Price Elasticity and the Growth of Computer Spending

Kar Yan Tam and Kai Lung Hui

***Abstract*—Recent works have indicated that the price of computers is a key factor in explaining the growth of computer spending. However, it remains unclear whether the price elasticity of the demand for computers is constant over time. Findings on the pattern of price elasticity will have important implications in the study of information technology (IT) innovation diffusion. To test the hypothesis of dynamic price elasticity, we extend existing growth models to include a price factor with different elasticity specifications. Nested specifications of three growth models were tested using spending data from 1955 to 1984 adjusted by a quality price index for computers. The results indicate that three out of four competing models depict dynamic price elasticity over the investigated period. A similar pattern is also observed when the models are estimated using more recent data on mainframe computer spending. Our results underscore the dynamic behavior of price sensitivity in computer spending over time. They offer a new perspective to study innovation attributes and to examine their impacts empirically over time. Implications for information systems (IS) management and IT suppliers are also discussed.**

***Index Terms*—Computer spending, growth model, innovation diffusion, price elasticity.**

I. Introduction

OVER the last three decades there has been a significant increase in information technology (IT) investment worldwide. According to recent estimates of OECD [39], the average annual growth rate of the worldwide IT market was almost double that of the world GDP over the last decade. Spending on computers contributes a major share of the growth. While computer spending continues to grow, it has remained unclear, until recently, whether the growth can be explained by a pure diffusion effect as suggested by social diffusion theory or a combined effect of diffusion and the pricing trend of computers.

Assuming an S-shaped growth process of information system (IS) spending, Gurbaxani and Mendelson [21] incorporate a price factor into the S-shaped growth models and by performing time-series analysis on U.S. data processing spending, they conclude that the pure S-shaped growth models should be rejected in favor of the price-adjusted models. Both this and the OECD [38] study indicate that price is a key factor driving the information systems (IS) spending of major firms in the United States. Their work supplements an early study by Chow [10], who investigated the technological characteristics of and the demand for computers in the United States. Surprisingly, although it has become apparent that rapid price decline is the driving force behind the growth of IT spending, little has been reported on the response of adopters to the price trend of computers over time.

In economic terms, adopters' sensitivity to price changes is referred to as price elasticity. The majority of IT diffusion literature either does not consider price or assumes a constant price elasticity. In view of the steep learning curve and knowledge barrier of IT [1], it is doubtful that we can assume IT adopters at different points in the diffusion process will have the same reaction to price changes.

As noted by Simon [48], the topic of dynamic price elasticity is empirically not well researched. Much of the existing work on elasticity dynamics focuses on consumer durables. Little has been done on IT products such as computers, which have experienced a rapid improvement in performance and drop in price that are hardly matched by any other consumer product in the last three decades. Empirical work on the elasticity dynamics of computer spending will provide a number of valuable insights. First, one can infer the perceived necessity of computers from estimates of its price elasticity. A low elasticity indicates a strong perceived necessity and vice versa. Second, the trend of elasticity sheds light on the behavior of adopters in different stages of the diffusion process. Third, guidelines for setting pricing strategies can be developed.

With this objective in mind, we extend previous work by including a price factor with varying elasticity into three growth models of computer spending. Through analyzing the growth of computer spending in the United States and its elasticity over 30 years from 1955 to 1984, the current work attempts to look at the elasticity dynamics of the demand for computers in the United States using a longitudinal approach.

The main data set employed in this study is based on annual purchases of computers from 1955 to 1984. Although application software and other related operating expenses constitute an important share of a firm's IT budget, they are not included for two reasons. First, reliable data on these items reside at the firm level and are not available over the investigated period. Second, by focusing on computers, we are able to calibrate more precisely the growth pattern of hardware spending and to leverage on the availability of quality-adjusted price indices developed specifically for computers.

The rest of the paper is organized as follows. In Section II, we present the S-curve growth model and its theoretical foundation. Section III introduces three growth models which all depict an S-curve pattern. Section IV introduces the quality-adjusted price index and describes how it is incorporated into the three models. Section V describes the source of data and

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the results of the analysis. Section VI discusses the findings and the limitations of the study. Future research directions are also outlined. Section VII concludes the paper.

II. Innovation Diffusion and the S-Curve Growth Model

Over the last three decades, a considerable body of literature has accumulated on the characterization of the life cycle of innovations. Interest in understanding the factors and the environment conducive to the adoption of new innovations spans across different disciplines, most notably marketing, economics, and social science. One line of research involves empirical studies using cross-sectional data with a focus on the relationship between the adoption decision, the innovation, and the organizational characteristics. The majority of IS innovation studies fall into this category [2], [6], [17], [23], [35], [55], [56].

Another line of research, popularized in the marketing literature, focuses on the diffusion pattern of innovations over time. Aggregate diffusion models have been proposed to study the rate and pattern of the diffusion process. While originally developed to capture the essential features of growth patterns, these models have been used increasingly in testing diffusion related hypotheses.[1] Mahajan and Muller [28] provided a review on the early development of these diffusion models. The application of these models to study diffusion related phenomena has started to receive attention by IS researchers. For example, an article by Loh and Venkatraman [26] adopted the Bass model [3] to study the diffusion pattern of outsourcing projects in the United States. A similar approach was adopted by Dos Santos and Peffers [12] in studying the aggregate adoption of ATM's.

A common thread in these studies is that the aggregate adoption of an innovation over time can be approximated by an S-curve. Many have offered explanations on the peculiar shape of the pattern. Rogers [46] classified adopters into five categories[2] which follow a normal distribution. With this distribution, the cumulative number of adopters over time should follow an S-shaped pattern. The Bass model proposes that the cumulative adoption of an innovation at any particular point in time depend on both internal and external influences. The Bass model also depicts an S-shape diffusion curve. Over the years, the original Bass model has been extended to incorporate other aspects of diffusion. In a recent paper, Mahajan, Muller and Bass [31] summarized a number of empirical generalizations based on the Bass model. Detailed review on the diffusion models and their applications can be found in Parker [41].

