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Prices over the Product Life Cycle: Implications for Quality-Adjustment and the Measurement of Inflation

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Abstract: The 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. Using a large US scanner data set on supermarket products and applying flexible regression methods, we find that on average prices decline as items age. This life cycle price change is often attributed to quality difference in the construction of CPI as items are replaced due to disappearance and at sample rotations. This introduces a systematic bias in the measurement of inflation. For our data we find that the life cycle bias underestimates the measurement of inflation by around 0.30 percentage points each year.

JEL Codes: C43, D22, E31.

Keywords: Consumer price index (CPI); cost of living; matched-model index; quality change bias; sample rotation; scanner data.

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I Introduction

One of the most distinctive features of modern economies is the extraordinary array of product varieties, brands, sizes, colors, editions and flavors. 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turnover in product varieties has been driven by technology in some areas—such as electronics, where old models are superseded by faster, smaller, and better models—but is also unequivocally apparent in less dynamic product categories.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 amount of literature addressing issues around the product life cycle. We focus on two issues in particular: first, identifying price trends as products mature, and second, examining the implications these life cycle price trends have on matched-model price indexes as disappearing items are replaced with new items.

Identifying the life cycle price trends is important for the measurement of inflation because they represent price dynamics which are unrelated to quality but which can easily be confounded with quality difference in the construction of price indexes. Much of the interest in life cycle pricing is focused on the price dynamics as products enter and exit the market. For example, retailers adopting a 'price skimming' approach may sell their products at high prices to take advantage of the novelty factor, or they may sell at low prices as suggested by the 'market penetration' hypothesis (Kotler and Armstrong, 2011). The goods may exit the market at rock-bottom prices in order to clear shelf space for new items, or at relatively high prices in order to cater for market segments exhibiting strong preferences for old brands. Additionally, the prices of the product may systematically change over time for reasons related to technological advances, cost reduction, competition, firms' pricing strategies and many other reasons internal to the industry which are conceptually distinct from what is conventionally meant by quality differences. Hence, in a constant-utility cost-of-living index these price changes over the product life cycle should be included in the measurement of inflation.

The life cycle price change is treated asymmetrically by statistical agencies in the construction of some matched-model price indexes. When a product is carried over from the current period to the next, the life cycle price difference is included, and correctly so, in the price index. But when a product disappears or is rotated out of the index, and is replaced by a new product, the life cycle price difference between the old and new products is often attributed, and this time wrongly, to a quality difference and hence is removed from the index. We argue that this systematically biases the measurement of quality change, and consequently the measurement of inflation. For example, suppose that after adjusting for quality change the entry prices are higher than the exit prices for items in a product category, implying that the life cycle price difference between the new and disappearing items is positive. If this positive life cycle price difference is added to the quality change then the calculated measure of quality change gets overestimated. Since this measure of quality change is removed from the index, the measure of price change gets underestimated.

Using data on 29 supermarket product categories included in the Dominick's scanner data set, we find that the life cycle component of price change is indeed significant. While there is variation in the size and direction of these life cycle pricing effects, after controlling for other inflationary factors that cause prices to change over time, we find that prices fall over their life for around two-thirds of our product categories. The average price change over the life of an item across the 29 supermarket products is a fall of around 3.93%. Given that the average age of items in our data is 22.6 months, this implies that the prices on average fall by around 2.09% per year due to aging. We estimate that ignoring this life cycle price change when items are replaced due to disappearance and at sample rotations leads to an annual downward bias of 0.30 percentage points in the measurement of inflation. Interestingly, the life cycle bias affects the measurement of inflation in the opposite direction to the quality change and substitution biases.

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, Cockburn and Griliches (1996), while investigating the effects of patent expiration and the entry of generic producers on the price of prescription drugs, find that the entry prices of new generic products tend to be lower than the prices of their patented antecedents. They conclude that the non-priced quality changes in the new generic products and how these new products are linked to their patented antecedents are potential sources of bias in official indexes. Berndt, Griliches and Rosett (1993) report that the prices of older drugs increased more rapidly than the prices of newer drugs during 1986–91. In another work, Berndt, Kyle and Ling (2003) find 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. In other work, de Haan (2004) outlined a hedonic regression model which allowed for the systematic effects of 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 sample degradation and systematic differences in the quality-adjusted prices of new, old and continuing items.

Given the paucity of empirical evidence, there has been speculation about the likely path of prices as products age. For example, a passage from the ILO (2004) 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 & 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)

Some other studies have supported this view—that new goods are relatively highly priced and old goods are cheaper even after adjusting for quality difference (see Silver & Heravi, 2001; Schultze &

Mackie, 2002, p. 162; Pakes, 2003; Triplett, 2006, chapter 2, p. 30). However, there remains little work in the literature quantifying such a phenomenon and particularly how this life cycle price difference influences the measurement of inflation. The studies, such as Boskin et. al. (1997), and Lebow and Rudd (2003), which provide estimates of the overall bias in the CPI did not explicitly take account of life cycle bias. In contrast, a great deal of attention has been given to identifying and quantifying quality change bias in the CPI.[1]

The paper is organized as follows. In the next section, we discuss how matched-model indexes incur the life cycle pricing bias. Section III describes our data and how the life cycle variables are identified. Section IV introduces the regression models that are estimated in order to separate life cycle pricing patterns from the myriad of other effects that determine the price of a product. Section V discusses the regression results and the estimated life cycle functions. Section VI examines the implications of the estimated life cycle price trends for matched-model price indexes. Finally, section VII provides a summary of the findings and draws some conclusions.

II Methods of Item Replacement and the Life Cycle Bias

The change in the available set of commodities and their expenditure shares over time necessitates that statistical agencies have some mechanism for systematically including new items and for replacing price quotes for disappeared items. The methods used to do this aim to account for the fact that the new items may differ in terms of quality from the old items. Hence statistical agencies look for similar items, and when similar items are not found, they seek to make adjustments to the prices of the new and disappearing items to ensure, as much as possible, that like is compared with like and any quality differences between new and old items are netted out.

When an item disappears, perhaps the most common practice is to select a similar item as a replacement and attribute the price difference between the two items to inflation. The life cycle bias, as defined in this paper, is not incurred in these comparable replacements because all the price difference between the new and disappeared items is included in the measured inflation. In the case where a comparable item is not found, statistical agencies may undertake direct quality adjustment which involves assigning a monetary value to the quality difference between items through the use of the knowledge of field agents, consultations with store managers and manufacturers and, in some cases, using the implicit prices of characteristics obtained from hedonic regressions. Given that these methods are applied on a case-by-case basis and judgements are applied it is difficult to

[1]For example, some recent papers include: Aizcorbe and Pho (2005), who compare matched-model and hedonic quality adjusted price indexes for high technology goods; Bils (2009), who estimates quality bias for durable goods; Broda and Weinstein (2010), who estimate quality bias due to the failure to update the sample in concordance with market turnover rates; Greenlees and McClelland (2011) for quality adjustment in technologically stable products such as food items; and Hill and Melser (2008) for quality adjusted price indexes for houses. See also Aizcorbe, Corrado and Doms (2003) and Pakes (2003) who estimate quality adjusted price indexes for computers.

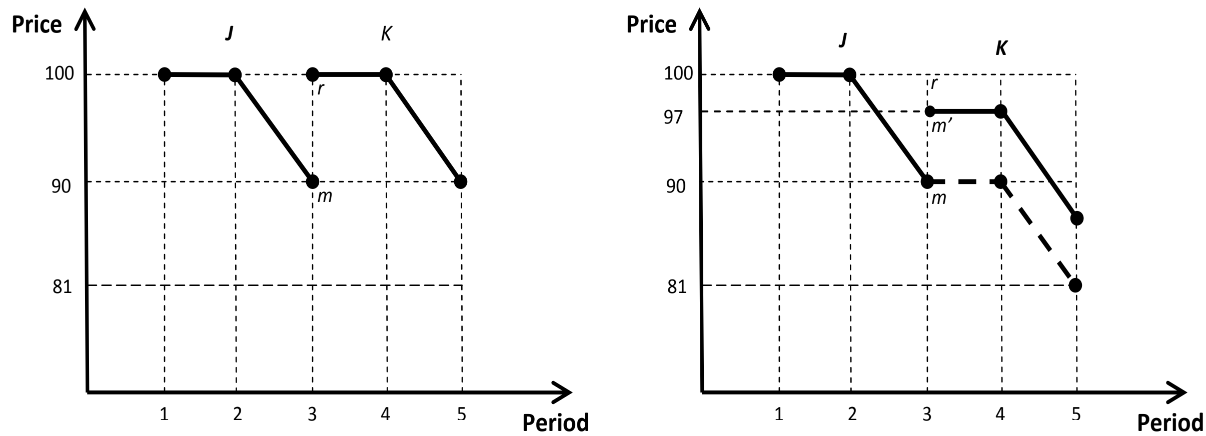
understand exactly how the price difference is allocated between the quality change and pure price change. These methods are not the focus of our study.

We now address the methods used by agencies which are likely to confound the effects of life cycle pricing with those of quality adjustment. Let us first focus on forced substitution methods where the price of both new and disappearing items are available in a common period. In this situation, the agencies may use what the ILO (2004) terms the overlap price method, where the new item is spliced into the existing price sample and the whole price difference is attributed to the quality difference (see ILO, 2004, ch. 7, p. 106; ABS, 2009, ch. 9, p. 80).

Consider an example of the overlap price method. Suppose we have two items, J and K, and the price of the two items differs by 10% in the overlap period. We suppose that 30% of the price difference is due to quality difference and the remaining 70% is due to the life cycle price difference. 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 10% price difference between items J and K in period 3, as K replaces J in the sample, is wholly attributed to quality difference. As a result, in period 3 the price for K would be adjusted down multiplicatively by the relative price difference of 10% and then this adjusted price m (at 90) would be fed into the index. This is shown by the dashed line in Figure 1b. However, it is clear that the correctly adjusted price is m' (at 97) and the quality adjustment is overdone by $m'm$ percentage points. The distance $m'm$, as we define, is the life cycle bias and in this case leads to an index which is biased downward by 7 percentage points. We formally estimate $m'm$ in section VI.

