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Life Cycle Pricing and the Measurement of Inflation

Daniel Melser
School of Finance and Economics
University of Technology, Sydney
Haymarket, NSW 2007
Australia
Email: daniel.melser@uts.edu.au

Iqbal Syed
School of Economics
University of New South Wales
Sydney, NSW 2052
Australia
Email: i.syed@unsw.edu.au

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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 a large scanner data set of supermarket products. Evidence is found for the existence of both economically and statistically significant life cycle pricing effects. This is important because the methods routinely used by statistical agencies pay little attention to life cycle as a price driver. When index samples face attrition or are refreshed, and price quotes are moved into and out of the index, the price differences between new and old items is often wholly attributed to quality differences. Much of these differences, however, are likely to be due to product life cycle factors. This has the potential to bias the measurement of inflation. We investigate the magnitude of this bias for various product categories and find that it is significant.

Keywords: Product life cycle; quality adjustment; consumer price index; scanner data; smoothing spline.

JEL Classification Codes: C43, C50, E31.

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. This has been of significant benefit to many consumers who can now choose from products that cater to their specific needs and desires. But not every new product variety is destined to be a best seller, 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turnover in product varieties has been driven by technology in some areas—such as electronics, where old models are superseded by faster, smaller, and better models—but is also unequivocally apparent in less dynamic product categories. This process of product birth, evolution, maturity and death is termed the product life cycle.

This paper builds upon a modest literature addressing issues around the product life cycle. We focus on one issue in particular—identifying price trends as products mature. The primary motivation for such a study comes from the important implications such trends have for the construction of price indexes. If prices change as products age then standard matched model price indexes may not adequately reflect these effects and fail to correctly record inflationary price change. This source of measurement bias is potentially very significant, as almost all types of consumer goods could exhibit price dynamics related to the product life cycle. Our study systematically investigates the effects of life cycle pricing on the methods currently used by statistical agencies to measure inflation.

Also, more generally, having a better understanding of pricing trends over the product life cycle will inform a primarily theory-driven industrial organization literature on intertemporal price discrimination. This is one of the reasons why life cycle price trends may arise in practice. Stokey (1979) was the first to note that there may be conditions under which a profit maximizing monopolist would charge different prices over time. Her results have been developed and extended by others—such as Landsberger and

Meilijson (1985), Varian (1989) and Koh (2006)—who have found that it may be optimal to price discriminate across time if consumers are impatient, or at least less patient than sellers, 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 of the market provide further reasons for intertemporal price discrimination.

But clearly price discrimination is not the only reason why prices may shift over the product life cycle. Changing marginal costs of production is another likely reason. For many products the costs of production are likely to fall over time as firms improve processes and make technological advances. This implies declining prices as products age. The introduction of competition later in the product cycle, perhaps induced by the entry of competitor firms who have reverse-engineered a product, provides further impetus for falling prices as products mature.

Much of the interest in life cycle pricing focuses on the price dynamics as products enter and exit the market. Do new goods enter the market at relatively high prices? This implies retailers adopt a 'price skimming' approach, taking advantage of the novelty factor to earn a premium at introduction. Or do new products enter at low prices such as suggested by the 'market penetration' hypothesis. Here firms lower prices to generate a sufficient number of consumer trials and build a market following. Moreover, do goods exit the market at rock-bottom prices in order to clear shelf space for new items, or do they exit at relatively high prices in order to cater for market segments exhibiting strong preferences for old brands? These possibilities have not as yet been fully explored empirically so there is little idea of the stylized facts of life cycle pricing. We investigate this as well as considering the effects of these price trends on the measurement of inflation.

Life cycle pricing trends are relevant to the measurement of inflation because they represent price dynamics which are unrelated to quality but yet which can easily be confounded with quality differences. Clearly the physical characteristics of a product are fixed over time so the way in which a consumer may gain utility from the product is also unchanged temporally. Yet the prices for the product may systematically change over time for reasons related to technological advance, cost reduction, competition, firms' pricing strategies and many other reasons internal to the industry. Hence, in a constant-utility cost-of-living index these price changes across the product life cycle should be included in a consumer price index (CPI). But we argue that the methods commonly used by statistical agencies implicitly attribute life cycle price differences to quality differences. Hence these effects are removed from the index rather than recorded as price change. This will lead to biased estimates of inflation.

While the possibility of systematic life cycle effects on price indexes has been recognized in the measurement literature, there has been little quantification of this phenomenon. There are a few notable exceptions. Berndt, Kyle and Ling (2003) investigate the effect of patent expiration, and the entry of generic producers, on the price of prescription drugs. They come to the startling conclusion that prices for the established branded varieties tend to rise after patents expire. A select group of consumers with a strong preference for the branded variety remain willing to pay a premium for it. Haan (2004) outlined a hedonic regression model which allowed for systematic effects for entering and exiting varieties, though he did not proceed to estimate such a model. Silver and Heravi (2005), in a hedonic regression framework, show that indexes estimated only on matched products are biased because of systematic differences in pricing patterns between new and disappearing items.

In the absence of substantial empirical evidence, there has been speculation about the likely path of prices as products age. For example, a passage from the ILO CPI 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, 2004, p. 100)

Other researchers have supported the view that new goods are relatively highly priced and old goods are cheaper (see Triplett, 2004, chapter 4, p. 17; Schultze and Mackie, 2002, p. 162). However there remains little evidence in the literature for such a belief. Our goal is to resolve the uncertainty surrounding the path of prices over a product's life cycle and then look at the impact of these trends on price indexes.

The paper is organized as follows. In the next section, we discuss in more detail how life cycle pricing may impact upon the measurement of inflation. Section 3 describes our data and how the life cycle variables are identified. Section 4 outlines the regression models that are estimated in order to separate life cycle pricing patterns from the myriad of other effects that determine prices. Section 5 discusses the regression results while section 6 examines the implications of these results for price indexes. Section 7 provides a summary of the findings and draws some conclusions.

2 Price Indexes and the Product Life Cycle

Systematic changes in product prices, which relate to age, have the potential to significantly influence how inflation is measured, both at the index level and in the construction of individual price relatives. To illustrate this let us begin with the assumption that life cycle effects exist. Identifying these effects is left to later in the paper. Hence we suppose that the price for a given item n in time t, p_{nt}, is influenced by both the stage of the product life cycle, denote this l_{nt}, along with some utility-determining quality characteristics, z_n. Prices are also driven by a purely inflationary factor, represented by the variable x_t. This yields the functional relationship, $p_{nt} = p(l_{nt}, z_n, x_t)$.

First, if the prices of items themselves are driven by life cycle factors then it is clear that an index of these prices must also be. To make this more concrete consider the case of the simple geometric mean (Jevons) price index across $n = 1, 2, \ldots, N$ matched items with weight w_n. Using the functional relationship between price and its determinants we may decompose the index into two components,

$$\prod_{n=1}^{N}\left(\frac{p_{nt}}{p_{nt-1}}\right)^{w_n} = \left[\prod_{n=1}^{N}\left(\frac{p(l_{nt}, z_n, x_t)}{p(l_{nt-1}, z_n, x_t)}\right)^{w_n}\right]\left[\prod_{n=1}^{N}\left(\frac{p(l_{nt-1}, z_n, x_t)}{p(l_{nt-1}, z_n, x_{t-1})}\right)^{w_n}\right] \quad (1)$$

The first component represents price change due to life cycle pricing effects while the second component represents pure price change. The size of the former relative to the later, and hence the influence of production maturation on inflation measurement, will depend primarily on the magnitude and nature of the life cycle pricing effects. Furthermore, it may matter exactly what items are selected for inclusion in the index sample. A product's life cycle price movements may differ depending upon its age. So, say, it may be that products fall in price as they age but prices of younger products may fall more slowly than older products. In this case the specific age profile of sampled products will influence recorded inflation.

