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Prices Over the Product Life Cycle: An Empirical Analysis

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School of Economics Discussion Paper: 2008/25

ISSN 1323-8949
ISBN 978-0-7334-2723-7

Prices Over the Product Life Cycle: An Empirical Analysis

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Draft: 26 August 2007

Abstract: This paper explores the extent to which goods follow systematic pricing patterns over their life cycle. The theoretical literature, and anecdotal evidence, suggests that new products are often introduced at high prices which decline as the good ages while, older goods exit the market at a discount. We outline and apply a smoothing-spline approach to the estimation of life cycle pricing effects using data on two different types of goods; supermarket products (beer, canned soup and cereals) and high-tech goods (desktop and laptop computers, and personal digital assistants). We interpret these results within a simple conceptual framework and find evidence for the existence of significant life cycle pricing effects. This implies that hedonic pricing functions which exclude age a misspecified. Furthermore, in order to eliminate bias price index samples must be constructed carefully. Using a simulation we show that the bias introduced by the traditional match-model method may be non-trivial.

Keywords: Product life cycle; Hedonic regression; Price index; Spline smoothing.

JEL Classification Codes: C43, C50, D00, E31.

* The authors gratefully acknowledge both the BEA and the James M. Kilts Center, Graduate School of Business, University of Chicago who made data available for this project. Any opinions expressed in the paper are those of the authors.

1. Introduction

In modern economies there is an extremely wide range of goods from which to choose. Moreover there is a regular churn with varieties appearing and disappearing from retailers shelves at great frequency. These trends are evident right across the product spectrum, from computers to digital cameras, to clothing and canned goods. In this paper we examine whether there are systematic trends in the *prices* of products over their life cycle, from entry to exit.

Strangely, while the theoretical work in this area of *intertemporal price discrimination* is well developed there has been little empirical analysis. This is a major omission because the existence or otherwise of systematic life cycle price trends has implications for price index construction and hence, the measurement of inflation and economic growth. First, if prices do vary across product age then methods of quality adjustment–such as the now widely used hedonic regression approach–must take account of this. If hedonic functions fail to reflect age then they suffer from a potentially important omitted variable bias and the results are potentially erroneous. Second, if prices vary due to the age of a product, holding other factors constant, then the selection of a representative sample of items across the age spectrum will be vital in accurately representing price change. In this paper we investigate the potential magnitude of this new age-selection bias in price indexes.

Theoretical models of intertemporal price discrimination abound. These modeling efforts have focused on cases where sellers have some sort of monopoly pricing power so that prices deviate from marginal cost. Perhaps the first paper to address the question of intertemporal price discrimination was Stokey (1979) who noted that pocket calculators, the PCs of yesteryear, tended to enter the market at high prices which fell over time. She showed, however, that for a continuum of consumers and time periods, with a monopolist having the same rate of time preference as the consumers and perfect information, that it was not generally profitable to price discriminate. The more recent literature has focused on relaxing some of these assumptions and challenged this conclusion. Landsberger and Meilijson (1985) argued that price will tend to decrease over time if the monopolist has a flatter – less impatient – rate of time preference than consumers. Those with a high willingness to pay will buy the product immediately at a higher price while those with lower reservation prices will wait until later. Koh (2006) shows that prices can either decrease or increase over time depending on the particular distribution of purchasers' characteristics and rate of time preference. Imperfect information and liquidity constraints on the consumer-side can also have an effect on the results. Changing marginal costs of production as a product ages provide further motivation for life cycle pricing. For many high-tech goods costs of production are likely to fall leading to a declining price as the product ages. The introduction of competition later in the product cycle, perhaps induced by the entry of firms as they reverse-engineer a product or by patent expiration, provides further impetus for declining prices as a product ages. Much interest focuses on the product entry and the particular price dynamics at this point. Do new goods enter the market at relatively high prices, with retailers taking advantage of the novelty factor to earn a premium at introduction, or do they enter at rock-bottom prices in order to generate a sufficient number of consumer-trials to build a market following? These interesting theoretical possibilities have not been accompanied by detailed empirical work aimed at identifying the features of life-cycle pricing.

In this paper we aim to resolve the uncertainty surrounding the path of prices over a product's life. In this regard we develop a simple conceptual framework and build a flexible model of pricing over the life-cycle in section 2. Section 3 applies this methodology to two U.S. scanner data sets, first, for supermarket products; beer, canned soup, and cereals, and second, to the high-tech goods; desktop and laptop computers, and personal digital assistants (PDAs). These two expenditure classes provide an interesting contrast of the potential effects on price indexes of life cycle price trends, a topic which is also addressed in section 3. Section 4 concludes our discussion while some additional results are contained in the Appendix. In the remainder of this section we discuss the effect on price indexes of pricing over the life cycle.

