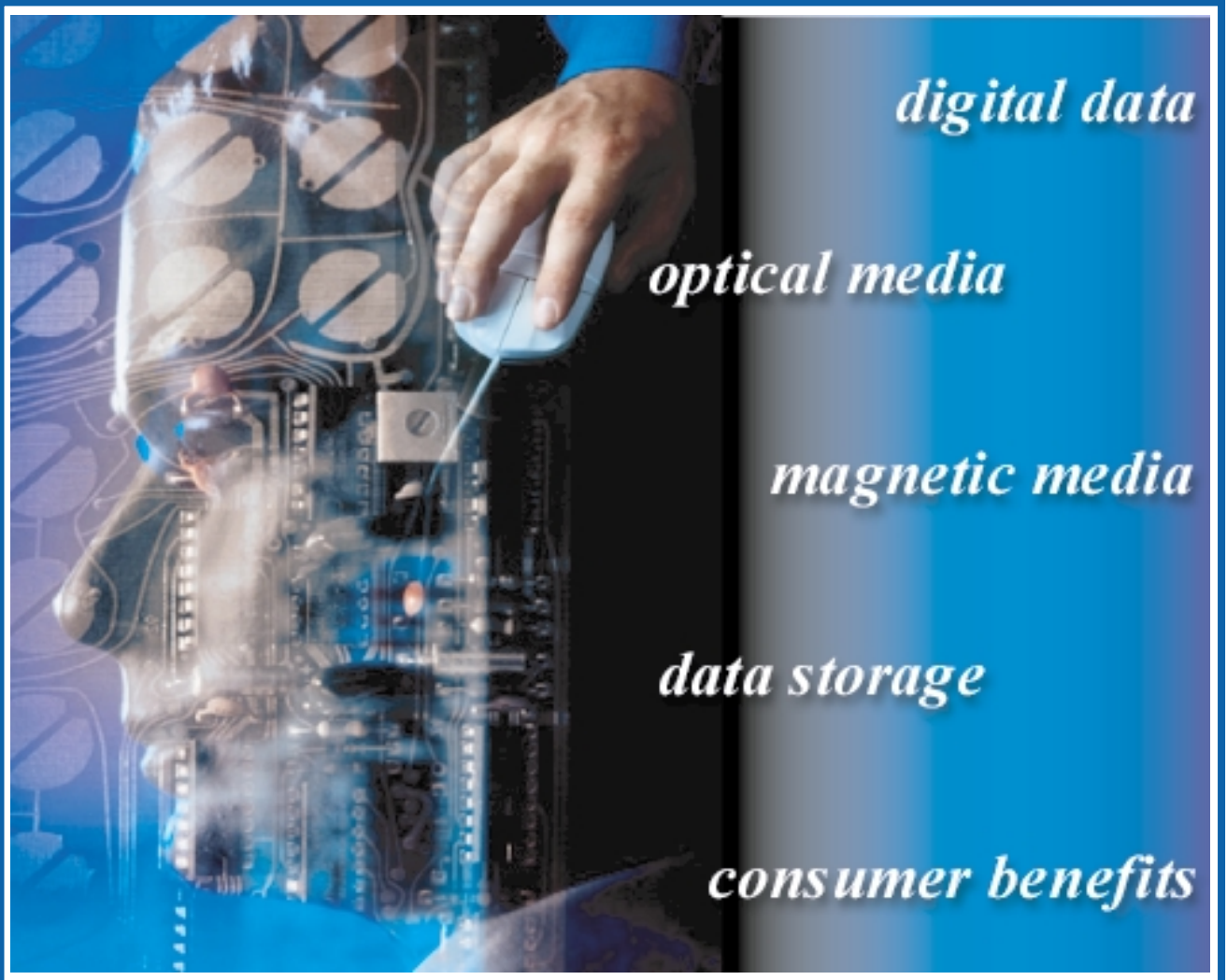




# *Estimating Future Consumer Benefits from ATP-Funded Innovation: The Case of Digital Data Storage*



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**Estimating Future Consumer Benefits from  
ATP-Funded Innovation:  
The Case of Digital Data Storage**

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## **ABSTRACT**

This report develops a method that uses a quality-adjusted cost index to estimate expected returns to investments in new technologies. The index method addresses the problem of measuring social benefits from innovations in inputs in the service sector, where real output is not directly observable. The study forecasts consumer benefit gains from two innovations in digital data storage that were funded in part by the Advanced Technology Program (ATP): one innovation pioneers the use of optical tape, and the other replaces helical with linear scanning of magnetic tape. The estimated consumer benefit gain for the optical tape technology exceeds \$1 billion, and for the linear scanning technology, \$2 billion, taken over a five year period, when compared to the existing trend in current technologies. The model's probabilistic parameters reflect uncertainty about prospective outcomes and also in the hedonic estimates of shadow values for selected product attributes. While applied here to new technologies funded by ATP, the cost index method can be adopted readily by other R&D managers in industry and government to estimate the benefits of technological advances.

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

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## EXECUTIVE SUMMARY

### A Model for Estimating Consumer Benefit Gains

Measuring or forecasting consumer benefits is an important part of any 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 benefits, that is, “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 observed price and performance for an innovated product against hypothetical, best-available price and performance had the technical advance not occurred. Since prices of other goods and services in consumers’ choice sets cancel out, the index is a function only of observed and hypothetical technology product 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 evaluating 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.<sup>1</sup> 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 for consumers’ preferences for differentiated product characteristics, which provide 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 investment, as well as for evaluation *per se*.

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<sup>1</sup> This kind of analysis would satisfy the requirements of the 1993 Government Performance and Results Act for federal government programs.

## **Applying the Model to Two ATP-Funded Projects**

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 to existing tape drives. We estimate how much better off consumers will be with the innovations, relative to the new technologies not being introduced.<sup>2</sup>

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., file access times) of digital tape data-storage devices. Given our data sources, we adopt conservative parameter assumptions with respect to price and performance of the innovations, their rates of adoption, and the size of the market. We also provide qualitative conclusions based on our model's 5<sup>th</sup>-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 best available performance, though in most dimensions lagging that of the would-be innovations, improves at the same rate as the new technologies 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.

### **Results of Estimation**

Our analysis shows that these first generation technologies, if successfully introduced, should generate over five years consumer welfare gains of approximately \$2.2 billion (linear scanning) and \$1.5 billion (optical tape), relative to the best existing technologies, even

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\* See Appendix for project profiles.

<sup>2</sup> 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.

assuming the existing technologies improve at faster than historical rates. These estimates are medians of probability distributions; the corresponding 5<sup>th</sup>-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 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.<sup>3</sup>

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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<sup>3</sup> 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.

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## I. A COST INDEX APPROACH TO MEASURING CONSUMER BENEFITS

Bresnahan (1986) shows that a Törnqvist cost index (Caves, *et al.* (1982)), can be used to measure consumer benefits, or “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).<sup>4</sup> 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.<sup>5</sup> If there is downstream market power, the cost index will give a lower bound estimate of consumer gain. Therefore, while we do not believe downstream market power is a significant issue in our analysis, omitting consideration of it is in fact consistent with a conservative estimate of consumer benefit gains.

Figure 1 illustrates the expected gain in consumer surplus from an outward shift in the supply curve (*e.g.*, due to 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 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 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.

<sup>4</sup> 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.

<sup>5</sup> 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. In either case, the cost index provide a correct measure of consumer gains.