Figure 1: Quality Adjustment Using the Overlap Price Method

(a) Prices of New and Disappearing Items (b) The Life Cycle Bias



In practice, however, it is relatively uncommon to have overlap prices for new and disappearing items because most items disappear without any advance warning (Moulton and Moses, 1997). But this problem of quality adjustment in the presence of life cycle pricing is not confined to the overlap method. When an overlap is not available, a common procedure is to extrapolate the price of the disappearing item forward to artificially create an overlap. In other words, the overlap is created between the imputed price of the disappeared item and the observed price of the new item. Typically, a group of similar items are used in the price extrapolation, though details of what defines similar items vary between methods and across statistical agencies.[2] The price difference in this artificially created overlap period is used as a measure of quality difference. But this leads to just the same sort of error as the one that occurs in the overlap pricing method. This is because the ages of the new and old items are likely to differ and hence life cycle pricing effects are again confounded with quality differences.

In order to obtain estimates of the life cycle bias in a particular product category, it is important to know what proportion of replacements in that product are undertaken using the overlap and imputation methods. It is most likely that the importance of different methods in undertaking the replacements vary from period to period, across products and statistical agencies. Moulton and Moses (1997) provide information of their relative importance in the US CPI for 1983, 1984 and 1995 (see also Hulten, 1997). In 1995, the replacements undertaken through indirect methods—consisting of overlap and imputation methods which are the subject of our study—accounted for 24.1% of all forced substitutions (see Moulton and Moses, Table 4). The corresponding percentage is 46.0% for the food and beverage items (many of the items in our data fall in this category). This shows that a significant proportion of forced substitutions may incur the life cycle bias. We use this information to build our simulations discussed in section VI. In particular, we consider two scenarios with regard to the percentage of forced substitutions which we subject to the life cycle bias: $\Lambda = 40\%$ and 25%. While the higher proportion may provide us with an upper bound of the potential life cycle bias (or the potential bias of some specific products), the lower proportion may be reflective of the average life cycle bias that is relevant to many statistical agencies who replace their items mostly through comparable replacements and using the direct quality adjustment method. We should note that the replaced items in any given period have a proportionately large impact on the reported inflation, accounting for around 50% of the overall price change in the US in 1995 (Moulton & Moses, Table 5 and 6). Therefore, the life cycle bias, applicable to 40% or 25% of total replacements, can be quite significant.

We now turn to sample rotations. Through sample rotations in each year a certain proportion of items are replaced before they disappear to reflect the change in expenditure patterns in the market. The Bureau of Labor Statistics (BLS) in the US reports that around 25% of the sample of price quotes are rotated each year (BLS, 2007, Ch. 17). At sample rotations, all the price differences are attributed to quality differences (see Bils, 2009). Hence, if the life cycle price effect exists, it gets added to the quality effect. The sample rotation implicitly applies an aggregate version of

[2] The methods used by the US Bureau of Labor Statistics (BLS) are known as the *class mean imputation method* and the *link method* (for details see Moulton & Moses, 1997; ILO, 2004, ch. 7; Triplett, 2006).

the overlap method (ILO, 2004, Ch. 7). The prices of both the outgoing and incoming items are collected in period t. While the price change between period t and $t-1$ is calculated from the prices of the old items, the price change between period t and $t+1$ is calculated from the prices of the new items. The splicing together of these price movements is justified if a group-to-group rather than item-to-item level differences in price levels at a given time accurately reflect differences in qualities (ILO, 2004, Ch. 7, p. 107). Hence, if systematic life cycle pricing patterns exist, such as that prices decrease as products age, then the quality change is overestimated and the inflation is underestimated.

However, the use of rotation to update samples is not practiced routinely by all statistical agencies. Therefore, in section VI, we calculate the life cycle bias under scenarios with and without sample rotations. In particular, we consider three scenarios with annual sample rotation rates: $\Pi =$ 0%, 12% and 24%. The introduction of sample rotation, or a larger sample rotation rate, on the one hand subjects more items to the life cycle bias and on the other hand reduces the age difference between the new and disappearing items and the number of forced substitutions. It is interesting to see how these different dynamics play out on balance for the life cycle bias at the overall index level.

On a more general level, it is argued that any procedure, such as routine sample rotations, that reduces the age difference between the new and disappearing items tends to reduce the life cycle price effect on inflation. However, this may not always be the case if the life cycle price function is non-monotonic. Suppose, for example, that the life cycle price function increases and then decreases. In this case items which are either younger or older will have more similar prices than those of middling age. Therefore, it is important to know the pricing pattern over the entire life cycle to minimize the life cycle price difference between the new and disappearing items. In the following sections we estimate the shape and magnitude of the price changes as products mature before addressing the issue of index bias formally in section VI.

III Data and Extracting Life Cycle Variables

This paper investigates 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.[3] We study all 29 product categories included in the data. There are 96 stores with prices for hundreds of items for each product category 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).[4] We aggregate the data across stores to monthly unit values, as

[3]The data set is available at http://research.chicagogsb.edu/marketing/databases/dominicks/index.aspx.

[4]An item is identified by a unique Universal Product Code (UPC), referring to a unique bundle of characteristics, e.g. "a 14 ounce can of Coca Cola available in a 6-pack".

monthly is the most common calculation frequency for CPIs globally. The long coverage of the data set—the longest readily available scanner data set known to the authors—provides the richness required to extract and estimate the 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. 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 (see for example Berndt, Griliches and Rappaport, 1995; Silver, 1999). While age is indeed a key characteristic of an item'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*. Note the identity: *age + reverse age = length of life.* Therefore, we need only two of these three variables in order to fully define the stage of an item's life cycle. The reverse age is potentially important because if there are specific price dynamics associated with end of life, such as run-out sales near product death, then this can be linked with reverse age. In the data set, items with different length of life appear and disappear throughout time. This implies that in a given time there are a range of items at different points in their life having different values for the age and reverse age variables. 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.

The extraction of the life cycle variables from the data is not straightforward. Table 1 illustrates the problem faced for different types of items. For items of type A, which are available in the market in both the first and the last period of the sample, we are unable to identify either their birth or death. Consequently, we cannot determine the age and reverse age of these items. The B items were available from the beginning of the sample period and, therefore, their first appearance in the market is unknown. However, since these items disappeared before the end of the sample, we can identify the death of these items. The situation for the C items is just the opposite, where the age can be determined but reverse age cannot. Finally, in the case of the D items both the age and reverse age can be determined. These are the items which appear in and disappear from the market within the coverage of the sample period and, therefore, their whole life cycle is observed. The inability to calculate age and/or reverse age for all items led us to run different versions of our empirical model based upon different combinations of the B, C and D items. Because we do not have any information about the stage of the life cycle for A items these have been removed from the analysis. This is discussed in more detail in the next two sections.

There are two further data issues to be addressed. First, there are some very short-lived products in the data set and we need to decide how short is too short for the minimum length of a product's life. We chose 3 months as the minimum life length and all products with a shorter

Table 1: Constructing the Life Cycle Variables

Items	Period (valid observation [O], missing obs. [-])												Observed†	
	1	2	3	4	5	6	7	8	9	10	11	12	a_{nt}	d_{nt}
A: Birth & death unknown	O	O	O	O	O	O	O	O	O	O	O	O	$\times$	$\times$
B: Death unknown	-	-	-	-	O	O	O	O	O	O	O	O	$\surd$	$\times$
C: Birth unknown	O	O	O	O	O	O	O	O	O	-	-	-	$\times$	$\surd$
D: Birth & death known	-	-	-	O	O	O	O	O	-	-	-	-	$\surd$	$\surd$

† a_{nt} and d_{nt} refer to age and reverse age, respectively.

life-span were dropped. However, we did also undertake subsequent analysis assuming a 6-month minimum life length and the results were very similar. Second, because an item may be temporarily out of stock, or it may not sell and hence would not be observed in our data, we must be careful in defining when an item appears and disappears relative to the start and end of our data set. We allowed for a break of 3 months at the start and end of our data where no products were assumed to appear or disappear. This provides a buffer so that we do not mistakenly define an item as being of D-type, and construct its life cycle characteristics, when in fact it had just been out of stock for a couple of months at the start or end of the data. As in the previous case, we also considered other sized breaks, 6 and 9 months, but this did not alter the main thrust of the results, particularly in terms of their implications for quality adjustment and the measurement of inflation.

Our data is summarized in Table 2. Around 13.91% of items are of the A type, i.e. items where both age and reverse age cannot be identified. The highest proportion of these long-lived items belongs to the oatmeal product category (35.87%), while the lowest is seen in laundry detergents (1.48%). On the other hand, 32.82% of items are D-type items, i.e. the items whose both age and reverse age can be identified. Of these D-type items we find that more than 88.16% of them disappear within a period of 4 years, which is much lower than the sample coverage of 8 years and explains why there are a relatively small number of long-lived items. However, the long-lived items account for a larger share of expenditure, with 29.22% of the monthly expenditure for all products on average. The average monthly expenditure shares for the B and C items is 52.78% and it is 18.00% for D items. We find that the average of the median life span of the 29 products is 22.6 months. However, there is considerable dispersion in the distribution of product length of life, both within and across product categories. The median life of the products ranges from 18 months (bottled juices, cheeses and grooming products) to 35 months (canned soup and canned tuna). The wide variation in the age profile of items allows us to obtain a comprehensive picture of the age effect on price movements.