Existing parsimonious diffusion models have several assumptions that need to be recognized in their applications. First, one has to differentiate between first purchase and repeated purchases. For example, the Bass model incorporates a key assumption that all purchases taken into account should be first purchases. This is premised on the assumption that the adopting innovation will remain identical (or very similar in terms of performance level) over the entire diffusion process. While it is relatively easy to differentiate between initial purchases and repeat purchases for consumer durables, the rapid improvement in storage and processing capabilities of computers renders new computer models very different from existing ones. Not only does the performance of new models improve considerably, complementary items such as operating system and application software also evolve rapidly over time. Very often, the "repurchase" (or upgrade) of computers entails a substantial learning process that resembles the adoption of a new innovation.

Second, computers are characterized by successive generations of models with each generation outperforming the antecedent in terms of computing power or memory storage. The growth patterns of such multigeneration innovations are not easily modeled as there is a wide array of confounding factors that has impact on the diffusion process of each model. Although recent work, such as [29] and [37], has attempted to model the multigeneration innovations, these works are restricted to a single product line, e.g., IBM mainframe computers in [29]. At the industry level, substitution and complementary effects exist across different brands and models. For example, an organization can choose between a mainframe and a client–server architecture for its IT infrastructure. Simply aggregating the total number of units without differentiating between different categories of computers will likely distort the actual demand for computing over time. The growth patterns of multigeneration computer classes and models are interrelated and need to be delineated in the analysis in order to correctly calibrate the growth pattern.

Third, the growth pattern in many of these models is expressed in the number of adoption units. An adoption unit is typically used for consumer items such as TV's and refrigerators in marketing studies. However, in the case of computers, number of units adopted may not provide an accurate picture on the general growth pattern unless they can be segregated into different classes and models to address the heterogeneity of different computer products.

The complications involved in repurchases, multigeneration computers, and adoption units are addressed using computer spending to calibrate the diffusion pattern of computers. Spending is preferred rather than adoption unit in the current study because the latter involves classifying computers into different categories, i.e., mainframe, mini, workstation, PC, all of which are likely to exhibit their own growth patterns. By aggregating spending of different computer categories, we avoid imposing assumptions on the change of IT architecture over the years. The focus is on the total spending on IT irrespective of the underlying system configuration.

Few IS research studies have addressed factors which distinguish early from late adopters and which identify the determinants of the innovations' pattern of adoption and diffusion over time [16], [49]. The difficulties in conducting longitudinal studies are threefold. First, there is a lack of reliable sources of secondary data. Second, the price trend of an innovation is difficult to gauge. The trend must account for not only changes in price but also the improvements in quality

[1] For a good review on the diffusion model literature, readers should refer to [7] and [30].

[2] Adopters are classified into five categories: innovators; early adopters; the early majority; the late majority; and laggards.

and performance of an innovation over time. To accurately characterize the diffusion process in a longitudinal study, a quality-adjusted price index is needed to discount the nominal spending on an innovation. Third, enough data points must be collected to obtain reasonable estimates with an acceptable degree of freedom. As will be discussed in the next few sections, we have addressed these shortcomings in the current study.

III. Computer Spending Model and Calibration

Diffusion theory suggests that in the absence of any other influence, the diffusion pattern follows an S-curve. Over the last three decades, a number of specifications with respect to the S-curve have been developed for a large array of innovations. The work by Nolan [36] is an early application of the S-curve model in the IS context. We follow the approach of Gurbaxani and Mendelson [21] and use three models with an S-shaped pattern to calibrate the growth of computer spending. The three models are presented below.

A. Gompertz Model

The Gompertz model has been used in a number of econometric studies on the growth of new products. Chow [10] used it to study the growth rate of computers. It has the following form:

$$B(t) = K \cdot A^{b^t} \tag{1}$$

where $B(t)$ is the value of a computer purchased in year t; A, K, and b are parameters of the model.

B. Logistic Model

The Logistic model was introduced by Mansfield [32] to study the diffusion of several technological innovations and has also been used in many innovation studies over the last three decades. The model has the following form:

$$B(t) = \frac{1}{K + A \cdot b^t} \tag{2}$$

where $B(t)$ is the value of the computer purchased in year t; A, K, and b are parameters of the model. It can be easily shown that the curve is symmetrical at its midpoint where it attains its highest growth rate.

C. Modified-Exponential Model

The Modified-Exponential model was used by Lucas and Sutton [27] to study the stage hypothesis and has the following form:

$$B(t) = e^{A - b/t} \tag{3}$$

where $B(t)$ is the value of the computer purchased in year t; A and b are parameters of the model.

Equations (1)–(3) all depict an S-curve pattern when certain conditions on their parameters are satisfied (see Table I). They form the basic growth models of computer spending used in the current work.

TABLE I
Model Parameters

Model	Parameters			
	K	A	b	*inflection point at time*
Gompertz	$K > 0$	$0 < A < 1$	$0 < b < 1$	$\frac{K}{e}$
Logistic	$K > 0$	$A > 0$	$0 < b < 1$	$\frac{1}{2K}$
Modified-Exponential	-	$A > 0$	$b > 0$	$\frac{b}{2}$

IV. Incorporating Price Elasticity in Spending Models

A. Quality-Adjusted Price Index for Computers

Few studies have explicitly incorporated price in the study of IT innovation. As noted by Leonard-Barton [24], the form and function of an innovation are modified throughout its life cycle. However, the impact of price changes has been largely ignored by many past IS research studies. One possible reason for this may be the lack of widely available reliable pricing and performance information. Until recently, there was no systematic compilation of statistics on computer price index. Computers have been grouped together with other office machinery into the general office, computing, and accounting machinery OCAM category for more than 30 years.

