Life Cycle Pricing and the Measurement of Inflation

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Abstract: This paper explores the extent to which products follow systematic pricing patterns over their life cycle and the impact this has on the measurement of inflation. We apply a novel smoothing-spline approach to the estimation of life cycle price effects using data on two different product categories; supermarket consumerables and high-tech goods. We find evidence for the existence of both economically and statistically significant life cycle pricing effects. The implications of this are that hedonic pricing functions which exclude age-related variables are mis-specified a priori and that many price indexes mix life cycle price trends with purely inflationary price change. We investigate the influence of life cycle price trends on price indexes for our product categories and find that it is significant.

Keywords: Product life cycle; hedonic regression; consumer price index; spline smoothing; scanner data.

JEL Classification Codes: C43, C50, E31.

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1. Introduction

They say variety is the spice of life. If so then today's consumers are getting plenty of it. One of the most distinctive features of modern economies is the extraordinary array of product varieties, brands, sizes, colours, editions and flavours. These developments have been of significant benefit to many consumers who can now choose from products which cater to their specific needs and desires—Hausman (2003) somewhat facetiously calls this the "invisible hand of imperfect competition." But not every new product variety is destined to be a bestseller, and product churn, along with choice, has also characterized this new economy. The rapid turnover in product varieties has been driven by technology in some areas—such as electronics where old varieties are superseded by new faster, smaller, and better models—but is also unequivocally apparent in less dynamic product categories. By analogy to the natural world this process of product birth, evolution, maturity and death is termed the product life cycle.

In this paper we extend what has been relatively scant research on the product life cycle. We focus on one particular aspect of this issue—price trends as products mature. Our primary motivation for such a study comes from the potentially important implications for price index construction stemming from the existence of life cycle pricing trends. If prices change as products age then standard price indexes will be contaminated by these effects and fail to record purely inflationary price change. This is potentially very significant as almost all types of consumer goods could have prices which vary over the life cycle. Unfortunately, little if any research has been undertaken on understanding the product life cycle, estimating life cycle pricing effects, or examining their impact on price indexes.

More generally, developing a better understanding of pricing trends over the product life cycle will inform a primarily theory-driven industrial organization literature on intertemporal price discrimination—one of the reasons why life cycle price trends may arise in practice. Stokey (1979) was first to note that there may be conditions under which a monopolist would charge different prices over time purely in order to maximize profits. Her results have been developed and extended by others (Landsberger and Meilijson, 1985; Varian, 1989; Koh, 2006) who have found that it may be optimal to price-discriminate across time if consumers are very impatient, or at least less patient than the seller, or if different types of consumers can be separated by charging a premium to those who have the strongest desire for the new variety. Imperfect information and liquidity constraints on the consumer-side provide further reasons for intertemporal price discrimination.

But clearly price discrimination is not the only reason why prices may shift over the life cycle. Changing marginal costs of production is another likely source of life cycle price trends. For many high-tech goods the costs of production are likely to fall over time, as firms improve processes and make technological developments. This implies declining prices as products age. The introduction of competition later in the product cycle, perhaps induced by the entry of competitor-firms that have reverse-engineered a product, provides further impetus for falling prices as products' mature. Importantly, life cycle price trends are also driven by the consumer-side of the market, with buyers' preferences across the age profile allowing firms firms to charge more (or less) for older products.

Much of the interest in life cycle pricing focuses on the price dynamics at the point of entry and exit from the market. 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 possibilities have not as yet been accompanied by detailed empirical work aimed at identifying the stylized facts of life-cycle pricing.

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 cited below) there has been little quantification of this phenomena. There are a few notable exceptions. The path-breaking paper on the estimation of hedonic functions for computers by Cole et al. (1986) included the age of the product as an explanatory variable. They found that it was an important driver of price. Few, however, have taken up where these authors left off. In an interesting paper Berndt, Kyle and Ling (2003) (following earlier work by Berndt, Griliches and Rosett, 1993) 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 expired as a select group of consumers, with strong preference for the branded variety remain willing to pay a premium for it. This unexpected result emphasizes that the empirical findings in this area can potentially turn theory on its head. In another interesting contribution Haan (2004) outlined a hedonic regression model which allowed for systematic effects for entering and exiting varieties, though he did not proceed to estimate it empirically.

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 CPI Manual argues that:[1]

> It may be that the prices of old items being dropped are relatively low and the prices of new

[1] Triplett (2004, Chap. 4, p. 17) and the Schultze and Mackie (2002, p. 162) panel also share the view outlines in this quote, i.e. that new goods are priced relatively high and old goods more cheaply.

> 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, 2004, p.100).

While this ‘price-skimming’ hypothesis for new goods sounds plausible so does the possibility that firms charge a low price for new varieties so as to build a market share (see for example Triplett, 2004, Chap. 4, p. 5). One possible reason for such a strategy could be that firms must overcome consumers’ inertia and uncertainty about trying a new product; lowering the price sufficiently, relative to substitutes, is enough to ‘tempt’ buyers to purchase the item.

The existence or otherwise of distinctive product price trends over the life cycle has potentially very significant implications for price indexes and hence the measurement of both inflation and economic growth. Somewhat surprisingly these issues have not been examined to any great extent in the index number literature.

Fundamentally, we make the observation that if products exhibit distinct pricing patterns over the course of their lives then, unless these are explicitly accounted for by the statistician, these price trends are implicitly reflected in the measure of price change. This is likely to be undesirable. While prices can change for a variety of reasons the systematic and predictable nature of life cycle movements means that measures of price change which include these are likely to be unsuitable for use in setting monetary policy. Here the primary focus is upon the effects of monetary conditions on prices and not systematic market characteristics. We also argue that under a cost-of-living approach to price measurement the most prudent course of action is to remove age-related price movements from the index. This is because these effects are likely to arise at least partially from consumers placing different values on products of different ages. In this case, by allowing the age profile of the products surveyed to shift the index may be unwittingly contaminated by changes in consumer welfare. The implications of this for price indexes are far-reaching as almost any consumer good has the potential to exhibit life cycle price trends. While age-related bias has the potential to contaminate conventional measures of price change it may also distort price indexes derived using hedonic regression techniques. Hedonic methods, which relate product prices to product characteristics, may suffer from omitted variable bias if they do not include ‘age’ in some fashion. The failure to include features of the life cycle in the model, when they are robust price-determining characteristics, can distort results especially if there are changes in the age profile of items over time.

Our goal in this paper is to resolve the uncertainty surrounding the path of prices over a product’s life and then look at the impact of these trends on price indexes. In the next section we outline our data and the approach taken to defining and identifying a product's life cycle characteristics. We use two large U.S. scanner data sets. The first is for supermarket products while the second is for high-tech goods. These two expenditure classes provide an interesting contrast, both in their potential life cycle pricing trends and in the impact of these trends on price indexes. We extract the required life cycle variables from our data and apply a spline-smoothing, and linear regression, model in section 3. Section 4 examines the implications of these results for consumer price indexes and shows that price indexes can be significantly distorted by life cycle price effects. Section 5 provides a summary and some conclusions.

2. Data and Extracting Life Cycle Characteristics

We investigate the pattern of life cycle pricing using two different but complementary scanner (or barcode) data sets. The first is for supermarket products sold at the *Dominick's Finer Foods* chain of food stores in-and-around the Chicago area.[2] For the purposes of this research we focus on data for the product groups; analgesics, beer, laundry detergent, and soft drinks. There are 96 stores which have recorded prices for these product categories in the database from September 1989 to May 1997—a period of almost eight years (though not all the products are available for the entire sample).

The product group covered by the second scanner data set are high tech goods; notebook and desktop computers. This data set was made available to the authors for the purposes of this research by the Bureau of Economic Analysis (BEA) and contains sales data for a period of three years from October 2001 to September 2004.[3] This product group provides an interesting contrast with the supermarket products. Whereas the market for supermarket consumables is relatively stable, that for high tech goods is characterized by continual technological improvement, short product life spans, and significant price deflation. For this reason this expenditure class poses considerable difficulties in terms of accurately measuring price trends (Gordon and Griliches, 1997; ILO, 2004; Triplett, 2004).