1.1. Price Indexes and the Product Life Cycle

Price indexes and accounting for quality change in particular, have received a great deal of attention in recent reviews of consumer price index methodology such as; the Boskin Commission (Gordon and Griliches, 1997), the Schultze Report (Schultze and Mackie, 2002) and the recent ILO Manual on CPIs.[1] While there are multiple dimensions to the quality

[1] The CPI Manual was drafted by an international group of experts and compiled in consultation with the IMF, OECD, UNECE, Eurostat, The World Bank as well as the ILO. The Manual serves as a guide in the construction of price indexes and represents the conventional wisdom accumulated by some of the most experienced statisticians in this area and has a similar status to the System of National Accounts Manual.

change issue in price indexes one particularly pertinent issue is the the existence of price trends over the product category life cycle. That is product categories exhibit particular price trends as the technology of production and market dynamics change over time. One issue of adequately allowing for quality improvements in price indexes over time is to include these product categories in the index in timely fashion.

Statistical agencies have often encountered problems in this regard. As a characterisation statistical agencies have been slow to introduce new products and focused too much on mid- and late-life products. Armkneckt (1997) gives the example of video recorders which were introduced into the U.S. CPI in 1987 when they sold for around \$500 but the price change from 1978, when they first appeared on the market at around \$1200, was ignored. The stories for cellular telephones (Hausman, 1999), air conditioners and microwave ovens are similar (Gordon and Griliches, 1997). The omission of product categories early in their life cycle has the potential to introduce bias into the index. In these cases there is a strong supposition that the products discussed had strongly declining prices early in their life hence there exclusion tends to bias the index upward.

While the omission of whole product categories, such as those discussed above, is important it is also likely that omitting new varieties of an existing set of products will matter. If firms, say, charge lower prices for new items in their product range then the failure to incorporate this in the index may also lead to bias. These quality adjustment biases are clearly parallel and both are fundamentally sampling issues

Note that potentially the bias introduced by unrepresentative age-related sampling is large. Unlike other sources of quality change and new goods bias it may not be confined to a narrow subset of product categories and only a few items within those product categories. All goods have an age and hence the possibility of age-related price movements.

There are other ways in which the existence of age effects may intrude on price index measurement. Hedonic regression methods, which relate prices to characteristics, may suffer from omitted variable bias if they do not include 'age'. The failure to include age, if it is found to be a robust price-determining characteristic, could distort results particularly if there are changes in the age profile over time. Yet, another way in which the existence of age-related price effects can be important for price index construction is when goods enter and exit the index sample. Often overlap pricing methods are used which 'splice' the new product into the index in place of the old product at the relative prices for which they trade in the market.[2] This form of quality adjustment is used in the U.S. CPI each year where 20% of the sample is replenished as products are rotated into and out of the index (Abraham, 1997). However, this overlap price method will clearly be influenced by the stage of the respective products' life cycles, which may serve to distort the comparison of relative prices.

While the possibility of systematic life cycle effects has been recognized in the measurement literature (see for example, Silver and Heravi, 2002, and the references below) there has again been very little quantification of this phenomenon. Though there are a few exceptions. In an interesting paper by Berndt, Kyle and Ling (2003) (following earlier work by Berndt, Griliches and Rosett (1993)) who investigate the effect on the price of prescription drugs of patent expiration and the entry of generic producers. They come to the startling conclusion that prices for the established branded varieties tend to *rise* after patents ran out. This emphasizes that the empirical results in this area can potentially turn theory on its head. In another interesting paper, Haan (2004), a researcher at a statistical agency, was keenly aware of life cycle pricing issues, outlined a hedonic regression model which allowed for systematic effects for entering and exiting varieties. However, this was not empirically estimated.

In the absence of substantial empirical evidence there has been speculation about the likely path for prices as products age. For example, a passage from the ILO Manual argues that,

> It may be that the prices of old items being dropped are relatively low and the prices of new ones relatively high, and such differences in price remain even after quality differences have been taken into account (Silver and Heravi, 2002). For strategic reasons, firms may wish to dump old models, perhaps to make way for the introduction of new models priced relatively high. (ILO, 2005, p.100).

This view is shared by Triplett (2004, Chap. 4, p. 17) as well as Schultze and Mackie (2002, p. 162). While this hypothesis of price-skimming for new goods sounds plausible (and is consistent with much of the theoretical literature) so does the possibility that firms charge a low price for new goods so as to build a market share (Triplett, 2004, Chap. 4, p. 5). One reason for such a strategy, which does not appear to have been fully explored in the literature, is that firms must overcome consumers' inertia and uncertainty about trying

[2]If we want to replace item i with j in period 1 then we use the ratio, p_{i1}/p_{j1} to adjust the numerator in the comparison of prices, p_{j1}/p_{i0}. For a more detailed discussion see for example ILO (2004, p. 106).

a new product and 'tempt' buyers to sample the variety by lowering its price relative to substitutes.

The existing empirical literature gives us very few strong priors about the pattern of these pricing strategies. With this in mind we seek to develop as flexible a model as possible of pricing over the life cycle in the next section.