Using industry-wide deflators such as the GNP deflator for computers in longitudinal studies may be problematic because quality improvement is not accounted for in these deflators. Tellis [51] reports that omitting the quality information will have a positive bias on price elasticity. If quality improvement is not taken into account, estimates on price elasticity will be less elastic. It will underestimate the spending on computers which has been contributing to the economic growth of the United States in the last three decades [8].

The deflator for computers used here is based on Gordon [19]. Gordon applied hedonic regression on two data series and combined the results to derive a quality-adjusted price index which covers 1955 to 1984. The first series he used was the Phister [44] data set which covers the period from 1951 to 1979, while the second was the one reported from *Computerworld*, which covers 1977 to 1984. The annualized price decline is about 20% from 1954 to 1984, which is in the range of estimates obtained from previous empirical studies [5], [9], [34] and that of the Bureau of Economic Analysis.

The quality-adjusted price index as shown in Fig. 1 represents the price trend of computers from 1955 to 1984, with 1965 as the base year. Although the overall trend is decreasing, it is interesting to note that the trend is not smooth. Unlike previous empirical works on IT diffusion, which assume a constant rate of price decline, we are able to obtain a pricing trend that more accurately reflects the temporal changes in the price level of computers.

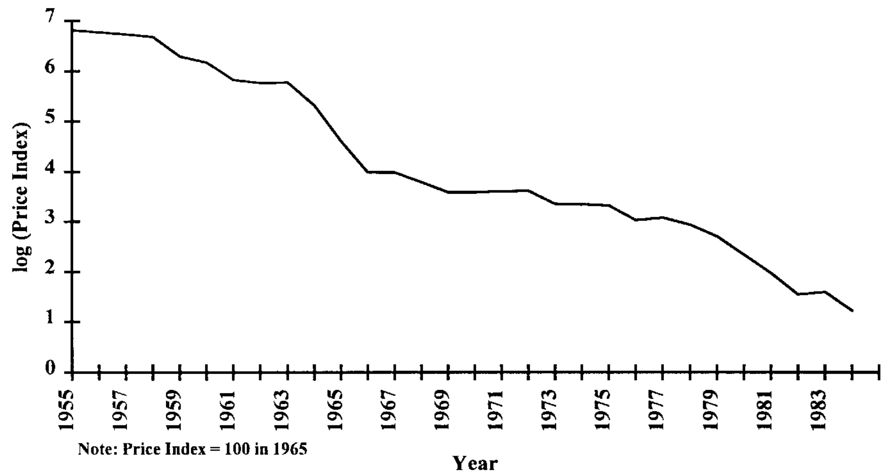

Fig. 1. Quality-adjusted price index for computers.

B. Price Elasticity

There is supporting evidence that many innovations exhibit dynamic price elasticity behavior [40]. In a meta-analysis of econometric studies on price elasticity, Tellis [51] finds elasticity changes over the life cycle of a product. Price elasticity is reported to be less negative in the initial stage than in the final stage of the life cycle. A plausible explanation is that early adopters have a reservation price higher than the market price. These adopters are typically large organizations with extra resources to experiment with new ideas. As an innovation goes through its life cycle according to the S-Curve pattern, total spending increases and competition among vendors intensifies. Such competition drives up the price sensitivity of consumers, resulting in a more informed and selective buying behavior. If this is true, it should be reflected in the pattern of price elasticity over time.

The central research question of the current study is posed as the following hypothesis.

H1: The price elasticity of demand for computers is dynamic over time.

To address this research question, the hypothesis of dynamic price elasticity is tested against a number of alternative elasticity specifications using a nested model approach. The following model is employed throughout this study to test the dynamic price elasticity hypothesis:

$$B_p(t) = B(t) \cdot P(t)^{\alpha_0+\alpha_1 t+\alpha_2 t^2} \tag{4}$$

where $B_p(t)$ is the price-adjusted computer spending and $P(t)$ is the quality-adjusted price level at time t. The model is closely related to previous works by Bass [4] and Robinson and Lakhani [45]. It represents a separable demand function consisting of two terms. The first term on the right-hand side (RHS) of (4) is spending based on a growth model [i.e., (1)–(3)]. The second term $P(t)^{\alpha_0+\alpha_1 t+\alpha_2 t^2}$ represents the elasticity dynamics of spending.

The current study postulates that price elasticity varies over time. However, the elasticity function needs not be linear, and therefore the time path of elasticity dynamics may take on any form. A quadratic form is used here as it consists of most of the patterns suggested in previous work.[3] Depending on the magnitude and the signs of $\alpha_0, \alpha_1, \alpha_2$, different patterns can be represented. The model specifications are shown in Table II.

TABLE II
SPECIFICATIONS FOR EACH GROWTH MODEL

Version	Equation
1	$B_p(t) = B(t)$
2	$B_p(t) = B(t) \cdot P(t)^{\alpha_0}$
3	$B_p(t) = B(t) \cdot P(t)^{\alpha_0+\alpha_1 t+\alpha_2 t^2}$

Version 1 in Table II represents the base S-curve model, Version 2 represents the price-adjusted S-curve model with constant elasticity, while Version 3 represents the price-adjusted S-curve model with dynamic elasticity.

V. DATA AND EMPIRICAL ANALYSIS

As mentioned earlier, the data set used in this study is based on Gordon [18], who in turn utilized data presented by Phister [44] and Einstein and Franklin [15]. Phister [44] integrated a number of different surveys and publications on figures concerning data processing industry and generated an integrated series on computer spending in the United States that covers 1955 to 1974. On the other hand Einstein and Franklin [15], based on data provided by the Computer and Business Equipment Manufacturers Association, presented a data series on U.S. domestic computer spending covering 1960 to 1984. The two data series have been used in a number of empirical studies, and they have been employed in the construction of price indices for computers. The work of Gurbaxani and Mendelson [21] also utilized data provided in Phister [44]. Both data sources are well researched and reliable.