Table 2: Life Cycle Statistics

Products	Expenditure Share across Products (%)†	Months of Data	Number of Items	Percentage of Items in Type:*				Average Expenditure Share (%) of Items in Type:				*D*-type Items			
												No. of	% Disappear by:		Median Life
				A	*B*	*C*	*D*	*A*	*B*	*C*	*D*	Obs.	2 years	4 years	Span (months)
Analgesics	1.42	100	587	16.87	29.81	21.64	31.69	36.94	34.91	11.60	16.55	4973	46.24	86.02	27.5
Bath Soap	0.12	69	491	6.52	44.81	16.09	32.59	21.89	49.00	12.05	17.06	2521	65.63	98.50	18.5
Beer	3.71	78	680	6.18	29.85	31.91	32.06	7.80	11.14	53.25	27.82	4214	63.76	94.95	18.5
Bottled Juices	3.58	100	465	11.61	24.95	16.13	47.31	27.86	30.51	17.05	24.58	4946	69.06	88.64	18.0
Cereals	10.33	100	430	21.16	28.84	21.86	28.14	40.50	31.14	15.82	12.54	2448	59.50	87.60	19.0
Cheeses	8.84	100	615	19.35	31.87	19.19	29.59	46.60	27.51	11.90	14.00	3691	66.48	90.66	18.0
Cigarettes	1.84	100	700	12.14	63.57	3.71	20.57	16.64	46.32	35.44	1.61	2599	55.58	82.23	20.5
Cookies	4.64	100	1,038	10.31	22.09	27.65	39.98	27.38	29.92	18.64	24.06	8761	53.49	89.64	22.0
Crackers	1.30	100	300	18.00	28.00	27.33	26.67	35.58	41.36	8.93	14.14	1522	66.25	96.50	19.0
Canned Soup	3.26	100	414	19.32	17.87	33.09	29.71	29.56	19.84	25.31	25.28	4329	30.89	73.17	35.0
Dish Detergent	1.65	100	264	13.26	27.65	22.35	36.74	19.60	25.66	29.73	25.01	2395	56.70	84.50	20.0
Front-end-candies	1.40	100	436	14.68	24.54	26.15	34.63	38.20	29.37	14.14	18.29	3644	54.30	90.73	22.0
Frozen Dinners	1.49	65	231	13.85	27.27	24.24	34.63	26.56	38.26	16.38	18.80	1634	73.75	90.0	20.0
Frozen Entrees	5.28	100	820	10.24	31.22	21.59	36.95	22.14	37.30	17.93	22.63	6909	61.72	89.77	21.0
Frozen Juices	2.64	100	166	28.92	23.49	13.86	33.73	59.18	16.52	10.14	14.17	1334	53.57	85.71	23.0
Fabric Softeners	1.68	100	298	7.05	36.91	20.81	35.23	8.20	33.94	31.82	26.04	2814	52.33	79.05	23.0
Grooming Products	1.56	69	1,225	15.43	38.69	19.35	26.53	32.96	48.50	8.79	9.76	4369	64.00	96.31	18.0
Laundry Detergents	5.53	100	540	1.48	24.07	25.19	49.26	0.69	29.90	29.42	39.99	7133	54.89	82.33	23.0
Oatmeal	1.10	78	92	35.87	20.65	21.74	21.74	63.51	20.57	8.76	7.16	497	50.00	100.00	24.5
Paper Towels	2.36	100	136	7.35	23.53	14.71	54.41	15.59	35.59	21.46	27.36	1623	43.24	63.00	29.0
Refrigerated Juices	5.67	100	207	14.01	37.20	14.98	33.82	41.07	35.20	21.46	12.48	1647	55.00	86.43	20.0
Soft Drinks	17.95	100	1,470	12.79	42.24	13.27	31.70	33.29	47.19	9.91	9.62	9527	54.08	89.70	23.0
Shampoos	1.73	69	2,571	12.14	31.12	29.52	27.23	27.01	40.88	19.64	12.47	10186	50.86	97.00	24.0
Snack Crackers	2.59	100	381	13.91	28.87	21.26	35.96	33.06	33.43	13.47	20.04	3264	54.74	87.01	21.0
Soaps	1.45	70	306	15.69	42.81	21.90	19.61	33.37	39.28	13.13	14.22	1458	51.01	95.50	24.5
Toothbrushes	0.42	100	438	5.94	29.68	29.45	34.93	12.29	40.44	28.63	18.64	3232	58.17	88.51	20.0
Canned Tuna	1.91	100	260	17.31	34.62	30.77	17.31	40.37	35.30	18.23	6.10	1461	36.02	78.88	35.0
Toothpastes	1.13	100	567	7.94	35.98	22.22	33.86	21.02	44.28	13.43	21.27	4382	48.44	92.19	25.0
Bathroom Tissues	3.42	100	114	14.04	35.09	15.79	35.09	28.55	33.57	17.58	20.31	1014	52.50	92.05	23.5
Average All Items‡	100.00	93.03	16,242	13.91	31.63	21.65	32.82	29.22	34.03	18.75	18.00	108,527	55.25	88.16	22.6

† Share of each product in the total expenditure on all product categories. * See Table 1 for definitions of different types of items.
‡ The figures for "Expenditure Share across Products (%)", "Number of Items" and "No. of Obs." are summations while the others are averages across products.

IV Modeling Life Cycle Price Trends

Using the data sets outlined in the previous section we proceed to estimate the age effect on prices for our products. We specify different models depending on whether the data contains the age and/or reverse age of the items. The models take the natural logarithm of prices as the dependant variable and control for the cross-sectional and time-series variation in the prices of items using fixed effects. We include dummy variables for items to control for cross-sectional price differences. These dummy variables 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. We include dummy variables for time periods to control for product-wide temporal variations in price. This gives a model which is the temporal variant of the widely used country-product dummy (CPD) method due originally to Summers (1973). Here, however, we have added a life cycle function.[5]

More formally let us define dummy variables for varieties (z_{nj}) such that $z_{nj} = 1$ when $n = j$ for item n and zero otherwise, and for time periods (x_{ts}) such that $x_{ts} = 1$ when $t = s$ for time t and zero otherwise, and leave the life cycle 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:

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

With regard to $f(a_{nt}, d_{nt})$, let us begin by supposing that it takes the following form:

$$f(a_{nt}, d_{nt}) = \alpha I_a \log(a_{nt}) + \gamma I_d \log(d_{nt}) \tag{2}$$

Here a_{nt} and d_{nt} denote the age and reverse age of item n in period t, I_a denotes the indicator function taking the value of 1 if the model includes a_{nt} and I_d denotes the indicator function taking the value of 1 if the model includes d_{nt}. Note that though the time dummy and age are perfectly correlated, there is no such perfect collinearity problem in equation (1) because $f(a_{nt}, d_{nt})$ is specified in a non-linear (logarithmic) form. The life cycle function has the interpretation of age and reverse age acting as depreciation/appreciation factors upon price.[6]

[5] The CPD method or variants of the CPD method are widely used in different contexts. For example, most regions in the International Comparisons Program (ICP) used CPD models and their extensions to calculate the within-region basic-heading price indexes for each country. These price indexes form the basis for constructing the official World Bank Purchasing Power Parities (PPP) across the countries (see Rao, 2004; Diewert, 2005). See also de Haan and Krsinich (2012) for some features of this method—which they refer to as the time-product dummy (TPD) method—in the context of constructing price indexes.

[6] The papers on price indexes which include age within the hedonic regression framework include Berndt, Griliches and Rappaport (1995), Berndt, Griliches and Rosett (1993), Cole et al. (1986) and Silver (2000). This approach of including the logarithm of age as an independent variable in a regression on log-price is also a familiar approach in the housing literature related to the estimation of the depreciation rate (see, for example, Shilling, Sirmans and Dombrow, 1991; Lee, Chung & Kim, 2005; Harding, Rosenthal & Sirmas, 2007).

However, the log-linear functional form places a great deal of a priori structure on a potentially very complex empirical relationship. A flexible alternative is to model $f(a_{nt}, d_{nt})$ non-parametrically, inserting dummy variables for each unique value of a_{nt} and d_{nt}. However, this is not fully identified and will also place too few restrictions on the function, meaning that the results are likely to be driven by sampling variability rather than the underlying data generating process. It seems 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:

$$\min._{\beta,\delta,f_a,f_d} \sum_{n=1}^{N}\sum_{t=1}^{T}\left[\log(p_{nt}) - \sum_{j=1}^{N}\beta_j z_{nj} - \sum_{s=2}^{T}\delta_s x_{ts} - f_a[\log(a_{nt})] - f_d[\log(d_{nt})]\right]^2 + \lambda_a \int [f_a''(v)]^2 dv + \lambda_b \int [f_d''(v)]^2 dv \quad (3)$$

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 $\lambda_a, \lambda_b \to 0$. The smoothing parameters themselves are chosen using the generalized cross validation approach (GCV) of Craven and Wahba (1979). This is similar to the standard cross validation approach but tends to be more robust to outliers.

V Model Results and Life Cycle Price Trends

Table 3 shows the different models we estimate. Our a priori preference lies with the models where both age and reverse age are included, i.e. the $D(a, d)$ and $D(a_s, d_s)$ models. However, these models can only be run using the D-type items. This is because age is not identified for the C-type items and the reverse age is not identified for the B-type items.

We estimate other log-linear models on larger sets of items in order to check whether different sets of items make any significant difference in the age and reverse age effects on prices. For example, $BD(a)$ refers to the model which is run using the B and D items but includes only age in the life cycle function specified in equation (2). The $CD(d)$ model is run on C and D items and includes only reverse age in the life cycle function. Note that while the $BD(a)$ model includes the maximum number of items where the age is identified, the $CD(d)$ model includes the maximum number of items where the reverse age is identified.

Table 3: Empirical Models and the Relevant Data

Model Name	Model Type	Items Used	Includes:	
			a_{nt}	d_{nt}
$BD(a)$	Log-linear	B & D	√	×
$D(a)$	Log-linear	D	√	×
$CD(d)$	Log-linear	C & D	×	√
$D(d)$	Log-linear	D	×	√
$D(a,d)$	Log-linear	D	√	√
$D(.)$	Log-linear	D	×	×
$D(a_s,d_s)$	Spline	D	√	√

Note: All models include time and item dummies.

First, let us turn to the linear model for D-type items with both age and reverse age included, $D(a,d)$. The estimated coefficients of age ($\hat{\alpha}$) and reverse age ($\hat{\gamma}$) of equation (2) for our 29 products are shown in Table 4. Here $\hat{\alpha}$ is negative for 22 products (14 are significant) and positive for 7 products (2 are significant), and $\hat{\gamma}$ is positive for 17 products (12 are significant) and negative for 12 products (6 are significant).[7] At least one of the coefficients between $\hat{\alpha}$ and $\hat{\gamma}$ is significant for 25 products (the products where both the coefficients are insignificant are bath soaps, cheeses, cookies and soaps). The average of $\hat{\alpha}$ is –0.0071 which corresponds to a monthly change in prices of approximately –0.71% (–1.21% for the significant coefficients) and the average of the $\hat{\gamma}$ is 0.25% (0.45% for the significant coefficients). The F-test for the joint significance of a_{nt} and d_{nt} is significant for 22 product categories (see Table 5, col. 2). These results are supportive of the hypothesis that both age and reverse age are important determinants of price.

The negative value of $\hat{\alpha}$ and the positive value of $\hat{\gamma}$ indicate falling prices over the life of products. Therefore, the results of the $D(a,d)$ models indicate that the price skimming strategy—where the item's entry price is higher than its exit price—is the dominant strategy followed by firms. It now remains to be seen whether a similar conclusion with regard to the life cycle pricing pattern can be drawn from the other models run on other data sets.

The $D(a,d)$ results may not be representative of all items as these models just use the D-

[7] All our discussions on statistical significance refer to the 5% significance level.