Second, at the elementary index level the change in the available set of commodities over time necessitates that statistical agencies have some mechanism for systematically including new items, or at least for replacing price quotes for disappeared items. The methods used to do this aim to account for the fact that the new items will differ in terms of quality from the old items. Hence they seek to make adjustments to these prices to ensure as much as possible that like is compared with like and any quality differences between new and old items is netted out.

However, often price differences between the new and disappearing items will include a component that results from differences in items' ages. This component is primarily attributable to supply-side factors which influence prices as products mature and is conceptually distinct from what is conventionally meant by quality differences. If consumers pay a different price for the same item simply because the product has reached a certain age, then a constant-utility price index should reflect these effects.[1] However, this life cycle component of prices is not explicitly taken into account in the

[1] A life cycle pricing pattern could be attributable to quality change if it reflected the fact that consumers had preferences defined across the age profile of an item. This may happen for product categories like fresh food, fashion items, newspapers, movies and books, but is unlikely for the regular supermarket products like cereal, laundry detergent, soft drinks and grooming products that this paper

current implementation of quality adjustment methods. As a result it gets mixed up with the quality component and removed from the index. This biases the measurement of inflation.

This is unlikely to be a trivial issue. The Bureau of Labor Statistics (BLS) has made a significant commitment to sample rotation in the US CPI (Schultze and Mackie, 2002, p. 164; Armknecht, Lane and Stewart, 1997). They intentionally rotates items into and out of the index on a regular basis. Greenlees (1997) and Abraham (2003) indicate that around 20% of the sample of price quotes is rotated each year. This coupled with sample attrition leads to significant turnover in price quotes. Moulton and Moses (1997) report that roughly 4% of the 80,000 prices sampled by the BLS per month were for replaced items and approximately 30% of item quotes are turned over each year.

The standard way that new items are introduced to the sample is using the *overlap price method* (see for example, ILO, 2004, pp. 106–108; Schultze and Mackie, 2002, pp. 117–119; ABS, 2009, chapter 9, p. 80). Here the price of both the new and old items are available in a common time period and the price ratio between the two items is used to measure their relative quality. However, this widely used approach is likely to be problematic in the presence of life cycle pricing effects as these will potentially be confounded with quality differences.

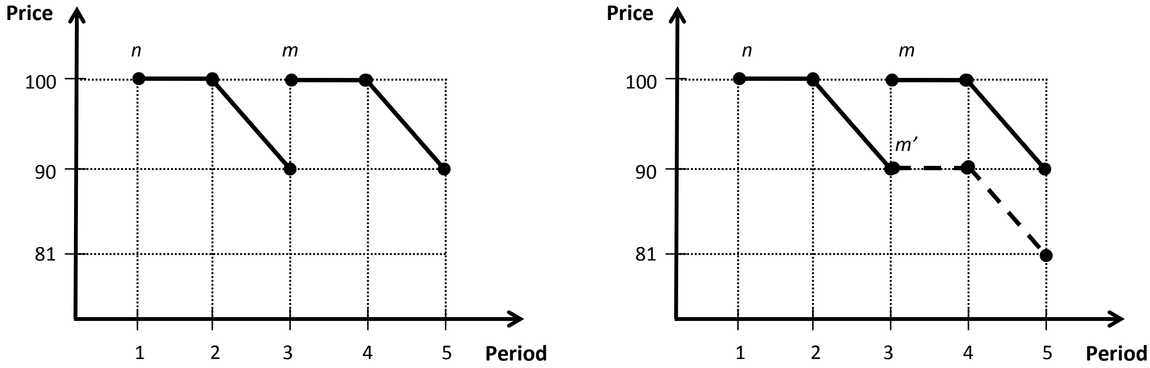
Consider a simplified example of the overlap price method. Suppose we have two items, n and m. In this example we will suppose that these items are identical in terms of their quality ($z_n = z_m$), there is no temporal inflation, and the only price driver is their respective life cycle effects. We suppose that these items live for 3 periods, their prices are constant in the first two periods and fall in the final period of their lives. This is illustrated in Figure 1a. The problem with the overlap pricing method in this case is that the price difference between items n and m in period 3, as m replaces n in the sample, is wholly attributed to quality differences. In actuality it reflects life cycle pricing trends. If the overlap pricing method were used in such a case then in

considers. Moreover, for the latter type of products, it is unlikely that consumers are even aware of each item's age and hence are unlikely to discriminate between them on this basis.

Figure 1: Quality Adjustment Using the Overlap Price Method

(a) The Overlap Method

(b) A Resulting Price Relative



period 3 the price for m would be adjusted down multiplicatively by the relative price difference of 10% and then this adjusted price m' would be fed into the index. In this case, illustrated in Figure 1b, it is clear that the quality adjustment is inappropriate. It leads to an index which is biased downwards by the size of the life cycle effect.

But the problem of quality adjustment in the presence of life cycle pricing is not confined to the overlap method. When an overlap price is not available, perhaps because a price has suddenly disappeared, the *class mean imputation method* is usually the preferred approach (Moulton and Moses, 1997). Here, because the price of a different item is available in each period, the base period price is extrapolated forward by the movement of some group of matched items and the price difference in the later period is used as a measure of the quality difference. This will lead to just the same sort of error as for the overlap pricing method as the age of the new and old items will likely differ and hence life cycle pricing effects will again be confounded with quality differences.

More generally, we may consider the decomposition of the price difference between two products, n and m, using our model, into 'quality' and 'life cycle' components as follows,

$$\frac{p_{mt}}{p_{nt}} = \left[\frac{p(l_{mt}, z_m, x_t)}{p(l_{mt}, z_n, x_t)}\right] \left[\frac{p(l_{mt}, z_n, x_t)}{p(l_{nt}, z_n, x_t)}\right] \tag{2}$$

Here the first component is an index of quality difference between the products, holding product life cycle fixed. The second component is an index reflecting differences in prices due to differences in the life cycle properties of the items, holding quality fixed. We argue that it is the former which should be linked out of the CPI while the latter is a legitimate source of price change with the introduction of item m into the index.

Clearly there is the potential for life cycle pricing effects—and the way these effects are treated in undertaking quality adjustment and sampling—to have a significant effect on measured inflation. Given this it is surprising that more is not known about the shape and magnitude of these effects. It is to this which we turn in the following sections before coming back to the issue of index bias in section 6.

3 Data and Extracting Life Cycle Characteristics

We investigate pricing patterns over the product life cycle using a large scanner data set 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, cereal, cigarettes, grooming products, laundry detergent, soft drinks and toilet paper. There are 96 stores with prices recorded at a weekly frequency from September 1989 to May 1997—a period of almost eight years (though not all the products are available for the entire sample). We aggregate the data to monthly unit values as monthly is the most common calculation frequency for CPIs globally. The data set is large and provides the richness required to extract and estimate age-related price effects.

While 'product life cycle' is a relatively familiar term in marketing and economics, there has been little explicit specification of exactly how it is characterized. Though it should be noted that Berndt, Griliches and Rappaport (1995) have gone some way

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

in this regard, and we build upon their work. A natural 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 likely to be insufficient and one-sided. What is also relevant is the number of periods from the current period until an item disappears from the market. We refer to this as *reverse age*. If there are specific price dynamics associated with product death, such as run-out sales, then this can be linked with reverse age. Examining both age and reverse age implies a symmetric and balanced treatment of the product life cycle and gives us the ability to model price dynamism throughout the life cycle.