2. Models of Life-Cycle Pricing

In this section we propose a flexible modeling framework for estimating life cycle price trends for products. The objective of our estimation is to isolate the effects of age on the price of a product from the myriad of other contributing factors. The approach we adopt is a non-parametric spline smoothing model where we solve an optimization problem penalizing both for deviations from the data and irregularity (i.e. curvature) in the estimated function. This approach is somewhat novel in this context and allows for the very flexible estimation of the desired parameters.

However, prior to to outlining this model it will be useful to develop a simple conceptual framework in which we can more clearly think about exactly what we are measuring and how. In this regard, consider a the general problem of a set of firms producing and selling a differentiated product to consumers (following Pakes, 2003). The price and quantity traded of a particular good will depend on the prices and quantities of competitor products as well as the incomes and preferences of buyers. Let $x_{nt}(x_t, p_t, E)$ denote the demand for product $n = 1, \ldots, N$ in period $t = 1, \ldots, T$ then from the familiar profit maximisation problem, the first order condition becomes,

$$p_{nt} = \frac{\partial c(x_{nt})}{\partial x_{nt}} + \frac{\partial p_{nt}}{\partial x_{nt}} x_{nt}, \quad n = 1, \ldots, N,\ t = 1, \ldots, T \tag{1}$$

This indicates that the hedonic function, will in general, be a complicated reduced form relationship between numerous competing influences including both consumer preferences and market characteristics–reflected in the elasticity of demand–and producer technology–embodied in the marginal cost.

An alternative approach and complementary approach is to view the hedonic function from a consumer perspective as in Diewert (2003). Here we consider the consumer utility maximisation problem and note that this gives the following equation where λ denotes the marginal utility of income,

$$p_{nt} = \lambda \frac{\partial U(x_{nt})}{\partial x_{nt}}, \quad n = 1, \dots, N, \ t = 1, \dots, T \tag{2}$$

Both these relations provide a different perspective on the hedonic relationship ad will be useful in interpreting the results.

2.1. A Statistical Framework

Following the hedonic literature, our basic formulation will model prices as a function of the product characteristics with any additional idiosyncracies absorbed into the error term. Suppose that item n has the characteristics $z_n = (z_{n1}, z_{n2}, ...z_{nC})$ where there are $c = 1, ..., C$ characteristics. To the list of usual attributes we add the product age, both from birth (a_n) and to death (d_n). By definition the length of life (u_n) satisfies, $u_n = a_n + d_n$.

The basic problem that we faced was to construct a model which would control adequately for extraneous factors and enable us to identify the underlying influence of a product's age on its price. A natural approach is a panel fixed effects model with particular attention to the specification of product-age effects. For each time period there is a cross-section of varieties of each good.[3] Both dimensions can be represented by a set of fixed effects so we define the dummy variables; $b_{nj} = 1$ if observation $n = j$ and zero otherwise, while $h_{ts} = 1$ if the observation is from period $t = s$ and zero otherwise.

In addition to these factors we have a dependence of price on the age of a good. The fact that out data is finite, and hence we do not observe the date of birth and death of every single product, means we have two bits of age related information; the age from *appearance*, a_n, for those goods that we have seen arrive on the market, and the age to *disappearance*, d_n, for the goods which we have observed to disappear in our data.[4] Controlling for fixed effects using the dummy variables, with log-prices as the dependent variable and normalizing on the first period, gives the model:

$$\ln(p_{nt}) = \sum_{j=1}^{N} \beta_j b_{ntj} + \sum_{s=2}^{T} \delta_s h_{nts} + f(a_{nt}, d_{nt}, u_n) + e_{nt}, \quad n = 1, \dots, N, t = 1, \dots, T \tag{3}$$

[3]What we mean by a variety i is a unique bundle of characteristics, e.g. "a 14.25 ounce can of Campbells pumpkin soup." The use of dummy variables provides a very flexible way of constructing a hedonic function (Diewert, 2003).

[4]That is, if $a_n = 2$ then the product has existed for two periods while if $d_n = 3$ then it is three periods before it disappears from the market.

The basic estimation problem revolves around how to best represent the effect of new and disappearing goods, $f(a_{nt}, d_{nt}, u_n)$, on price. Note that we have written included three terms in the age-effect function; age from birth, age to death and length of life. But as only two of these are independent we can write the function as depending on any two to these variables. We outline some of the estimation options below,

2.2. Functional Forms

The most straightforward approach is to parameterize the age effects as a linear or log-linear function. If the effects decompose additively, and considering the latter, we have,

$$f(a_{nt}, d_{nt}, u_n) = \alpha_1 log(a_{nt}) \tag{4}$$

$$f(a_{nt}, d_{nt}, u_n) = \alpha_2 \log(d_{nt}) \tag{5}$$

The interpretation of this in the context above is informative. First, turning to the consumer theoretic formulation of the hedonic function, it can be seen that this implies the following model of consumer utility.

$$\frac{\partial U(x_{nt})}{\partial x_{nt}} = B(z_{nt})H(h_{nt})a_{nt}^{\alpha_1} d_{nt}^{\alpha_2}, \quad n = 1, \ldots, N, \ t = 1, \ldots, T \tag{6}$$