Table 4: Regression Results for the Log-Linear Models

Products	Estimated Age Coefficients ($\hat{\alpha}$) Obtained from the Model:†			Estimated Reverse Age Coefficients ($\hat{\gamma}$) Obtained from the Model:		
	$BD(a)$	$D(a)$	$D(a,d)$	$CD(d)$	$D(d)$	$D(a,d)$
Analgesics	–0.0155***	–0.0103***	–0.0081***	0.0123***	0.0088***	0.0081***
Bath Soap	–0.0194***	0.0092	0.0094	0.0067***	0.0008	0.0011
Beer	–0.0052***	0.0017	0.0007	–0.0035***	–0.0041***	–0.0040**
Bottled Juices	–0.0134***	–0.0250***	–0.0202***	0.0120***	0.0133***	0.0100***
Cereals	–0.0136***	–0.0297***	–0.0249***	0.0094***	0.0184***	0.0158***
Cheeses	–0.0041**	–0.0022	–0.0015	0.0008	0.0017	0.0015
Cigarettes	0.0029	0.0085***	0.0065***	–0.0065***	–0.0051***	–0.0041***
Cookies	–0.0077***	–0.0030	–0.0036	–0.0005	–0.0013	–0.0018
Crackers	0.0032	–0.0112**	–0.0115**	0.0001	–0.0024	–0.0027
Canned Soup	–0.0154***	–0.0261***	–0.0241***	0.0161***	0.0253***	0.0024***
Dish Detergent	–0.0129***	–0.0095***	–0.0102***	–0.0018	-0.0008	–0.0018
Front-end-candies	–0.0164***	–0.0110***	–0.0116***	0.0071***	–0.0058***	–0.0061***
Frozen Dinners	–0.0245***	–0.0058	–0.0021	0.0203***	0.0162***	0.0160***
Frozen Entrees	–0.0220***	–0.0175***	–0.0185***	0.0023	0.0002	–0.0025
Frozen Juices	–0.0091*	–0.0171**	–0.0154*	0.0102***	0.0078	0.0060
Fabric Softeners	–0.0104***	–0.0082***	–0.0094***	–0.0109***	–0.0046**	–0.0054***
Grooming Products	–0.0160***	0.0035	0.0040	0.0012	0.0080***	0.0012
Laundry Detergents	–0.0143***	–0.0245***	–0.0233***	0.0005	0.0062***	0.0035**
Oatmeal	0.0043	–0.0278***	–0.0276***	0.0023	–0.0035	–0.0031
Paper Towels	0.0062*	0.0015	–0.0007	–0.0111***	–0.0112***	–0.0118***
Refrigerated Juices	–0.0106***	–0.0125***	–0.0144***	–0.0008	–0.0013	–0.0041
Soft Drinks	–0.0124***	–0.0178***	–0.0166***	0.0039***	0.0058***	0.0038***
Shampoos	0.0008	–0.0010	–0.0002	0.0037***	0.0096***	0.0095***
Snack Crackers	0.0014	–0.0039	–0.0007	0.0048***	0.0077***	0.0076***
Soaps	–0.0073***	0.0023	0.0023	0.0000	0.0025	0.0025
Toothbrushes	0.0075***	0.0026	0.0286***	–0.0104***	0.0030	0.0064***
Canned Tuna	0.0053*	–0.0139**	–0.0124**	0.0063***	0.0105***	0.0099***
Toothpastes	–0.0070***	–0.0076**	–0.0055	0.0116***	0.0085***	0.0079***
Bathroom Tissues	–0.0072*	0.0084	0.0058	–0.0144***	–0.0167***	–0.0164***
Averages:‡						
Simple: All	–0.0080	–0.0086	–0.0071	0.0025	0.0034	0.0025
Simple: Significant	–0.0111	–0.0140	–0.0121	0.0032	0.0048	0.0045
Weighted: All	–0.0098	–0.0127	–0.0117	0.0029	0.0047	0.0032

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

‡ The first average is for all products, the second average is for those products with coefficients which are significant at the 5% level, while the final weighted average uses the expenditure shares in column 2 of Table 2.

type items. We raise this issue because the D-type items tend to have shorter life spans and the length of life may be related to the life cycle effects on prices. In order to check whether there is any evidence of this happening, we compare the $\hat{\alpha}$ and $\hat{\gamma}$ obtained from different models. First, we compare $BD(a)$ and $D(a)$ models to check whether the exclusion of B-type items makes any significant difference in the estimated age coefficient in the $D(a)$ models, and compare $CD(d)$ and $D(d)$ models to check whether the exclusion of C-type items makes any significant difference in the estimated reverse age coefficient in the $D(d)$ models. Second, we compare $D(a)$ and $D(a, d)$, and compare $D(d)$ and $D(a,d)$ to check whether the difference in the model specification makes any significant difference in the *signs* of estimated age and reverse age coefficients. In the first set of comparisons, we vary the data set while keeping the model specification the same, whereas in the second set of comparisons we vary the model specification while keeping the items the same.

The $\hat{\alpha}$ coefficients obtained from the $BD(a)$ models and their averages across products exhibit results similar to those obtained from the $D(a,d)$ models. The t-tests show that the differences in the $\hat{\alpha}$ are not significantly different for 19 products between the $BD(a)$ and $D(a)$ models. Similarly, the $\hat{\gamma}$ coefficients estimated from the $BD(d)$ models and their averages across products exhibit results similar to those obtained from the $D(a,d)$ models. The t-tests show that the differences in the $\hat{\gamma}$ are not significantly different for 21 products between the $BD(d)$ and $D(d)$ models. The results show that the life cycle prices on average trend downward, with the price skimming strategy being the dominant strategy practiced by the firms.

The next set of tests compare $D(a)$ and $D(a,d)$, and $D(d)$ and $D(a,d)$ models. The F-tests favor $D(a,d)$ over $D(a)$ for 18 products and $D(a,d)$ over $D(d)$ for 16 products (see Table 5, col. 3 and 4). We also test the stability of coefficients between these models. More specifically, we conduct sign-tests to check whether there is any significant difference in the sign of $\hat{\alpha}$ between $D(a)$ and $D(a,d)$ and the sign of $\hat{\gamma}$ between $D(d)$ and $D(a,d)$. The tests show that there are no significant differences in the paired $\hat{\alpha}$ and the paired $\hat{\gamma}$ coefficients. This is expected because the number of positive and negative differences are found to be around the same for both $\hat{\alpha}$ and $\hat{\gamma}$ coefficients (see Table 4). But the sign test has the disadvantage that it does not take into account the magnitude of the paired differences. It may happen that the magnitude in one direction is much higher than in the other direction, and in that case the sign test can give misleading results. Therefore, we conduct a Wilcoxon signed-rank test which takes into account both the direction and magnitude of the paired differences. The p-values of these tests are 0.46 and 0.37 for $\hat{\alpha}$ and $\hat{\gamma}$, respectively, thus indicating that these paired differences are random.[8]

As a whole, the estimation of different models and the subsequent tests indicate that there is not any systematic differences in the life cycle pricing function across different sets of items, such as B and C compared with D items. However, note that none of the regressions above use the A-type items, i.e. the items where neither age nor reverse age is identified. The A-type items account for 13.91% of the total items which correspond to 29.22% of the monthly expenditure shares of all items. It is possible that these very long-lived items have a different life cycle pricing pattern

[8] The null hypothesis of the sign test states that for a random pair of measurement (x_i, y_i), x_i and y_i are equally likely to be larger than the other. For our purpose, to conduct the test, we take the paired difference of the estimated coefficients, replace each positive difference with a positive sign and each negative difference with a negative sign. When the null hypothesis of no difference is true, the sum of the positive signs is approximately equal to the sum of the negative signs. The test statistic W is binomially distributed, $W \sim Bin(n, 0.5)$, irrespective of the population F_x (see for example Garthwaite, Jolliffe and Jones, 2002 for description of the test).

Table 5: Model Diagnostics

Products†	F-test: Log-Linear Model $D(a,d)$			F-test: Spline Model $D(a_s,d_s)$			F-test:
	$\log(a_{nt})$ + $\log(d_{nt})^{\S}$	$D(a,d)$ vs $D(a)$	$D(a,d)$ vs $D(d)$	$log(a_{nt})$	$log(d_{nt})$	$\log(a_{nt})$ + $\log(d_{nt})$	$D(a_s,d_s)$ vs $D(a,d)$
Analgesics	24.95***	33.15***	10.02***	2.78***	13.06***	13.74***	9.91***
Bath Soap	1.15	0.15	2.22	10.70***	15.74***	11.09***	14.39***
Beer	2.79*	5.17**	0.05	2.89**	2.94**	3.10***	3.20***
Bottled Juices	47.07***	28.81***	39.55***	8.69***	3.33**	16.83***	6.64***
Cereals	23.57***	20.57***	17.95***	4.84**	1.70	8.60***	3.56***
Cheeses	0.64	0.77	0.21	10.76***	3.59**	5.88***	7.62***
Cigarettes	8.97***	7.65***	5.59**	5.64***	7.89***	7.22***	6.60***
Cookies	1.89	1.81	2.75*	5.34***	1.33	3.04***	3.43***
Crackers	2.59*	0.97	4.38**	1.67	9.94***	5.37***	6.28***
Canned Soup	40.25***	45.44***	29.88***	2.40*	9.69***	15.60***	7.27***
Dish Detergent	5.02***	1.06	9.84***	0.68	0.57	1.76*	0.68
Front-end-candies	9.78***	10.22***	10.51***	5.08***	3.38**	6.27***	5.08***
Frozen Dinners	4.22***	7.99***	0.06	10.51***	9.28***	9.54***	11.26***
Frozen Entrees	12.19***	1.26	24.38***	7.51***	4.50***	8.13***	6.76***
Frozen Juices	2.48*	1.11	3.03*	5.34***	3.59**	4.47***	5.12***
Fabric Softeners	5.85***	6.34**	7.01***	2.31*	2.52*	3.45***	2.64**
Grooming Products	0.82***	0.45	1.43	3.20**	1.81	2.53***	3.10***
Laundry Detergents	41.82***	4.35**	69.46***	14.27***	4.50***	18.20***	10.22***
Oatmeal	3.58**	0.41	6.62**	3.42**	5.28***	4.31***	4.49***
Paper Towels	5.53***	10.99***	0.02	1.14	0.79	2.12**	0.98
Refrigerated Juices	3.79**	1.44	7.43***	2.46*	0.88	2.26**	1.74
Soft Drinks	25.24***	5.41**	37.57***	1.70	2.93**	8.23***	2.55**
Shampoos	25.20***	50.23***	0.01	11.81***	2.18*	11.83***	7.34***
Snack Crackers	8.93***	16.35***	0.05	2.86**	1.55	3.81***	2.10***
Soaps	0.31	0.44	0.17	1.08	0.83	0.80	0.97
Toothbrushes	18.69***	5.49***	36.13***	26.52***	4.11***	18.82***	18.64***
Canned Tuna	6.16***	7.35***	3.96**	2.03*	1.99	3.06***	2.01*
Toothpastes	7.86***	11.63***	2.08	3.81***	2.48*	4.51***	3.38***
Bathroom Tissues	13.19***	24.18***	1.06	5.45***	13.71***	12.17***	11.52***

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

§ Tests the joint significance of $\log(a_{nt})$ and $\log(d_{nt})$ by comparing $D(a,d)$ and $D(.)$.

compared to their relatively short-lived counterparts. However, note that the life cycle bias takes place at the time of replacement of disappeared items with new items. The A-type items do not disappear, and therefore the question of forced substitution and the consequent life cycle bias does not arise. However, the case may be different if some A items are replaced through the routine sample rotations followed by statistical agencies. Let us suppose that the life cycle pricing pattern is a flat straight line for the A-type items. In that case, if both the old and new items are sampled from the A-type items, because there is no life cycle price difference, there would be no life cycle bias. We deal with this situation in the next section where we discount the life cycle bias of each product by the proportion of A-type items in that particular product category.