[3] Parsons [43] suggests that elasticity should increase and then decrease. Nagle [33] remarks that elasticity is the lowest during early phases of the diffusion process and will grow over the life cycle of an innovation. Empirically, Simon [47] reports that elasticities fall and then increase for a number of consumer and pharmaceutical products.

TABLE III
PARAMETER ESTIMATES OF PRICE-ADJUSTED GOMPERTZ MODEL

Version	Parameters						Adjusted R^2
	log K	*log A*	*b*	α_0	α_1	α_2	
1	8.668** (0.069)	-4.778** (0.14)	0.869** (0.008)				0.981
2	9.11** (0.13)	-3.8** (0.225)	0.805** (0.025)	-0.234** (0.054)			0.987
3	9.292** (0.201)	-2.389** (0.716)	0.439** (0.167)	-0.602** (0.052)	0.033** (0.006)	-8.66×10^{-4}** (2.085×10^{-4})	0.988

Standard errors in parentheses.
** Significant at the 1% level.

Since the two data series cover different years and were derived by different authors, one may question their compatibility in forming a single reliable data set. To ensure that it is legitimate to combine the two data sources, a correlation analysis is performed for the overlapping period of the two series (1960 to 1974). The correlation coefficient so obtained equals 0.991, indicating that the two series are highly correlated and are consistent with each other. Therefore, we can conclude that the integrated data series presented is acceptable. The single data series covers annual sales of computers in the United States from 1955 to 1984, converted into 1965 dollars. 1955 and subsequent years are assigned $t = 1$, $t = 2, \ldots, t = 30$, respectively. The year 1955 is selected as the starting point for two reasons. First, it is reasonably close to the time when computer was first introduced to the industry. Second, spending data on computers before 1955 are scant and reliable data may not be available for analysis. The amount of computer spending before 1955 is very small, thus ignoring them in our estimation will not impact the results very much given the long time series studied here.

A three-step procedure to test the dynamic price elasticity hypothesis is proposed as follows. First, all three versions (base, constant, and quadratic) of (1) to (3) are estimated using nonlinear regression. Second, the versions or models will be discarded from further analysis if the following conditions are not satisfied: 1) all parameters of price elasticity are significant and 2) the price elasticity of the model is negative over the period of investigation. Third, the most appropriate version(s) among all specifications is identified using the log-likelihood test.[4] Version 3 (the quadratic form) is used as the full version in which all other versions are nested.

Note that in estimating the parameters, different test conditions are imposed on different parameters. The S-curve parameters (K, A, and b for the Gompertz and the Logistic model, and A and b for the Modified Exponential model) are all nonnegative, and therefore one-tailed tests are applied to test their significance. For the price elasticity specifications, since we have no prior knowledge about the sign and magnitude, these parameters may assume any value, and therefore two-tailed tests are applied. Estimation results of each model are discussed below.

[4]The log-likelihood test works as follows. Let Model A be a special case of Model B by setting some restrictions on the value of B's parameters. The log-likelihood obtained for model $A(LL_A)$ and that for model $B(LL_B)$ is used to calculate the statistic $-2(LL_A - LL_B)$, which has a chi-square distribution. The degree of freedom of the statistic depends on the number of restrictions on B [20]. The null hypothes is that the nested model (i.e., A) is rejected if the statistic is larger than the critical value at a certain significance level.

TABLE IV
LIKELIHOOD-RATIO TEST OF NESTED PRICE-ADJUSTED GOMPERTZ MODEL

Log-likelihood of Nested Version	Nested Version	Unrestricted Version		
		1	2	3
13.924	1	-	13.757**	17.641**
20.803	2	-	-	3.884
22.745	3	-	-	-

+ Blank cells represent non-nested pairs of versions.
** Nested version is rejected in favor of unrestricted version at the 1% level.

A. Estimation Results

1) Price-Adjusted Gompertz Model: The model is transformed by taking the natural logarithm for ease of estimation. All three versions show a good fit of the data. As shown in Table III, the adjusted R^2 of the full version is 0.988, indicating an excellent goodness of fit. A strong diffusion effect is observed. All the coefficients of the base model are significant with the correct sign and magnitude. The elasticity parameters for both Versions 2 and 3 are highly significant, indicating plausible effect exerted by price elasticity. The results of the likelihood ratio test in Table IV indicate that the base version can be rejected in favor of the constant elasticity version and also the dynamic elasticity version. However, the likelihood ratio test cannot reject the constant elasticity version.

2) Price-Adjusted Logistic Model: The adjusted R^2 of all versions are very high, as shown in Table V, with the dynamic elasticity version again achieving the highest adjusted R^2. Like the price-adjusted Gompertz Model, the diffusion effect is very obvious and all coefficients for the base model are significant. The elasticity parameters for both constant and dynamic versions are highly significant. Results of the likelihood ratio test are shown in Table VI. The test indicates that all nested versions should be rejected in favor of the dynamic elasticity version. The latter depicts an elasticity pattern which first decreases and then increases.

TABLE V
PARAMETER ESTIMATES OF PRICE-AJUSTED LOGISTIC MODEL

Version	Parameters						Adjusted R^2
	$K(10^{-3})$	A	b	α_0	α_1	α_2	
1	0.211** (0.012)	0.011** (0.002)	0.702** (0.016)				0.971
2	0.104** (0.013)	0.002** (6.019×10^{-4})	0.646** (0.026)	-0.273** (0.042)			0.984
3	0.091** (0.018)	5.093×10^{-4}* (2.489×10^{-4})	0.305* (0.133)	-0.613** (0.044)	0.034** (0.005)	-9.035×10^{-4}** (1.848×10^{-4})	0.988

Standard errors in parentheses.
** Significant at the 1% level.
*Significant at the 5% level.