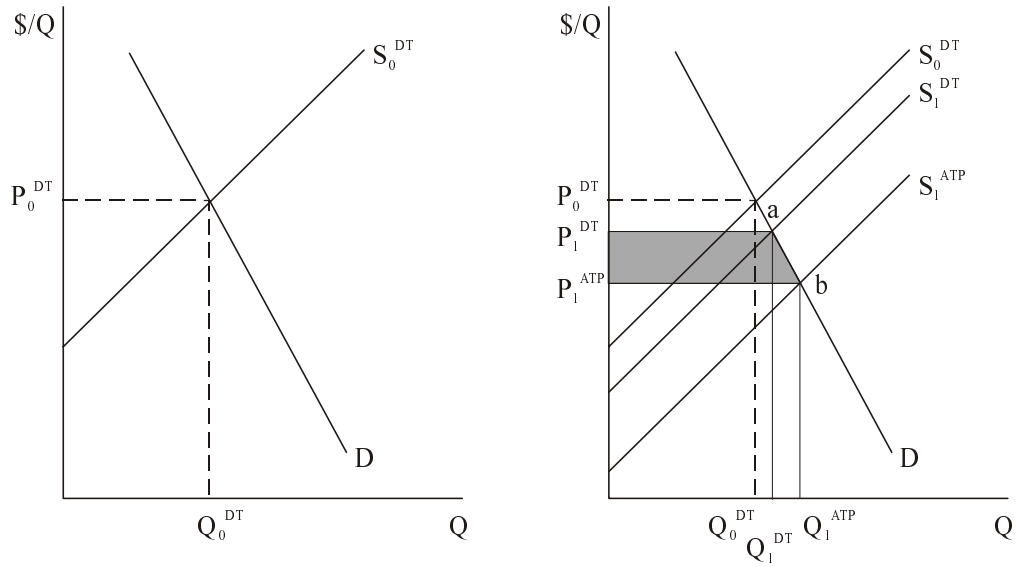


Figure 1. Derived Demand for New Technologies:  
Illustration of Net Surplus Change

## II. 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.<sup>6</sup> 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  $x$ ,  $y \in \{\text{defender technology } (DT), \text{ Innovation } (I)\}$ , and  $\Delta \dim_x$  represent the absolute value of the difference in performance between innovation and defender, *i.e.*,

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

where  $x \in \{\text{Capacity } (CAP), \text{ Transfer Rate } (TR), \text{ File Access Time } (FAT)\}$ . We estimate shadow values  $\beta_x$  in a hedonic regression,<sup>7</sup> and then add  $(\beta_x \cdot (\Delta \dim_x))$  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, off-the-shelf (nominal) price, and bracketed terms being indicator variables, our quality adjustments to price of defender  $DT$  and the innovation  $I$  are:<sup>8</sup>

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<sup>6</sup> Competition in these markets leads to a level of services production—and demand for DDS—that is the same as if consumers were producing those services themselves, since without market power, production is at consumers' optimal level.

<sup>7</sup> See appendix for a description of the hedonic data and analysis.

<sup>8</sup> 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.



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

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

We assume shadow values decline over time,<sup>9</sup> 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* the 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 geometric average of the two.<sup>10</sup>

Following Caves *et al.* (1982), we assume digital data storage devices are separable from other consumption in the consumer's utility function,<sup>11</sup> 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 Equation (1) is then the cost of achieving utility  $u^{DT}$ , which is optimal in the baseline scenario, relative to the cost of  $u^{DT}$  given the ATP innovation, where  $W^{DT}$  and  $W^A$  are baseline prices and post-innovation prices for DDS services. Similarly,  $C^{*I}$  is

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<sup>9</sup> Time subscripts have been suppressed in this expression.

<sup>10</sup> 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).

<sup>11</sup> Marginal rates of substitution for other consumption goods are unchanged at different levels of DDS consumption.

the cost of achieving optimal utility  $u^I$  under the innovation scenario, relative to cost of  $u^I$  in the baseline case:

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

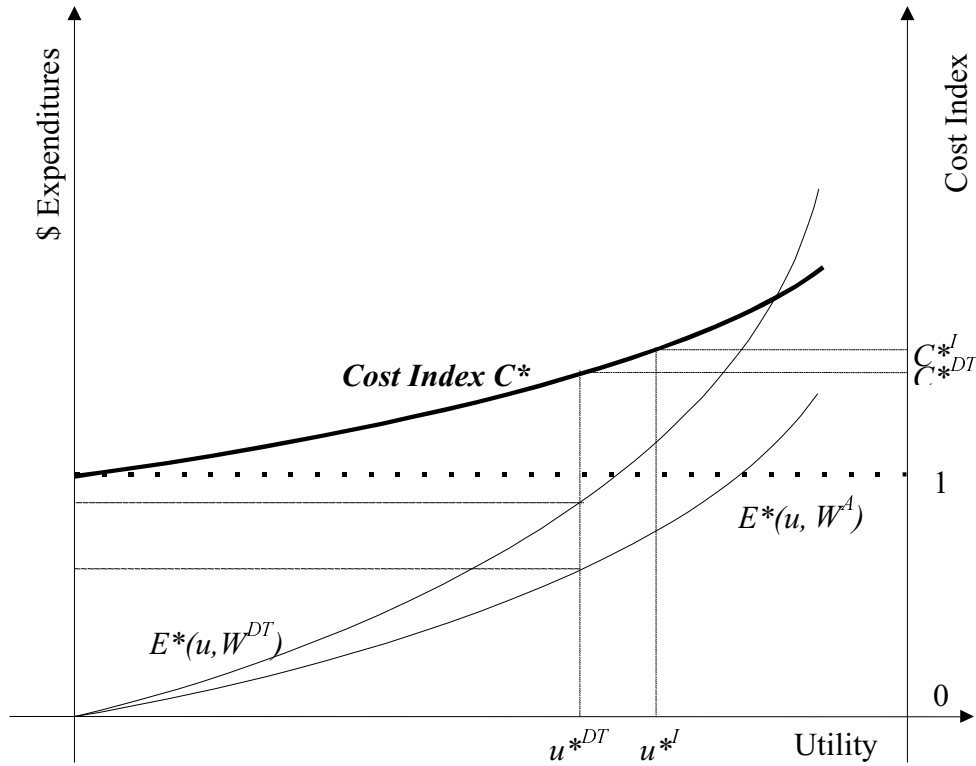
Because we assume an innovation is adopted gradually, the quality-adjusted DDS prices faced by post-innovation consumers is not  $W^I$ , the price of the new technology. Instead, on average the post-innovation price for DDS is  $W^A = \rho W^I + (1-\rho)W^{DT}$ , where  $\rho$  is the adoption rate of the innovation.<sup>12</sup> Prices  $P$  of other commodities can change over time, but we assume that they are unaffected by innovation in DDS, so  $P^{DT} = P^I$  at all times.

Figure 2 depicts the relationship between expenditure function  $E$ , utility  $u$ , and the two cost indexes  $C^{*DT}$  and  $C^{*I}$ . 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  $u^{*DT}$ . This means that here the Paasche willingness-to-pay index  $C^{*I}$  exceeds the Laspeyres willingness-to-accept measure  $C^{*DT}$ , which fixes DDS consumption at a lower level.

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<sup>12</sup> 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 comprising a new product category).

Figure 2. Relationship Between Expenditure Function and Cost Index <sup>13</sup>



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<sup>14</sup>:

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

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.<sup>15</sup> We forecast values for the

<sup>13</sup> To simplify figure labeling, prices  $P$  have been omitted from the expenditure functions.

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

<sup>15</sup> See appendix for description of the expenditure-share parameter. PCE data are from “Personal Income and Outlays,” Bureau of Economic Analysis. We assume the additional DDS expenditures in the innovation scenario do not affect PCE (as DDS is a tiny fraction of PCE, there would be very little displaced consumption).

cost index, Equation (2), for the years 2000 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.<sup>16</sup> This corresponds to the area of the shaded rectangle in Figure 1.

Unlike the familiar Consumer Price Index which compares prices over time, Equation (2) compares prices in a *single* period—expected, future prices given the innovation *versus* hypothetical, future prices assuming no innovation. 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 of the consumer utility function assures that these parameters cancel out in Equation (2).

Changes in relative DDS prices will affect the mix of inputs used in production. However, no assumptions about input substitutions are necessary because the translog function places no restrictions on the elasticities of technical substitution between inputs.<sup>17</sup> The translog function also does not restrict the income and price elasticities of demand for DDS-using services. DDS innovation may affect equilibrium prices for these services, implying movement along their respective demand curves. The translog expenditure function also permits arbitrary shifts in these demand curves—say due to innovation in complements to these 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 function can accommodate taste-driven changes in demand for DDS, as for computer technologies generally.<sup>18</sup> This assumption on consumers’ elasticities of substitution is a restriction on changes in consumers’ tastes for DDS-using services relative to other consumption. Because our forecasting window is relatively short, this is not an overly restrictive assumption.