Our focus on both age and reverse age has implications for our treatment of the data. In our approach, in order to completely characterize the current state of a product's life cycle we must observe its entire life, from its birth to its death. But for those products which were sold in the first and last periods we are unable to determine date of birth and death respectively. Since the focus of the study is to investigate pricing patterns over the product life cycle, products whose life cycle characteristics could not be identified have been removed from the analysis. However, the impact of this is likely to be relatively modest because the data set covers a period of almost 8 years. Indeed, to the best of our knowledge, among different scanner data sets that have been used for academic research, the *Dominick's Finer Foods* data set covers the longest time-span. So the impact is likely to be minimized by our use of this data source. The percentage of items which have been excluded from the analysis for this reason is the highest for cereals, 21.2%, and is lowest, at only 1.5%, for laundry detergents.[3]

There are two further data-issues to be addressed. First, there are some very short-lived products in the data set. How should these be treated? In investigating life cycle pricing we constructed two data sets, the first excluded all products which had a life

[3]For the other products, the percentage of items excluded from our estimation sample because it was not possible to determine age or reverse age was: 16.1% for analgesics, 7.2% for beer, 12.1% for cigarettes, 15.8% for grooming products, 13.3% for soft drinks and 14.0% for toilet paper.

of less than 3 months while the second excluded those that did not live for at least 6 months. However, the results were essentially the same for these two data sets hence, we only present the results corresponding to the products with a minimum life length of 3 months.

Second, for some items there are long stretches where prices are missing. This may be due to products not being sold—as in our data we only see sales, a product may still be available in store. Or it may simply be that some supply issues affected the availability of an item for a period. Nevertheless, the absence of a product in the market for a stretch of time does raise questions about the reliability of the observations on the product. Hence, in the interests of robustness, we constructed two different data sets. In the first we removed all items which had a stretch of more than 3 months of missing prices. In the second we removed those items with a 6-month run of missing prices. However, for each of these, in constructing the age and reverse age variables, a product was aged continuously even when the item was not available in the data set. In Table 1 these two data sets correspond to samples $S(3,3)$ and $S(3,6)$. The first digit refers to the minimum length of life of 3 months and the second digit refers to the maximum 3- and 6-month runs of missing prices.

Our data is summarized in Table 1. We show the number of observations, time periods and items as well as some indicators of the life cycle. More than 90% of all the products disappear within a period of 5 years which is much lower than the sample coverage of 8 years. Thus our removal of some long-lived products, because neither their birth nor death was observed in the data, is unlikely to have a major influence on our results. There is considerable dispersion in the distribution of product length of life, both within and across products categories. The median life of the products is found to be highest for beer (36 months) and lowest for cigarettes (14 months). Variable life lengths points towards the need to consider both age and reverse age in modeling life cycle pricing effects.

Table 1: Life Cycle Statistics

Product†	Months of data	Number of included: Items	Observations	% of products disappear by: 1 year	3 years	5 years	Length of life (months): Pctile:	25th	50th	75th
Analgesics:	93									
$S(3,3)$		167	4,816	21.6	76.7	93.4		14	26	36
$S(3,6)$		179	5,103	20.1	76.0	93.3		14	27	36
Beer:	77									
$S(3,3)$		369	13,335	18.7	50.1	97.3		17	36	58
$S(3,6)$		407	14,317	17.4	51.1	97.1		17	34	58
Cereal:	96									
$S(3,3)$		77	1,294	45.5	97.4	100.0		9	14	18
$S(3,6)$		100	2,084	35.0	88.0	95.2		10	17	26
Cigarettes:	96									
$S(3,3)$		73	1,376	45.2	84.9	94.5		7	14	20
$S(3,6)$		96	1,811	43.8	82.3	92.7		8	14	21
Grooming Products:	64									
$S(3,3)$		357	7,562	35.0	86.0	96.4		10	17	28
$S(3,6)$		436	9144	34.4	83.3	96.8		9	17	29
Laundry Detergent:	96									
$S(3,3)$		218	5,887	21.1	78.0	90.8		14	21	31
$S(3,6)$		225	6,051	20.4	77.3	90.7		15	21	32
Soft Drinks:	95									
$S(3,3)$		278	6,130	28.8	84.9	99.3		12	18	30
$S(3,6)$		335	7,326	31.0	82.4	98.2		11	18	30
Toilet Paper:	92									
$S(3,3)$		34	1,010	14.7	73.5	97.1		16	19	38
$S(3,6)$		38	1,114	13.2	73.7	97.4		16	22	38

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

4 Modeling Life Cycle Price Trends

Using these data we set out to identify the effects of the product life cycle on price, after controlling for cross-sectional and time-series factors. We propose a straightforward yet flexible panel data model which controls for cross-sectional and time-series variation using fixed effects. We insert dummy variables for each item to control for cross-sectional price differences.[4] These variables will reflect the difference in price for the quality-related features of the products. For example, in the case of cigarettes, the item-dummies will reflect the difference in price related to factors such as packet size, nicotine content, packaging and so forth. To control for product-wide temporal variations in price we insert dummy variables for each time period. We take the natural logarithm of price as the dependent variable.[5] 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 the price changes as an item matures. This gives a model which is essentially the temporal variant of the well known and widely used country product dummy (CPD) method due originally to Summers (1973). Here, however, we have added a life cycle function.

More formally let us define dummy variables for varieties (z_{nj}) such that, $z_{nj} = 1$ when $n = j$ and zero otherwise, and for time periods (x_{ts}), such that $x_{ts} = 1$ when $t = s$ and zero otherwise, and leave the life cycle maturation function, $f(a_{nt}, d_{nt})$, general at this stage. This gives us our basic model, with a mean zero error term (e_{nt}) appended:

$$\ln(p_{nt}) = \sum_{j=1}^{N} \beta_j z_{nj} + \sum_{s=2}^{T} \delta_s x_{ts} + f(a_{nt}, d_{nt}) + e_{nt}, \quad n = 1, \ldots, N, t = 1, \ldots, T \tag{3}$$

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

The most straightforward approach is to parameterize the age effects as a linear or

[4]What we mean by an item n is a unique barcode or bundle of characteristics, e.g. "a 14 ounce can of Coca Cola available as a 6-pack".

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

log-linear function. We prefer a logarithmic transformation of the maturation variables because it means the effects of age and reverse age are more significant at either end of the life cycle. This is appealing a priori. A simple and parsimonious log-linear form for the life cycle effects is shown below. This has the interpretation of age and reverse age acting as depreciation/appreciation factors upon price.

$$f(a_{nt}, d_{nt}) = \alpha \log(a_{nt}) + \gamma \log(d_{nt}) \tag{4}$$

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 function—forcing it to have a certain number of turning points and a certain degree of smoothness. Additionally, the behavior of the function at the end points can be problematic as these will tend to exhibit rapidly increasing or decreasing behavior. This would pose difficulties for our analysis as we are particularly interested in the path of the pricing functions at the extremities.

A flexible alternative is to model $f(a_{nt}, d_{nt})$ fully non-parametrically, inserting dummy variables for each unique value of a_{nt} and d_{nt}. However, this is likely to place too few restrictions 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 relatively 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, age 25. Similarly for reverse age. We use this intuition to place some light-handed continuity restrictions on the maturation pricing function.