Both data sets are large and provide the required richness to extract and estimate age-related price effects. We use the data at a monthly frequency, as this corresponds to the calculation frequency of consumer price indexes in most countries. Price and characteristics information is available for each product so standard hedonic methods can be applied.

[2]The data is made publicly available, free of charge, by the James M. Kilts Center, Graduate School of Business, University of Chicago (http://research.chicagogsb.edu/marketing/databases/dominicks/index.aspx). The authors gratefully acknowledge the Center for making the data accessible in this way.

[3]We are particularly grateful to the BEA, Ana Aizcorbe and Kevin Fox, for facilitating the use of these data in this research project. Previous research with this data includes; Aizcorbe and Pho (2005), Ruder and To (2004), Thompson (2003).

However, our investigation involves an additional step compared with most hedonic studies—extraction of the life cycle variables and inclusion of these in the hedonic price function. But what are the key features of the life cycle and how can they be extracted from our data set?

While the product life cycle is now a relatively familiar term in the Marketing and Economics nomenclature there has been little explicit specification of exactly what factors characterize the life cycle (though Berndt, Griliches and Rappaport (1995) have gone someway in this direction). A natural first approach is to identify the state of the life cycle with reference to an item's *age*—the length of time between the current period and the 'birth' of the product. While age is indeed a key characteristic of a product's life cycle focusing only upon this feature is, we argue, insufficient and one-sided. If the life cycle is to be treated symmetrically then an equally important, but somewhat less intuitively obvious concept, is that of *reverse age*, the number of periods from the current period until an item disappears from the market. A symmetric analysis of the life cycle must allow for price trends to be driven by both these factors.

There are in fact six ingredients needed to fully characterize the state of a product's life cycle. Consider an item n in time period t, then two of these factors are its date-of-birth (b_n) and death (v_n). If we define the current time period (h_{nt}) then we can determine, the age of an item (a_{nt}) as the number of periods elapsed since its birth. Symmetrically, we can define the reverse age, or age-to-death, (d_{nt}), as the number of periods until a product disappears from the market. A final ingredient in the measurement and definition of the product life cycle is the length of life for a product (l_n). Together these factors fully characterize the product life cycle and are illustrated in Figure 1. Some points are worthy of note.

Firstly, from Figure 1, and the preceding discussion, it is clear that not all the age-related variables are independent—indeed some are related by identities. This means that it will not always be possible to identify the effects of the age-related variables independently of one another. It can readily be seen from Figure 1 that the characteristics of the life cycle are linked by four identities.[4]

$$l_n = v_n - b_n \tag{1}$$

$$l_n = a_{nt} + d_{nt} \tag{2}$$

$$h_{nt} = b_n + a_{nt} \tag{3}$$

$$h_{nt} = v_n - d_{nt} \tag{4}$$

Secondly, in order to completely characterize the current state of a product's life cycle we

[4]Note, however, that the four equations imply only three restrictions as not all the equations are independent. This is reflected in our hedonic model which follows where we include only three of the life cycle variables.

must observe the entire life cycle, from the birth of the product to its death. This is important because it will be particularly demanding of our data as observations for some items will be truncated at the beginning and/or end of the data set. For these censored products it will not be possible to fully characterize the state of the life cycle.

Censored observations can arise for a number of reasons. For very long-lived items, which are observed in every period of the data set, it is clearly not possible to identify either the age or reverse age, as date of birth and death are unknown. Fortunately, given the extended nature of our supermarket data this problem arose only very infrequently, while in the shorter high-tech data set it did not arise at all because of the relatively brief life spans for these items. However, censoring also arose for products at either edge of the data sets. For products at the beginning of the data it was not possible to identify the birth-date and hence age could not be determined while for products at the end of data set reverse-age could not be calculated. These three types of censored observations were removed from the analysis as the failure to include values for one or both of the age-related variables would almost certainly lead to biased

Figure 1: Depiction of Product Life Cycle Characteristics

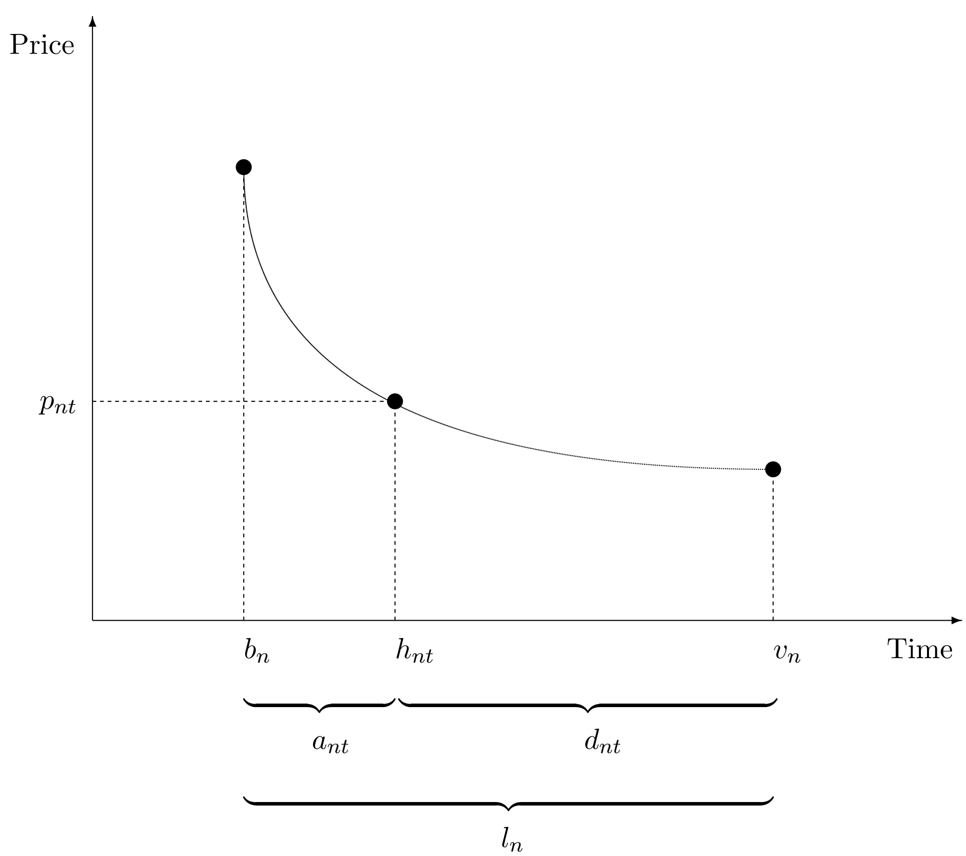

Table 1: Problem Constructing the Life Cycle Product Variables

Item: Description	Time (valid obs. [O], missing obs. [-])										Observed	
	1	2	3	4	5	6	7	8	9	10	a_{nt}	d_{nt}
A: Censored (birth)	O	O	O	O	-	-	-	-	-	-	×	✓
B: Censored (death)	-	-	-	-	-	O	O	O	O	O	✓	×
C: Censored (birth & death)	O	O	O	O	O	O	O	O	O	O	×	×
D: Missing (two periods)	-	-	O	O	-	-	O	O	O	-	✓	✓
E: Short life-span (two periods)	-	-	-	-	-	O	O	-	-	-	✓	✓

results if both factors influence price.

An additional problem, familiar to users of barcode data, is the presence of very short-lived items and a multitude of missing observations. Missing observations may simply arise because a product was not sold in a given period, while short-lived products may represent an actual phenomenon. However, more worryingly, both factors could reflect the fact that sales have not been recorded correctly or that the barcode is somewhat unreliable and is being used sporadically by retailers. This makes us cautious about using these observations.