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<sup>16</sup> Equation (2) is actually the percentage change in consumer surplus from DDS innovation, which takes values near zero because DDS is a very small portion of the cost of living. To calculate the cost index in absolute terms, Equation (2) must be exponentiated. Note that 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).

<sup>17</sup> We have introduced expenditure functions with respect to consumers. Here it is appropriate to discuss the production of information services, because our assumption of a competitive market structure implies that producer profit maximization and consumer expenditure minimization are equivalent.

<sup>18</sup> These features of translog functions are noted in Bresnahan (1986), p. 751.

### III. DATA AND ESTIMATION

The cost index is a function of estimated total DDS expenditures as a share 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 rate of adoption of the innovation. The index also incorporates expectations about the values of all of these parameters over the relevant time horizon.

The cost index itself is simply the ratio of quality-adjusted DDS prices, scaled by the average share 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. Benefits per unit of DDS, however, will be large.

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

Lognormal density functions have long upper tails and might be used to model this pioneer bias. But since we have only one or two point estimates per product—from interviews with innovators—there is no empirical basis for choosing one family of curves over another. We therefore use triangular functions to model the asymmetrical distributions: they are easy to use 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 parameter distributions for the existing products. We make our forecasts of these parameters on the basis of recent trends in leading DDS devices. We assume, conservatively,

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<sup>19</sup> The model’s initial period is linked to the introduction of a new product.

<sup>20</sup> 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.

that prices of the existing products will decline—and their performances improve—at the same rate as for the innovations.<sup>21</sup>

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 use to construct the initial-period probability distributions for the shadow values. For the other 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 the later years. We use 30% standard deviations for the upper tails of the asymmetric distributions of the innovations.

The randomness in the model's parameters derive from 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 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 be explored. Sensitivity tests reveal the extent to which it is necessary to consider alternatives, and allow us to bound the expected benefits in a meaningful way.<sup>22</sup>

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 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, we report specific details about our data sources and parameter assumptions.

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<sup>21</sup> 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 probably have already been achieved.

<sup>22</sup> In addition to making conservative forecasts, our analysis ignores benefits from second-generation products, and any 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.

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## IV. RESULTS

We calculate an index to compare costs at a single point in time, with and without the DDS innovations. Since DDS expenditures comprise a tiny fraction of total consumption expenditures, the value of the index is only slightly greater than one. On a per-unit basis, however, both of the innovations are predicted to generate significant consumer benefits.<sup>23</sup> The performance specifications for the new technologies are clearly superior to those of existing products, and their target prices are similar, so welfare gains are expected. The purpose of this analysis is to estimate their magnitude, and to see how uncertainties about parameters propagate through the model to affect the benefit estimate.

In present-value terms, we find that the median estimate for consumer welfare gains over five years is \$2.2 billion for the linear scanning technology, and \$1.5 billion for optical tape, discounting at a 5% annual rate. Compared to current DDS trends, the innovations would create approximately \$2,400 in additional consumer welfare per linear scanning device sold—about 23% of the expected unit price—and \$20,800 per optical tape device—about 50% of the unit price.<sup>24</sup> 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 initial total welfare gains will be lower due to minimal early market penetration. By the 5<sup>th</sup> year, we assume rates of adoption for linear scanning and optical tape devices will reach 40% and 30% of new medium- and high-capacity unit sales, respectively. Knowledge spillovers and follow-on improvements are not estimated here. If knowledge spillovers occur, our benefit 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 statistical variation in our estimates implicitly allows for these possibilities, provided our assumptions about market shares and price changes (or equivalently, 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<sup>th</sup>-percentile estimate of benefits are driven to zero only by large changes in specific parameter assumptions.

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<sup>23</sup> 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 comprises a very small part of the economy.

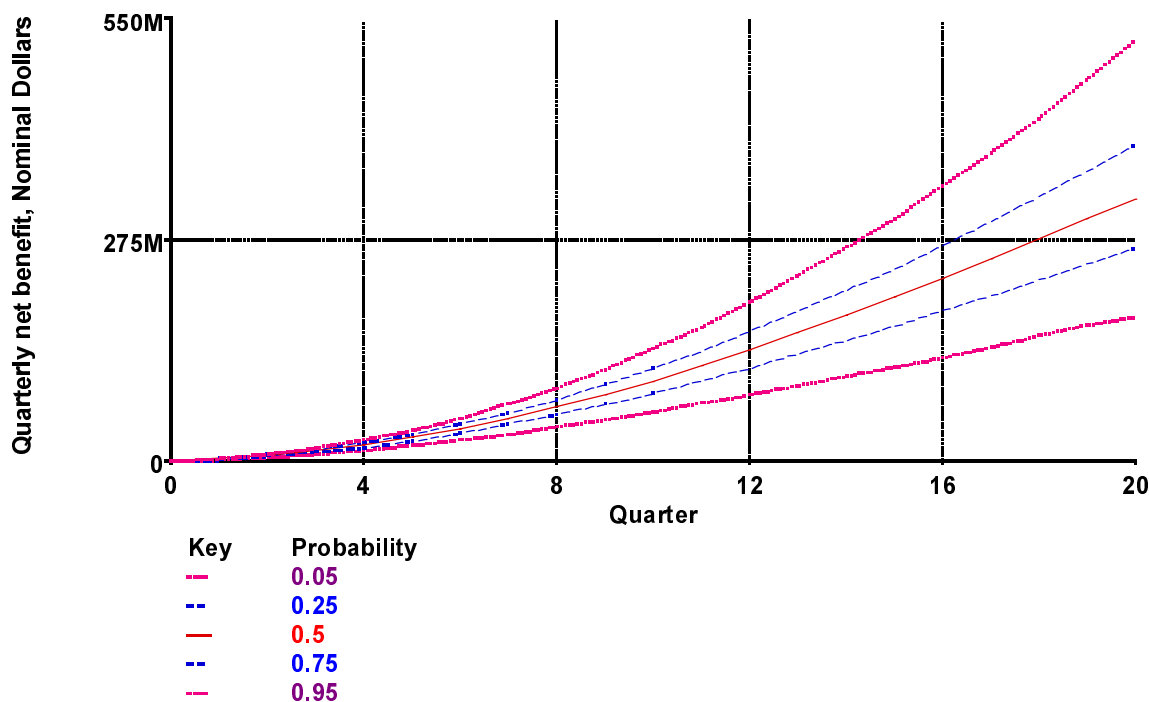
<sup>24</sup> The mean model forecast for unit sales in (2004, Q4) is approximately 133,790 linear scanning devices, and 10,670 optical tape units. Innovators of the linear-scanning technology report cost *and* price expectations; based on this, their producer surplus in the 5<sup>th</sup>-year would be approximately 30% of expected price.