Having shown the robustness of the results obtained from the simple log-linear models, and using different data sets, we now move to the estimation of the spline models, $D(a_s, d_s)$. These spline models enable us to capture the non-linearity of the age effect, if any, over the life cycle. The F-test of no life cycle price effect is rejected in this model for every product category except dish detergents and soaps (see Table 5, col. 7). While both the log-linear and spline models are statistically significant for most products, F-tests support the more flexible spline model for 24 products (see Table 5, col. 8). This leads us to use the results from the spline models in the next section.

The life cycle pricing functions for the spline model corresponding to products living for 2 years are shown in Figure 2. The figure shows that the price falls for 18 products, rises for 8 products and is unchanged or non-monotonic (U or inverse-U shaped) for 3 products. The $D(a, d)$ and $D(a_s, d_s)$ models exhibit life cycle price trends which are broadly similar for most products. The exceptions are the products where the curvature of the life cycle price trend obtained from the spline models is non-monotonic and changes its direction over the life cycle.

While the life cycle pricing effects are statistically significant, they are also of a magnitude that is economically meaningful. Since $D(a, d)$ and $D(a_s, d_s)$ models in general perform better than the other models, we look at the magnitudes of the age effect obtained from these models. The results are given in Table 6. Because of the inclusion of reverse age in the model, the age effect becomes conditional on the length of life of items. That is, once we fix the length of life, the age effect can be obtained from the life cycle price difference between two points in the life of items. For example, using the age function in equation (2), the difference in the log of prices at two ages is: $\log(p_n^*/p_n) = \alpha[\log(a_{nt}^*/a_{nt})] + \gamma[\log(d_{nt}^*/d_{nt})]$, where the asterisk denotes the later stage of life. Take, for example, an analgesic item, which lived for 12 months. We want to obtain an estimate of the life cycle price difference from the items's birth to its death. Substituting $\alpha = -0.0081$ and $\gamma = 0.0081$ (see Table 4 for the estimates of the age effects) and setting $(a_{nt}, d_{nt}) = (1, 12)$ and $(a_{nt}^*, d_{nt}^*) = (12, 1)$, we obtain $\log(p_n^*/p_n) = -0.0403$. This means that the price of this analgesics item, which lives for a year, falls by approximately 4.03% over the course of its life. This fall in price takes place after controlling for price variations across different items in the product category (through the use of item dummies) and product-wide temporal variations in price (through the use of time dummies). Table 6 shows that the largest rise is seen for bathroom tissues while the largest fall is for canned soup.

The magnitude of the age effects from the spline models can be obtained in a similar way. However, in the case of spline functions, unlike the log-linear functions, because of the curvature, the same age difference at two different stages of life may not produce the same life cycle price difference. Take, for example, the case of cheeses, where while the first six months of life produces a positive age effect, the next six months produces a negative age effect. Table 6 shows the magnitude of age effects for the products with a length of life of 1 year, 3 years, and the median life span of the product (median life span is provided in Table 2). For the spline models these age effects are obtained by taking the life cycle price difference between the beginning and end of the life. The

Figure 2: Life Cycle Price Trends

(For a Life Span of 2 Years for Each Product)

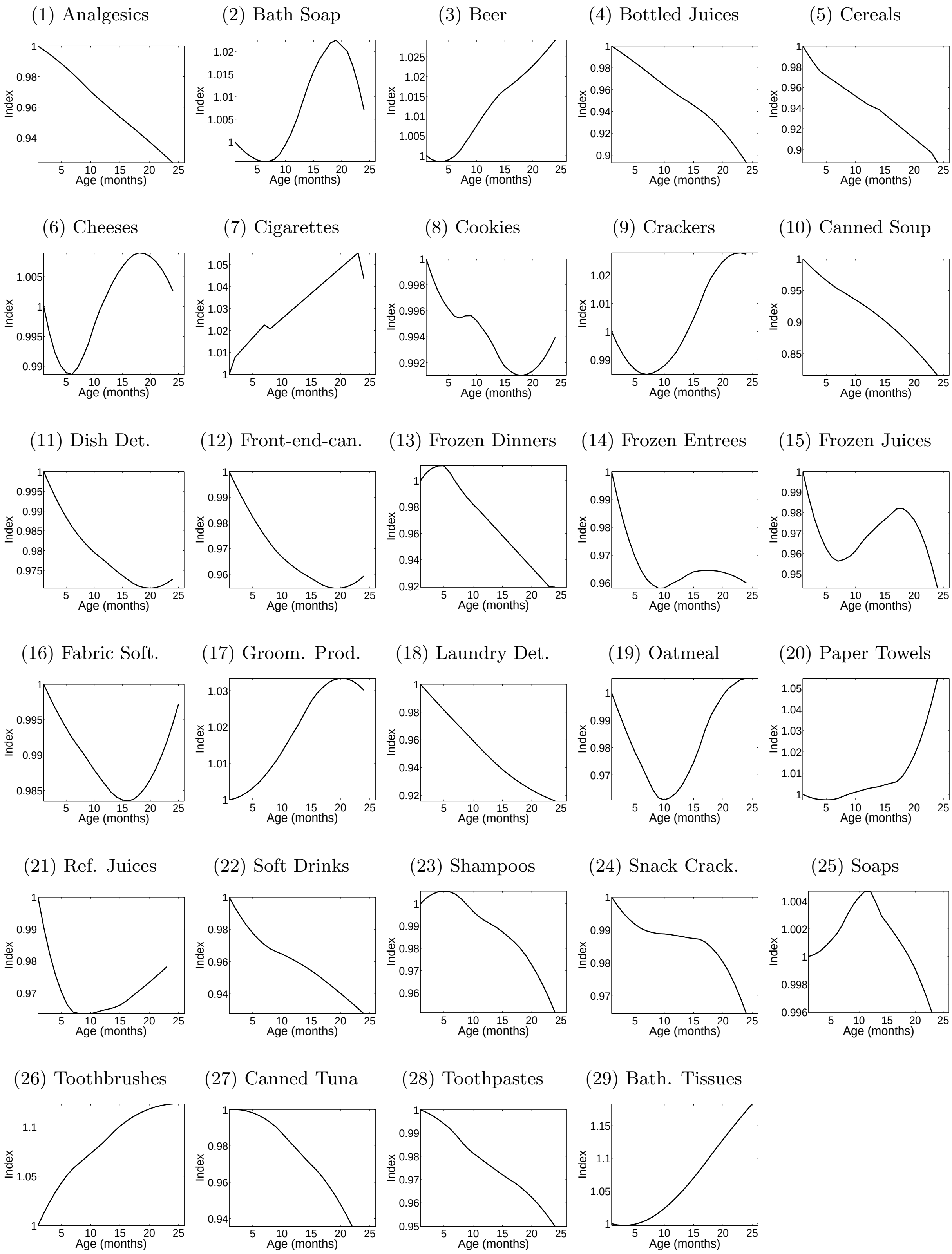


Table 6: Summary of Price Trends over the Life Cycle (%)

Products	Log-Linear Model			Spline Model		
	Average life cycle price change of items with length of life equal to:			Average life cycle price change of items with length of life equal to:		
	1 year	3 years	Median†	1 year	3 years	Median†
Analgesics	–4.03	–5.81	–5.37	–4.81	–9.30	–8.24
Bath Soap	2.06	2.97	2.42	1.86	–2.58	1.98
Beer	1.17	1.68	1.37	1.53	3.48	2.45
Bottled Juices	–7.50	–10.82	–8.73	–7.80	–12.21	–9.54
Cereals	–10.11	–14.58	–11.98	–11.52	–9.87	–11.38
Cheeses	–0.75	–1.08	–0.87	-2.08	1.41	-0.95
Cigarettes	2.63	3.80	3.20	3.42	5.01	4.55
Cookies	–0.45	–0.65	–0.56	0.04	–0.66	–4.18
Crackers	–2.19	–3.15	–2.59	–0.81	3.48	1.71
Canned Soup	–11.95	–17.24	–17.10	–13.60	–20.04	–19.89
Dish Detergent	–2.09	–3.01	–2.52	–1.43	–3.21	–2.40
Front-end-candies	–1.37	–1.97	–1.70	–0.74	–6.03	–3.37
Frozen Dinners	–4.50	–6.49	–5.42	–7.41	–10.89	–8.07
Frozen Entrees	–3.98	–5.73	–4.87	–4.67	–4.29	–3.94
Frozen Juices	–5.32	–7.67	–6.71	–9.30	–6.12	–5.92
Fabric Softeners	–0.99	–1.43	–1.25	0.42	–0.72	–0.10
Grooming Products	0.70	1.00	0.81	0.76	3.84	2.18
Laundry Detergents	–6.66	–9.60	–8.40	–4.87	–9.63	–8.26
Oatmeal	–6.09	–8.78	–7.84	–0.37	1.47	0.73
Paper Towels	2.76	3.98	3.74	5.41	6.00	5.90
Refrigerated Juices	–2.56	–3.69	–3.09	–3.44	–2.37	–2.48
Soft Drinks	–5.07	–7.31	–6.40	–5.35	–11.25	–5.10
Shampoos	–2.41	–3.48	–3.08	–3.80	–4.44	–4.88
Snack Crackers	–2.06	–2.97	–2.53	–3.75	–6.24	–2.07
Soaps	–0.05	–0.07	–0.06	–0.34	–0.93	–0.23
Toothbrushes	5.52	7.96	6.65	5.85	19.38	10.30
Canned Tuna	–5.54	–7.99	–7.93	–6.00	–6.60	–6.50
Toothpastes	–3.33	–4.80	–4.31	–3.44	–5.91	–5.21
Bathroom Tissues	5.52	7.96	7.01	8.17	22.05	18.14
Averages:‡						
Simple	–2.37	–3.41	–3.04	–2.35	–2.32	–2.23
Weighted	–3.71	–5.35	–4.63	–3.99	–4.66	–3.93

† Median life length of each product is provided in Table 2 with the average being 22.6 months.