These various cases of troublesome observations are depicted in Table 1 for a hypothetical ten-period data set. While there is little that can be done with the censored items (i.e. A, B and C in Table 1) some care must be taken in incorporating the short-lived items (E), and those with missing observations (D), into the analysis. We aim to use as much of the data as possible but remain wary that including less reliable observations could contaminate the results. As a compromise, and to ensure the robustness of our results, we construct three different data sets based on different rules for excluding products with short life spans and missing observations.

We first allow a minimum life length of 3 months and consider a maximum 3-month, then 6-month, run of missing observations. This gives the samples, $S(3,3)$ and $S(3,6)$. For the supermarket products, which are relatively long-lived compared to the high-tech goods, we also consider a minimum life length of 6 months coupled with a maximum 3-month run of missing observations, i.e. $S(6,3)$. The various data sets are summarized in Table 2.

The summary data show that the difficulties of truncated observations, coupled with the problem of short-lived items and missing observations, significantly reduces the amount of useable data. However, because the data sets are relatively large to begin with, sufficient information remains to estimate life cycle pricing effects. A notable feature of the data is the high rates of product churn with around a quarter of supermarket varieties disappearing

Table 2: Life Cycle Statistics

Product†	Months of Data	Number of Items: Total	Number of Items: Included	Percent of products that disappear by: 6 months	1 year	2 years	3 years	Average Age (months)
Analgesics:	91	641						
$S(3,3)$			176	5.7	21.6	49.4	77.3	27.6
$S(3,6)$			191	5.8	24.1	50.8	77.0	27.0
$S(6,3)$			165	—	19.4	47.3	75.8	28.4
Beer:	71	790						
$S(3,3)$			190	11.1	33.7	68.4	85.3	20.8
$S(3,6)$			209	13.4	38.8	71.3	88.5	19.6
$S(6,3)$			165	—	26.1	66.1	85.5	22.4
Laundry Detergent:	94	582						
$S(3,3)$			220	3.6	21.7	64.7	78.3	26.0
$S(3,6)$			229	4.4	21.8	65.5	79.9	25.3
$S(6,3)$			211	—	18.5	64.0	78.7	26.4
Soft Drinks:	93	1746						
$S(3,3)$			279	7.5	29.0	67.4	84.9	21.6
$S(3,6)$			339	14.5	36.0	68.7	84.4	20.4
$S(6,3)$			254	—	26.4	66.1	83.9	22.2
Desktops:	30	3168						
$S(3,3)$			438	41.3	78.3	95.9	—	9.4
$S(3,6)$			490	51.6	83.1	98.8	—	8.2
Notebooks:	30	3234						
$S(3,3)$			539	41.0	85.7	99.4	—	8.3
$S(3,6)$			608	57.7	91.0	100.0	—	7.1

† $S(a,b)$ denotes the restrictions used to derived the data set such that, a = the minimum length of life permited in months, b = the maximum run of missing observations that was permitted in months.

within a year and roughly three-quarters of the high tech goods over the same period. The average life spans for the supermarket products are generally around 2 years but less than a year for the high tech goods. Reassuringly the summary statistics for the life cycle profile of the three different samples are not too dissimilar.

3. Modeling and Estimation of Life Cycle Pricing Trends

The data sets constructed above provide a firm basis on which to model life cycle pricing trends. Our primary objective is to identify the effects of the product life cycle on price after controlling for cross sectional and time series 'nuisance' factors.

Following the hedonic literature we take the natural logarithm of price as the dependent variable.[5] We propose a straightforward yet flexible panel data model which controls for cross

[5]The logarithmic functional form has been advocated by Diewert (2003b) who argues that it will tend to

sectional and time series variation using fixed effects. We insert dummy variables for each item to control for cross-sectional price differences.[6] These variables will reflect the difference in prices related to the different quality-related features of the products. For example, in the case of computers the item-dummies will reflect the difference in price related to factors such as processor speed, hard drive capacity and so forth. To control for product-wide temporal variation in prices we insert dummy variables for each time period. Finally, and most importantly in terms of our objectives, we explicitly incorporate both age (a_{nt}) and reverse-age (d_{nt}) into our regression model. The relationship between price and these two variables indicates how prices change as an item matures.

Defining dummy variables for varieties such that, $u_{ntj} = 1$ when $n = j$ and zero otherwise, and for time periods, $w_{nts} = 1$ when $t = s$ and zero otherwise, and leaving the life cycle maturation function general at this stage, we have our basic model with a mean zero error term (e_{nt}) appended:

$$\ln(p_{nt}) = \sum_{j=1}^{N} \beta_j u_{ntj} + \sum_{s=2}^{T} \delta_s w_{nts} + f(a_{nt}, d_{nt}) + e_{nt}, \quad n = 1, \ldots, N, t = 1, \ldots, T \tag{5}$$

Note that there are no inherent problems of identification in the model as age and reverse age are not linearly related to time. Items appear and disappear throughout time meaning that in a given month we will have a range of items at different points in their life cycle. A key question in the model, is what functional form should be used for the life cycle component (i.e. $f(a_{nt}, d_{nt})$)?

The most straightforward approach is to parameterize the age effects as a linear or log-linear function. We prefer a logarithmic transformation of the maturation variables for two reasons. First, conceptually a logarithmic transformation will mean that the effects of age and reverse-age are more significant at either end of the life cycle. This is appealing a priori. Second, the use of a logarithmic transformation will help to limit multicollinearity between age, reverse-age and the item- and time-dummy variables. A simple and parsimonious log-linear functional form for the life cycle effects is shown below and has the interpretation of age and reverse-age acting as depreciation/appreciation factors upon price:

$$f(a_{nt}, d_{nt}) = \alpha \log(a_{nt}) + \gamma \log(d_{nt}) \tag{6}$$

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limit heteroscedasticity. Also the logarithmic functional form has often been preferred to the linear model in Box-Cox tests (see for example, Berndt, Griliches and Rappaport, 1995), a result which we confirmed in preliminary work on the choice of functional form for our data.

[6] What we mean by an item (n) is a unique bundle of characteristics, e.g. "a 14.25 ounce can of Campbells pumpkin soup", for which there is a barcode in our data sets. The use of this generalized dummy variable approach provides a very flexible way of constructing a hedonic function (Diewert, 2003a).

While we will investigate this model in the empirical section that follows, the log-linear functional form places a great deal of a priori structure on a potentially very complex empirical relationship. An alternative to this functional form is a more flexible, but still fully parametric, quadratic or polynomial function in age and reverse-age. However, even polynomials place a high degree of restrictiveness upon the global nature of the functional form—forcing the function to have a certain number of turning points and degree of smoothness. Additionally, the behaviour of the function at the end points can be problematic as they will tend to exhibit rapidly increasing or decreasing behaviour. This would pose difficulties for our analysis as we are particularly interested in the path of the pricing functions at the extremities.

A very flexible alternative is to model $f(a_{nt}, d_{nt})$ fully non-parametrically as a step function, inserting dummy variables for each unique value of a_n and d_n. However, this may place too little restriction on the function meaning that the results will be driven by sampling variability rather than the underlying data generating process. It seems quite reasonable to impose some continuity restrictions on the life cycle function as pricing effects are likely to change slowly. For example, the price of a good of age 5 is likely to be more similar—after controlling for other factors—to the price of a good of age 4 and 6 than, say, 15. Similarly for reverse age. We can use this intuition to place some light-handed continuity restrictions on the maturation pricing function, $f(a_{nt}, d_{nt})$.