**Table 1: DDS Innovations, Net Present Value of Consumer Welfare Gains Over Five Years (\$ billions, 2000)**

Percentile	LINEAR SCANNING	OPTICAL TAPE
5 <sup>th</sup>	1.25	1.05
25 <sup>th</sup>	1.79	1.30
Median	2.16	1.45
75 <sup>th</sup>	2.53	1.62
95 <sup>th</sup>	3.17	1.88

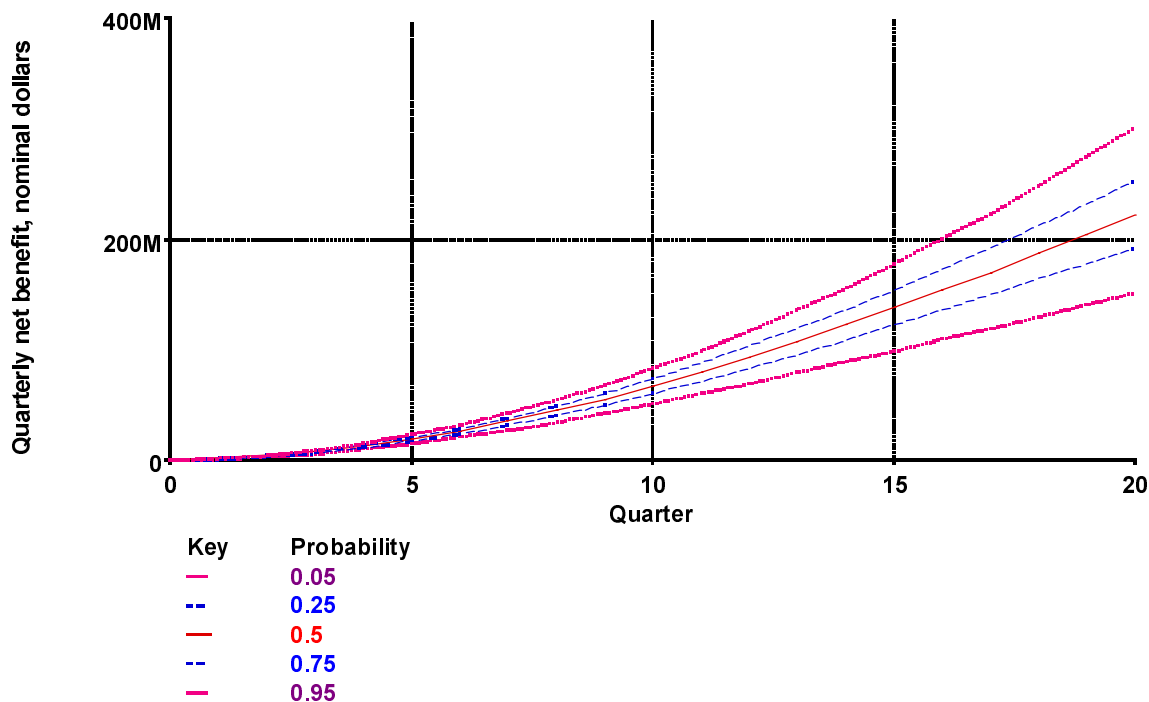
Figures 3 and 4 show how gains are expected to accumulate over time. The shapes of these curves are determined principally by our assumptions about rates of adoption, growth in demand for DDS devices, and changes in price. Our five-year forecasting window is a compromise between forecasting into the indefinite future—which is to assume the ATP has pushed DDS technology permanently to a higher level—and making no forecast at all, which would be to assume the innovations would have been achieved anyway with no change in timing.

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





**Figure 4. Consumer Benefit Given Successful Introduction:  
Optical Tape Innovation vs. Defending Products**



### Sensitivity Analysis

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 the uncertainty parameters. Second, we consider the effects of parameters that affect 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 adoption rate is slightly greater than one. Raising the price of the innovation, and lowering the rate of adoption and the rate of 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.

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The market and consumer valuation parameters 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 changes in these parameters. This is also why benefits are not very sensitive to the performance parameters. For the current model configuration, then, applying marginal shadow valuations to large changes in performance does not pose problems. The key market parameter is market size. The elasticity of benefits is roughly unity with respect to this parameter, since 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 the two market parameters is most highly correlated with uncertainty in the benefits forecast. 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 summary, in our model, market size for DDS tape technology and the adoption rate for the innovations are the most important factors for estimated consumer benefits.<sup>25</sup> Lowering both parameters simultaneously by 50% reduces estimated benefits by 75%. To drive 5<sup>th</sup>-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).

Details of our sensitivity analysis can be found in the Appendix.

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<sup>25</sup> 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.

## V. CONCLUSIONS

Our analysis has shown that consumer welfare gains from ATP investments in digital data storage are likely to be substantial. The median estimate for expected benefits of innovation, given successful completion of these projects, is equivalent to approximately 23% of the target price of the linear scanning device, and 50% of the price for the optical tape drive. We compare the anticipated innovations to a hypothesized scenario that assumes current technological trajectories continue as before. The estimated welfare gains are relative to consumer surplus already produced by the 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 median estimate of total consumer welfare gains from these innovations would be several billion dollars each.

A full assessment of the ATP's DDS investments would also consider other, failed DDS investments the ATP has made, as well as the opportunity costs of all of these investments. However, we note that just one success on the scale of the forecasts in this paper would far outweigh the ATP's total annual investments in all areas of technology.

The "total" consumer 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 course, or accelerated developments that would have occurred eventually. While we do not address that issue, 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 details of the model in its application to one new area of 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 A: Data and Methods

### Data

Our data on the ATP supported innovations—and on technologies considered to be future competitor technologies—come from structured interviews we conducted in the Spring of 1998 with the leaders of the innovating teams.<sup>26</sup> The interviews concerned specific details about the proposed technologies and the market conditions they are expected to face. 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.<sup>27</sup> 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.<sup>28</sup> 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.<sup>29</sup>

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. While there are in principle three sources of uncertainty that can affect the parameters of the model—variability in manufacturing and market conditions; imperfectly observed data; uncertainty about future outcomes—we believe the third source dominates. In our analysis, we assume uncertainty increases over time.

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<sup>26</sup> Our access to project leaders and their information was gained through the assistance of the Advanced Technology Program. 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.

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

<sup>28</sup> 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 the latter segment.

<sup>29</sup> The technical experts we consulted are employees of NIST’s National Measurement and Standards Laboratory. They suggested a number of changes in our assumptions, which we implemented.

**Table A-1—Structured Interview**

<b>I. TECHNOLOGY</b>
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: <i>megabytes per second; terabyte capacity; meters/sec tape speed</i>
ii. Digital linear scanning: <i>megabytes per second; terabyte capacity; meters/sec tape speed</i>
3. At the start of your project, the best available technologies were capable of:
<b>File access time:</b> <i>secs</i> . Your project was initially expected to achieve <i>XX secs</i> , a <i>YY%</i> gain in average access time over the then current best available technology (BAT). Is this information still correct? What is now the best <i>currently available</i> file access time?
<b>Storage capacity:</b> <i>gigabytes</i> . Your project was expected to achieve <i>XX gigabytes</i> , a <i>YY%</i> gain in capacity over the current BAT. Is this still correct? What is now the best <i>currently available</i> capacity?
<b>Data transfer rate:</b> <i>MB/sec</i> . Your project was expected to achieve <i>XX MB/sec</i> , a <i>YY%</i> improvement over the then-current BAT. Is this still correct? What is now the best <i>currently available</i> 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? <i>(List specific dimensions of product performance.)</i>
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?
<b>II. MARKET</b>
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? <i>(As driven by continued R&amp;D or learning-by-doing, as well as anticipated market dynamics.)</i>
7. What are your most important market-related hurdles? <ul style="list-style-type: none"> <li>• Is it critical to be first to market?</li> <li>• How likely is it that improvements in the defender technology would render yours uncompetitive?</li> <li>• Does the success of your innovation depend on new applications arising for digital data storage?</li> <li>• Will it be necessary for users to adopt complementary technologies to take advantage of yours?</li> </ul>
8. What is the “off-the-shelf” price of the defender technology? <i>[This item probes respondent’s familiarity with or identification of its competitors. The model uses manufacturer data.]</i>
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)? <i>[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 of disinterested experts. We conclude 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 that the innovations will create.]</i>
12. Do you expect your innovation will drastically change any of these [shadow prices]?
13. Have we omitted any important market issues?

### Shadow Values

Compared to existing products, the DDS innovations promise improved performance at comparable prices. If they are successfully introduced, it is likely the innovations will enhance consumer welfare. The interesting question is therefore 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.

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*<sup>30</sup> dating from 1994-1998.

The model we estimate is:

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

<sup>30</sup> Ziff-Davis



where the intercept term  $\alpha$  and the coefficients  $\beta_x$  are parameters to be estimated, and  $\varepsilon$  is a mean-zero, normally-distributed error term. The fitted coefficients  $\hat{\beta}_x$  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,<sup>31</sup> and *time* in quarters since (1994, Q1). 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.<sup>32</sup> 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 1 GB than when it is 100GB.<sup>33</sup> 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.<sup>34</sup> 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.

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<sup>31</sup> 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.