A natural approach, given these imperatives, is a smoothing spline regression with individual functions for age and reverse age. Here the functions themselves are left completely general except that we penalize for rapid changes in their curvature. This gives a balanced approach. It models life cycle price trends using a highly flexible technique, which can provide a robust global approximation to the underlying function. But the estimated function still exhibits a degree of smoothness and hence is more easily interpreted and less likely to be affected by data variability. Consider the penalized smoothing problem shown below where we specify a spline function for each of the age variables:

$$\min{}_{\beta,\delta,f_a,f_d} \sum_{n=1}^{N}\sum_{t=1}^{T}\left[\log(p_{nt}) - \sum_{j=1}^{N}\beta_j z_{nj} - \sum_{s=2}^{T}\delta_s x_{ts} - f_a[\log(a_{nt})] - f_d[\log(d_{nt})]\right]^2 + \lambda_a \int [f_a''(v)]^2 dv + \lambda_b \int [f_d''(v)]^2 dv \qquad (5)$$

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 reflected in the integral over the squared second derivative of f_a and f_d. The smoothing parameters, λ_a and λ_b, represent the relative weights that are given to fidelity and smoothness. As $\lambda_a, \lambda_b \to \infty$ the selected functions will have no second-order curvature. This implies that the estimators are linear, i.e. $f_a(a_{nt}) \to \alpha \log(a_{nt})$ and $f_d(d_{nt}) \to \gamma \log(d_{nt})$. It can also be seen that the spline smoothing model nests the non-parametric dummy variable approach as $\lambda_a, \lambda_b \to 0$.

Green and Silverman (2000), and Wahba (1990), show that problem (5) 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_a and λ_b is somewhat arbitrary but may also be important in determining the results. A way around this subjectiveness is to use cross validation (CV). Here one observation is withheld from the model and its actual and estimated values are compared for different smoothing parameters. The value for the smoothing parameters is chosen 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). This ascribes lower weight to high-influence observations. This robustness to outliers is an important advantage and hence we use GCV to derive λ_a and λ_b.

5 Model Results

Using the data outlined in section 3, we estimate both the linear, (3) and (4), and smoothing-spline (5) models. The results are shown in Table 2. The life cycle pricing functions for the spline model corresponding to products living for 2 years are shown in Figure 2. In Figure 3 the functions corresponding to the 25th, 50th (median) and 75th percentiles of products' length-of-life are shown. Together the tables and figures 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 being almost universally statistically significant. This implies that both age and reverse age are required to adequately represent life cycle price movements. The F-test of no life cycle effects is rejected for every product category, and for each of the data sets, at the 1% level for both the linear and spline models. While both the linear and spline models are statistically significant, F-tests support the more flexible spline models at the 1% level in all but one case (soft drinks using the $S(3,3)$ data set), but this is supported at the 5% significance level. The results provide statistically compelling and robust evidence—across product categories, models and data sets—for the existence of life cycle pricing effects.

While the life cycle pricing effects are statistically significant, they are also of a magnitude that is economically meaningful. Table 3, along with Figures 2 and 3, summarize the life cycle price trends derived from the various models. For example, for the data set $S(3,3)$, a product that lives for one year falls in price over the course of its life by 6.09% for analgesics, 11.07% for cereals, 3.98% for laundry detergent, and 9.12% for soft drinks. Conversely prices rise by 2.40% for beer, 8.76% for cigarettes, 3.30% for grooming products and 10.75% for toilet paper. Price changes of this magnitude are clearly economically relevant and imply a hitherto neglected driver of product price trends.

Table 2: Model Results and Diagnostics

Product[†]	Linear Model				Spline Model			Comparison
	R^2	Coefficients:		F-Test:	F-Tests:			F-Test:
		$\log(a_{nt})$	$\log(d_{nt})$	$\log(a_{nt}) + \log(d_{nt})$	$f_a[\log(a_{nt})]$	$f_d[\log(d_{nt})]$	$f_a[\log(a_{nt})] + f_d[\log(d_{nt})]$	Spline vs Linear
Analgesics:								
$S(3,3)$	0.97	–0.0098***	0.0077***	24.21***	3.72**	14.17***	13.14***	9.35***
$S(3,6)$	0.97	–0.0100***	0.0074***	25.05***	3.73**	15.82***	13.82***	9.97***
Beer:								
$S(3,3)$	0.98	0.0063***	–0.0031**	7.69***	6.55***	6.27***	6.77***	6.46***
$S(3,6)$	0.98	0.0056**	–0.0037***	9.04***	6.46**	7.26***	7.47***	6.94***
Cereal:								
$S(3,3)$	0.80	–0.0215***	0.0140***	15.50***	2.07*	3.18**	7.07***	4.12***
$S(3,6)$	0.80	–0.0260***	0.0149***	17.03***	5.82***	2.28*	7.36***	4.07***
Cigarettes:								
$S(3,3)$	0.98	0.0212***	–0.0059***	20.27***	3.69**	10.44***	10.16***	6.58***
$S(3,6)$	0.98	0.0227***	–0.0033**	26.29***	2.18**	9.313***	10.87***	5.56***
Grooming Products:								
$S(3,3)$	0.94	0.0115***	–0.0001	5.39***	8.65***	3.18**	5.82***	5.96***
$S(3,6)$	0.94	0.0108***	0.0024*	6.74***	6.24***	2.10*	4.73***	4.05***
Laundry Detergent:								
$S(3,3)$	0.97	–0.0172***	0.0013	19.20***	3.77***	5.20***	8.47***	4.86***
$S(3,6)$	0.97	–0.0199***	0.0014	24.80***	6.83***	5.70***	11.31***	6.76***
Soft Drinks:								
$S(3,3)$	0.97	–0.0223***	0.0052***	21.11***	4.45***	0.64	7.24***	2.61**
$S(3,6)$	0.97	–0.0238***	0.0045***	27.62***	4.46***	2.13*	9.53***	3.47***
Toilet Paper:								
$S(3,3)$	0.98	0.0152***	–0.0152***	16.16***	9.99***	18.51***	16.13***	15.51***
$S(3,6)$	0.98	0.0048	–0.0185***	15.45***	6.42***	19.64***	14.63***	13.89***

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

These life cycle pricing patterns are interesting in and of itself. The heterogeneity across product categories implies that quite different dynamics are likely at play in different industries. For analgesics, cereals, laundry detergent, and soft drinks the distinct downward trend in price provides credence to the price skimming hypothesis. That retailers take advantage of the novelty factor for new items to earn a premium upon introduction. It may also go some way towards explaining the willingness of manufacturers to introduce new product varieties—what Hausman (2003) calls "the invisible hand of imperfect competition"—the reward for the development of a new item is a price premium received by the seller early in a product's life. Silver and Heravi (2005) also found evidence in support of the price skimming hypothesis for electronic products, though it does not hold for all the product categories they consider.

The price trends for the other four products we consider—beer, cigarettes, grooming products and toilet paper—provide an interesting contrast. They exhibit a generally positively sloped pricing function. The pricing pattern for beer, cigarettes and grooming products is likely to reflect the important part that taste and brand loyalty play in these particular markets. New products are apparently introduced relatively cheaply and, once the consumers are habituated to them and an adequate market is established, prices are increased. Here there is an apparent parallel with the results of Berndt, Kyle and Ling (2003) for prescription drugs following patent expiration. There a range of consumers was willing to pay a premium for the product because of established consumption patterns. These types of results appear consistent with our a priori expectations of how markets operate for products where brand preferences are strongest. However, brand loyalty is likely to play a lesser role in the case of toilet paper. Here it may be the market penetration strategy that prevails. Price are set low at introduction to attract a large number of customers and gain the benefit of economies of scale.