With these imperatives in mind a natural approach is spline smoothing regression with individual functions for age (a_n) and reverse age (d_n), but which are left completely general except that we penalize for rapid changes in the curvature of these functions.[7] This approach gives the best of both worlds; it models life cycle price trends using a very flexible function, which can provide a robust global approximation to the underlying function, and is still smooth and hence less effected by data variability and more easily interpreted. Consider the penalized smoothing problem shown below where we specify a spline function for each of the age variables:

$$\min{}_{\beta,\delta,f_a,f_d} \quad \sum_{n=1}^{N}\sum_{t=1}^{T}\left[\log(p_{nt}) - \sum_{j=1}^{N}\beta_j u_{ntj} - \sum_{s=2}^{T}\delta_s w_{nts} - f_a[\log(a_{nt})] - f_d[\log(d_{nt})]\right]^2 + \lambda_1\int[f_a''(x)]^2dx + \lambda_2\int[f_d''(x)]^2dx \qquad (7)$$

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 functions. This is reflected in the integral over the

[7] The most well known use of smoothing 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 Whittaker (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) for a recent application.

squared second derivative of these functions. The smoothing parameters, λ_1 and λ_2, represent the relative weights that are given 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. $f_a(a_{nt}) \to \alpha \log(a_{nt})$, and $f_d(d_{nt}) \to \gamma \log(d_{nt})$). 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 and potentially be very 'jagged'.

Green and Silverman, (2000), and Wahba (1990), show that the problem (7) has a unique solution—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 important in determining the results. A way around this subjectiveness is to use the method of Cross Validation (CV). Here we withhold one observation from the model and compare actual and estimated values for different smoothing parameters, choosing that which minimizes the model's 'forecast error'. However, one problem with CV, noted by Craven and Wahba (1979), is that it tends to give too much influence to outliers. They suggested Generalized Cross Validation (GCV), which ascribes lower weight to these high-influence observations. This robustness to outliers is an important advantage and hence we use GCV to derive $\hat{\lambda}_1$ and $\hat{\lambda}_2$.

Using the data outlined in the previous section we estimate both the linear model, (5) and (6), and the smoothing-spline model (7). The results are shown in Table 3 while the life cycle age functions for the spline model are shown in Figures 3 to 8. Together they provide compelling evidence for the existence of life cycle pricing effects.

The age-related parameters for both the linear and spline models are strongly supported statistically. The age and reverse-age variables are almost universally statistically significant. The F-test of no life cycle effects is rejected for every product, and for each of the data sets, at the 1% level for all the spline models. For the linear models, the F-test of joint insignificance of the two life cycle related coefficients is rejected at the 1% level for all data sets and products except beer, which is significant for $S(6,3)$ at the 1% level and $S(3,3)$ at the 5% level. While the linear models are generally statistically significant, F-tests support the more flexible spline models at the 5% level or higher in all but one case (for desktop computers using the $S(3,3)$ data set). This implies that a linear function provides too simple a representation of life cycle price trends. Generally speaking, the results provide statistically compelling and robust evidence for the existence of life cycle pricing effects.

Table 3: Model Results and Diagnostics

Product†	Linear Model††					Spline Model††			Comparison††
	d.f.	R^2	Coefficients:		F-Test:	F-Tests:			F-Test:
			$\log(a_{nt})$	$\log(d_{nt})$	$\log(a_{nt}) + \log(d_{nt})$	$f_a[\log(a_{nt})]$	$f_d[\log(d_{nt})]$	$f_a[\log(a_{nt})] + f_d[\log(d_{nt})]$	Linear v Spline
Analgesics:									
$S(3,3)$	4474	0.95	–0.0218***	0.0039***	18.68***	4.65***	4.02***	7.29***	6.31***
$S(3,6)$	4870	0.96	–0.0050	0.0122***	16.60***	3.09**	2.10*	6.10***	2.59**
$S(6,3)$	4429	0.95	–0.0075*	0.0148***	21.23***	2.00	3.10**	7.26***	2.59**
Beer:									
$S(3,3)$	3555	0.98	–0.0024	–0.0055***	4.20**	1.93	7.66***	4.91***	2.78**
$S(3,6)$	3805	0.98	–0.0010	–0.0034*	1.66	2.26*	4.03***	2.93***	3.35***
$S(6,3)$	3451	0.98	–0.0022	–0.0062***	4.87***	1.82	7.56***	4.96***	4.98***
Laundry Detergent:									
$S(3,3)$	5306	0.98	–0.0177***	–0.0032*	22.51***	4.12***	4.78***	9.24***	3.62***
$S(3,6)$	5480	0.97	–0.0209***	0.0029*	27.98***	8.54***	5.10***	12.48***	7.24***
$S(6,3)$	5265	0.97	–0.0179***	0.0032*	22.55***	4.04****	4.75***	9.18***	4.69***
Soft Drinks:									
$S(3,3)$	5391	0.97	–0.0218***	0.0058***	21.18***	6.02***	0.68	7.87***	7.34***
$S(3,6)$	6492	0.96	–0.0231***	0.0049**	27.03***	5.82***	2.26*	9.95***	4.22***
$S(6,3)$	5299	0.97	–0.0237***	0.0071***	25.32***	5.84***	0.58	8.77***	3.23***
Desktops:									
$S(3,3)$	3080	0.79	0.0574***	–0.0209***	18.59***	1.94	1.75	5.99***	1.64
$S(3,6)$	3491	0.78	0.0456***	–0.0254***	17.80***	3.49**	3.15**	6.87***	3.20***
Notebooks:									
$S(3,3)$	3247	0.81	0.0598***	–0.0194***	23.34***	3.92***	3.00**	8.68***	4.79***
$S(3,6)$	3676	0.77	0.0594***	–0.0198***	17.66***	1.23	3.76*	6.31***	2.51**

† $S(a, b)$ denotes the restrictions used to derived the data set such that, a = the minimum life length in months, b = the maximum run of missing observations that was permitted in months.

†† Note: *=significant at the 10% level, **=significant at the 5% level, ***=significant at the 1% level.

An immediate implication of these findings is that the standard approach to hedonic regression, which neglects life cycle characteristics, is inherently mis-specified and likely to suffer from omitted variable bias. This finding has important implications as hedonic regression is now very widely used in both academic research and the construction of official statistics. The omission of an important price determinant has the potential to distort the results from an hedonic analysis, particularly as the size of the life-cycle-related effects we find are large.

While the life-cycle pricing effects are statistically significant they are also of a magnitude where they are economically meaningful. Table 4 summarizes the life cycle price trends derived from the models. For the data set $S(3,3)$, a product that lives for one year falls in price over the course of its life by 3.0% for analgesics, 5.1% for laundry detergent, and 7.7% for soft drinks, conversely prices rise by 2.3% for beer, and an extraordinary 52.0% for notebooks, and 27.0% for desktop computers. Price changes of this magnitude are clearly not only statistically significant but also of economic relevance, implying a hitherto neglected driver of product price trends. Moreover, the size of the price movements are of similar significance to purely temporal price changes. F-tests of no life cycle effects gave similar values to an F-test which excluded the time dummy variables, indicating that these two components of the model are of commensurate importance.

The pattern of life cycle pricing is interesting in and of itself, both in providing an understanding of the drivers of pricing patterns and also in identifying the likely influence on price indexes. For analgesics, laundry detergent, and soft drinks a distinct downward trend in price is evident as products age across the various data sets. This provides some credence to the price skimming hypothesis—that consumers value novelty and are willing to pay to sample new products. It also may go someway to explaining the willingness of manufacturers to introduce new product varieties—Hausman's (2003) "invisible hand of imperfect competition"—the reward for the development of a new item will be a price premium received by the seller early in a product's life.

However, the price trends for beer provide an interesting contrast, exhibiting a positively sloped pricing function. This pricing pattern is likely to reflect the important part that taste and brand loyalty plays in the alcoholic beverages market. Beer varieties are apparently introduced to the market relatively cheaply and once a following is established, prices rise. There is an apparent parallel with the Berndt, Kyle and Ling (2003) results for prescription drugs following patent expiration, where a range of consumers who are willing to pay a premium for the product because of established consumption patterns. These types of results appear consistent with a priori expectations of how markets operate for those products where there is significant brand loyalty and/or preference cultivation.