<sup>32</sup> The coefficient on *Access Time* is negative, as expected for the same reason.

<sup>33</sup> 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.

<sup>34</sup> NIST technical expert, personal communication.

**Table A-2: Shadow Value Forecasts<sup>35</sup>**

Attribute	Shadow Value (std. dev.) Estimate: 2000	Forecast: 2005
Data Transfer Rate	<b>\$791</b> /MB/sec (\$208)	<b>\$433</b> /MB/sec
Storage Capacity	<b>\$39</b> /GB (\$9.88)	<b>\$13</b> /GB
File Access Time <sup>36</sup>	<b>\$49</b> /sec (\$12.25)	<b>\$40</b> /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.

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 reach 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 is now the most important constrain—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.<sup>37</sup> See Figure A-1.

<sup>35</sup> 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 for file access time. These guesses appear to be quite optimistic; given their price targets the manufacturers clearly have no intention of extracting this prospective consumer surplus. The third guess for file access time is somewhat more plausible, as we will discuss.

<sup>36</sup> Estimated shadow value of *reduction* in access time is based on a heuristic argument. Hedonic methods did not work well for this attribute, as we explain below.

<sup>37</sup> 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,

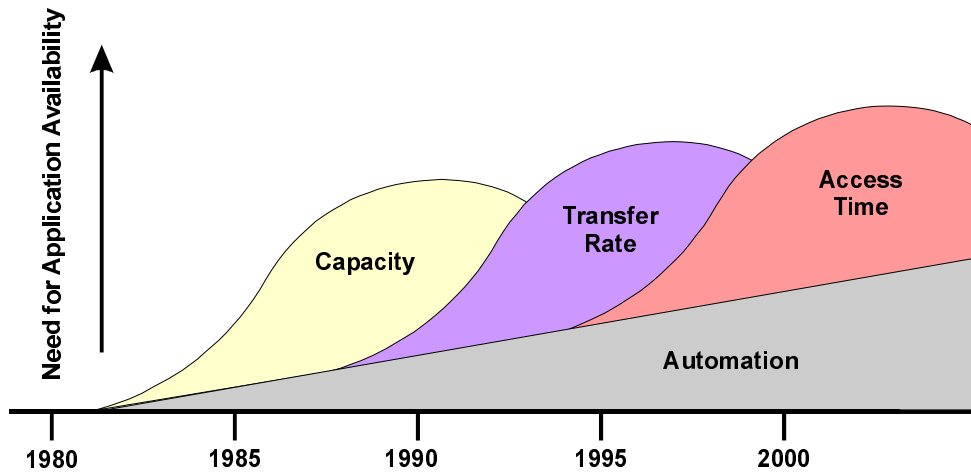


Figure A-1: Technological Constraints in Digital Data Storage<sup>38</sup>

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:

$$(\text{file requests/day}) * (\text{service days/year}) * (\text{years of service life}) * (\text{value of worker time/second}).$$

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.<sup>39</sup> 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

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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.

<sup>38</sup> Figure taken from “Tape Opportunities for the ‘90s and Beyond”, *op. cit.*

<sup>39</sup> 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.

data storage demands sufficient to induce the purchase of a DDS device. We conservatively assume average usage of a device does not grow over time.

**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

At ten 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.

#### *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. For file access time, we assume shadow values will decline at a 1% rate. We specify shadow values to decline according to an exponential function, so as to prevent forecasting of negative shadow values by 2005. So shadow values are specified as:

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

where  $\beta_{x,0}$  is the estimated shadow value for quality attribute  $x$  in the initial period,  $r_x$  is the estimated coefficient of interaction term ( $x \cdot t$ ) in the hedonic regression, and  $t$  is time in quarters, from (2000, Q1) to (2005, Q1). These functions yield rates of decline which appear nearly linear in the initial years, and which 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 below.

## **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 (comprising, 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.<sup>40</sup>

Our assumptions for the probability distributions of 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

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<sup>40</sup> 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
Linear Scanning Innovation	Triangular (9,10,12)	\$10k price target. 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 1999, Quantum's price was \$4.8k, but this is similar to our model's projection for that time. We assume 2.5% standard deviation.
Optical Tape Innovation	Tri (38,40,48)	\$40k price target. We assume (-5%,+20%) dispersion.
Virtual Defender (magnetic tape)	N(63.3, 1.6)	IBM (\$47.3k), Ampex (\$115k); 2.5% standard deviation.

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

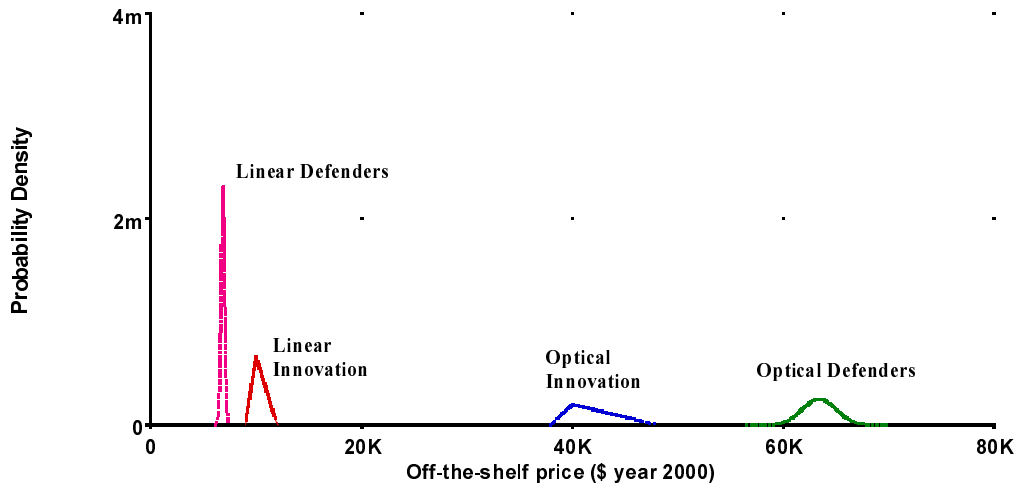


Figure A-2:  
Nominal Price Distributions For Defender Technologies and Innovations

Quarterly Rate of Change in Nominal Prices

We assume that nominal prices decay exponentially according to  $p_t = p_0 \cdot e^{-\rho t}$ , where  $p_0$  is the initial off-the-shelf price and  $\rho$  is the rate of decline per quarter  $t$ . For each innovation,

we solve for the rate  $\rho$  such that the expected price for the 20<sup>th</sup> quarter equals the innovator’s year-5 forecast. For all of these products, the resulting  $\rho$  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
Linear Scanning Innovation	Tri (-0.06,-0.0578,-0.018)	Initial price of \$10k, \$5k after two years. Upper tail of this distribution is consistent with price of \$7k after <i>five</i> years. Lower tail gives nominally faster decline.
Virtual Defender (helical scanning)	Tri (-0.06,-0.0578,-0.018)	Assumed distribution set equal to the innovation.
Optical Tape Innovation	Tri (-0.03,-0.024,-0.014)	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)	Assumed distribution set equal to the innovation.

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

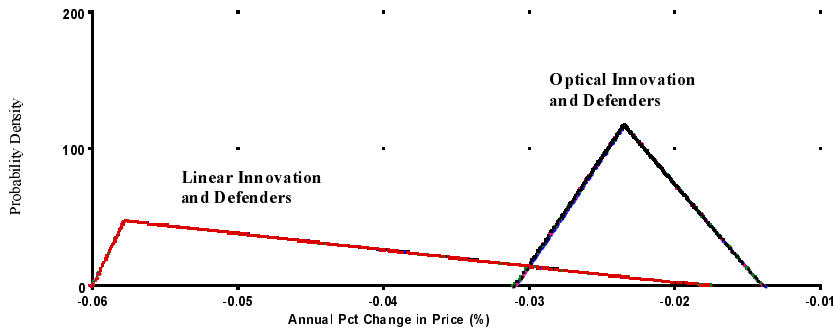


Figure A-3: Rates of Exponential Price Decay

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  $P_{err}(t) = P(t) * (1 + \text{perturbation} * t)$ , 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
Linear Scanning Innovation	Tri(18, 25, 30)	Expected range 20-30 MB/sec. While we hold quality fixed (changing only price), innovators report expectation of faster rates by 2000.
Virtual Defender (helical scanning)	N(5.8, 0.145)	Market weighted average transfer rate; 2.5% std. dev.
Optical Tape Innovation	Tri (23, 25, 26)	Expected 25 MB/sec. We assume (-10%, +5%) dispersion.
Virtual Defender (magnetic tape)	N(14.3, 0.3575)	Market weighted average transfer rate; 2.5% std. dev. Best current transfer rate is 15 MB/sec (Ampex DST312).