Table 3: Summary of Price Trends Over the Life Cycle (%)

Product	Spline Model: Annual average price change due to life cycle for life length equal to: 1 year	Spline Model: 3 years	Linear Model: Annual average price change due to life cycle for life length equal to: 1 year	Linear Model: 3 years
Analgesics:				
$S(3,3)$	–6.09	–4.42	–4.34	–2.09
$S(3,6)$	–6.10	–4.26	–4.32	–2.08
Beer:				
$S(3,3)$	2.40	1.97	2.34	1.12
$S(3,6)$	2.45	1.96	2.31	1.11
Cereal:				
$S(3,3)$	–11.07	–5.07	–8.82	–4.24
$S(3,6)$	–9.80	–2.82	–10.16	–4.89
Cigarettes:				
$S(3,3)$	8.76	5.55	6.73	3.24
$S(3,6)$	7.73	5.45	6.46	3.11
Grooming Products:				
$S(3,3)$	3.30	2.64	2.88	1.38
$S(3,6)$	1.93	1.60	2.09	1.00
Laundry Detergent:				
$S(3,3)$	–3.98	–2.93	–4.59	–2.21
$S(3,6)$	–4.89	–3.87	–5.29	–2.54
Soft Drinks:				
$S(3,3)$	–9.12	–5.50	–6.83	–3.28
$S(3,6)$	–8.80	–5.30	–7.03	–3.38
Toilet Paper:				
$S(3,3)$	10.75	10.19	7.55	3.63
$S(3,6)$	11.35	11.34	5.79	2.78
Average Change:				
$S(3,3)$	–0.63	0.30	–0.64	–0.31
$S(3,6)$	–0.77	0.51	–1.27	–0.61
Average Absolute Value:				
$S(3,3)$	6.93	4.78	5.51	2.65
$S(3,6)$	6.63	4.58	5.43	2.61

6 Implications for Price Indexes

The immediate implications of these findings are that price indexes are likely to be strongly influenced by life cycle pricing effects. In this section we focus on the impact of these results for quality adjustment as items are introduced and removed from the index. More specifically we address the question, what is the impact on the measurement of inflation of using the overlap pricing method and class mean imputation in the presence of life cycle price effects? In order to quantify this we mesh together our data, the empirically estimated life cycle functions, an index which is the object of estimation and assumptions about the rate at which statistical agencies samples turnover.

We begin by supposing that the object of estimation is a simple weighted geometric mean (Jevons) index for a product category. In modifying our notation from earlier, we now use n to represent each component in the index, that is each observation in the sample. In a given period this corresponds to a particular item, but as items disappear or are removed from the index the item which fills position n in the index may change. At any one time the sample is made up of the following index set of observations $V = \{1, 2, \ldots, N\}$. In comparing two periods, $t-1$ and t, these observations may be divided into three mutually exclusive sets: (a) those observations for which the same item is included, or matched, in both periods $n \in V_M$, (b) those observations for which an item is rotated out of the index in a given month $n \in V_R$, and (c) those observations for which the item disappeared and needed to be replaced in the sample $n \in V_D$. When the item which corresponds to observation n in time period $t-1$ is different from that for period t we denote this by including an asterisk on the later-period price. This gives a price relative of the form, $\frac{p^*_{nt}}{p_{nt-1}} = \frac{p(l^*_{nt}, z^*_n, x_t)}{p(l_{nt-1}, z_n, x_{t-1})}$. In this case the price drivers—time, life cycle and quality—between the two items at position n are likely to take on different values. Hence an adjustment, κ_n, is required to ensure that the price for the new item is comparable to the old item.

Given the three sets of items we may decompose the index $P_{t-1,t}$ as follows,

$$P_{t-1,t} = \left[\prod_{n \in V_M} \left(\frac{p_{nt}}{p_{nt-1}} \right)^{w_n} \right] \left[\prod_{n \in V_R} \left(\frac{p^*_{nt}/\kappa^R_n}{p_{nt-1}} \right)^{w_n} \right] \left[\prod_{n \in V_D} \left(\frac{p^*_{nt}/\kappa^D_n}{p_{nt-1}} \right)^{w_n} \right] \tag{6}$$

For those items which are being rotated into the index, and for which an overlap price exists, the standard statistical agency quality adjustment is $\bar{\kappa}^R_n$. Here we have a price for the new product in the previous period so the adjustment simply compares the ratio of prices in this period $\bar{\kappa}_n^R = \frac{p^*_{nt-1}}{p_{nt-1}}$. But note this price ratio includes any price differences between the two items that may result from life cycle differences in period $t-1$. The use of this adjustment removes it from the index. We propose an alternative adjustment, $\tilde{\kappa}_n^R$, which does not remove this important source of price change. Instead we compare the new and old prices but only on the basis of their quality, reflected in the z variable. We do not include in our adjustment any price differences due to the state of the item's life cycle. By doing this we are instead including these differences in the index. These two approaches are shown below where we have used our model of prices in (3) to illustrate the precise nature of the adjustments.

$$\bar{\kappa}_n^R = \frac{p^*_{nt-1}}{p_{nt-1}} = \frac{p(l^*_{nt-1}, z^*_n, x_{t-1})}{p(l_{nt-1}, z_n, x_{t-1})} = \exp\left(\beta^*_n - \beta_n + f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1})\right) \tag{7}$$

$$\tilde{\kappa}_n^R = \frac{p^*_{nt-1}}{p(l^*_{nt-1}, z_n, x_{t-1})} = \frac{p(l^*_{nt-1}, z^*_n, x_{t-1})}{p(l^*_{nt-1}, z_n, x_{t-1})} = \exp\left(\beta^*_n - \beta_n\right) \tag{8}$$

For those prices which disappear, and for which no overlap price exists, we suppose that the class mean imputation method is used. Here the movement of matched varieties is used to impute an overlap price. The standard approach is to take p_{nt-1}, inflate it by an index of the matched items, $n \in V_M$, and compare this price with the new price p^*_{nt}. This is shown in $\bar{\kappa}_n^D$. But this again removes any price change from the index due to differences in age between the new and old items. Our preferred approach is shown in $\tilde{\kappa}_n^D$. We begin with a period $t-1$ price for a good with quality variable z_n and life cycle characteristics l^*_{nt-1} and impute this forward using matched items. We start with a product with life cycle characteristics l^*_{nt-1}, i.e. $p(l^*_{nt-1}, z_n, x_{t-1})$, because we are inflating this price forward so in essence, when the quality adjustment is undertaken in period t, the item will implicitly have matured to have l^*_{nt}. Our adjustment allows for the effects of the changes in the sample's age profile to be reflected in the index while the standard approach removes this.

$$\bar{\kappa}_n^D = \frac{p_{nt}^*}{p_{nt-1}\left[\prod_{n\in V_M}\left(\frac{p_{nt}}{p_{nt-1}}\right)^{w_n^M}\right]} = \frac{\exp\left(\beta_n^* - \beta_n + f(a_{nt}^*, d_{nt}^*) - f(a_{nt-1}, d_{nt-1})\right)}{\exp\left(\sum_{n\in V_M} w_n^M \left[f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})\right]\right)} \tag{9}$$

$$\tilde{\kappa}_n^D = \frac{p_{nt}^*}{p(l_{nt-1}^*, z_n, x_{t-1})\left[\prod_{n\in V_M}\left(\frac{p_{nt}}{p_{nt-1}}\right)^{w_n^M}\right]} = \frac{\exp\left(\beta_n^* - \beta_n + f(a_{nt}^*, d_{nt}^*) - f(a_{nt-1}^*, d_{nt-1}^*)\right)}{\exp\left(\sum_{n\in V_M} w_n^M \left[f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})\right]\right)} \tag{10}$$

Where,

$$w_n^M = \left(\frac{w_n}{\sum_{n\in V_M} w_n}\right) \tag{11}$$

Our objective is to compare an index which does not remove life cycle pricing effects at the time of entry and exit, and hence uses the $\tilde{\kappa}$ adjustments, with that which uses the standard approaches to overlap pricing and class mean imputation reflected in $\bar{\kappa}$. In order to gauge the size of the aging bias when items are rotated out of the index, or disappear, we use our model of prices (3) in place of actual prices in (6). This abstracts from random fluctuations in prices and allows us to focus on the mean of the index under the two scenarios.