Table 4: Summary of Price Trends Over the Life-Cycle

Product†	Pure Price Change†† (%)		Spline Model Life Cycle Price Change Over (%):		Linear Model Life Cycle Price Change Over (%):	
	1 year	2 years	1 year	2 years	1 year	2 years
Analgesics:	6.0	12.4				
$S(3,3)$			–3.0	–10.1	–6.2	–7.8
$S(3,6)$			–1.8	–7.2	–4.2	–5.3
$S(6,3)$			–3.3	–10.6	–5.4	–6.8
Beer:	–1.8	–3.6				
$S(3,3)$			2.3	7.4	0.8	1.0
$S(3,6)$			1.6	4.9	0.6	0.8
$S(6,3)$			2.2	7.5	1.0	1.3
Laundry Detergent:	2.3	4.6				
$S(3,3)$			–5.1	–8.6	–3.5	–4.5
$S(3,6)$			–6.4	–10.9	–5.7	–7.3
$S(6,3)$			–5.2	–8.6	–5.1	–6.5
Soft Drinks:	9.3	19.5				
$S(3,3)$			–7.7	–15.0	–6.6	–8.4
$S(3,6)$			–7.4	–14.0	–6.7	–8.5
$S(6,3)$			–8.1	–15.9	–7.4	–9.3
Desktops:	–49.3	–74.2				
$S(3,3)$			27.0	34.6	21.5	28.3
$S(3,6)$			22.8	26.7	19.3	25.3
Notebooks:	–55.4	–80.1				
$S(3,3)$			52.0	72.3	21.8	28.6
$S(3,6)$			36.1	46.2	21.8	28.6

† $S(a,b)$ denotes the restrictions used to derived the data set such that, $a =$ the minimum life length, $b =$ the maximum run of missing observations that was permitted.

†† Calculated using the time-dummy method, see equation (8).

Like beer, prices for desktop and laptop computers generally increase in price, though probably not for entirely the same reasons. The size of these life cycle price rises are huge; as is the extent of pure-price deflation with prices falling by around 50% per annum in our sample. The strong deflationary trends over time, coupled with an upward tendency in prices during their life, suggest one plausible explanation for the positively sloped pricing function is that desktop and notebook computers exhibit some stickiness around their introduction price. Much of the price falls for this product category results from new products being introduced at lower prices leading to an upward tendency in the life cycle pricing function. Moreover tech products, such as desktop and notebook computers, are complex goods and consumers may take some time to learn about a particular variety's capabilities. Time-on-market may be used as an indirect quality indicator by consumers, who judge that only good products will survive for any length of time on stores' shelves. This raises, rather than lowers, consumers' willingness to pay and increase prices as a product ages.

The strong life cycle effects that we find introduces an additional reason for price variation other than pure temporal or quality differences. This has implications for price indexes because an item's maturity and *time* are intimately related—in fact they are collinear for a given product—so there is the potential for purely inflationary price trends to be contaminated by age-effects.

4. Implications for Price Indexes

Our results are strongly indicative of economically and statistically significant life cycle pricing trends. But how should these be interpreted, what is the ideal measure of price change in such a case, and how should life cycle pricing effects be accounted for in the practical construction of price indexes?

As shown by Diewert (2003a) the hedonic price-characteristics function can be interpreted from a consumer perspective as representing buyers' willingness to pay for the various characteristics. But it is also possible to view the hedonic function from a producer perspective (see Pakes, 2003), or as the complex interaction between both producer and consumer sides of the market (Feenstra, 1995). This makes it difficult to provide a simple interpretation of exactly what the hedonic function represents. A fairly uncontroversial, but weak, statement is that the hedonic function is a reduced form relation which traces out the price-characteristics function—which represents the price paid for different combinations of characteristics—but that this does not necessarily provide information about consumer preference or producer technology. This raises questions about how the hedonic function should be used to construct a price index, and indeed, more fundamentally what the index should aim to measure.

Economists define the ideal measure of consumer price change as the ratio of cost functions (Diewert, 1976); the minimum cost of obtaining a given level of utility under two alternative price regimes. The hedonic function is particularly useful in this regard; because of the heterogeneity in some goods and their rapid appearance and disappearance from the market, the hedonic function can be used to estimate the price of any 'missing varieties', those products that do not appear on the market in both periods, for inclusion in the cost of living index (see for example Hill and Melser, forthcoming). The fact that hedonic regression can be used to impute missing prices and hence hold consumer welfare fixed is one of the key reasons why the use of hedonic regression has expanded so rapidly in research and official use in the past decade. But holding welfare fixed in the presence of life cycle pricing trends adds a new level of complexity in the estimation of cost-of-living indexes.

As we have discussed, the price differences related to life cycle are likely to reflect the complex interaction of consumer preferences, producer technology and imperfectly competitive product markets where markups and price discrimination are widespread. Because the hedonic function is a reduced form relation it is not possible to identify the source of these influences on prices. However, given the strength of the effects and our intuition about what matters to buyers it is likely that the life cycle pricing effects partially reflect consumer preferences. For example, consumers may value the novelty of a new product in the sense that the utility derived from a 'new' variety may be greater than for a more mature item, even after controlling for all other differences. Or perhaps the 'age' of a product conveys some information about the quality of the product to the consumer. Hence we argue for the exclusion of life cycle pricing effects from the index calculation, to avoid any possibility of changes in welfare contaminating pure price change.[8] This has far reaching implications for the construction of price indexes as most price indexes implicitly include age effects. But what error does this introduce into price index construction? We consider the impact of life cycle pricing trends on two types of index construction methods; the hedonic time-dummy method and the matched model approach. First to the hedonic method.

Our model of prices allows for a fixed effect in log-prices (i.e. a proportional impact on price level) for each time period. This approach has been widely used in the literature and implies that the index can be calculated directly from the time-dummy coefficients (see for example, Gordon, 1990; Nelson, Tanguay, and Patterson 1994; Berndt, Griliches, and Rappaport 1995; Silver, 1999; Berndt and Rappaport 2001; Silver and Heravi, 2001). The natural estimator for the price index is the ratio of price relatives across time, which are parallel for each characteristics configuration, and after holding the age of products fixed. The time-dummy index ($\hat{P}^T_{01}$) is defined as:[9]

$$\hat{P}^T_{01} = \frac{\hat{p}(u_m, w_{m1}, a_m, d_m)}{\hat{p}(u_m, w_{m0}, a_m, d_m)} = \exp\left[\hat{\delta}_1 - \hat{\delta}_0\right] \tag{8}$$

[8] While we have argued for the exclusion of life cycle effects from the perspective of a cost-of-living index we believe a similar conclusion would be reached if the desired measure of price changes was a price index for use in formulating monetary policy. Ideally such an index would measure the general level of prices which in turn is influenced by monetary conditions. The regular and predictable nature of life cycle pricing trends are distinct from price changes due to the state of monetary policy so ideally would be excluded from such an index.

[9] However, note that simply exponentiating the time-dummy variables as in (8) will not give an unbiased estimate of the price index given the non-linearity of the transformation. This issue has received some attention in the literature (see for example, Goldberger, 1968; Kennedy, 1981; Garderen and Shah, 2002). In what follows we make the standard (almost unbiased) adjustment of adding half the variance of the coefficient (see Chap. 3, Triplett, 2004; Wooldridge, 1999).

Table 5: Effects on Price Index from Excluding Life Cycle Characteristics

Product[†]	Comparison of Price Indexes (%)[††]	Matched Model Simulation Bias (%)[††]			Average Pure Price Change (%)
		Young Sample	Uniform Sample	Mature Sample	
Analgesics	–3.6	–4.1	–4.7	–3.6	6.0
Beer	3.0	2.9	3.7	3.0	–1.8
Laundry Detergent	–2.9	–3.1	–2.9	–2.3	2.3
Soft Drinks	–6.2	–6.4	–6.4	–5.3	9.3
Desktops	20.3	14.9	23.4	13.3	–49.3
Notebooks	52.2	38.2	50.0	32.6	–55.4

[†] The results are for the $S(3,3)$ data set.