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

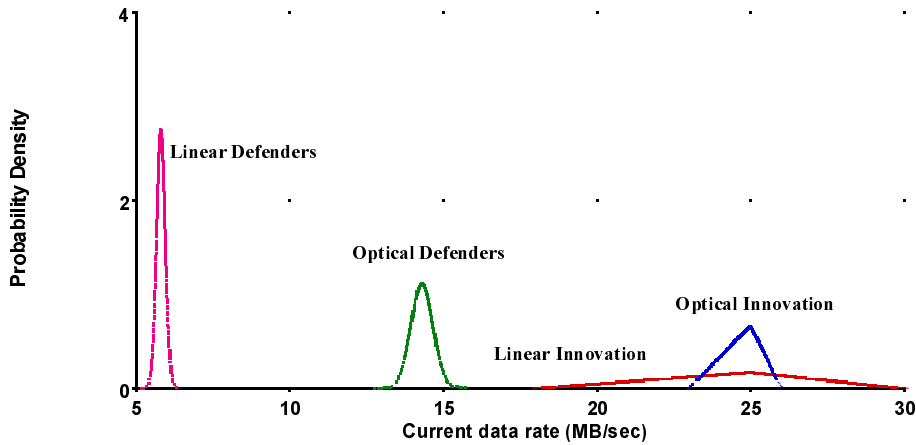


Figure A-4:  
Current transfer rate – Innovations and Defender Technologies

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



Drive	Capacity (Gigabytes)	Notes
Linear Scanning Innovation	Tri(14.7,16,16.66)	Confident expectation 16 GB. Lower and upper bound set at 5 <sup>th</sup> percentile of N(16,8) and 95 <sup>th</sup> percentile of N(16,4) distribution, respectively.
Virtual Defender (helical scanning)	N(36, 0.90)	Mean reflects figures reported in current product literature. Standard deviation is 2.5% of mean.
Optical Tape Innovation	Tri(918,1000,1041)	Confident expectation 1000 GB. Lower and upper bound set at 5 <sup>th</sup> percentile of N(1000,50) and 95 <sup>th</sup> percentile of N(1000,25) distribution, respectively.
Virtual Defender (magnetic tape)	N(233.5, 5.84)	Mean reflects figures reported in current product literature. Standard deviation is 2.5% of mean.

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

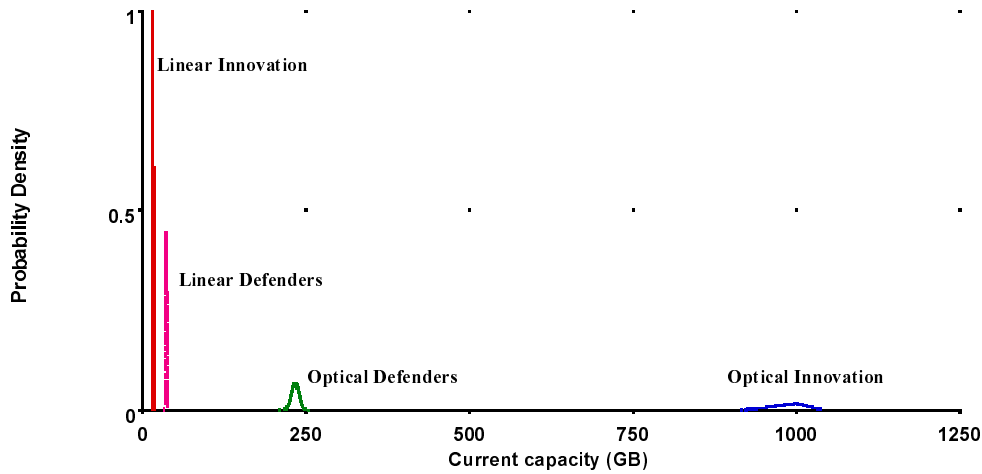


Figure A-5: Storage Capacities: Innovations and Defender Technologies

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 are choosing as their standard.

Drive	Access Time (seconds)	Notes
Linear Scanning Innovation	Tri (7.2, 7.5, 10)	Expected 10-second access time as of 1997; expected 7.5 by 2000. Upper assumes no progress after 1997. Lower bound is analogous to lower bound for optical innovation (below).
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)	Expected range 20-25 seconds spool time. We assume 24 seconds +2.5 / -1.0; access time is half of spool time.
Virtual Defender (magnetic tape)	N(38.6, 0.965)	Mean reflects figures reported in current product literature. Ampex offers access time comparable to the innovation. IBM's plans to introduce longer tape some time in 1999 are not reflected here. 2.5% standard deviation is assumed.

Figures A-6 illustrates these assumptions.

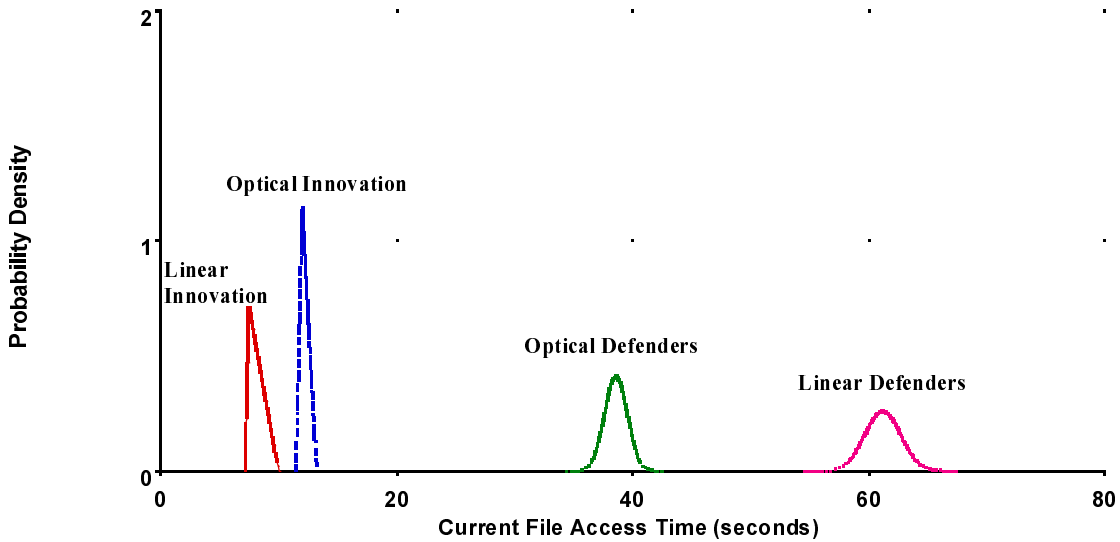


Figure A-6: File Access Times for Innovators and Defenders

Market Size

Market Segment	Unit Sales (000s)	Notes
<b>Medium-capacity drives</b> (Digital, Linear Scanning Innovation & Defenders)	Uniform (198.05,267.95)	Our model (described below) predicts year 2000 sales as: 27,000 units of Sony GY2120; 206,000 units of Quantum DLT 7000. Total is 233,000 for medium-capacity market segment. Bounds reflect 15% variation around this value.
<b>High-capacity drives</b> (Optical Tape Innovation & Defenders)	Uniform (20.71, 28.03)	Our model (described below) predicts year 2000 sales as: 18,600 units of IBM 3590; 5,700 units of Ampex DST 412. Total is 24,300 for high-capacity market segment. Bounds reflect 15% variation around this value.