An alternative to the simple linear functional form is a more flexible a fully parametric approach could be adopted where we hypothesize a functional form for $f_a(a_n)$ and $f_d(d_n)$. For example, we could use a polynomial, say of third order such as is shown below. A motivation for this functional form could be given on the basis that it represents a Taylor series approximation around the point, $a_n = 0$ and $d_n = 0$.

$$f_a(a_n) = \theta_{a_0} + \theta_{a_1} a_n + \theta_{a_2} a_n^2 + \theta_{a_3} a_n^3 \tag{7}$$

$$f_d(d_n) = \theta_{d_0} + \theta_{d_1} d_n + \theta_{d_2} d_n^2 + \theta_{d_3} d_n^3 \tag{8}$$

While the polynomial approach has some appeal it has the drawback that it places a lot of structure on the problem. Even a third order polynomial places a high degree of restrictiveness upon the global nature of the functional form – forcing the function to have two turning points and a certain degree of smoothness. Perhaps the biggest problem with polynomial regression, from a practical perspective, is that the behaviour of the function at end points can be problematic in that it will tend to be rapidly increasing or decreasing. This poses problems for our analysis as we are particularly interested in the path of the pricing functions at the extremities.

We could pursue a purely non-parametric approach where a dummy variable is included for each unique value of a_n and d_n. This functional form is shown below where we introduce the dummy variables, $u_{anj} = 1$ ($u_{dnj} = 1$) if $a_n = j$ ($d_n = j$) and zero otherwise, where $j = 1, \ldots, J$ are the values taken by a_n and d_n, over the sample, as well as an index of these values.

$$f_a(a_n) = \sum_{j=1}^{J} \theta_{aj} u_{anj} \tag{9}$$

$$f_d(d_n) = \sum_{j=1}^{J} \theta_{dj} u_{dnj} \tag{10}$$

In contrast the fully non-parametric dummy variable approach has the advantage of great flexibility. In fact, it may place too little restriction on the model with the results being driven by sampling variability rather than the underlying data generating process. It seems reasonable to impose some continuity restrictions on the function as pricing life-cycle effects are likely to change slowly – the price of a good of age 5 is likely to be more similar, controlling for other factors, to the price of a good of age 4 and 6 than, say, 15. We can use this intuition to place some light-handed continuity restrictions on the dummy variable model.

With this in mind we adopt a spline smoothing approach where the life cycle functions take the form shown in (9) and (10) but we penalize, in a transparent fashion, for rapid changes in their values.[5] This approach gives the best of both worlds in that we have a very flexible function which can provide a robust global approximation, rather than the local approximation of the Taylor polynomial, and is still smooth and hence more easily interpreted. Consider the penalized smoothing problem shown below,

$$\min{}_{\beta,\delta,f_a,f_d} \quad \sum_{n=1}^{N} \left[\ln(p_n) - \sum_{i=1}^{I} \beta_i b_{ni} - \sum_{t=2}^{T} \delta_t h_{nt} - f_a(a_n) - f_d(d_n) \right]^2$$

[5] The most well known use of splines in Economics is the Hodrick-Prescott filter (Hodrick and Prescott, 1980) where the smoothing parameter is chosen a priori, though their use dates back to Whitaker (1923). Spline methods are becoming increasingly popular in the applied literature, particularly for hedonic regression and spatial models, see for example Bao and Wan (2004).

$$+\lambda_1 \int [f_a''(x)]^2 dx + \lambda_2 \int [f_d''(x)]^2 dx \tag{11}$$

The first objective of the optimization is fidelity to the data. In addition, we add a penalty for rapid changes in the curvature of the function. This is reflected in the integral over the squared second derivative of the functions. The smoothing parameters, λ_1 and λ_2, represent the relative weights that we give to fidelity and smoothness. As $\lambda_1, \lambda_2 \to \infty$ the selected functions will have no second-order curvature which implies that the estimators are linear (i.e. $f_a(a_n) = \theta_{a_0} + \theta_{a_1} a_n$, and $f_d(d_n) = \theta_{d_0} + \theta_{d_1} d_n$). Note also that the spline smoothing model has the desirable property of nesting the non-parametric dummy variable approach. When $\lambda_1, \lambda_2 \to 0$ the functions will collapse to non-smooth dummy variable functions, as in (9) and (10), and potentially be very 'jagged'. We discuss a method for choosing λ_1 and λ_2 below.

Green and Silverman, (2000) and Wahba (1990) show that the problem (11) has a unique solution and that efficient algorithms exist to solve the resulting system of equations. The minimizer is a natural cubic spline (Green and Silverman, 2000, pp. 13, 66).

The choice of the smoothing parameters λ_1 and λ_2 is somewhat arbitrary but also of some importance in determining the solution. A way around this subjectiveness is to use the method of Cross Validation (CV). This approach minimizes the 'forecast error' of the model in the sense that we withhold one observation from the model and compare actual and estimated values. However, one problem with CV, noted by Craven and Wahba (1979), is that it tends to give too much influence to outliers. They suggested a Generalized Cross Validation (GCV) score function which ascribes lesser weight to these high-influence observations.

$$GCV(\lambda_1, \lambda_2) = \sum_{n=1}^{N} \left[\frac{y_n - \hat{y}_n(\lambda_1, \lambda_2)}{1 - N^{-1}\mathrm{tr}(\mathbf{A})} \right]^2 \tag{12}$$

This robustness to outliers is an important advantage and hence we use the GCV approach to derive $\hat{\lambda}_1$ and $\hat{\lambda}_2$.