Let us first focus on the index produced under the standard assumptions, call this $\bar{P}_{t-1,t}$. In this case, if we write the index in log terms, then we have the following expression (the derivation is contained in the Appendix),

$$\ln \bar{P}_{t-1,t} = [\delta_t - \delta_{t-1}] + \left(\frac{\sum_{n\in V_M\cup V_R} w_n}{\sum_{n\in V_M} w_n}\right)\sum_{n\in V_M} w_n \left[f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})\right] + \sum_{n\in V_R} w_n \left[f(a_{nt}^*, d_{nt}^*) - f(a_{nt-1}^*, d_{nt-1}^*)\right] \tag{12}$$

That is, the price index is equal to pure price change, reflected in the δ parameters, plus a weighted average of the life cycle pricing effects for the matched and rotated items. But for the rotated and disappeared items any effect of the differences in price levels as a result of a change in the life cycle profile is removed from the index.

Turning to our preferred measure of price change, $\tilde{P}_{t-1,t}$. Here the effects of life cycle price change as products are linked into the index is included yielding the following expression (see the Appendix),

$$\ln \tilde{P}_{t-1,t} = [\delta_t - \delta_{t-1}] + \left(\frac{\sum_{n \in V_M \cup V_D} w_n}{\sum_{n \in V_M} w_n} \right) \sum_{n \in V_M} w_n \left[f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1}) \right]$$
$$+ \sum_{n \in V_R} w_n \left[f(a^*_{nt}, d^*_{nt}) - f(a_{nt-1}, d_{nt-1}) \right]$$
$$+ \sum_{n \in V_D} w_n \left[f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1}) \right] \qquad (13)$$

From these expressions we can conclude that the bias in the traditional index, which links out age effects for newly introduced products, is equal to (see the Appendix),

$$\ln \left(\frac{\bar{P}_{t-1,t}}{\tilde{P}_{t-1t}} \right) = - \sum_{n \in V_R \cup V_D} w_n \left[f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1}) \right] \qquad (14)$$

The difference between the two indexes reflects the difference in the life cycle price level between the new and old products. This rather simple expression enables us to estimate the aging bias of the standard index. However, in order to do this we are required to make some assumptions about the age profile of the sample, which items and what proportion of items disappear or are removed from the index and how these items are replaced. We adopt the following approach.

First, we fix the sample size at some number N. We then construct the empirical joint distribution of age and reverse age for each product category separately from the data. We suppose that the initial set of items is a random sample of size N from this distribution for a given product category. In each month a proportion of the items are rotated out of the sample, or disappear, while those that remain get one period older. We suppose that items are rotated out of the sample randomly.[6] In each such case a new item is linked in by again randomly sampling from the empirical distribution. This means we are not strictly replacing old items with new items. But because we start with a random sample from the empirical distribution, and because the sample ages over

[6] It is possible that statistical agencies are more likely to remove older items from the index. If this is the case then our results are likely to be an underestimate of the age-bias in the index.

time, the products which are removed or disappear from the index will *on average* be older than those which replace them. We repeat this exercise for twelve months and the difference in the age functions, as shown in (14), is recorded each month. The annual bias is the sum of these values. We considered three different rates of annual sample turnover; 10%, 20% and 30%. Given that the results will depend upon the initially selected sample, and which items are randomly chosen for replacement, we undertook this exercise 100 times and averaged the results to obtain the figures reported in Table 4.

The values in Table 4 represent annual estimates of the bias introduced by treating life cycle price differences as quality differences. For example, take analgesics. Here the bias is negative, indicating that the index constructed using standard assumptions lies below our preferred measure. For analgesics we saw that the life cycle function fell as products aged (Figure 2a). This means that as older items are removed from the sample and replaced with items that are on average younger, there will be a positive price difference between the new and old items. Our approach includes this effect whereas the standard approach links these price rises out. This leads to a downward bias in the conventional index. More generally the bias for each product category is in the same direction as the slope of its life cycle pricing function.

The results in Table 4 indicate the potential for significant bias due to currently used quality adjustment methods. Even with sample turnover of just 10%—less than 1% per month—the bias has the potential to be large. For statistical agencies which engage in more aggressive sample rotation schemes the effects are likely to be proportionately bigger. We construct an overall estimate of the bias in two ways. First, we take an average of the bias across our 8 product categories. This leads to an estimate of annual bias of 0.07% for sample turnover of 10% up to 0.22% for 30% turnover using the spline model for $S(3,3)$. But for the $S(3,6)$ data set, and for the linear model for both data sets, the effects are considerably smaller and almost negligible. The biases for individual product categories are much larger. But the fact these biases point in different directions means that when they are aggregated they offset each other to some extent. However, if the product category indexes themselves matter, which they are likely to as many specialist users will examine these, then a better measure of the bias is its mean absolute value. For just 10% sample turnover, and using the spline model, this implies an annual bias of 0.13% or 0.10% depending upon which data set is used. The bias rises to 0.38% or 0.30% when sample turnover is 30% per year.

To put these results in perspective, the findings of the Boskin Commission (Boskin et. al., 1997) into the US CPI reported an overall bias of around 1.1% per annum. This reflected a range of factors including quality adjustment methods, new goods, new outlets and upper- and lower-level substitution bias. As they noted, bias of this magnitude led to a massive increase in costs for government spending programs indexed to the CPI. The Boskin Commission did not explicitly explore the type of life cycle quality adjustment bias that we have outlined. So our estimates represent the quantification of a previously unmeasured source of CPI bias. Moreover the size of the bias in absolute value appears large and clearly has the potential to significantly distort measured price change in many subcomponents of the CPI. The implications for the index as a whole are less clear. We examined 8 product categories and this led to estimates of positive and negative bias depending upon the slope of the life cycle price function. While these offset each other to some extent in the aggregate for the commodities that we analyzed there can be no guarantee that such an outcome is likely across the index as a whole. More research is required into the product types not examined here to determine whether upward or downward sloping life cycle pricing functions are more prevalent and hence the likely direction of overall bias. Nevertheless, it is clear that widely used quality adjustment methods, in conjunction with life cycle pricing, is significantly distorting lower-level indexes in the CPI.