We intend these estimates to be somewhat conservative. We ignore smaller manufacturers. Since 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) provided by our interviews. This yields a linear inverse-demand curve of  $\log(Q) = 22.5 - 1.2 \cdot \log(P)$ , which seems to fit the data quite well ( $R^2 = 0.93$ ). We use this formula as the basis for predicting quantities sold in year 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.<sup>41</sup> 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.

<sup>41</sup> NIST technical expert, personal communication.

*Expected Growth in Market Size*

Scenario	Quarterly Growth Rate	Notes
<b>Baseline</b> (No public funding for DDS innovation)	N (1.5%, 0.225)	Linear growth assumed: Mkt-Size(t)=Mkt-Size(t-1)*(1+(t*Growth Rate)). See text.
<b>Innovation</b> (Public funding support results in Linear Scanning 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.<sup>42</sup> As we expect growth in 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 additional stimulated demand beyond the BEA linear forecast. To reflect our expectation that demand growth may be greater given public-sector funding support, 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, under a normal distribution.

Initially, the average innovation-scenario prediction is similar to the baseline market size forecast; after about the 8<sup>th</sup> quarter, however, the two predictions begin to diverge significantly, until in the 20<sup>th</sup> 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<sup>th</sup>-percentile growth rate is 2.7%, which is still less than some of our interviewees’ much more optimistic expectations. We address impact on estimates due to variation in expectations in our sensitivity analysis.

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<sup>42</sup> 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 conservative approach to use the smaller, information services forecast.

*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.

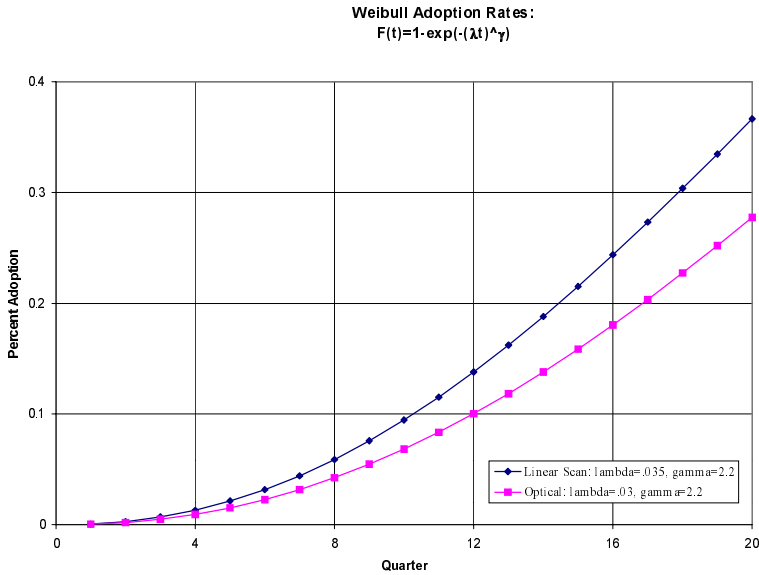
We assume that the innovation will partially displace sales of defender technologies and partially expand the market. In the model, innovation market shares increase monotonically with time according to the following Weibull process:

$$F(t) = 1 - \exp(-\lambda t^\gamma)$$

Here  $t$  is time in quarters,  $\lambda$  is a scale parameter,  $0 < \lambda < 1$ , having the interpretation of a hazard rate (which is therefore assumed to be constant), and  $\gamma > 0$  is a shape parameter. It is difficult to associate  $\lambda$  and  $\gamma$  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.<sup>43</sup> Figure A-7 shows a detail of the Weibull functions showing our assumed market shares over time for the two innovations, given they are successfully introduced.<sup>44</sup>

<sup>43</sup> 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  $\lambda$  and  $\gamma$ , requiring us to treat them as predetermined constants in our simulation model.

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



**Figure A-7: Weibull Adoption Rate Curves: Percent of Current Sales**

*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. 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 (1982, Q1), the resulting equation is  $PCE = 449,228 - 227.7 \cdot QTR$ , 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 (2000, Q1).<sup>45</sup> We assume uncertainty in PCE increases by an additional 0.25% per quarter thereafter.

<sup>45</sup> 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.

*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)

See Table A-2 and the earlier discussion of estimated shadow values and rates of change of shadow values. We base our assumptions for variance of shadow value estimates on the estimated standard errors from the fitted hedonic regression model. Because our estimate for file access time 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 assume the access-time shadow value has standard deviation equal to 25% of the mean.

**Sensitivity Analysis**

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

*Innovation Parameters*

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' rate of adoption and initial price than to their performance characteristics.<sup>46</sup> For the *linear scanning* innovation, benefits are also somewhat sensitive to the data transfer rate attribute, because that category provides most of its advantage over the products that we compare it to. For both new technologies, benefits are also slightly sensitive to rate of change in price.

<sup>46</sup> 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, in our base analysis, we assume that defender prices and innovation prices decline at the same rate.

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

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

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

† Rate of adoption, initial price, and rate of change in price all made better (or worse) simultaneously for the innovation technology. Rate of adoption and rate of price decline increased (decreased) while initial price decreased (increased).

Price and adoption rate are influential because total benefits equal per-unit benefits—which depend directly on price—times total unit sales, which is a direct function of the adoption rate. The elasticity of benefits with respect to rate of adoption is slightly greater than one because unit sales vary non-linearly with the rate of adoption, and this just cancels the effect of declining per-unit benefits over time.<sup>47</sup>

The last column of the table reports the effects of changing the rate of adoption and both price parameters 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 (for the innovation technology) reduces estimated benefits by more than 80%. The effect is the same for the opposite changes. For the initial price parameter, we consider such large changes to be unlikely: a 50% increase in introductory price is far outside even the wide bounds we set in our model. We also expect innovation prices should fall *faster*, not more slowly, than defender prices—for reasons stated earlier.<sup>48</sup>

<sup>47</sup> Per-unit benefits decline over time because consumer shadow values for quality differences decline as technologies improve.

<sup>48</sup> 5<sup>th</sup> 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.



Shadow Value 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 has a strong effect on benefits (though 5<sup>th</sup>-percentile forecasts are still well above zero). The elasticity of benefits with respect to market size is about one: market size acts as a scaling factor and can be factored out of the cost index.<sup>49</sup> For the same reason, the market size parameters has no effect on the sign of the benefits forecast.

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

<b>What if:</b>	Market size	Market growth	Market size and growth	Shadow value: transfer rate	Shadow value: capacity	Shadow value: access time	All shadow values
<b>Changed by:</b>							
LINEAR SCANNING (median present discounted value: \$2.18 billion)*							
<b>+50%</b>	<b>\$3.27 B</b>	2.44 B	<b>3.47 B</b>	<b>2.50 B</b>	2.16 B	2.28 B	<b>2.52 B</b>
<b>-50%</b>	<b>\$1.09 B</b>	1.94 B	<b>1.00 B</b>	<b>1.58 B</b>	2.19 B	2.06 B	<b>1.42 B</b>
OPTICAL TAPE (median present discounted value: \$1.46 billion)*							
<b>+50%</b>	<b>\$2.19 B</b>	1.64 B	<b>2.31 B</b>	1.51 B	1.58 B	1.47 B	1.62 B
<b>-50%</b>	<b>\$0.73 B</b>	1.30 B	<b>0.68 B</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, in order to provide valuation of differences in quality between products. The resulting valuations are added to the prices of the under-performing products. These price adjustments may be small, however, compared to the original price differences themselves, and their effects certainly pale in comparison to the effects of changing the numbers of units sold. In particular, the shadow value of access time,

<sup>49</sup> To see this, let  $\Phi$  represent the expression in Equation (2). Note that consumer benefits gain is  $(e^\Phi - 1) * PCE$ ; since  $\Phi$  takes values very close to zero,  $\Phi \approx (e^\Phi - 1)$ . The expression represented by  $\Phi$  contains factor shares  $s$ , whose numerators are DDS expenditures, *i.e.*, the product of DDS market size and average DDS price. Thus,  $\Phi$  can roughly be factored as:

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

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

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 ten (see Table A-3). Changing to the lower value drives median benefits down only to \$1.9 B and \$1.4 B, respectively, for the linear scanning and optical tape innovations.

