 1—exp( -l\, t^{g})$$

Here *t* is time in quarters, λ is a scale parameter, 0<λ<1, having the interpretation of a hazard rate (which is therefore assumed to be constant), and γ>0 is a shape parameter. It is difficult to associate λ and γ directly with specific curve shapes; experimentation was necessary to achieve the desired curves. We chose Weibull curves that reflect the lower range of our respondents' expectations about their future market shares.[43] Figure A-7 shows a detail of the Weibull functions showing our assumed market shares over time for the two innovations, given that they are successfully introduced.[44]

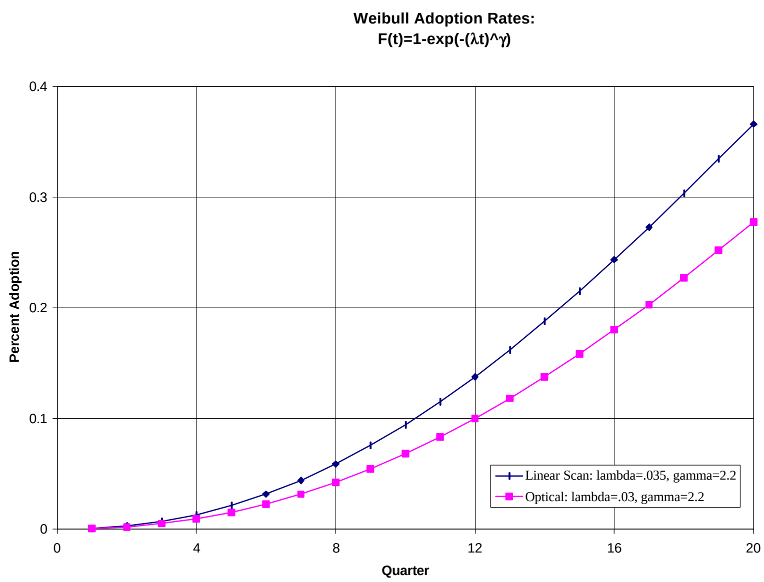


**Figure A-7: Weibull Adoption Rate Curves: Percent of Current Sales *(Detail: first five years)***

*Future Private Consumption Expenditures*

Data on U.S. personal consumption expenditures (PCE) are available from the National Income Product Account tables produced by the U.S. Bureau of Economic Analysis.

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[43] Lambda affects the curvature of the function, with larger values implying faster adoption rates. As gamma increases, the curve's inflection points are "delayed." The Weibull curves are quite sensitive to λ and γ, requiring us to treat them as predetermined constants in our simulation model.

[44] The complete graphs show S-shaped, cumulative distribution functions that cross 90% at about 10 and 12 years, respectively.

PCE serves as the denominator of the factor share calculations in the cost index, as well as the factor by which the index is multiplied to produce the model's estimate of benefits net of baseline.

The model requires a forecast of PCE out to 2005. We build our forecast by regressing annual PCE against time for the years 1982 through 1998. With time expressed in quarters since I-1982, the resulting equation is PCE=449,228-227.7*(qtr), and the model fits the data very well ($R^2$=0.997). We assume future expenditures are normally distributed with means equal to the predictions of this expression, and initial standard deviation equal to 2.759% of the mean in Q1 2000.[45] We assume uncertainty in PCE increases by an additional 0.25% per quarter thereafter.

*Shadow Values*

| Attribute | Shadow Value | Rate of Change (Quarterly) |
|---|---|---|
| **Transfer Rate** | N (791.3, 207.8) | N (-0.030, 0.002) |
| **Storage Capacity** | N (39.0, 9.9) | N (-0.056, 0.003) |
| **File-Access Time** | N (49, 12.25) | N (-0.01, 0.005) |

*(5% standard deviations assumed for rates of change)*

Because our estimate is based on heuristics rather than data, we assume the file-access-time shadow value has larger variance than the other two shadow values. We base our assumptions about their variation on the estimated standard errors from the fitted hedonic model. For the access-time shadow value, we assume a standard deviation equal to 25% of the mean.

45 This is the ratio of the difference between high and low estimates—produced by respectively adding and subtracting one standard error from the intercept and time coefficient in the fitted model—to the mean prediction.

## Sensitivity Analysis

The tests presented in this section are divided into those affecting the innovations, those affecting both innovations and defenders (these are taste and market parameters), and value-of-information tests examining correlations in uncertainties.

### Innovation Parameters Only

Here we ask how sensitive our results are to parameters whose values are informed by information provided by the innovators. The parameters examined here concern performance attributes of the innovations, along with their off-the-shelf prices initially and over time, and rates of adoption.