Table 4: Annual Quality Adjustment Bias Due to Life Cycle Pricing Trends (%)

Product	Spline Model			Linear Model		
	Annual sample turnover:			Annual sample turnover:		
	10%	20%	30%	10%	20%	30%
Analgesics:						
$S(3,3)$	–0.08	–0.15	–0.23	–0.03	–0.07	–0.10
$S(3,6)$	–0.06	–0.13	–0.19	–0.03	–0.07	–0.10
Beer:						
$S(3,3)$	0.03	0.07	0.10	0.02	0.03	0.05
$S(3,6)$	0.03	0.06	0.09	0.02	0.03	0.05
Cereal:						
$S(3,3)$	–0.26	–0.52	–0.77	–0.11	–0.22	–0.33
$S(3,6)$	–0.02	–0.04	–0.06	–0.10	–0.21	–0.31
Cigarettes:						
$S(3,3)$	0.04	0.07	0.11	0.09	0.18	0.27
$S(3,6)$	0.08	0.16	0.24	0.09	0.18	0.27
Grooming Products:						
$S(3,3)$	–0.16	–0.32	–0.48	0.04	0.08	0.12
$S(3,6)$	0.13	0.26	0.39	0.04	0.07	0.11
Laundry Detergent:						
$S(3,3)$	–0.10	–0.20	–0.30	–0.05	–0.10	–0.15
$S(3,6)$	–0.14	–0.28	–0.42	–0.06	–0.12	–0.18
Soft Drinks:						
$S(3,3)$	–0.21	–0.42	–0.62	–0.08	–0.15	–0.23
$S(3,6)$	–0.19	–0.38	–0.57	–0.08	–0.16	–0.24
Toilet Paper:						
$S(3,3)$	0.15	0.30	0.44	0.06	0.11	0.17
$S(3,6)$	0.13	0.27	0.40	0.03	0.06	0.09
Average Bias:						
$S(3,3)$	0.07	0.15	0.22	0.01	0.02	0.03
$S(3,6)$	0.01	0.01	0.02	0.01	0.03	0.04
Average Absolute Bias:						
$S(3,3)$	0.13	0.25	0.38	0.06	0.12	0.18
$S(3,6)$	0.10	0.20	0.30	0.06	0.11	0.17

7 Conclusion

The purpose of this paper has been two-fold. First, to shed light on the path of prices for commonly consumed supermarket products over their life cycle. Do life cycle price trends exist at all and are they of a sufficient magnitude to be economically meaningful? Second, we investigated the implications of these price-maturation effects for the estimation of price indexes. In particular, whether the failure to include these price changes in the index will introduce any systematic errors into the measurement of inflation.

We answer both questions in the affirmative. Using a flexible smoothing-spline modeling framework we found strong evidence for life cycle pricing effects. They were statistically significant for all the products that we examined—analgesics, beer, cereal, cigarettes, grooming products, laundry detergent, soft drinks and toilet paper. Importantly, the results were robust to different assumptions about the way in which the underlying data was constructed. The results illustrated that life cycle price trends differed by product group and were economically important.

The life cycle price function for half of the products—analgesics, cereal, laundry detergent and soft drinks—fell as products aged, while those for the remaining products—beer, cigarettes, grooming products and toilet paper—rose. The downward sloping life cycle price function provides some support to the price skimming hypotheses while the upward sloping life cycle price function is likely to reflect extensive efforts by firms to create brand loyalty to allow them to raise prices as products age. Generally, the lack of homogeneity in the life cycle pricing function leads us to the conclusion that the nature of age effects depends in complex ways on factors such as, technological standardization, cost reduction, increased competition and firms' pricing strategies. This points towards the need to use flexible modeling frameworks, such as splines, to reflect these factors.

We argue that there are significant implications for price indexes as a result of these findings. Index methods which ignore life cycle price differences during replacement of disappearing items, and inclusion of new items, produce biased measures of price change. This is because life cycle price change is implicitly attributed to quality change rather than inflationary price change. This is far from a trivial issue as statistical agencies indicate that as much as one third of the sample of prices may turnover annually. In this case currently used adjustment methods are likely to create a significant bias, of the order of 0.3% to 0.4% in absolute terms if sample rotation is around 30% per annum.

More generally, the paper has contributed to our understanding of life cycle pricing as a key driver of measured price change. It has emphasized that more attention needs to be paid to considering this price driver both in constructing index samples and in undertaking quality adjustment. Now that we have a clearer picture of the facts of life—with regard to product life cycle—more attention can be given to how to improve price indexes to more accurately reflect this phenomenon.

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9 Appendix

This appendix contains some of the derivations of the expressions in the text. We first examine the form of $\ln \bar{P}_{t-1,t}$, the log of the standard price index. This takes the form,

$$\begin{aligned}
\ln \bar{P}_{t-1,t} &= \sum_{n\in V_M} w_n \ln\left(\frac{p_{nt}}{p_{nt-1}}\right) + \sum_{n\in V_R} w_n \ln\left(\frac{p^*_{nt}/\bar{\kappa}^R_n}{p_{nt-1}}\right) + \sum_{n\in V_D} w_n \ln\left(\frac{p^*_{nt}/\bar{\kappa}^D_n}{p_{nt-1}}\right) \qquad (15)\\
&= \sum_{n\in V_M} w_n \Big[\{\delta_t + \beta_n + f(a_{nt}, d_{nt})\} - \{\delta_{t-1} + \beta_n + f(a_{nt-1}, d_{nt-1})\} \Big]\\
&+ \sum_{n\in V_R} w_n \Big[\{\delta_t + \beta^*_n + f(a^*_{nt}, d^*_{nt})\} - \big\{\beta^*_n - \beta_n + f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1})\big\}\\
&\qquad - \{\delta_{t-1} + \beta_n + f(a_{nt-1}, d_{nt-1})\} \Big]\\
&+ \sum_{n\in V_D} w_n \Big[\{\delta_t + \beta^*_n + f(a^*_{nt}, d^*_{nt})\} - \Big\{\beta^*_n - \beta_n + f(a^*_{nt}, d^*_{nt}) - f(a_{nt-1}, d_{nt-1}) -
\end{aligned}$$

$$\sum_{n \in V_M} \left(\frac{w_n}{\sum_{n \in V_M} w_n} \right) [f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})] \Bigg\} - \{\delta_{t-1} + \beta_n + f(a_{nt-1}, d_{nt-1})\} \Bigg] \tag{16}$$

$$= [\delta_t - \delta_{t-1}] + \sum_{n \in V_M} w_n [f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})]$$
$$+ \sum_{n \in V_R} w_n \left[f(a^*_{nt}, d^*_{nt}) - f(a^*_{nt-1}, d^*_{nt-1}) \right]$$
$$+ \sum_{n \in V_D} w_n \left[\sum_{n \in V_M} \left(\frac{w_n}{\sum_{n \in V_M} w_n} \right) [f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})] \right] \tag{17}$$

$$= [\delta_t - \delta_{t-1}] + \left(\frac{\sum_{n \in V_M \cup V_R} w_n}{\sum_{n \in V_M} w_n} \right) \sum_{n \in V_M} w_n [f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})]$$
$$+ \sum_{n \in V_R} w_n \left[f(a^*_{nt}, d^*_{nt}) - f(a^*_{nt-1}, d^*_{nt-1}) \right] \tag{18}$$