[††] Values represent % deviation from the index which includes age effects over a 12-month period.

This gives our ideal measure of price change when the quality and age of products is changing over time. Now consider a similarly defined price index but derived from a hedonic equation estimated from (7) which excludes life cycle pricing effects. This yields an index such as that below:

$$\tilde{P}_{01}^{T} = \frac{\tilde{p}(u_m, w_{m1})}{\tilde{p}(u_m, w_{m0})} = \exp\left[\tilde{\delta}_1 - \tilde{\delta}_0\right] \tag{9}$$

Traditionally hedonic price indexes have ignored the influence of age altogether and used (8) rather than (9). But does this introduce a statistically of economically significant bias into the price index? Using the data set $S(3,3)$ (i.e. with the maximum stretch of missing values and minimum length of life set at 3 months) we calculate the two indexes.

The results are shown in Figures 9 to 14 and for all products the differences in the two indexes is visually significant. Table 5 shows the annual average difference between the two indexes in column one. Of the supermarket products the annual average bias is largest for soft drinks at –6.2%, while it is an astonishing 52.2% for notebooks and 20.3% for desktop computers. For comparative purposes the last column of Table 5 shows annual average pure price change for each of the product categories (calculated from (8)). This shows that the differences between the two indexes are often larger than temporal price change indicating that life cycle effects can swamp inflationary price change.

The results indicate that price indexes which omit age effects can differ significantly from those which hold them fixed. Moveover, they will differ in systematic ways. For products that exhibit a falling price over the life cycle—analgesics, laundry detergent, and soft drinks—the hedonic index which excludes age effects lies below that which includes these factors. Because item-ageing and time are collinear, excluding the negative age effect instead apportions much of this effect to the time-dummy variables. For products with positive life cycle trends—beer, desktop and notebook computers—the effects are reversed.

Generally, the influence of age-related price movements will depend on both the size and pattern of the life cycle pricing effects as well as the change in the age profile over time. To examine in greater detail the role played by the age profile in determining the extent of the bias we turn to a second price index methodology the matched model approach.

The matched model approach is very widely used by statistical agencies (ILO, 2004). Under this approach a sample of products is taken at a point in time and these are tracked in succeeding months; the index is estimated as some average of these price changes. This matched model approach to price index construction clearly has some advantages in that it effectively controls for physical quality change by holding the basket of items and their characteristics fixed through time. However, one potentially significant disadvantage, which has received scant attention in the literature to date, is that it must inherently allow the age structure of the sample to change over time simply as a result of sampling the same products in different months. If the age effects are large enough then this has the potential to lead to a significant divergence between recorded and ideally measured price change.

In comparing the ideal approach with a matched sample the key difference will be what is reflected in the price relative. The ideal index, which simplifies to the ratio of estimated price relatives, as in equation (8), excludes the effect of life cycle trends on price. In contrast the matched-model approach holds the particular items fixed across time and hence by its inherent nature allows the age composition of the products to change. More formally, suppose the index aggregation formula for the matched model index ($\hat{P}_{01}^{M}$) is an equally weighted geometric mean (or Jevons index[10]) then:

$$\hat{P}_{01}^{M} = \prod_{m=1}^{M}\left[\frac{\hat{p}(u_m, w_{m1}, a_m+1, d_m-1)}{\hat{p}(u_m, w_{m0}, a_m, d_m)}\right]^{1/M} \tag{10}$$

$$= \prod_{m=1}^{M}\left[\frac{\exp(\sum_{j=1}^{N}\hat{\beta}_j u_{mj} + \hat{\delta}_1 w_{m1} + \hat{f}(a_{m0}+1, d_{m0}-1))}{\exp(\sum_{j=1}^{N}\hat{\beta}_j u_{mj} + \hat{\delta}_0 w_{m0} + \hat{f}(a_{m0}, d_{m0}))}\right]^{1/M} \tag{11}$$

$$= \exp\left[\hat{\delta}_1 - \hat{\delta}_0\right]\prod_{m=1}^{M}\exp\left[\frac{\hat{f}(a_{m0}+1, d_{m0}-1)}{\hat{f}(a_{m0}, d_{m0})}\right]^{1/M} \tag{12}$$

While the item characteristics (u_m) are held fixed between periods, the age (a_m) of each of the varieties must increase, while reverse-age (d_m) decreases. That is, between periods 0 and 1 the products get one period further from introduction and one period closer to disappearing from the market. The deviation of the matched model index (12) from the ideal index is equal to the geometric mean of the life cycle price effects, the second component of equation (12).

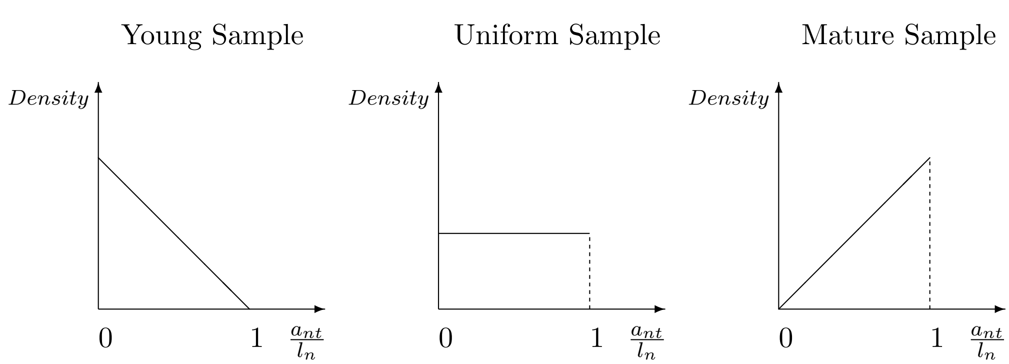
[10]The Jevons index is a common target elementary index (ILO, 2004) and is also a natural choice in this case given its geometric nature and the logarithmic form of the hedonic function. However, the fundamental point would be little changed if the target index was of an alternative form.

To investigate the extent of this bias we undertake a simulation looking at the difference between the ideal index (i.e. equation (8)) and the matched model approach where the sample of products gets older each period. Note that the matched model index depends on the life cycle variables so the age profile of the sample will influence the extent of the index bias. In simulating the effects of the matched model approach on price indexes we make use of model estimates, and the empirical distribution of the length of items' lives, from the $S(3,3)$ data set. This gives l_n, but we require some additional assumption in order to identify age and reverse-age. We proceed by randomly sampling values for age-proportion, i.e. $\frac{a_{nt}}{l_n} = 1 - \frac{d_{nt}}{l_n}$, which must lie in the range of 0 to 1, and determine *age* and *reverse age* from this data. We are particularly interested in how the age profile of the sample influences the results so we look at three cases where we hypothesize particular distributions for age-proportion. First, we assume a uniform distribution of age-proportion and sample from this to obtain the age-related variables. Second, we sample disproportionately from younger newer products, and third from the older disappearing varieties. These distributions are shown in Figure 2 and are known, respectively, as the Uniform Sample, the Young Sample and the Mature Sample. Note that in each of these cases there will be both young and old products in the sample but in different proportions.

The results of the simulations are shown in Figures 15 to 20 and in Table 5. The figures show the second component of equation (12) under the three different samples for a period of 12 months; the further this line is from one the more significant is the deviation of the matched model index from the ideal index. The magnitude of the difference after 12-months is reported in the middle section of Table 5.