‡ Weights for the weighted average are the expenditure shares of the products obtained using the full data set.

table shows that, on a weighted average basis, the fall in price due to life cycle pricing is 3.93% for all products living their respective median length of life. This corresponds to an annual fall in price of 2.09% given that the average of the median life span of products is 22.6 months.

In summary, the results provide statistically compelling and robust evidence—across models and data sets—for the existence of life cycle pricing effects. The results also show that both the physical age and the stage-of-life (reflected in reverse age) are important in adequately representing life cycle price movements. Moreover, allowing for the possibility of curvature in these effects, via spline functions, generally provides a better representation of the life cycle effect. A distinctive downward price trend was evident for around two-thirds of the products. This provides empirical support for the prevalence of the price skimming strategy—similar to that reported by Silver and Heravi (2005)—where producers and retailers take advantage of the novelty factor for new items to earn a premium upon introduction.

While the downward sloping price trend is the dominant pricing pattern, the price trend is found to be upward sloping for some products. These products include: beer, cigarettes, crackers, grooming products, paper towels, toothbrushes and bathroom tissues. This pricing pattern 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. However, brand loyalty is likely to play a lesser role in the case of paper towels and bathroom tissues. Here it may be that the market penetration strategy prevails. Prices are set low at introduction to attract a large number of customers and gain the benefit of economies of scale.

VI Implications for Price Indexes

In this section we focus on the impact of these results for quality adjustment as items are introduced and removed from the index. Let us begin by supposing that the object of estimation is a simple geometric mean index (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 and $t+1$, these observations may be divided into two mutually exclusive sets: (a) those observations for which the same item is included, or matched, in both periods $n \in V_M$, and (b) those observations for which an item either disappears, $n \in V_D$, or is rotated out of the index, $n \in V_R$. When the item which corresponds to observation n in time period t is different from that for period $t+1$ we denote this by including an asterisk on the later-period price. This gives a price relative of the form $\frac{p^*_{nt+1}}{p_{nt}} = \frac{p(f^*_{nt+1}, z^*_n, x_{t+1})}{p(f_{nt}, z_n, x_t)}$, where f_{nt} denotes the point in the life cycle pricing, z_n the utility-determining quality characteristics, and x_t denotes pure inflationary factors. In this case, the price drivers—life cycle, quality and pure inflationary factors—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 two sets of items we may decompose the index $P_{t,t+1}$ as follows:

$$P_{t,t+1}(\kappa) = \left[\prod_{n \in V_M} \left(\frac{p_{nt+1}}{p_{nt}} \right)^{1/N} \right] \left[\prod_{n \in V_R \cup V_D} \left(\frac{p^*_{nt+1}/\kappa_n}{p_{nt}} \right)^{1/N} \right] \tag{4}$$

For those items which are being rotated into the index or disappear, and for which an overlap price exists, the quality adjustment is obtained from the ratio of prices in the common period, t. This is shown in the following, where we use equation (1) to illustrate the precise nature of the adjustment:

$$\begin{aligned} \widehat{\kappa}_n = \frac{p^*_{nt}}{p_{nt}} = \frac{p(f^*_{nt}, z^*_n, x_t)}{p(f_{nt}, z_n, x_t)} &= \frac{\exp\left(\beta^*_n + f(a^*_{nt}, d^*_{nt}) + \delta_t x_t\right)}{\exp\left(\beta_n + f(a_{nt}, d_{nt}) + \delta_t x_t\right)} \\ &= \exp\left(\beta^*_n - \beta_n\right) \times \exp\left(f(a^*_{nt}, d^*_{nt}) - f(a_{nt}, d_{nt})\right) \end{aligned} \tag{5}$$

$\widehat{\kappa}_n$ measures the distance rm shown in Figure 1a. The first term in $\widehat{\kappa}_n$ expresses the quality difference between the new and disappearing items, where β^* and β are the estimates of the fixed effect corresponding to the new and disappearing item dummies obtained from equation (1). The new and disappearing items are likely to have different life cycle durations and be at different stages of their life, meaning that a^*_{nt} and d^*_{nt} differ from a_{nt} and d_{nt}, respectively. The second term provides an estimate of the life cycle price difference between the new and disappearing items. Thus the use of $\widehat{\kappa}_n$ removes the life cycle price difference from the index.[9,10]

We now specify an alternative adjustment, which does not remove this important source of price change and where we compare the new and old prices only on the basis of their quality reflected in the z variable. By doing this we are instead including the life cycle price difference in the index. The adjustment is the following:

$$\widetilde{\kappa}_n = \frac{p^*_{nt}}{p(f^*_{nt}, z_n, x_t)} = \frac{p(f^*_{nt}, z^*_n, x_t)}{p(f^*_{nt}, z_n, x_t)} = \exp\left(\beta^*_n - \beta_n\right) \tag{6}$$

$\widetilde{\kappa}_n$ estimates the distance rm' shown in Figure 1b. Given $\widehat{\kappa}_n$ and $\widetilde{\kappa}_n$, it is easy to see that the life cycle bias in the quality adjustment for a particular item, denoted by Θ_n, is equal to:

$$\Theta_n = \frac{\widehat{\kappa}_n}{\widetilde{\kappa}_n} = \exp\left(f(a^*_{nt}, d^*_{nt}) - f(a_{nt}, d_{nt})\right) \tag{7}$$

Θ_n provides an estimate of distance $m'm$ shown in Figure 1b. Note that if the price skimming strategy is followed by firms (i.e. the entry price is higher than the exit price), then $f(a^*_{nt}, d^*_{nt}) -$

[9] The derivation assumes that overlap prices exist. As noted previously, if there is no overlap price then an inflation factor is estimated using a group of similar items to extrapolate the price of disappearing goods forward, or new goods backward, in order to create an artificial overlap. Since the age difference between the new and disappearing goods still remains, as we argued above, this leads to just the same error as for the case when overlap prices exist. Because the extrapolation introduces additional complications without adding any further insight into the nature and extent of the life cycle bias, we have focused on the overlap price method in this section.

[10] This requires making an assumption that $E(\exp(e_{nt})) = 1$, which is not the case. Possible corrections have been proposed by Goldberger (1968), Kennedy (1981) and Giles (1982). From our experience, however, these corrections are small enough that they can be ignored.

$f(a_{nt}, d_{nt}) > 0$. Therefore, from equation (7), $\widehat{\kappa}_n$ overestimates the quality difference between the new and disappearing items. On the other hand, if the market penetration strategy is followed (i.e. the entry price is lower than the exit price), then $f(a^*_{nt}, d^*_{nt}) - f(a_{nt}, d_{nt}) < 0$. In this case, $\widehat{\kappa}_n$ underestimates the quality change between the new and old items.

Given that our target index is the Jevons index, we can find the average life cycle bias at replacement by taking the geometric mean of the bias incurred at each replacement:

$$\Theta = \left[\prod_{n \in V_R \cup V_D} \left(\frac{\widehat{\kappa}_n}{\widetilde{\kappa}_n} \right) \right]^{1/(N_R+N_D)} = \left[\prod_{n \in V_R \cup V_D} \Theta_n \right]^{1/(N_R+N_D)} \tag{8}$$

Here N_R and N_D denote the number of rotated items and forced substitutions which are subjected to the life cycle bias, respectively. If, for example, Θ is 1.05, the quality adjustment at replacement is biased upward on average by 5 percentage points. The overall bias is equal to the average quality change bias (Θ) scaled by the weight of these items in the index, and is obtained as follows:

$$\Psi = \left[\Theta \right]^{(N_R+N_D)/N} \tag{9}$$

Note that Θ and Ψ provide estimates of the life cycle bias on the quality adjustment. The effect of the life cycle bias on the price index is just the opposite of its effect on the quality adjustment. This is because an over-estimate of quality change translates into an underestimation of price change, and vice versa. The life cycle bias in the measurement of inflation is obtained as follows:

$$\frac{P_{t,t+1}(\widehat{\kappa})}{P_{t,t+1}(\widetilde{\kappa})} = \left[\prod_{n \in V_R \cup V_D} \left(\frac{\widetilde{\kappa}_n}{\widehat{\kappa}_n} \right) \right]^{1/N} = \left[\prod_{n \in V_R \cup V_D} \left(\frac{1}{\Theta_n} \right) \right]^{1/N} = \left[\frac{1}{\Theta} \right]^{(N_R+N_D)/N} = \frac{1}{\Psi} \tag{10}$$

The life cycle functions estimated from our data show that the price skimming strategy is the dominant strategy followed by firms (see Figure 2 and Table 6). Therefore, from equation (10), we see that the life cycle bias *underestimates* the measurement of inflation in our data. Importantly, the life cycle bias works in the opposite direction to how the quality change bias typically affects the measurement of inflation. But how large is this bias?

A crude measure of the life cycle bias can be obtained from the estimated life cycle function in the following way. We show that for the spline model the weighted average price fall across product categories was 3.93% for the items living their median life length (see Table 6). Now suppose that the average difference in the age-to-life ratio between the newly introduced and removed items is 0.50 (for example, for forced substitution it means that the age-to-life ratio of the new items is 0.50 and disappeared items is 1). This means that the life cycle price difference between the new and disappeared items is $3.93\% \times 0.50 = 1.97\% = \Theta$, which we argue is wrongly attributed to the quality difference. Let us suppose that for each month around 4% of sampled items are replaced through forced substitutions and routine sample rotations. We further suppose that only one-fourth of these replaced items, i.e. 1% of the sampled items, incur the life cycle bias. Then the annual bias at the product level is likely to be around $1.97\% \times 0.01 \times 12 = 0.24\% = \Psi$. However, the magnitude of this estimate depends upon the age profile of old and replacement items as well as the particular shape of the life cycle function. In order to explore the impact these factors have on the bias estimate we undertake a simulation.