The form of $\ln \tilde{P}_{t-1t}$, the log of our preferred price index, is shown below,

$$\ln \tilde{P}_{t-1,t} = \sum_{n \in V_M} w_n \ln \left(\frac{p_{nt}}{p_{nt-1}} \right) + \sum_{n \in V_R} w_n \ln \left(\frac{p^*_{nt}/\tilde{\kappa}^R_n}{p_{nt-1}} \right) + \sum_{n \in V_D} w_n \ln \left(\frac{p^*_{nt}/\tilde{\kappa}^D_n}{p_{nt-1}} \right) \tag{19}$$

$$= \sum_{n \in V_M} w_n \Bigg[\{\delta_t + \beta_n + f(a_{nt}, d_{nt})\} - \{\delta_{t-1} + \beta_n + f(a_{nt-1}, d_{nt-1})\} \Bigg]$$
$$+ \sum_{n \in V_R} w_n \Bigg[\{\delta_t + \beta^*_n + f(a^*_{nt}, d^*_{nt})\} - \{\beta^*_n - \beta_n\} - \{\delta_{t-1} + \beta_n + f(a_{nt-1}, d_{nt-1})\} \Bigg]$$
$$+ \sum_{n \in V_D} w_n \Bigg[\{\delta_t + \beta^*_n + f(a^*_{nt}, d^*_{nt})\} - \Bigg\{ \beta^*_n - \beta_n + f(a^*_{nt}, d^*_{nt}) - f(a^*_{nt-1}, d^*_{nt-1})$$
$$- \sum_{n \in V_M} \left(\frac{w_n}{\sum_{n \in V_M} w_n} \right) [f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})] \Bigg\} - \{\delta_{t-1} + \beta_n + f(a_{nt-1}, d_{nt-1})\} \Bigg] \tag{20}$$

$$= [\delta_t - \delta_{t-1}] + \sum_{n \in V_M} w_n [f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})] + \sum_{n \in V_R} w_n [f(a^*_{nt}, d^*_{nt}) - f(a_{nt-1}, d_{nt-1})]$$
$$+ \sum_{n \in V_D} w_n \Bigg[f(a^*_{nt-1}, d^*_{nt-1}) + \sum_{n \in V_M} \left(\frac{w_n}{\sum_{n \in V_M} w_n} \right) [f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1})]$$
$$- f(a_{nt-1}, d_{nt-1}) \Bigg] \tag{21}$$

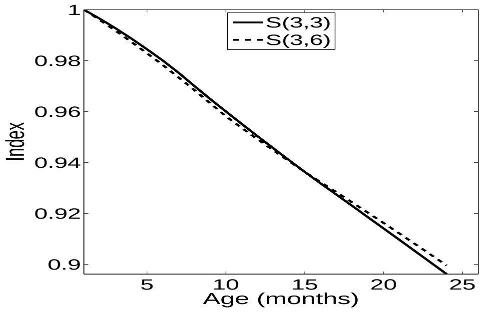
$$= [\delta_t - \delta_{t-1}] + \left(\frac{\sum_{n \in V_M \cup V_D} w_n}{\sum_{n \in V_M} w_n} \right) \sum_{n \in V_M} w_n \left[f(a_{nt}, d_{nt}) - f(a_{nt-1}, d_{nt-1}) \right]$$
$$+ \sum_{n \in V_R} w_n \left[f(a^*_{nt}, d^*_{nt}) - f(a_{nt-1}, d_{nt-1}) \right]$$
$$+ \sum_{n \in V_D} w_n \left[f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1}) \right] \tag{22}$$

The difference between these two indexes is equal to,

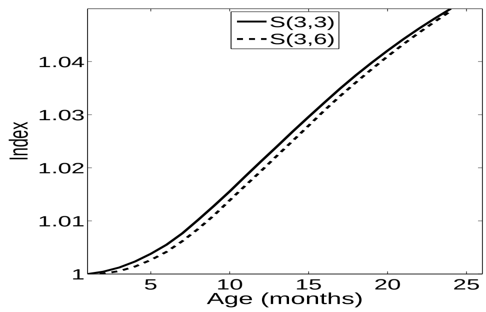
$$\ln \left(\frac{\bar{P}_{t-1,t}}{\tilde{P}_{t-1,t}} \right) = \sum_{n \in V_R} w_n \left[f(a^*_{nt}, d^*_{nt}) - f(a^*_{nt-1}, d^*_{nt-1}) \right]$$
$$- \sum_{n \in V_R} w_n \left[f(a^*_{nt}, d^*_{nt}) - f(a_{nt-1}, d_{nt-1}) \right]$$
$$- \sum_{n \in V_D} w_n \left[f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1}) \right] \tag{23}$$
$$= - \sum_{n \in V_R} w_n \left[f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1}) \right]$$
$$- \sum_{n \in V_D} w_n \left[f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1}) \right] \tag{24}$$
$$= - \sum_{n \in V_R \cup V_D} w_n \left[f(a^*_{nt-1}, d^*_{nt-1}) - f(a_{nt-1}, d_{nt-1}) \right] \tag{25}$$

Figure 2: Life Cycle Price Trends
(For a Life Span of 2 Years for Each Data Set)

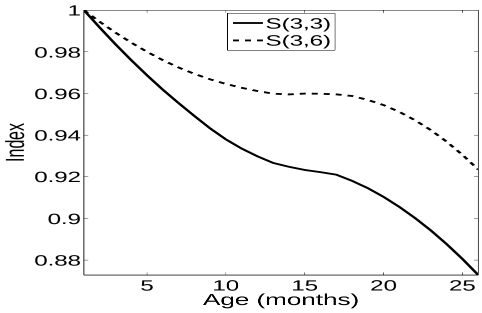
(a) Analgesics



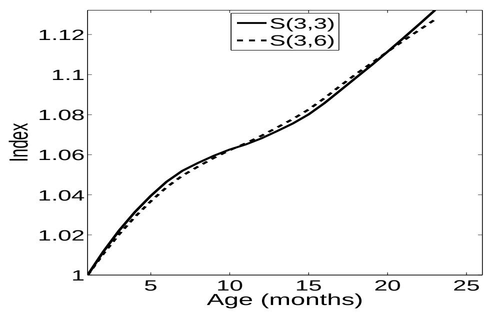
(b) Beer



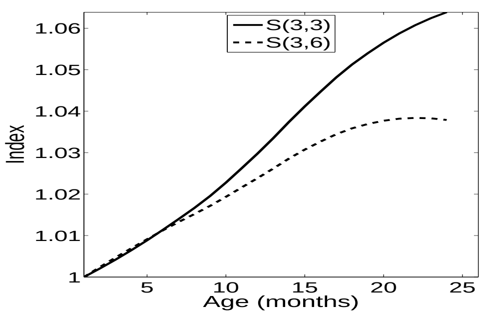
(c) Cereal



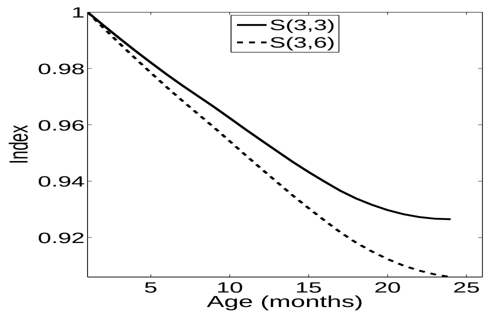
(d) Cigarettes



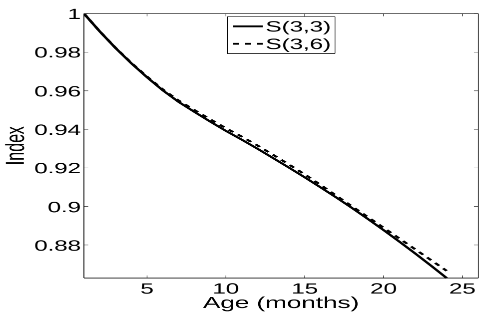
(e) Grooming Products



(f) Laundry Detergent



(g) Soft Drinks



(h) Toilet Paper

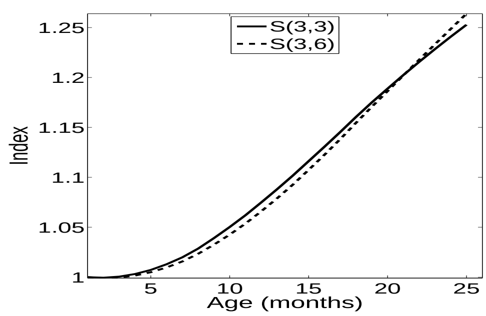


Figure 3: Life Cycle Price Trends
(For the 25th, 50th and 75th Percentiles of Item Lives)