The simulations confirm the previous results and show that indexes which include age

Figure 2: Sampling Distributions for Proportion of Product Life Cycle



effects are significantly different from those which exclude them, and in the case of the matched model method these differences are robust to the sample's initial age profile. The magnitude of the bias varies by product and is naturally biggest for those with large life cycle effects, and has the smallest spread for those products which have the most linear life cycle pricing function. As we saw for the time-dummy indexes which excluded age-effects, the bias to the index operates in the same direction as the life cycle price trends. For those goods which have negatively sloped life cycle pricing functions—analgesics, laundry detergent, and soft drinks—the bias is also negative and quite large. For soft drinks, for example, the matched model index overstates price change by as much as 6.4% over a period of just 12-months. The bias for analgesics and laundry detergent is smaller but still significant relative to overall price change. Beer, desktop computers and notebooks have an upward slant to the age-price function which imparts a corresponding impact upon the matched model index. The simulated differences between the matched model and ideal indexes for desktops and notebooks are staggering—between 13.3% and 23.4% for the former and as much as 32.6% to 50.0% for the latter. Differences of this magnitude are very significant and must give pause for thought to those who so readily advocate the matched model approach—the statistical agency method of choice—particularly for high tech electronics which exhibit large age effects. While this approach successfully controls for much of product quality change it does not hold the age profile of varieties fixed—and we have shown in this paper that this is a key price-determining quality characteristic which can contaminate measured price change.

5. Conclusion

The purpose of this paper has been two-fold. First, to shed some light on the path of prices for commonly consumed supermarket products and high-tech goods over their life cycle. Do they in fact exist at all and are they of sufficient magnitude to be economically meaningful? Second, we investigated the implications of these price-maturation effects for the estimation of indexes, and in particular whether the failure to control for these price changes will impart any systematic errors upon the price index.

We answer both questions emphatically in the affirmative. Using a flexible smoothing-spline modeling framework we found strong evidence of life cycle pricing effects. These systematic effects were statistically significant for all the products that we examined—analgesics, beer, laundry detergent, soft drinks, desktop and notebook computers—but were particularly strong for the high tech goods. Importantly the results were robust to different assumptions on the way in which the underlying data was constructed. The results illustrated that life cycle trends differed by product group and that, with the exception of beer, prices for the supermarket products tended to fall over time. This is likely to reflect the value consumers place on novelty in these product categories. The price dynamics were slightly different for beer, where the extensive efforts at branding and market cultivation are likely to engender customer loyalty allowing sellers to raise prices as varieties' age. Similarly, desktop and notebook computers recorded significant price increases as they aged. This is likely to be a result of the increased market credibility that a variety develops as it ages, boosting consumers' willingness to pay, coupled with some price stickiness in the presence of rapid price deflation. Generally, the lack of any precise homogeneity across products in the age-price function leads us to conclude that the nature of age effects will depend on the particular product category and the way that an item's maturity influences consumer welfare, producer costs and competition.

We argue that there are significant implications for price indexes from the existence of life cycle pricing patterns. First, hedonic functions which exclude age-related characteristics from the equation are mis-specified a priori. This is far from a trivial issue. As we demonstrated empirically, the failure to include the age-characteristics in the hedonic function results in estimates of price change which are quite different from the ideal measures. Furthermore, our simulations of a matched model approach to price index construction show that the impact on price change of ignoring life cycle trends can be significant and the difference between ideal and measured price change is large. These results call for greater investigation of the phenomenon of life cycle pricing and also for efforts to be directed towards controlling for age-related effects in official price indexes.