Table A-4 indicates that benefits are more sensitive to assumptions about the innovations' price and adoption rate than to their performance.[46] For the *linear scanning* innovation, benefits are also somewhat sensitive to the data transfer rate assumption, because that category provides most of its advantage over the products to which we compare it (see appendix). For both new technologies, benefits are also a little sensitive to whether price changes at a different rate than the defender technology prices.

[46] Recall that we hold performance fixed in our model, but that lowering the price has the same effect, mathematically, as improving performance. To be conservative, we usually assume that defender prices of the defender technologies drop at the same rate.

**Table A-4: Effects of Changing Selected Innovation-Parameter Values by +/-50%; Medians**

| ***What if:*** / ***Changed by:*** | Access time | Capacity | Transfer rate | Rate of adoption | Off-the-shelf price | Rate of change in price | Adoption, price, and change in price† |
|---|---|---|---|---|---|---|---|
| ***LINEAR SCANNING (median present discounted value: $2.15 billion)**** | | | | | | | |
| **+50%** | $2.13 B | 2.16 B | **2.52 B** | **3.46 B** | **1.51 B** | 2.36 B | **4.60 B** |
| **-50%** | $2.16 B | 2.13 B | **1.26 B** | **1.00 B** | **2.82 B** | 1.76 B | **0.39 B** |
| ***OPTICAL TAPE (median present discounted value: $1.46 billion)**** | | | | | | | |
| **+50%** | $1.45 B | 1.6 B | 1.57 B | **2.21 B** | **0.81 B** | 1.64 B | **3.48 B** |
| **-50%** | $1.46 B | 1.26 B | 1.31 B | **0.72 B** | **2.12 B** | 1.22 B | **0.24 B** |

* Median values differ slightly from those in table 1 due to statistical variability
† Adoption rate, price, rate of change in price all made better ("+50%") or worse simultaneously for innovation. Rates of adoption and price-decrease raised (lowered) while initial price is lowered (raised).

Prices and adoption rates are influential because total benefits equal per-unit benefits—which depend directly on price—times total unit sales, a direct function of the adoption rate. The adoption elasticity of benefits is slightly greater than one: unit sales vary nonlinearly with the rate of adoption, and this just cancels the effect of declining per-unit benefits over time.[47] Benefits are somewhat less sensitive to the prices of the innovations, because the effects of price are mediated by the quality adjustments, which are additive.

The last column of the table reports the effects of changing the adoption rates and both types of price parameter simultaneously. On *a priori* grounds, we expect these variables will be correlated: a higher price, or a slower rate of price decline, should slow a new product's rate of adoption. When we change all of these parameters, the effect on benefits is considerable. A 50% deterioration in the parameters (from the point of view of the innovation) cuts estimated benefits by more than 80%. The effect is the same for the opposite changes. For the price parameter, we consider such large changes to be unlikely, however: a 50% increase in introductory price is far outside even the conservatively wide bounds we set

[47] Per-unit benefits decline over time because consumer shadow values for quality differences decline, as technologies improve.

in our model. We also expect innovation prices should drop *faster*, not more slowly, than defender prices—for reasons stated elsewhere.[48]

## Taste and Market-Size Parameters

Next, we consider the effects of parameters affecting both defender and innovation. Here, we focus on shadow values and market size. It is particularly important that we test shadow value sensitivities, because in the model we are applying estimates of *marginal* valuations to large changes in quality. This may overstate benefits, although the bias may be offset by the consistently conservative approach we have taken with our other parameter assumptions.

In table A-5, only the market-size parameters have a strong effect on benefits—though $5^{th}$-percentile forecasts are well above zero. The elasticity of benefits is roughly unity with respect to market size because it can be factored out of the cost index, and so acts as a scaling factor.[49] For the same reason, however, the market size parameters do not affect the sign of our benefits forecast.

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48 $5^{th}$ percentile benefits of the linear scanning innovation are negative (-$0.27 B; equivalent optical tape benefits are $0.02 B)) for this simultaneous sensitivity test (not shown).

49 To see this, let $F$ represent expression (2). Note that benefits $(e^F-1)*PCE;$ however, since $F$ takes values very close to zero, $F$»$(e^F-1)$. The expression represented by $F$ contains factor shares *s*, whose numerators are DDS expenditures, i.e., the product of DDS market size and average DDS price. Thus, $F$ can roughly be factored as:

$$\textbf{(DDS market size)*(Avg. DDS price)}*(2*\mathrm{PCE})^{-1}*ln(W^{dt}/W^{A})$$

(the factoring is not exact because DDS expenditures differ slightly in the two simulation scenarios). The average DDS price across all units sold is as influential as the market size parameter, but because it is more accurately observed, we need not do a sensitivity analysis on it. The results would obviously be the same as for DDS market size.