A. Simulation Evidence on Index Bias

In order to quantify the impact of life cycle bias we undertake a simulation which meshes together: (a) the initial age profile of the products in our data, (b) the empirically estimated life cycle functions, (c) the index which is the object of estimation, (d) assumptions about the rate at which statistical agencies rotate samples, and (e) assumptions about the proportion of replaced items incurring the life cycle bias. We undertake this simulation for each product though primarily focus on results averaged over all product categories.

We begin the simulation by drawing an initial random sample of N items from the empirical joint distribution of age and reverse age in our data for each product. Once the initial sample is constructed, these products are followed over time. In subsequent periods an item either continues to be available in the market, $n \in V_M$, disappears, $n \in V_D$, or is rotated out of the index, $n \in V_R$. We follow the actual items in the data so the rate of matched and disappearing items is determined empirically by that observed for a particular product category.

When items disappear we introduce new items which we draw randomly from the initial sample of items. The new items are obviously at a different stage of their life to the items which have disappeared. More specifically, the new items are located at an earlier stage of their life than the disappeared items. This difference in the life cycle between the new and disappeared items introduces a price difference at the time of replacement and, if netted out as being wrongly attributed to quality difference, leads to life cycle bias.

The annual rotation rates considered are, $\Pi = 0\%$, 12% and 24% or equivalently, $\pi = 0\%$, 1% and 2% per month. In each period we randomly remove items in proportion to π from the sample of all items in that period and similarly randomly introduce the same number of items which are drawn from the full sample of initial items. There will be an age difference between the two sets of items because these are drawn from samples of items of two different periods (the initial and current period). If the sample ages over time, then the removed items will, on average, be older than the new items. Whether, and to what extent, the sample ages over time depends on the initial age profile of the sample, the evolution of age and reverse age distribution and the rotation rate.[11]

[11] Note that here the new and disappeared items are drawn independently from each other and sample rotations do not target any particular group of items in terms of their age. However, there may be a tendency for some sample rotation procedures to deliberately remove older items from and introduce younger items into the sample. As a robustness check, we considered another scenario where in each period we remove items that have crossed over the halfway mark of their life cycle and randomly introduce items from the set of items which have reached no more than

It should be recognized that the design of our simulation may differ in some respects from the replacement procedures followed by statistical agencies. For example, agencies may not replace every disappeared items in each period, and the sample size is unlikely to remain the same over time. Also the agencies rarely know the period of exit of a product from the market, although we use this information in the simulation. Agencies may gather a lot more information, such as sales figures, through outlet surveys and correspondence with store managers, and may also use the expert judgement of the field officers before replacing an item in the sample. Our purpose is not to reproduce the procedures followed by statistical agencies exactly but to design a simulation which provides insight into the dynamics of likely impact of life cycle pricing on price indexes. Our simulation is designed with the idea of imposing minimal restrictions and letting the specifics of the age profile of the product in the data and the estimated life cycle function provide us with estimates of the life cycle bias.

Note that when a sample rotation is introduced (or the rotation rate is increased), it subjects more items to the life cycle bias. Given that each replacement potentially incurs life cycle bias, sample rotation has the potential effect of increasing the bias at the overall index level. However, sample rotation also has positive effects in terms of reducing the life cycle bias. Generally a larger sample rotation is expected to contain more successfully the age difference between the new and disappeared items over time. Therefore, if the life cycle function exhibits a distinct upward or downward trend, the life cycle bias at replacement tends to reduce.

However, there may be situations where the age gap may in fact go up with a sample rotation. Note that our sampling mechanism draws items which are, on average, in an earlier stage of their life than the removed items, but this does not necessarily mean that each new item will be younger in terms of physical age than each replaced item. For example, suppose that an item disappears after a 6-months life in the market, and a new item, which lived for 2 years, is drawn into the sample when it reaches the halfway mark of its life, i.e. when its physical age is one year. In this case, more replacements do not contain the aging of the sample and may in fact raise the age difference between the new and removed items. To this one should add that the estimated life cycle functions, which are conditional on the length of the life of items, may also differ substantially between the new and disappearing items, which introduces another element of uncertainty with regard to the direction of the bias. However, having said all this, if a larger rotation *on average* reduces the age difference between the new and replaced items and if the life cycle functions are monotonic and exhibit similar patterns across items within a product category, then a larger rotation is expected to reduce the life cycle price difference at replacements.

We should also note that another way a sample rotation reduces the bias is through the reduction in the number of forced substitutions over time by allowing less items to reach their

the halfway mark of their life. We find that the results obtained from this scenario do not qualitatively differ from the base case scenario.

death while in the sample. Hence, once we acknowledge the presence of the life cycle bias, we see that a sample rotation may affect the life cycle bias both in positive and negative ways. Therefore, a priori it is not clear whether any particular pricing pattern or a more aggressive rotation strategy minimizes the bias.

In our simulation we fix the sample size N at 10,000 for each product category and run it for 10 years with 1,000 repetitions. The 10-year (120-month) run of the simulation was more than sufficient for the behavior of the sample to stabilize—so that it was not influenced by the initially selected sample—and for the bias estimates to converge. The last 12 months of results for the simulation are averaged and are shown in Table 7. In particular we focus on the values of Θ and Ψ, the average bias at replacement and total index bias respectively. At the bottom of the table we provide simple and expenditure-weighted averages across product categories, though we limit our discussion to the weighted average result. In order to see how the simulation evolves over the 120-month period, see Appendix Figures A-1 and A-2.

The average bias per replacement (Θ) and the overall bias in the index (Ψ) depend on the proportion of items which are subjected to the life cycle bias. With regard to the disappearance of items, on a weighted average basis, the disappearance rates for all products are 2.74%, 2.66% and 2.60% for rotation rates of $\Pi = 0\%$, 12% and 24% respectively.[12] This finding supports our earlier conjecture that a higher rotation rate leads to a lower disappearance rate. However, as discussed in section II, we subject only $\Lambda = 40\%$ and 25% of the disappeared items (forced substitutions) to incur the life cycle bias in each period. For the sample rotations, the percentage of items we subject to the life cycle bias is obtained by multiplying the rotation rate by the proportion of B, C and D items for that product. This way of calculating the weight for the bias assumes that the A-type items are not subjected to life cycle bias. We make this assumption because, as discussed in section III, we could not obtain estimates of life cycle pricing of A items. If, contrary to our assumption, the A-type items follow the pricing pattern similar to the other items, then Ψ for the A-type items would be positive. A less likely possibility is that the A-type items follow the pricing pattern which is, on average, in the opposite direction of the other items, then Ψ for the A-type items would be negative.[13]

Table 7 provides the estimates of Θ and Ψ obtained under four scenarios: $(\Lambda, \Pi) = (40\%, 0\%)$, $(25\%, 0\%)$, $(25\%, 12\%)$ and $(25\%, 24\%)$. With no sample rotation, Θ provides an estimate of the average life cycle bias per forced substitution. On a weighted average basis across products, the average life cycle bias per forced substitution—the same for Λ equal to 40% and 25%—is 2.26%.

[12] This is broadly consistent with Bils, Klenow and Malin (2012) who report that the monthly average forced substitution rate was about 3% in the US CPI Research Database they use for their study.

[13] Note that the A-type items account for only 13.91% of the total items. If we had not discounted the number of rotated items subjected to the life cycle bias by the proportion of A-type items then Ψ would have on average increased by 0.05 percentage points.

Table 7: Quality Adjustment Bias due to Life Cycle Pricing (%)

Products	Scenarios*	Bias at Replacement (Θ)†			Overall Annual Bias (Ψ)			
	Λ	40%, 25%	25%	25%	40%	25%	25%	25%
	Π	0%	12%	24%	0%	0%	12%	24%
Analgesics		5.56	3.08	2.28	0.73	0.45	0.55	0.63
Bath Soap		1.24	0.77	0.58	0.20	0.13	0.16	0.18
Beer		–2.38	–1.38	–1.01	–0.46	–0.29	–0.32	–0.34
Bottled Juices		6.73	4.52	3.67	1.09	0.68	0.93	1.14
Cereals		7.53	3.58	2.46	0.88	0.55	0.59	0.64
Cheeses		–0.11	–0.31	–0.34	–0.02	–0.01	–0.06	–0.10
Cigarettes		–2.37	–0.61	–0.37	–0.11	–0.07	–0.08	–0.09
Cookies		–0.17	0.09	0.15	–0.03	–0.02	0.02	0.05
Crackers		–1.46	–0.87	–0.63	–0.26	–0.17	–0.18	–0.19
Canned Soup		13.56	7.56	5.53	1.79	1.12	1.32	1.48
Dish Detergent		0.43	0.73	0.77	0.06	0.04	0.13	0.22
Front-end-candies		0.54	1.15	1.27	0.08	0.05	0.22	0.37
Frozen Dinners		7.74	3.30	1.81	1.27	0.79	0.66	0.55
Frozen Entrees		1.03	1.23	1.22	0.15	0.10	0.25	0.37
Frozen Juices		5.77	3.65	2.89	0.57	0.35	0.53	0.66
Fabric Softeners		–1.15	0.08	0.37	–0.15	–0.09	0.02	0.11
Grooming Products		–1.09	–0.98	–0.90	–0.16	–0.10	–0.19	–0.26
Laundry Detergents		4.13	3.05	2.62	1.68	0.67	0.66	0.87
Oatmeal		–1.71	–0.80	–0.44	–0.24	–0.15	–0.13	–0.10
Paper Towels		–6.44	–2.93	–1.94	–0.82	–0.51	–0.54	–0.57
Refrigerated Juices		0.18	0.64	0.69	0.02	0.01	0.11	0.19
Soft Drinks		3.49	2.18	1.79	0.38	0.24	0.37	0.49
Shampoos		4.19	2.29	1.62	0.70	0.44	0.47	0.50
Snack Crackers		3.55	1.53	0.94	0.47	0.30	0.28	0.27
Soaps		1.23	0.44	0.23	0.14	0.09	0.07	0.06
Toothbrushes		–6.56	–5.72	–5.15	–0.98	–0.62	–1.16	–1.62
Canned Tuna		4.28	2.05	1.48	0.43	0.27	0.32	0.38
Toothpastes		4.57	2.34	1.66	0.64	0.40	0.45	0.50
Bathroom Tissues		–11.68	–6.52	–4.84	–1.58	–0.99	–1.20	–1.38
Averages‡								
Simple		1.40	0.83	0.64	0.19	0.12	0.15	0.17
Weighted		2.26	1.37	1.08	0.28	0.18	0.24	0.30

∗ Λ refers to the percentage of forced substitutions subjected to the life cycle bias and Π refers to the annual sample rotation rate.