TABLE VI
LIKELIHOOD-RATIO TEST OF NESTED PRICE-ADJUSTED LOGISTIC MODEL

Log-likelihood of Nested Version	Nested Version	Unrestricted Version		
		1	2	3
7.62	1	-	19.646**	30.087**
17.443	2	-	-	10.442**
22.664	3	-	-	-

+ Blank cells represent non-nested pairs of versions.
** Nested version is rejected in favor of unrestricted version at the 1% level.

3) Price-Adjusted Modified Exponential Model: As shown in Table VII, all nested Modified-Exponential models show a good fit of data as indicated by their adjusted R^2. Once again, the dynamic elasticity version achieves the highest adjusted R^2. The sign and magnitude of A and b are correct implying the estimated versions all depict an S-shaped pattern. All parameters of the base model are significant, indicating a strong diffusion effect. Again, all parameters for the elasticity variables are significant. The likelihood ratio test results are shown in Table VIII. All nested versions can be rejected in favor of the dynamic elasticity version.

VI. DISCUSSION AND LIMITATIONS

After starting with nine model/version possibilities, four models are still in contention: 1) price-adjusted Gompertz model with constant elasticity; 2) price-adjusted Gompertz model with dynamic elasticity; 3) price-adjusted Logistic model with dynamic elasticity; 4) price-adjusted Modified Exponential model with dynamic elasticity. Plots of the four models against the actual spending are shown in Fig. 2(a)–(d).

As shown in the figures, all four models provide a good data fit for the first ten years. After that, the spending trend depicted fluctuations that were dampened in the 1980's. All models miss the rapid increase in computer spending in 1967–1968. The spending fluctuation in this period could well be explained by the introduction of new generations of computing platforms. Note that the period coincided with the introduction of the popular IBM 360 series mainframes which was a great success in the computer industry. The second peak of spending occurred around 1973–1974, which again coincided with the introduction of the IBM 370 series machine. The price-adjusted Gompertz model with constant elasticity provides a long-term view of spending by averaging out the fluctuations. On the other hand, all the full quadratic models seem to better capture the peaks at the expense of overestimating spending in 1969–1972 and 1974–1977.

The consistent result of highest adjusted R^2 for all quadratic versions indicates that the quadratic versions can best capture the growth patterns of computer spending. Three of the four significant models depict dynamic price elasticity. Note that in both the Logistic and Gompertz base versions (i.e., Version 1), the adjusted R^2 is higher than that of the Modified-Exponential model, indicating that these two models better match the actual spending pattern in the absence of pricing effect. Apparently, the price effect is different for different base models. It follows that a test of price elasticity is a joint test of the underlying growth model and the price effect. The current study controls the model effect by employing three different S-curve models suggested in the literature. Each of these models is modified to include a multiplicative price term. It turns out that all base versions were rejected in favor of the price-adjusted version.

Plots of price elasticity over time are shown in Fig. 3. Except the constant elasticity model (Version 2 of the Gompertz curve), all three quadratic elasticity specifications depict a pattern which first decrease and then increase. The initial decline in elasticity shows that computer spending was less price sensitive in the first two decades. However, elasticity increases afterwards.

A. Estimation Results Based on Mainframe Spending

Since the Gordon data set covers aggregate spending data up to 1984, this section presents additional estimation results based on mainframe computer spending from 1965 to 1994. The mainframe computer spending data that we used here is obtained from International Data Corporation (IDC). The data set contains annual domestic shipment value of mainframe computers of U.S. computer vendors. By combining shipment value of all vendors, we obtain a series of mainframe computer spending that goes from 1965 to 1994. The mainframe computer price index is provided by the Bureau of Economic Analysis.

Similar to aggregate spending data, we applied nonlinear regression and the likelihood ratio test to the mainframe series.

TABLE VII
PARAMETER ESTIMATES OF PRICE-ADJUSTED MODIFIED-EXPONENTIAL MODEL

Version	A	b	α_0	α_1	α_2	
1	8.318** (0.13)	5.191** (0.56)				0.745
2	9.688** (0.119)	2.839** (0.284)	-0.409** (0.032)			0.962
3	9.342** (0.194)	1.338** (0.245)	-0.568** (0.04)	0.031** (0.004)	-8.433×10^{-4}** (1.579×10^{-4})	0.989

Standard errors in parentheses.
** Significant at the 1% level.