**Table A-5: Effects of Changing Selected Parameter Values by +/-50%; Medians**

| ***What if:*** <br> ***Changed by:*** | Market size | Market growth | Market size and growth | Shadow value: *transfer rate* | Shadow value: *capacity* | Shadow value: *access time* | All shadow values |
|---|---|---|---|---|---|---|---|
| **LINEAR SCANNING (median present discounted value: $2.18 billion)*** | | | | | | | |
| **+50%** | **$3.27 B** | 2.44 B | **3.47 B** | **2.50 B** | 2.16 B | 2.28 B | **2.52 B** |
| **-50%** | **$1.09 B** | 1.94 B | **1.00 B** | **1.58 B** | 2.19 B | 2.06 B | **1.42 B** |
| **OPTICAL TAPE (median present discounted value: $1.46 billion)*** | | | | | | | |
| **+50%** | **$2.19 B** | 1.64 B | **2.31 B** | 1.51 B | 1.58 B | 1.47 B | 1.62 B |
| **-50%** | **$0.73 B** | 1.30 B | **0.68 B** | 1.40 B | 1.32 B | 1.45 B | 1.22 B |

* Median values differ slightly from those in table 1 due to statistical variability.

Interestingly, the shadow value assumptions have relatively little effect on benefits. The reason relates to how shadow values enter the model, to value differences in quality between products. The resulting valuations are added to the prices of the underperforming products. These price adjustments may be small, however, compared with the price differences themselves, and their effects certainly pale in comparison with that of changing the numbers of units sold. In particular, the shadow value of access time, which we derived heuristically, barely changes the benefits forecast even when we assume $5 instead of $49—corresponding to one file request per day rather than 10 (see table A-3). Changing to the lower value drives median benefits down only to $1.9 B and $1.4 B, respectively, for DLS and optical.

Benefits would be more sensitive to shadow values if less uncertainty were assumed about innovation prices. We assume the price of the optical tape innovation lies between $38,000 and $50,000 (see appendix). At the lower end of this range, the difference between innovation and defender prices is almost twice that at the high end, and this variability simply dominates the quality adjustments.[50]

[50] Benefits are, similarly, not very sensitive to our assumptions about shadow value *rates of change.*

## Other Sensitivity Tests

We test other effects of changes in our demand-growth assumptions. Lowering the exponential rate assumed for the innovation scenario from 1.8% to 1.5%, to match the (linear) rate in the baseline scenario, lowers forecasted benefits slightly, to $2.11 B and $1.42 B for DLS and optical, respectively. When we assume innovation-scenario demand growth is *linear* at 1.5%, estimated benefits only decline to $2.08 B and $1.40 B, respectively. Our baseline growth assumption is conservative in light of expectations that the actual rate could be as high as 2.5%.[51] Increasing the baseline growth rate to 2.5%, and the innovation-scenario rate to 3.0% to keep their ratio constant, makes median benefits $ 2.50 B and $1.68 B, respectively—about the same as our 75$^{th}$-percentile default forecasts.

Exploring parameter shifts that drive 5$^{th}$-percentile benefits estimates to zero, we find that it is necessary to reduce all shadow values by 85% (DLS) to 90% (optical) to accomplish this. If we assume that new technology prices will remain fixed for five years, while defender prices drop as originally assumed, 5$^{th}$-percentile DLS benefits are slightly less than zero (median $1.1 B); however, defender prices would have to drop more than twice as fast as we assume they will to eliminate optical-tape innovation benefits.[52] We expect new technology prices will actually drop more quickly than defender prices, due to learning economies and other sources of inexpensive cost savings that will already have been exploited in existing products.

Finally, we find that the *rate* at which we assume shadow values will drop has, as expected, little effect on forecasted benefits. Rates must be increased more than three and a half times to drive 5$^{th}$-percentile DLS benefits to zero, and even a quadrupling does not push 5$^{th}$-percentile optical benefits to zero. This result is predictable because the shadow values themselves turn out not to be very sensitive assumptions.

## Value of Information

Aside from parameters that affect the *level* of benefits, we look also at the determinants of *uncertainty* in our forecasts. That is, variation in *which* parameters is most

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[51] "Computers and Peripheral Equipment"; Survey of Current Business NIPA table (August, 1998), U.S. BEA.

highly correlated with variation in the benefits? We find that there are only two kinds of parameters whose uncertainty is highly correlated with uncertainty in the benefits estimate. These are the DDS market-size parameters, and their rates of change over time. Recall that our assumptions about DDS market size are not based on direct market research, but on responses elicited in our innovator interviews. Because we have not identified market data with which to corroborate that information, we have assumed significant uncertainty for these parameters. Better market-size data would produce correspondingly more precise benefits estimates, and this analysis suggests that additional research on parameter assumptions would most cost-effectively improve precision if expended on these two kinds of parameters.

52 With optical prices fixed, and defender prices falling as originally assumed, median forecasted benefits are \$0.95 B, or \$0.57 B at the 5th percentile.