XXX We use a somewhat novel approach to calculate standard errors for the semi-parametric model by recasting the model within a maximum likelihood framework. This approach is relatively new in the literature, and is due to Reeves *et al.* (2000). The method gives a familiar expression for the variance with the details left to the Appendix. Other approaches taken to the calculation of standard errors in the spline case have been to recast the smoothing model within a Bayesian framework, which involves adopting this conceptual framework, or estimating bootstrap confidence intervals by constructing sample replicates (see Wahba (1990) for discussion of both these approaches). While the latter approach is attractive it will be computational prohibitive for the large data sets used in the next section.XXX

With this model of life cycle pricing we move to apply it to two large U.S. scanner data sets. Additionally, we undertake an investigation of the effects of life-cycle pricing on price indexes.

3. An Empirical Investigation

We apply the non-parametric smoothing methods discussed above to two data sets. The first is a supermarket scanner (or barcode) data set for the Dominick's chain of food stores in the Chicago area.[6] There are 96 stores included in the database with price data available at a monthly frequency from September 1989 to May 1997 – a period of almost eight years (though not all the products are available for all this period). We focus on prices for; beer, canned soup, and cereals.[7]

The other data set is also scanner data that was purchased by the BEA for research purposes and made available to the authors.[8] This data set is particularly interesting because it includes the high tech goods; desktop and laptop computers as well as personal digital assistants (PDAs). These electronic goods provide an interesting contrast with the supermarket products also analysed and correspond most closely to the types of products for which the literature has modelled life cycle price discrimination. The high tech products are also of considerable interest because of the difficulty inherent in calculating price indexes for these rapidly changing and dynamic expenditure classes (Gordon and Griliches, 1997; ILO, 2004; Triplett, 2004). This data runs for a period of 3 years, from October 2001 to September 2004.

Before we begin on the estimation we provide some discussion of the data and in par-

[6] The data is made publicly available, free of charge, by the James M. Kilts Center, Graduate School of Business, University of Chicago. The authors gratefully acknowledge the Center for making the data accessible in this way.

[7] One point to note regarding the use of Dominick's data is that it represents the sales of just a single chain of stores. Any pricing strategies that we find may in this case be characteristic to this retailer and atypical of pricing patterns more generally.

[8] We are particularly grateful to the BEA for allowing the use of their data in this project.

Table 1: Product Life Cycle Statistics

Product	Proportion of the sample that has disappeared by:					Number of products			Average Age
	3 months	6 months	1 year	2 years	3 years	Total	Appeared	Disappeared	(in months)
Desktops	%	%	%	%	%		(%)	(%)	
Desktops	%	%	%	%	%		(%)	(%)	
Desktops	%	%	%	%	%		(%)	(%)	
Desktops	%	%	%	%	%		(%)	(%)	
Desktops	%	%	%	%	%		(%)	(%)	
Desktops	%	%	%	%	%		(%)	(%)	

tiuclar the process for calcualtion of the age variables discussed above.

3.1. Constructing the Age Variables

The age variable was constructed as...

We provide some summary information in Table 1 on the data sets focusing particularly on aspects of the product life cycle. It can be seen that the high-tech goods have a particularly short life span. For these products which were observed for at least 3 consecutive months the average length of life was just 7 months for desktops, 6 months for laptops and a meagre 4 months for PDAs. The short life span reflects a highly skewed distribution of product lives. While some models last for years, most varieties appear and disappear in very short order, pulling the averages down. Another way to demonstrate the short life span of these high-tech products is to look at the probability that a particular variety will be available over a certain time range. For desktop computers, for example, the probability that a model will disappear next month is 28.13%, in 6 months time, 50.94%, and in a year 67.33%. Of all varieties recorded in our data, 2427 in all, 711 (31.8%) were new during the period while 426 (17.6%) disappeared, further indicating significant turnover. The trends are similar for laptops and PDAs.

There is a strong contrast between the high tech goods and the supermarket products. The latter have a longer life span, around 20 months for all those products which lived at least 6 months, and a significantly less dramatic disappearance rate. Though, with a disappearance rate of around 15% for canned soup and cereals and 25% for beer, over 12 months, it is still far from trivial.

As emphasized earlier the turnover rates are potentially important as it influences the amount of quality adjustment which statistical agencies are required to undertake in their matched samples. It also reflects the extent to which products are likely to be in dynamic price transition as more 'action' in prices is likely to take place either early or late in life. The statistics also indicate the amount of information that we have to work with in estimating the life cycle pricing function. For laptops, for example, we have around 813 varieties appearing over the sample and 489 disappearing, out of a total of 2,451. This gives a good amount of information by which to robustly estimate $f_a(a)$ and $f_d(d)$.