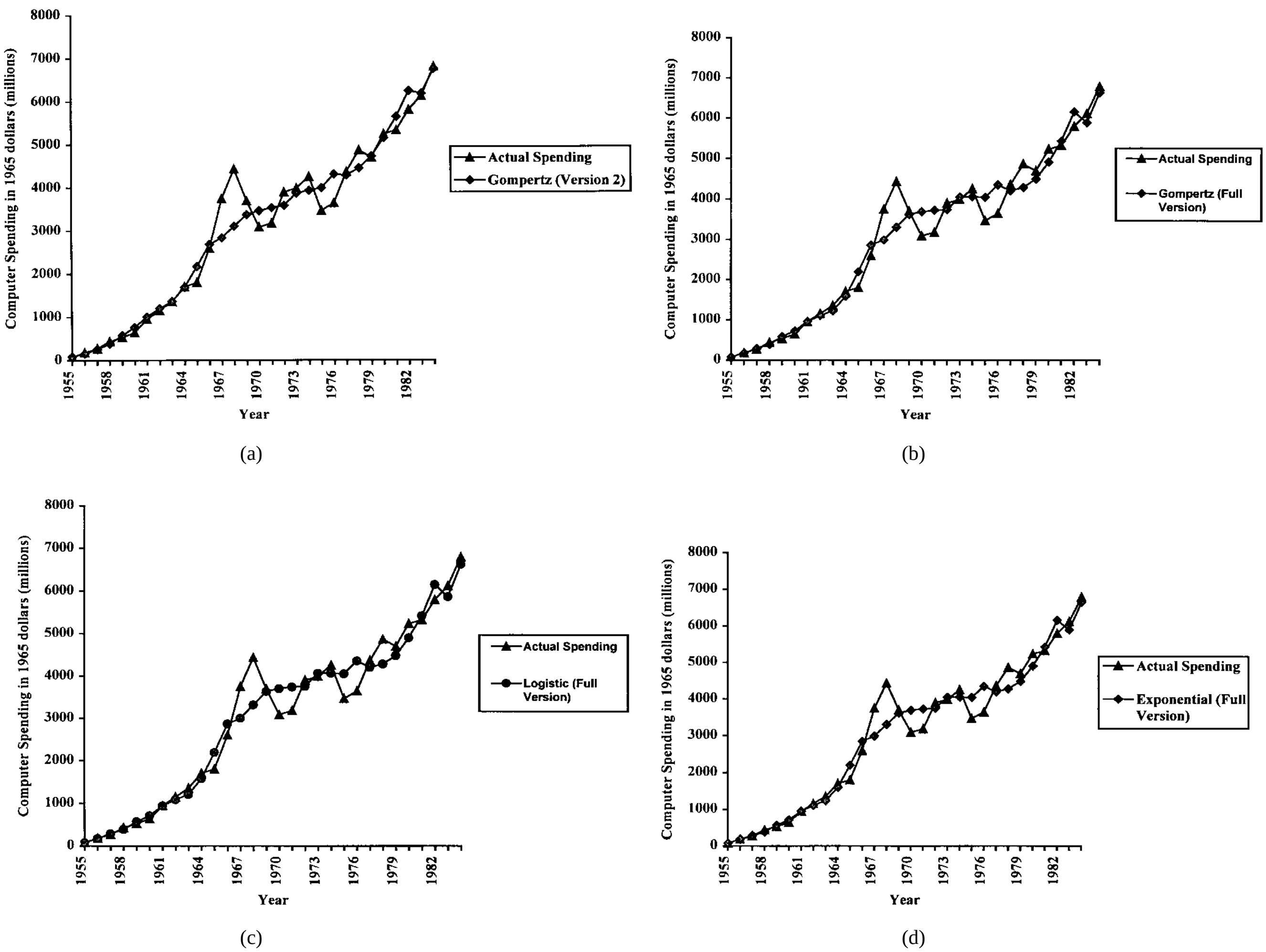

Fig. 2. (a) Plot of price-adjusted Gompertz model (Version 2). (b) Price-adjusted Gompertz model (full version). (c) Plot of price-adjusted logistic model (full version). (d) Plot of price-adjusted Modified Exponential model (full version).

Two diffusion models (Gompertz and Modified Exponential models) with dynamic price elasticity remain significant with adjusted over R^2 95%. Plots of the price elasticity of these two estimated models are shown in Fig. 4.

As shown, the price elasticity changes over time in a way similar to that of aggregate spending, despite the fact that the starting point of analysis is different ($t = 1$ at 1965 instead of 1955). This is in line with our expectation as there is significant overlap between mainframe and overall spending between 1965 and 1984. We should expect similar patterns of price elasticity dynamics. However, the magnitude of price elasticity of mainframe spending is larger than that of aggregate spending. This is expected because the elasticity dynamics shown in Fig. 3 corresponds to overall spending in all categories and models of computers while Fig. 4 represents mainframe spending only. The former aggregates all market segments of the computer industry and therefore averages out reaction to price changes in different segments. New market segments developed in the 1970's and 1980's, such as departmental and personal computing, are made possible by new computing platforms including minicomputers, PC's, and workgroup servers. While there is an overlap between

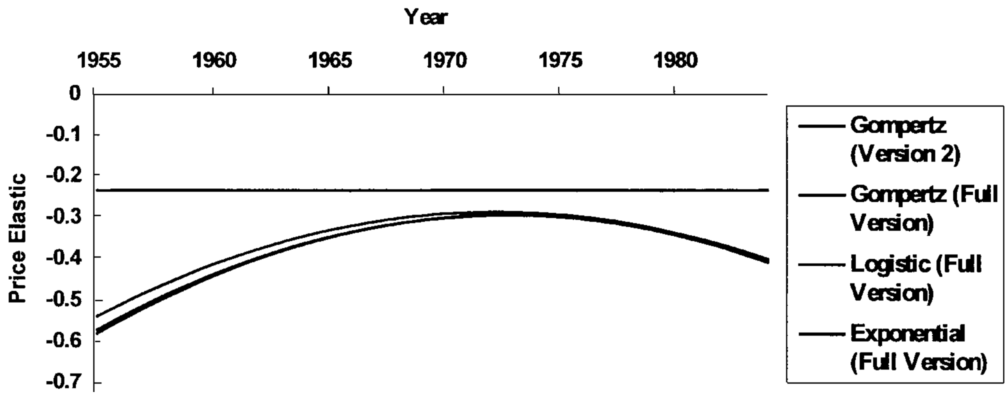

Fig. 3. Plot of price elasticities (aggregate spending, 1955–1984).

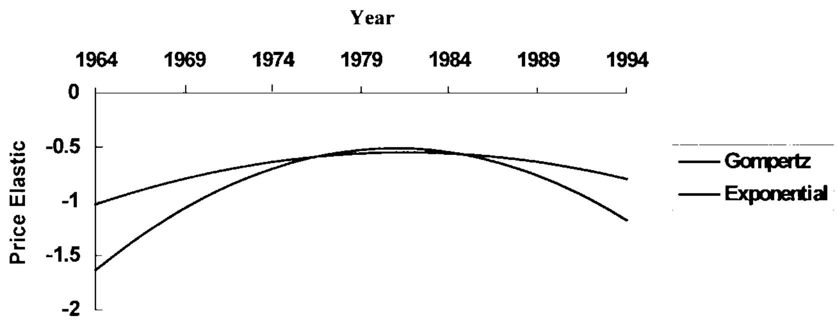

Fig. 4. Plot of price elasticity (mainframe computer spending, 1964–1994).