† Θ is the same for (Λ, Π) = (40%, 0%) and (25%, 0%).

‡ Weights for the weighted average are the expenditure shares of the products obtained using the full data set.

However, as we lower Λ from 40% to 25%, Ψ reduces from 0.28 to 0.18 percentage points.

The size of Θ varies quite significantly across product categories and to a lesser extent across the sample rotation rate. For canned soup, with no sample rotation and where only 25% of forced substitutions incur the life cycle bias, the bias at replacement is 13.56%. This is the result of a very large fall in price over its life. Bathroom tissues, on the other hand, have a bias of –11.68% at replacement, given the strong upward trend in prices over their life. The results show, as expected, that the life cycle pricing pattern plays a significant role in determining the direction and the magnitude of the bias. In all cases, a distinct downward trend in the life cycle pricing produces a positive bias, while a distinct upward trend produces a negative bias.

More sample rotations generally leads to the attenuation of the bias at replacement. These effects are often quite large. For paper towels, for example, with no rotation Θ is –6.44% but this falls to –1.94% with a 24% annual rotation rate. Sample rotation reduces Θ for 24 products. The five products for which rotation increases the bias are cheeses, dish detergents, front-end-candies, frozen entrees and refrigerated juices. The life cycle bias is quite small for these products. Of these five products, the life cycle functions exhibit clear non-monotonicity for cheeses, frozen entrees and refrigerated juices. If we aggregate over all products, we find that rotations do reduce the life cycle bias at replacement. On a weighted-average basis across products, Θ is reduced from 2.26% to 1.37% to 1.08% for annual rotation rates of 0%, 12% and 24%, respectively.[14]

With regard to Ψ, Table 7 shows that with more extensive use of rotation, Ψ decreases for 4 products, remains almost unchanged for 2 products, while it increases for the remaining 23 products. For many products, where rotations reduce Θ, the result reverses when looked at in terms of Ψ. For instance, in the case of Analgesics, as we move from 0% to 24% rotation per year, Θ falls from 5.56% to 2.28%, but Ψ rises from 0.45% to 0.63%. On a weighted average basis the bias estimates are $\Psi = 0.18$, 0.24 and 0.30 percentage points for rotation rates of $\Pi = 0\%$, 12% and 24% respectively.

Our simulations show that the life cycle bias is quite significant even when there is no sample rotation and only 25% of the forced substitutions are subjected to the bias. The simulations show that there is a clear benefit of sample rotation because it reduces the life cycle bias per replacement. However, this benefit is not large enough to outweigh the accompanying cost of subjecting more items to the bias. This finding indicates that the life cycle bias is required to be dealt with at its cause and reducing the age difference between new and disappeared items through sample rotations may not make any significant improvement in the life cycle bias at the overall index level.[15] Broadly, these results illustrate that the life cycle bias incurred during replacements is quite large, ranging between 0.2–0.3 percentage points, and relatively robust to assumptions made regarding exactly how sampling is undertaken.

[14] See the Appendix Figures for estimates of the life cycle bias separately for the forced substitutions and sample rotations.

[15] Note that these results should not be taken to mean that sample rotation is a bad idea or is not worth the additional cost. There are a range of other benefits of sample rotations, such as the fact that it means the sample will remain representative of the population of products, which are not taken into account in our calculations. This paper only focuses on the bias that takes place due to the mix-up of life cycle price change and the quality change during replacements of old items with new items. The argument made in this paper applies only to this particular type of bias.

B. Implications for the CPI

To put these results into perspective, the findings of the Boskin Commission (Boskin et. al., 1997) on the US CPI reported an overall upward bias of around 1.1% per annum (later, in 1999, the Commission revised down their estimates of bias by around 0.3 percentage point per year). The Commission calculated that this bias would contribute $1.07 trillion to the U.S. national debt over the period 1997–2008 (see also Gordon, 2006). The bias reflected a range of factors including quality adjustment methods, new goods, new outlets and upper- and lower-level substitution bias. Lebow and Rudd (2003) reported that the US CPI was biased upward by 0.9% per annum, with most of the bias originating from new goods and quality change.[16] These studies did not explicitly explore the life cycle bias that we have examined. So our estimates represent the quantification of a previously unmeasured source of CPI bias. Importantly, the life cycle bias, which works in the opposite direction to quality change and substitution bias, tends to lead to the underestimation of inflation, implying that on balance the upward bias in the CPI may be lower than what is frequently alleged.[17]

The focus of our study was day-to-day consumable supermarket products. Many of these products are considered as technologically stable products (see Greenlees and McClelland, 2011). The turnover rate for products such as electronic and some fashion items are typically quicker and the life cycle price changes are more significant than they are for supermarket items (see for example Cole et al., 1986; Pakes, 2003; Silver and Heravi, 2005; Bils, 2009; de Haan and Krsinich, 2012; Copeland, 2013). This implies that, even if a lower proportion of items incur the life cycle bias in these sectors (i.e. $\Lambda < 25\%$), the aggregated bias for these products can be potentially significant.

The significance of the life cycle bias for the supermarket products that we found in our paper warrants conducting further research focusing on other expenditure categories in the CPI. If, however, we assume that the average life cycle bias over all CPI components corresponds to that of the supermarket products that we found, then the annual CPI-wide downward bias of 0.2–0.3 percentage point is clearly not a trivial magnitude when compared with the bias estimates from the Boskin Commission, and the annual targeted inflation of 2-3% in many developed countries.

VII 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, to investigate the

[16] See Berndt (2006) and Johnson, Reed and Stewart (2006) for discussions on some methodological changes that the US CPI has undergone since the publication of Boskin Commission Report.

[17] See Hulten (1997) for some other potential sources of bias that operate in the opposite direction to quality change bias in the CPI.

implications of these price-maturation effects for the estimation of price indexes. In particular, whether the failure to include these price changes in some matched-model indexes introduces any systematic errors into the measurement of inflation.

Using a large scanner data set, we answer both questions in the affirmative. We found statistically compelling and robust evidence—across models, products and data sets—for the existence of the life cycle pricing effects. We also found these life cycle price trends to be economically significant. The dominant pricing pattern exhibits higher entry prices and lower exit prices of items for at least two-thirds of the products, providing support to the price skimming hypothesis. By taking the average of all products and after controlling from product-wide temporal variations in price, we found that prices fell by 2.09% per year due to aging.

The implication of this finding is that index methods which ignore life cycle price differences during replacement of disappearing and removed items produce biased measures of price change. Given that prices tend to fall over the life of a product, the life cycle bias leads to the overestimation of quality change and consequently the underestimation of price change. We found that with only 25% of forced substitutions incurring the life cycle bias and a 24% annual sample rotation policy, the price change is on average underestimated by around 1.08% for replaced items. This bias is far from trivial. At the product level this bias corresponds to an underestimation of annual price change of 0.30 percentage points.

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Figure A-1: Monthly Simulation Results Aggregated over all Products for Different Sample Rotations (Π) and fixed Λ at 25%—Aggregated by taking Simple Average

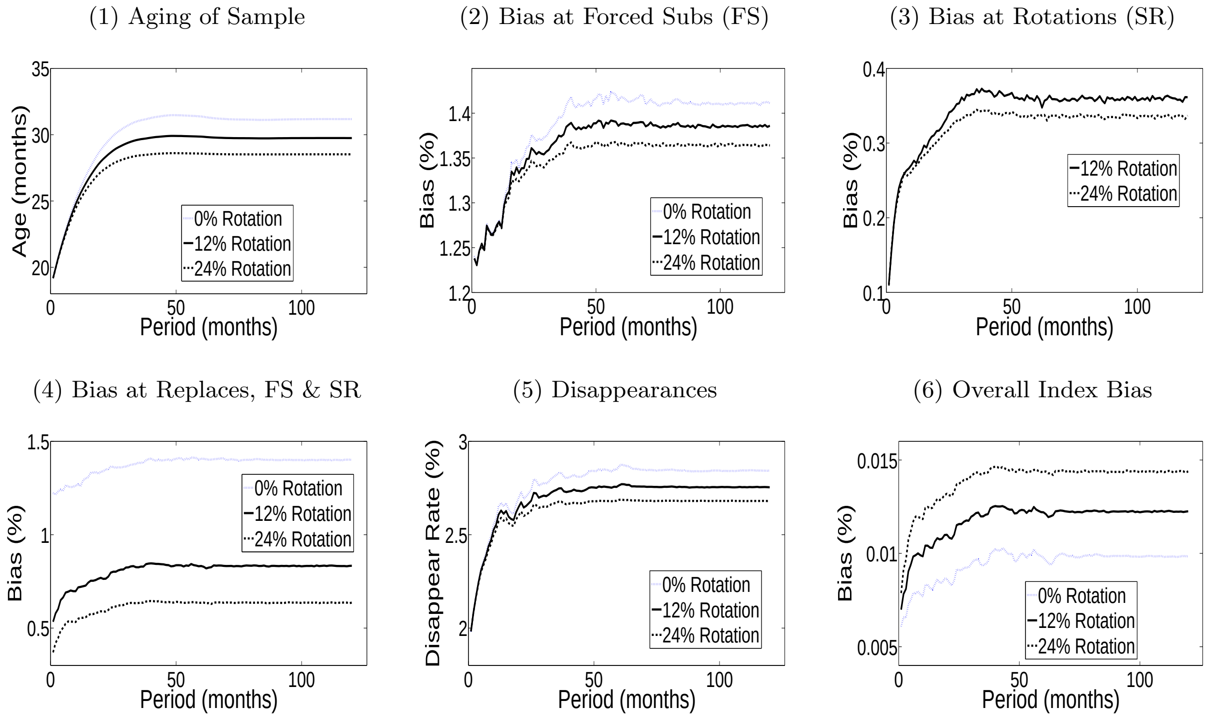

Figure A-2: Monthly Simulation Results Aggregated over all Products for Different Sample Rotations (Π) and fixed Λ at 25%—Aggregated by taking Expenditure Share Weighted Average