Which data was used in the estimation?

3.2. Results of Estimation

Using the data, and smoothing spline model outlined above, we estimated the effect of age, *from appearance* and *to disappearance*, on the prices for each of our product categories. Turning first to the model diagnostics. In Table **??** we report the value of the smoothing parameters chosen using GCV as well as the sample size and length, and pseudo-R^2.

The model generally performed well. The use of a smoothing spline serves to better elucidate the relationship between price and age than the dummy variables, which are quite volatile especially at the right-hand-side where there are fewer observations. The GCV method leads to a range of values for the smoothing parameters. More smoothing occurs for the high-tech goods, where the price effects are larger, than for the supermarket products where λ_1 and λ_2 are small though never equal to zero – as they would be for the pure dummy variable model. For desktops λ_2 reached our upper bound, where the function became effectively linear, indicating that significant smoothing was required in this case. The Pseudo-R^2 values, the squared correlation coefficient of actual and predicted values, show how well the models explain the data. While the regression model does not have a strict statistical interpretation we can undertake approximate F-tests of parameter restrictions by looking at changes in the sum of squared errors. We find that in all cases there are statistically insignificant differences between the spline model and the unsmoothed age-dummy model. However, for canned soup and cereals, there is a statistically significant difference between a regression model without any age effects and the unsmoothed model. This indicates to us that the spline smoothing model does almost as good a job of explaining data *within sample* as the dummy variable age specification.[9] The removal of age effects

[9]Note that our approach to choosing parameters, and the values of λ_1 and λ_2, was to focus on out of

reduces the explanatory power of the model in all cases though the large amount of variation explained by the other parameters in the model mean these changes are mostly insignificant. As we will see, however, the economic magnitudes of the parameters are often quite large.

Table 2: Model Diagnostics

Product	Number	Number of	Linear Model			Spline Model	
	of Months	Observations	Coefficient	T-Stat	R^2	R^2	F-Stat
Desktops							
Desktops							
Desktops							
Desktops							

The results from the model estimation are presented graphically in Figures 1–12. The Figures show the smoothing spline, the solid dark line, as well as the unsmoothed dummy variable estimates for the life cycle, the white line. The dashed lines represent our maximum likelihood confidence intervals, conditional on the value of smoothing parameter. The Figures record the influence of age, from appearance or to disappearance, on price over a 24-month period.

{Insert Figures About Here}

3.3. A Discussion of the Results

The pattern of life cycle pricing, as shown in the Figures, is interesting for a number of reasons. First, the pricing effects that we find are generally quite large. For laptops, for example, the price of a new product peaks at month 4 and then declines so that in month 12 the price is 10.04% lower. This is a significant price change due entirely to life cycle factors. This order of magnitude is fairly typical of the high-tech goods which show strong life cycle effects. However, the supermarket products exhibit considerably less pronounced swings in price due to age. New cereals, for example, decrease in price by 4.53% in the first 12 months of their life while canned soup falls by around 5.11%. New varieties of beer on

sample performance as in GCV. In this regard we judged the spline model as superior to the unsmoothed model.

the other hand appear to be relatively stable over the first year of life. One of the immediate implications of the existence of these life-cycle pricing effects is that hedonic functions which exclude 'age' as an explanatory variable may potentially be mis-specified.

Second, some stylized facts of life-cycle pricing emerge arise. For desktops and laptops prices generally tend to decline as products age. However, there appears to be an initial lip at around 4–6 months over which prices are flat or even weakly rising. While the same trends are apparent for PDAs the lip is more pronounced, products come in cheap and rise in price up to the 9th month and then begin declining. This pricing-lip may reflect introductory sales used to generate customer trials of the new variety. Interestingly, there does not appear to be any strong trend amongst the high-tech products for prices to decline as a variety reaches the end of its life. While this does occur for desktops, in contrast, for laptops, and to a lesser extent for PDAs, prices rise as death approaches. For the supermarket products prices appear to decline upon entry though beer is flat. Upon exit prices tend to fall and often quite markedly for canned soup and cereal. Beer varieties, on the other hand, actually rise in price as they disappear from the market. This may reflect the strong part taste and brand loyalty play in this market so that something like the Berndt, Kyle and Ling (2003) result arises with a smaller number of consumers willing to pay a premium for their preferred brand.

Third, it does appear that the beginning and end of the life cycle do generally represent pricing extremes. All the high-tech products are at or near life-cycle pricing peaks or troughs except PDAs which are disappearing. Similarly for the supermarket products, in all cases except new-beer varieties, are either at the top or bottom of the pricing life-cycle. This confirms our *a priori* supposition that much of the dynamism in product pricing is seen early and/or late in the cycle.