TABLE VIII
LIKELIHOOD-RATIO TEST OF NESTED PRICE-ADJUSTED MODIFIED-EXPONENTIAL MODELS

Log-likelihood of Nested Version	Nested Version	Unrestricted Version		
		1	2	3
-25.309	1	-	58.378**	96.455**
3.88	2	-	-	38.076**
22.918	3	-	-	-

+ Blank cells represent non-nested pairs of versions.
** Nested version is rejected in favor of unrestricted version at the 1% level.

mainframe and these computing platforms in serving these new market segments, reactions to price changes for different platforms are likely to be different. Being the first developed platform in the computer industry, mainframes have gone through a significant part of its diffusion process as compared with minicomputers, servers, and the PC's. The latter are likely to depict low price elasticities as they are in the early stage of the diffusion process. Thus, price elasticity of aggregate spending should be lower in magnitude than that of mainframe as shown above.

The findings in the current study are consistent with Parker and Neelamegham [42], who explored the elasticity dynamics of several categories of consumer durables. Using an adjusted Bass model, they reported that elasticity first decreased and then increased in the later stage of the product life cycle for some innovations.

B. Implications

The learning effect, the growing market competition, and the increasing importance of organizational computing all suggest a higher price effect during the later stage of the growth process than in the early stage, *ceteris paribus*. In other words, price elasticity in the latter stage of the growth process should be higher. Researchers should not only include price as a factor but also take into account the elasticity dynamics over time in studying the diffusion pattern of computers. Implications of our findings are discussed below.

1) Computers as a Corporate Asset: The role of computers may have shifted during these years, for example, from automating repetitive tasks in the early years to supporting corporate strategies in recent years, but its importance has always been increasing. When compared with estimates for other durable items [40], [51], it is surprising to find that price elasticity for computers, though growing, was quite low after 20 years into its life cycle. The low elasticity and the rapid growth of overall spending suggest that computers had become an essential asset in many organizations from 1955 to 1984. This is consistent with Clemons' [11] remark that IT has become a competitive necessity in modern organizations.

2) Innovation Attributes: Another view which has been advocated to have an impact on the adoption decision is adoption cost. Downs and Mohr [13] suggested that cost is a primary innovation attribute. The current study suggests that adopters are different with respect to price changes, and as such price sensitivity may help in characterizing adopters within the innovation diffusion cycle. The changing price sensitivity suggests that price elasticity itself can be represented as a function of time which is subject to empirical testing. Unlike popular innovation attributes such as size, diversity, and slack resources, which are useful only in the early stage of the process, the price elasticity is dynamic and should provide valuable information over the entire innovation diffusion life cycle. As Wolfe [54] points out, the inconclusiveness of many previous works can be attributed to the ambiguity and inconsistency concerning the various stages in the diffusion process in which innovation studies are conducted. In IS research, little has been done to study the time varying behavior of innovation attributes. In a review by Swanson [49], almost all IS innovation studies employ cross-sectional or short time-series data. Our findings suggest that results of cross-sectional studies must be interpreted in the context of the specific time frame in which the innovation was adopted. The reason being that the effects of some innovation attributes (price in this case) on the adoption decision change over time and if not accounted for may lead to conflicting results.

3) Capital Budgeting of Computer Investments: To probe further the impact of elasticity dynamics on adoption decisions at the firm level, an understanding of the budgeting procedure is essential. The cost of capital and transfer pricing policy within a firm are important factors to consider [50], [53]. The dynamic price elasticity of the demand for computers could be explained in part by the continuous adjustment of the firms' estimates of the discount rate and future operating profit streams as a result of their learning experience. To evaluate an IT investment using traditional capital budgeting methods such as the Net Present Value (NPV), estimates of the expected stream of future cash flows are made which will then be discounted by a discount rate reflecting the firms' opportunity cost of capital for the particular project. Very often in practice, the risks of adopting an innovation are factored in the formulation by inflating the discount rate. Recent studies have discovered that the discount rates used by managers are often three to four times their weighted average cost of capital [14]. A high discount rate will give less weight to distant cash flow, resulting in a more myopic evaluation of the investment. The tendency to overstate the discount rate could be severe when managers face a high level of uncertainty resulting from the adoption of computers in the early year. The outcome of the NPV evaluation in this case is likely not to favor adoption. A drop in price at this stage will not necessarily attract more adopters as illustrated by our findings. On the other hand, as managers become more informed about the potential of computers later in the diffusion process, more appropriate discount rates will be used and better estimates of cash flows developed. Price will have a stronger impact on the diffusion process in the later part of the life cycle.

4) Market Competition: The low elasticity also sheds light on the competitiveness of the computer industry in the period investigated. In the first two decades after the inception of computers, IBM was the dominant player in the market capturing about 60–75% of the revenue of the data processing industry [19]. As previously mentioned, the introduction of series 360 and 370 models sparked the rapid growth of spending in the late 1960's and early 1970's. This very much reflects the dominance of IBM in the first two decades of the computer industry.

Hardware and software were tightly bundled in the early days. Computer vendors were also the providers of the application software. Because of this tightly coupled arrangement, there had always been a lag in the development of software packages that utilized the extra computing power introduced by new hardware platforms. Sometimes the lag was very long as the notions of compatibility and interoperability were not well conceived and recognized. Very often, system migration meant rewriting an entire system from scratch. Thus, the incentive to select a different vendor was minimal even though a machine with better price performance was available. This is reflected by the low elasticity estimates of the models in the first decade.