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. 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.<sup>50</sup>

### *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 linear scanning and optical tape, 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 the actual rate could be as high as 2.5%.<sup>51</sup> 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<sup>th</sup>-percentile default forecasts.

Exploring parameter shifts that drive 5<sup>th</sup>-percentile benefits estimates to zero, we find that it is necessary to reduce all shadow values by 85% (linear scanning) or 90% (optical tape) to accomplish this. If we assume that new technology prices remain fixed for five years, while defender prices fall as originally assumed, 5<sup>th</sup>-percentile linear scanning benefits are slightly less than zero (with a median estimate at \$1.1 B); for optical tape, however, defender prices would have to drop more than twice as fast as we assume to eliminate innovation benefits.<sup>52</sup> In fact, we expect that new technology prices should drop more quickly than defender prices, due to learning economies and other sources of inexpensive cost savings that are likely to have already been exploited for existing products.

Finally, as expected, we find that the *rate* at which we assume shadow values will fall has little effect on forecasted benefits. Rates must be increased more than three and a half times to drive 5<sup>th</sup>-percentile linear scanning benefits to zero, and even a quadrupling does not push 5<sup>th</sup>-percentile optical tape benefits to zero. This result is predictable because the shadow values themselves do not have sensitive impact on benefit estimates.

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<sup>50</sup> Benefits are, similarly, not very sensitive to our assumptions about shadow value *rates of change*.

<sup>51</sup> “Computers and Peripheral Equipment”; Survey of Current Business NIPA table (August, 1998), U.S. BEA.

<sup>52</sup> With optical prices fixed, and defender prices falling as originally assumed, median forecasted benefits are \$0.95 B, and 5<sup>th</sup> percentile benefits are \$0.57 B.

### *Value of Information*

Aside from parameters that affect the *level* of benefits, we also look at the determinants of *uncertainty* in our forecasts. That is, variation in *which* parameters is most highly correlated with variation in the benefits? We find that there are only two parameters whose uncertainty is highly correlated with uncertainty in the benefits estimate. These are the DDS market-size parameter, and its rate of change over time. Recall that our assumptions about DDS market size are not based on direct market research, but on responses elicited in 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 parameters.

## APPENDIX B: Project Profiles

### 1. High-Performance, Variable-Data-Rate, Multimedia Magnetic Tape Recorder

*Develop the underlying technology for a tape-based storage medium and recorder system that can accommodate the high data capacity and data transmission and acquisition rates needed for digital formats ranging from satellite-based TV, to teleconferencing over phone lines, to terrestrial cable and broadcast television.*

**Sponsor:** *Imation Corporation  
1 Imation Place  
Oakdale, MN 55128-3414*

- Project duration: 10/01/1995 – 09/30/2000
- Total project (est.): \$21,094,896.00
- Requested ATP funds: \$10,441,972.00

An emerging irony in the information society is that ever more information is becoming available to individuals, yet it takes ever longer to acquire it. A major bottleneck rests in data storage technology, which affects over \$240 billion worth of U.S. industry. A joint venture assembled by the 3M Company, and continued by 3M spin-off Imation Corporation, proposes to address this dilemma by developing the technologies required for a small, reliable, affordable tape recording and cartridge system. In the proposed system, data will be recordable at rates greater than 30 megabytes per second with an ultimate goal of 100 megabytes per second. Moreover, the envisioned system would be capable of operating at the different data rates associated with satellite, cable, fiber-optic, and other digital data formats. The first major goal is to develop the technology for a linear tape drive that, at one-tenth the cost, can match and may exceed the performance and capacity of high-end helical-scan systems, a competing technology led by off-shore competitors. The second major goal is to build a flexible framework that can accommodate many different data rates and digital formats, resulting in a very versatile and flexible recording system. Some of the specific challenges include developing next-generation, thin-film, magnetoresistive read/write heads; new tape media that can withstand faster operating speeds; new electronics for processing data at the higher bit rates and for controlling future systems so they can accommodate multiple data formats; and new software and algorithms for integrating data from 16 or more tape channels. Members of the joint venture include Peregrine Recording Technology (St. Paul, MN), Seagate Technology, Inc. (Costa Mesa, CA) and Advanced Research Corp. (Minneapolis, MN).

**2. Digital Data Storage Technology via Ultrahigh-Performance Optical Tape Drive Using a Short-Wavelength Laser**

*Develop an optical tape storage technology in which up to 180 tracks can be simultaneously written and read with multiple, independently controllable laser beams that could lead to data systems for rapidly storing, retrieving, and transferring 1 trillion bytes of information.*

**Sponsor:**     *LOTS Technology, Inc.  
1274 Geneva Drive  
Sunnyvale, CA 94089-1122*

- Project duration: 09/01/1995 – 08/31/1997
- Total project (est.): \$2,850,000.00
- Requested ATP funds: \$1,950,000.00

As the technology of the Information Age continues to develop and diffuse throughout society, there is a need for increasingly greater speed and capacity for storing and retrieving data. LOTS Technology, Inc., proposes to develop an optical tape read/write technology capable of storing 1 trillion bytes (a terabyte) and capable of transferring that data at a rate of at least 100 million bytes (100 megabytes) per second. This will represent a 1,200-fold increase in capacity compared to the prevalent industry standard and a 100-fold increase compared to the next generation of cartridge storage tape drives being introduced. The key to the technology is the development of a holographic element that splits a single laser beam into 180 individually controllable beams that concurrently access an equal number of parallel tracks on the surface of the optical tape. If the project is successful, the first application of the technology will be an "IBM-3480"-style cartridge. Because this cartridge is a standard widely used throughout industry, integration into existing computing systems should be smooth. The high transfer rate is made possible by the parallelism created with the holographic element. The high capacity may be increased even further with the development of thinner and longer optical tape that would fit within the same cartridge housing. The greater capability of this storage technology ought to help a wide variety of industries and applications, including computer backup and archival storage; video recording; image storage; scientific computing and data acquisition; records from government, finance and business; and information services such as electronic libraries and video-on-demand.

## About the Advanced Technology Program

The Advanced Technology Program (ATP) is a partnership between government and private industry to conduct high-risk research to develop enabling technologies that promise significant commercial payoffs and widespread benefits for the economy. The ATP provides a mechanism for industry to extend its technological reach and push the envelope beyond what it otherwise would attempt.

Promising future technologies are the domain of the ATP:

- Enabling technologies that are essential to the development of future new and substantially improved projects, processes, and services across diverse application areas;
- Technologies for which there are challenging technical issues standing in the way of success;
- Technologies whose development often involves complex "systems" problems requiring a collaborative effort by multiple organizations;
- Technologies which will go undeveloped and/or proceed too slowly to be competitive in global markets without the ATP.

The ATP funds technical research, but it does not fund product development. That is the domain of the company partners. The ATP is industry driven, and that keeps it grounded in real-world needs. For-profit companies conceive, propose, co-fund, and execute all of the projects cost-shared by the ATP.

Smaller companies working on single-firm projects pay a minimum of all the indirect costs associated with the project. Large, "Fortune-500" companies participating as a single firm pay at least 60 percent of total project costs. Joint ventures pay at least half of total project costs. Single-firm projects can last up to three years; joint ventures can last as long as five years. Companies of all sizes participate in ATP-funded projects. To date, more than half of the ATP awards have gone to individual small businesses or to joint ventures led by a small business.

Each project has specific goals, funding allocations, and completion dates established at the outset. Projects are monitored and can be terminated for cause before completion. All projects are selected in rigorous competitions which use peer-review to identify those that score highest against technical and economic criteria.

Contact the ATP for more information:

- On the World Wide Web: <http://www.atp.nist.gov>;
- By e-mail: [atp@nist.gov](mailto:atp@nist.gov);
- By phone: 1-800-ATP-FUND (1-800-287-3863);
- By writing: Advanced Technology Program, National Institute of Standards and Technology, 100 Bureau Drive, Stop 4701, Gaithersburg, MD 20899-4701.

## About the Authors

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