Fourth, the approximate confidence intervals for the estimated life cycle function are generally fairly wide for the high tech products to reject the individual hypotheses that the life cycle effects are constant through time, i.e. the life cycle function is in fact flat. Only on the case of canned soup and cereals could we reject the joint hypothesis of no life cycle effects over the sample. This means we must be cautious in interpreting the results. In the case of the supermarket products the confidence intervals are generally tighter meaning we can reject the hypothesis of no life cycle effects in around half the cases. Unfortunately, while some of the estimated effects may not register as statistically significant, they are certainly of an economically significant magnitude. In the next section we show that life-cycle pricing effects of this magnitude can have a large influence on estimates of price change.

3.4. Implications for Price Indexes

The results above have some important implications for the construction of price indexes. If the stage of the life cycle is an important price-determining characteristic then this must be taken into account in constructing an index. More specifically, every effort must be made to ensure that change in the age structure of the sample between two periods does not contaminate measures of price change. Age effects are quality characteristics like any other and these should be held fixed in order to isolate the pure price effects.

The implications of age effects for standard price index construction are potentially quite significant. The basic matched model holds the sample of goods fixed between any two periods. This will clearly control adequately for standard quality change but by its nature must mean that the age of the products in the two periods differs. If age effects are large enough then this has the potential to lead to a significant divergence between measured and ideal price change. As noted previously, the existence of age effects has the potential to create widespread bias right across the index. Unlike quality change–which is usually confined to a small set of items within a product category–age effects are likely to be evident for each and every item within a product category and across almost every product category.

Our ideal measure of price change holds the age effect fixed across time. Let us adopt the hedonic imputations approach to price index measurement (Triplett, 2004; Hill and Melser, 2006a, 2006b). We use a geometric mean aggregator over M products with equal weights for each observation.[10] Using a general hedonic price function we can write such an index between periods 0 and 1 as,

$$\hat{P}_{01} = \prod_{m=1}^{M} \left[\frac{\hat{p}(b_m, h_{m1}, a_m, d_m)}{\hat{p}(b_m, h_{m0}, a_m, d_m)} \right]^{1/M} \tag{13}$$

Here the only component which changes is the purely temporal effect; the characteristics (b_m), as well as age from appearance (a_m) and to disappearance (d_m) is held fixed. Contrast

[10]We use the geometric mean because it has particular advantages when used in conjunction with the logarithmic price function adopted above (see Hill and Melser, 2006a), but its use, as well as the absence of weighting, does not change the substance of the point made.

this index with the standard matched model approach where by its nature the the age of the products changes.

$$\tilde{P}_{01} = \prod_{m=1}^{M} \left[\frac{\hat{p}(b_m, h_{m1}, a_m + 1, d_m - 1)}{\hat{p}(b_m, h_{m0}, a_m, d_m)} \right]^{1/M} \tag{14}$$

While the characteristics b_m are held fixed between periods, the age of each of the varieties must increase. That is, between periods *0* and *1* the products get one period further from introduction and one period closer to disappearing from the market.

Now specializing the framework by using our general logarithmic model of price outlined in (3) we can write the matched model index in the following way.[11]

$$\begin{aligned} \tilde{P}_{01} &= \prod_{m=1}^{M} \left[\frac{\exp(\sum_{i=1}^{I} \hat{\beta}_i b_{mi} + \hat{\delta}_1 h_{m1} + f(a_{m0} + 1, d_{m0} - 1, u_m))}{\exp(\sum_{m=1}^{M} \hat{\beta}_i b_{mi} + \hat{\delta}_0 h_{m0} + f(a_{m0}, d_{m0}, u_m))} \right]^{1/M} && (15) \\ &= \exp\left[\hat{\delta}_1 - \hat{\delta}_0\right] \prod_{m=1}^{M} \exp\left[\frac{f(a_{m0} + 1, d_{m0} - 1, u_m)}{f(a_{m0}, d_{m0}, u_m)} \right]^{1/M} && (16) \end{aligned}$$

It can readily be seen that the index, while immune from compositional change due to matching, will be influenced by the aging of products. We will specialise the framework somewhat more below... In (**??**) the age distribution in the initial period clearly determines the age of products in the second period under a matched sample framework. The specific nature of the original age distribution will influence price change – an effect which is mediated by the size of the life cycle pricing parameters.

To consider the potential size of the sampling error we run a series of simulations using our estimated price function and data. We suppose that a sample is taken in some initial month and that this is kept constant over the remainder of the year. In this case note that while the initial sample may contain some varieties which are brand new to the market (i.e. have an age of *1*) the following month can only contain goods which are at least 2 periods old, and so forth. That is, the sample must age and hence move along the price function. We examine how this index is influenced by aging over a 12-month period. Unfortunately, it is not possible to be definitive about the bias because we cannot calculate the ideal index. The problem is that our data sets are finite so we do not observe the birth and death of all

[11]Note that if we want an unbiased estimator then we should make some adjustment to this index due to the fact that we are taking the exponent of estimated parameters (see for example, Garderen and Shah, 2002). We will not illustrate for the case of these adjustments because it complicates the problem without diminishing our essential point.

products hence we do not know the actual (i.e. population) distribution of product ages in our data. Ideally an index would use the actual distribution of ages amongst products and record price change for these products. Given our inability to do this we instead undertake a number of simulations looking at various distributions for the ages of products in the base period (i.e. how products are scattered along the age spectrum) and then compute the price change for this selection. The scenarios considered are:

(A) The empirical distribution of products for which we observed the entire life cycle. The features of this distribution are a high degree of skewness towards varieties which are new to the market and paradoxically also close to disappearing which reflects the relatively short life-span of products, at least for the high-tech products. (When a product disappears from the market a chained matched-sample approach is used.)