As more computer suppliers entered the market, IBM's market share steadily declined. The computer market became more segmented as new minicomputers were introduced in the mid-1970's. The ratio of shipment value of minicomputers to total shipment of computers raised from 1.6% in 1965 to 28.7% in 1984 [15]. A considerable amount of the market share of minicomputers was captured by emerging players such as DEC and HP. At the same time, IBM was facing competition in the mainframe market by clone makers such as Amdahl and Hitachi. As technology choices increased and better communication channels developed, adopters became more sensitive to discrepancies in prices among competing suppliers. This is reflected in an increase in price elasticity of overall spending in the 1970's and 1980's and the relatively high price elasticity of mainframe spending in the early 1990's.

5) Pricing Strategies of the Supplier: The dynamic nature of price elasticity should interest suppliers of computing equipment. For IT vendors, a constant price elasticity implies that early and late adopters are homogeneous in reacting to price changes. If all other factors are unchanged, this implies that a particular pricing strategy will produce the same effect at different stages of the innovation life cycle. Put it the other way, the timing of pricing strategy has no influence on potential adopters. On the other hand, dynamic price elasticity suggests that a change in price level will have different impact on demand at different point of time. Timing is crucial and should be considered by suppliers in developing the optimal pricing strategy [25], [47], [51].

Depending on the dynamics and other factors like discount rate and effects of learning on cost, there are a number of choices for an optimal pricing strategy. Penetration pricing (increasing), skimming (decreasing), or increasing then decreasing prices are common pricing strategies adopted by suppliers. Simon [47] suggests that penetration pricing is usually optimal when elasticity decreases in the early stage of the life cycle. This obviously fits into the case of computer spending in this study. In conducting simulation studies of optimal pricing strategy, Parker [40] concludes that the introductory price is negatively related to price elasticity. When combined with results of these studies, it becomes apparent that computer vendors can formulate optimal pricing strategies according to the elasticity dynamics of adopters.

Our findings are consistent with Attewell's observations [1] that external parties such as vendors play an important role in the overall IS innovation process. By setting the price level and launch time of new products, vendors could influence the diffusion pattern of an IT innovation. Expectations of new generations of products will reduce the rate of diffusion before the launch. Sales will decline as potential adopters expect new products to be available soon and restrain from adopting existing ones. The accumulated sales will release after the launch, raising the adoption level considerably in a very short time. The effects are illustrated by the introduction of the IBM 360 and 370 series in the late 1960's and the early 1970's. In some situations, the temporal diffusion pattern could be dominated by the pricing strategy of the supplier and the demand elasticity.

6) Planning Decisions of IT Adopters: Given that price elasticity increases after the initial declining period, potential adopters should consider when is the most suitable time in bringing in the new innovation. If they choose to act as early adopters (in other words, those lie within the decreasing elasticity region), they face the risk that suppliers may charge higher prices in face of the relatively inelastic demand. However, the corresponding competitive advantage is the early utilization of the new innovation that may bring in significant growth in productivity if properly deployed. On the other hand, if they choose to act as late adopters (those that lie within the increasing elasticity region), they enjoy the benefit that suppliers may adjust the price downward in face of the elastic demand. However, late adopters have to delay the deployment of new products.

A. Limitations

The work reported in this paper considers price of computers rather than the total cost of adoption. It is known that purchase price represents only a portion of the lifetime cost of adopting an innovation. As Tornatzky and Klein [52] suggest, adoption cost could be perceptually based and may not be easily measured. The use of price, though not a perfect substitute for the cost of adoption, provides a feasible vehicle to study the dynamic behavior of adopters at an aggregate level.

All analysis performed in this study relies on secondary data. Like other similar studies, (e.g. [22]), the scope of the study is limited by the availability of data. Reliable quality-adjusted price index for computers and spending data are only available during the period 1955 to 1984. Although it would be both interesting and insightful to extend the data set to include recent years, the current data set is simply not wide enough to allow such analysis. Nonetheless, a more recent data set (up to 1994) is included in the current study which allows us to draw more insight, albeit only for mainframe computers.

For most empirical research, a common consideration involves possible confounding factors. Given the macrolevel analysis of our work, economic variables and business cycle may have an effect on the spending pattern. Using GDP growth rate as a proxy to measure business cycle, we estimate a difference equation between $\Delta B(t_i)$ and $\Delta GDP(t_{i-j})$ with $j = 0, 1$, and 2 years. The results of t-test on the coefficients indicate no significant correlation between changes in computer spending and GDP growth rate for zero-, one-, and two-year lags.[5] Given this, one should not rule out the possibility of other macro factors. However, the impact of these factors will not be significant given the good fit of the models.

The limitations of the current study suggest a need for future research in this area. A direct extension of the current work is to employ additional growth models to control the specification effects. As mentioned earlier, a test for price elasticity is a joint test of the underlying growth model and the specification of price elasticity. By testing with alternative growth models, one may be able to delineate the effects of model specification and the elasticity dynamics using meta-analysis techniques.

VII. Conclusion

While a large body of work has accumulated in the IT diffusion literature, little has been done to study the price elasticity of IT adoption over time. In this paper, we study the price elasticity of computer spending in the United States over 30 years from 1955 to 1984. Using three growth models with an S-curve pattern, the hypothesis of dynamic price elasticity is tested using nested specifications of each growth model. The findings indicate that three out of four competing models depict dynamic price elasticity over the investigated period. A similar pattern is also observed when the models are estimated using more recent mainframe spending data. The findings provide evidence that not only the price trend is important, but also its elasticity over time must be taken into account in modeling the diffusion of an innovation. Our results underscore the dynamic behavior of price sensitivity in the diffusion process of computers and, to some extent, IT in general. Although no attempt should be made to generalize the findings directly to other technologies, the results should provide a valuable reference for work in this area.

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	No Lag	One Year Lag	Two Year Lag
Δ_{GDP}	0.0035	0.0005	-0.0008
	(0.0041)	(0.0042)	(0.0043)
R^2	0.0270	0.0005	$0.0013.$

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