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Figure 3: Analgesics

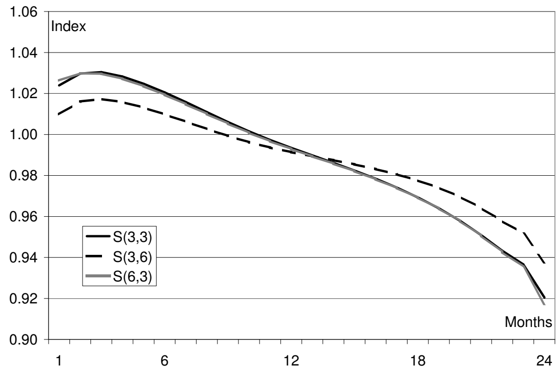

Figure 4: Beer

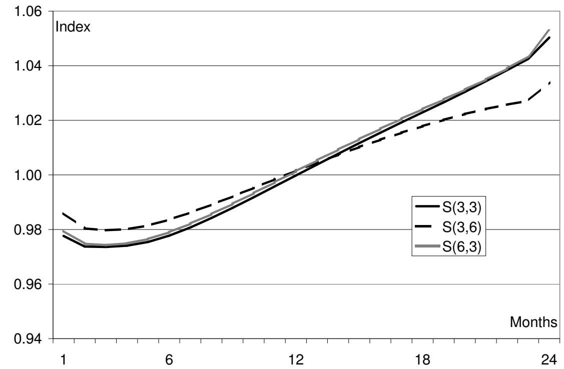

Figure 5: Laundry Detergent

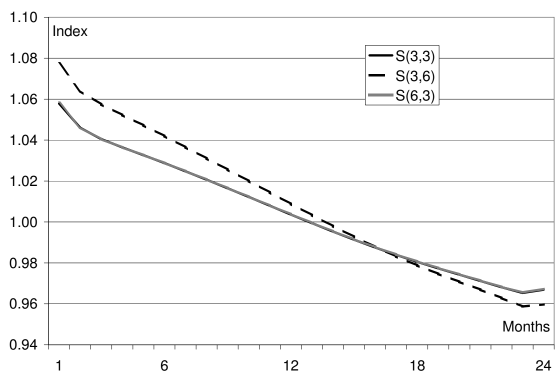

Figure 6: Soft Drinks

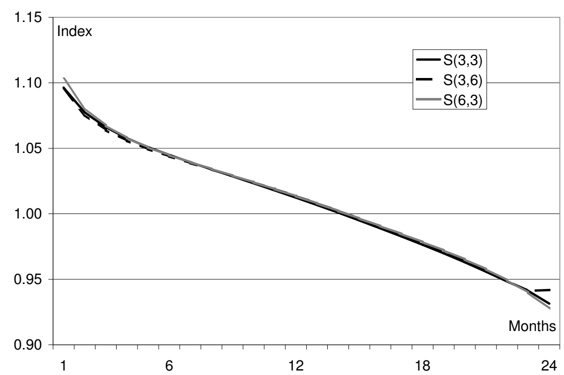

Figure 7: Desktop Computers

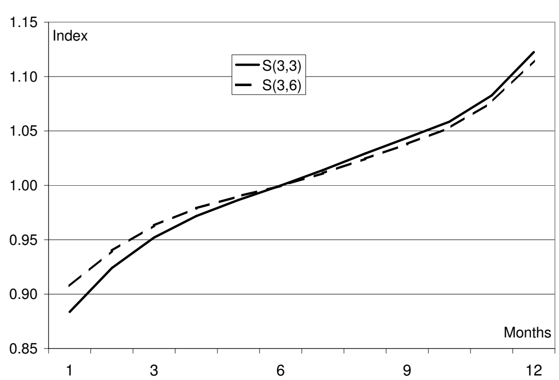

Figure 8: Notebook Computers

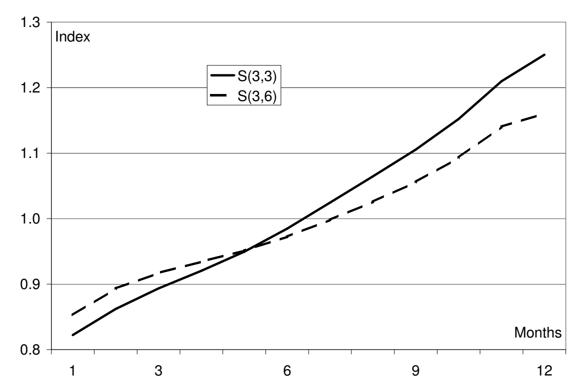

Figure 9: Analgesics Price Indexes

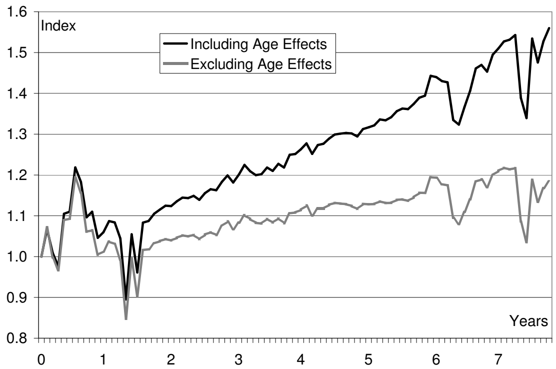

Figure 10: Beer Price Indexes

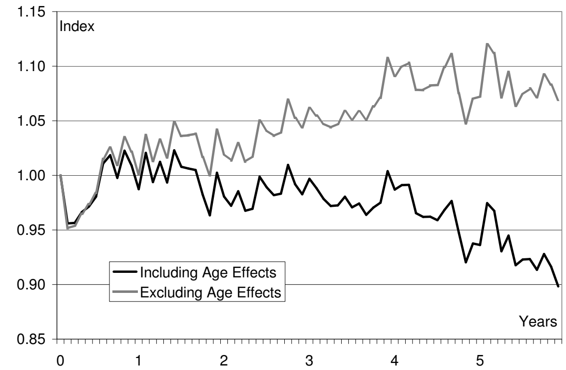

Figure 11: Laundry Detergent Price Indexes

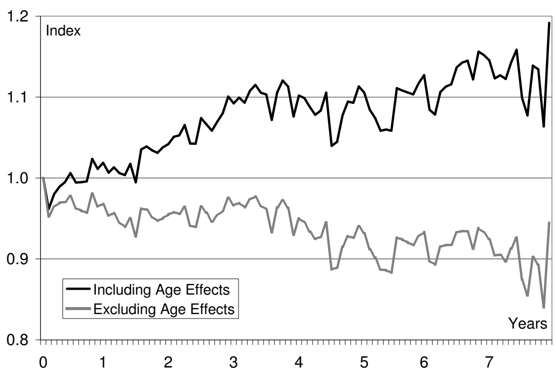

Figure 12: Soft Drinks Price Indexes

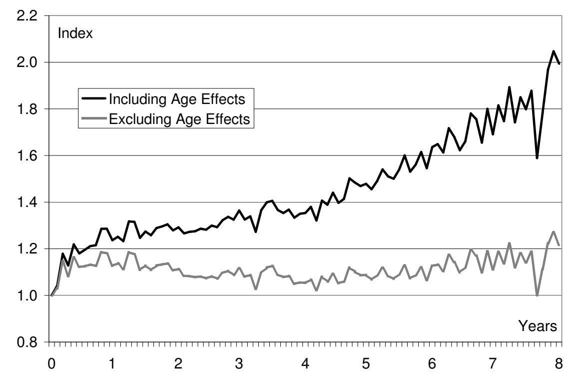

Figure 13: Desktop Computers Price Indexes

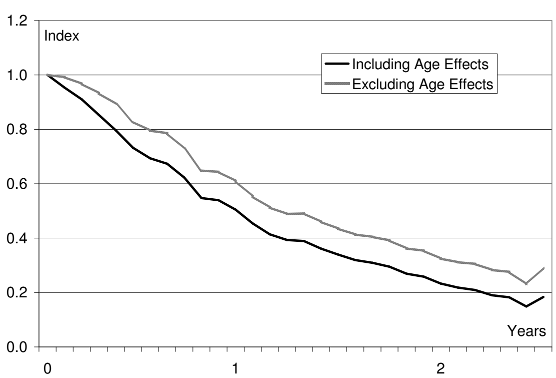

Figure 14: Notebook Computers Price Indexes

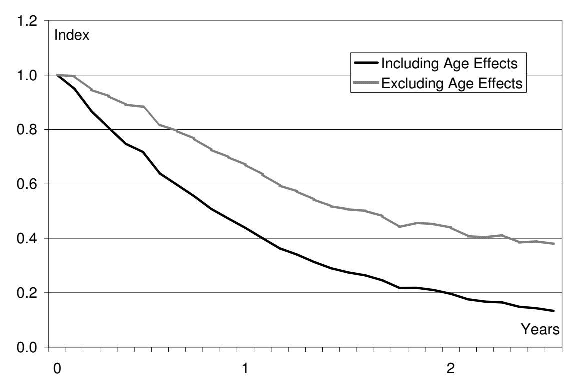

Figure 15: Analgesics Index Bias

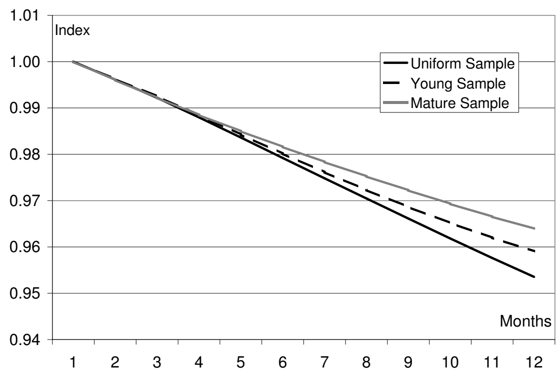

Figure 16: Beer Index Bias

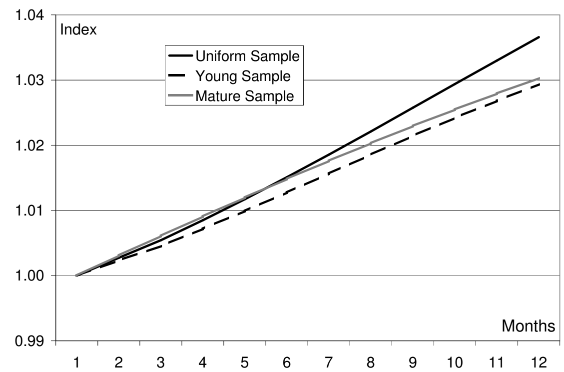

Figure 17: Laundry Detergent Index Bias

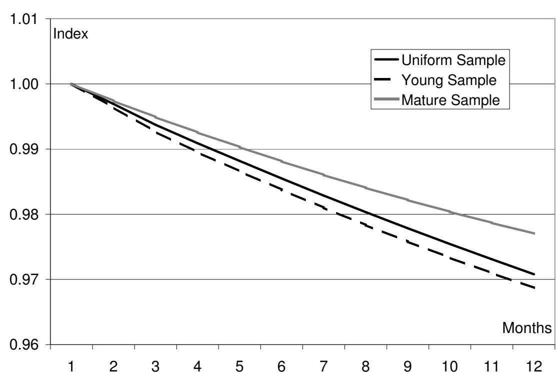

Figure 18: Soft Drinks Index Bias

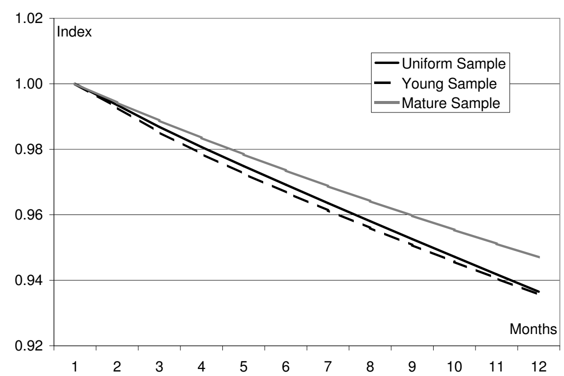

Figure 19: Desktop Computers Index Bias

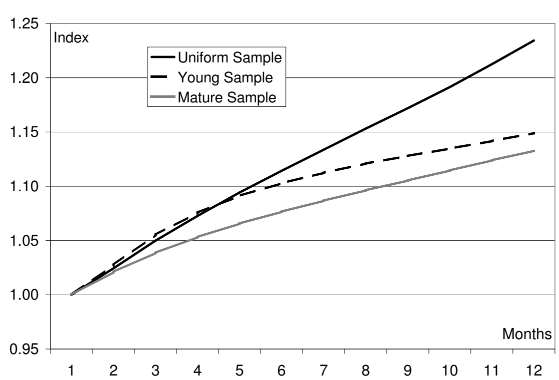

Figure 20: Notebook Computers Index Bias