(B) A uniform distribution of products is sampled for a 12-month period over the ages, 1 month to 12 months for new goods. We further supposed that these products were uniformly distributed as being between 12 to 23 months (inclusive) to disappearing from the market. (These assumptions mean that no products disappear from the sample over the 12 months for which the index is calculated.)

(C) A uniform distribution of products is sampled over a 6 month period from the ages of 7 to 12 months for new goods and we supposed that these products had between 18 to 23 months (inclusive) to go in their life until they disappeared. (These assumptions mean that no products disappear from the sample over the 12 months for which the index is calculated.)

Scenario (A) gives our best estimate of price change from our data, given the caveat of limited knowledge expressed above. Scenarios (B) and (C) contrast in that the former includes the effects from goods which are very early and late in their product cycle while scenario (C) excludes all effects from products which are of age 6 months or less and within 6 months of exiting the market.

We present a summary of our results in Table 3. The life cycle effects are decomposed into those due to *New Goods* and *Disappearing Goods*, as shown in equation (**??**). These effects along with pure price change, give the *Total* price change over the 12-month comparison.

Table 3: Life Cycle Effects on Price Indexes[(a)]

Product	(A)			(B)			(C)		
	Uniform	Left Skew	Right Skew	Uniform	Left Skew	Right Skew	Uniform	Left Skew	Right Skew
Desktops									
Desktops									
Desktops									
Desktops									
Desktops									
Desktops									

The results show that the effects of product age can be large in that the spreads between the price change under various sampling methods are big. In the case of desktop computers, for example, under scenario (A), which reflects the empirical distribution of ages, we get an annual average price fall of 33.98%. The price falls under scenarios (B) and (C) are even larger. The reason for this is that the latter methods do not have such as strong weight on items which are relatively young, in the case of scenario (C) items younger than 6 months are not sampled at all. As the price function for appearing products slopes down from around 4 months onward, having greater weight on the lower (righthand) end of the price function leads to larger price falls. The spread between scenarios for laptops is –46.19% for (A) and –48.49% for (C) a small fraction of overall price change. PDAs, the most recent and dynamic of the high-tech products, show a very large difference of –30.46% for (A) compared with just –18.30% for (C). Generally, because the appearing products life cycling tends to slope down, the aging of products leads to a fall in the price of appearing goods. This is reflected in the fact that for all the high-tech products the contribution to price change from the aging of appearing products to the index is always negative.

The effects for the supermarket products are less dramatic. For beer, for example, we saw that the life cycle effects were relatively small for appearing products – i.e. the price function was essentially flat. Consequently the effect of different sampling patterns for new products was small. However, the effect of age to disappearance for beer was larger and led to differences between total price change of over 2% between methods (A), and (B) and (C). Canned soup and cereal also show differences between methods of around 2%. While these differences are of a significantly smaller magnitude than for the high-tech goods, it makes up a large proportion of overall price change, around half. This indicates that even for fairly mundane product categories life-cycling pricing patterns are important for determining measured price change.

More generally, we have shown with our simulations that the effects of life cycle pricing are large enough so that different selection strategies will lead to different index numbers. While we can not be sure of the true price change in our data sets, because of its limitations, the existence of a big spread between index numbers under various methods emphasizes our point.

4. Conclusion

The purpose of this paper has been two-fold. First, to shed some light on the path of prices for commonly traded supermarket products and high-tech goods, over their life cycle. This is in the context of an ongoing modeling effort looking at intertemporal price discrimination. Second, we investigated the implications of these duration effects for the estimation of price indexes.

The results of our model, while not linked in a structural manner to the theoretical literature, do provide some support for their hypotheses. We generally found, most strongly for the high-tech goods, that prices decline as products age. Given the absence of more detailed information we were not able to identify the extent to which this was due to the various possible factors; declining costs, increased competition, customer segmentation or other reasons. One interesting feature of the results is that in the initial months of a good's introduction they often appear to be discounted. This 'pricing lip' is then followed by a more protracted and significant decline in prices. Further theoretical work could focus on motivations for this apparent pricing strategy while empirical work could try to flesh out more of the details of the systematic patterns in life cycle pricing.

The key empirical finding was that the age of a product, either from its birth or to its death, does contribute to its price level and that this has significant implications for price indexes. In a simple simulation, where we held the sample of products fixed for a year, we showed that bias could arise because of the effects of life cycle pricing. This must caution statistical agencies to take steps to ensure that their samples of products along the age spectrum are representative of the actual distribution. Failure to accurately reflect product age in a sample of goods is likely to lead to a sizeable error in the index.

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