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The Product Life Cycle and Sample Representativity Bias in Price Indexes

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Abstract: Official price indexes are usually calculated using matched samples of products. If products exhibit systematic price trends at different points in their life cycle then matched sample methods may introduce bias if the life cycle movement in the sample does not adequately reflect that in the population. This article explores the extent of these life cycle pricing effects and then examines the bias it can introduce in measured inflation. A large US supermarket scanner data set for 6 cities and 6 products over 12 years is used. Using hedonic methods we find that the life cycle component of price change is important across a range of products and cities. To explore the bias introduced by these movements we use simulations which construct indexes with different sample update frequency. For indexes which are never completely resampled we find an annual bias of 0.88 and 0.59 percentage points depending upon whether we use the actual prices or prices imputed from our hedonic model. This compares with absolute biases of 0.24 and 0.08 percentage points for the corresponding cases for samples which are re-selected annually. Thus our results provide strong support for more frequently updating index samples.

Keywords: Consumer price index (CPI); lifecycle pricing; hedonic regression; survey sampling.

JEL Classification Codes: C43, E31.

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1 Introduction

Systematic price trends across the product life cycle have implications for the measurement of inflation. This is because almost all price indexes—such as those used in constructing the Consumer Price Index (CPI) and in the National Accounts—are calculated from a sample, rather than a census, of products. The prices of goods vary across time due to inflation. But if product prices also vary as a function of their age then the composition of the statistician's sample will have an impact on measured inflation. For example, if prices generally rise more rapidly later in life than earlier, and the statistician over-samples from older items, then the price index will over represent these life cycle price rises and produce biased results.

This possibility has been appreciated in the economic measurement literature and also by statistical agency practitioners. For example, in the interesting summary of hedonic methods in Triplett (2006) he notes,

> ...new varieties may exhibit price changes after their introduction that differ from the price changes of older varieties... New products might also be initially introduced at low (quality adjusted) prices, to induce consumers to try them. In this case, their subsequent prices rise, relative to those of continuing products, especially if they are successful introductions. Though this also implies an error from use of the fixed sample of established varieties, the direction of price index error in this case is not always obvious. (Triplett, 2006, Chp. 4, p. 5)

The key issue is the interaction between life cycle price trends and the use of fixed samples of items over time. This has the potential to lead to the mismeasurement of inflation as a result of what we call life cycle representativity bias. The first factor—the existence of life cycle price trends—has recently been investigated by Melser and Syed (2016) in the context of the quality adjustment practices used by statistical agencies. They found statistically significant life cycle pricing effects and argued that this led to problems in the quality adjustment process. When new products are introduced into the index the price ratio at which they are spliced in will be effected by the stage of the life cycle. If this is not taken into account then the quality adjustment process can be distorted by these life cycle price movements.

The possibility of life cycle price effects has been considered theoretically going back many years (see for example, Stokey, 1979; Landsberger and Meilijson, 1985; Varian, 1989; Koh, 2006). But there has not been a great deal of work on quantifying life cycle pricing. Some notable exceptions, other than Melser and Syed (2016), are Berndt, Griliches and Rosett (1993) and Berndt, Kyle and Ling (2003), who found systematic life cycle effects for pharmaceutical products. Aizcorbe (2005) documented the pricing life cycle of Intel computer chips. In related work, Silver and Heravi (2005)—focusing on technology-driven products such as televisions and digital cameras—found some differences in price indexes as a result of differences in the way new and existing products are priced. Also de Haan (2004) outlined a hedonic regression model which included life cycle terms. In more recent work Bils (2009) examined the dynamics of price and demand as products age and found significant effects on both counts.

While the existence of life cycle price trends has been discussed in the literature there exists little evidence about the impact it is likely to have on the measurement of inflation. Melser and Syed (2016) examined the impacts at the point at which items are introduced or withdrawn from the index. However, there is also likely to be an important additional impact; that for continuing items, as their price movements will be determined by the state of their life cycle. This form of price index bias certainly has the potential to be non-trivial. This is because the standard matched model method of sampling followed by statistical agencies—select a certain product to include in the index and follow it until it disappears from the market—is likely to over-sample from older, more obsolete, products. This has been strongly argued by Pakes (2003). If the price of older and newer products move differently, controlling for other factors, then sampled price change will be different from what we would record were we to measure price change for all products. Moreover, this issue has the potential to effect at least a fifth of the CPI—this is the approximate weight of food and other branded consumable goods in the index and where there is high product churn.

In the next section we outline the life cycle bias that may arise in price indexes in more detail and discuss how we will quantify it. In section 3 we investigate the importance of the life cycle's influence on price. A highly flexible hedonic smoothing spline approach to the estimation of life cycle pricing or ageing effects is proposed. This takes account of the key dimensions of the product life cycle and extends the approach of Melser and Syed (2016). This model is applied to a large US scanner data set made available by IRI. We estimate life cycle pricing effects for 6 products—beer, carbonated beverages, cigarettes, coffee, soup and toothpaste—across 6 cities—Atlanta, Dallas, Detroit, Los Angeles, New York and Washington, DC. The data is extensive and spans many hundreds of items for each product category over a 12-year period from 2001-12. Across all products and cities we find that the existence of a life cycle component to the pricing function is strongly supported by the data. The life cycle pricing functions are quite diverse given the flexible estimation methods used. We find that for shorter-lived products—those that survive on the market for around 24 months—that their prices tend to fall as they age. However, for longer-lived products prices tend to rise. Though there are exceptions in both cases. In section 4 we undertake simulations to explore the effect of sample updating on measured inflation. We do this by simulating indexes which are constructed using samples which are either never re-sampled—that is the only sample changes occur when a product disappears from the market and needs to be replaced—or is re-sampled every 5 years, 2 years or annually. This is compared with an index which uses the matched population of items over time. We construct two simulations. First, using the actual prices for each product category and city. Second, using imputed prices, from our hedonic model, for a constructed sample of items. Overall we find a non-trivial level of bias in indexes which follow a fixed group of items through time. This bias varies in sign across product categories and cities. We estimate that the absolute value of the bias averages 0.88 percentage points per annum using the actual prices and 0.59 using imputed prices for samples that are never updated. More frequent sample updating almost always reduces the size of the bias. Annually updated the index samples significantly attenuates the bias, leading to an average absolute bias of 0.34 and 0.10 percentage points respectively per annum. This provides strong support for regular sample refreshing in order to ensure the representativeness of the sample. While frequent sample updating has been advocated previously, such as in CPI Manual (ILO, 2004), little empirical evidence has been available to support this exhortation. The final section provides some broad conclusions regarding the results.

2 Price Indexes and Life Cycle Bias

The focus of this paper is on how the price effects of product ageing interact with the calculation of price indexes. Given this, let us now consider the measurement objective more formally. We will suppose the target index, $P_{t,t+1}$, is of the Jevons unweighted geometric mean form on matched items. This index is commonly used by statistical agencies to construct elementary price indexes—that is indexes at the most basic product category level where quantity and expenditure information is not available. Our focus on matched price change is in order not to complicate the analysis with issues of quality change and new goods effects (Melser and Syed (2016) discuss issues around the product life cycle for non-matching items). The Jevons index has good axiomatic properties and is the preferred approach to constructing elementary aggregates outlined in the CPI manual (ILO, 2004) and by Diewert (1995). In logarithmic form we may write the target index as,

$$\ln P_{t,t+1} = \frac{1}{|I_{t,t+1}|} \sum_{i \in I_{t,t+1}} \ln \left(\frac{p_{it+1}(l_{it+1}, z_i, \delta_{t+1})}{p_{it}(l_{it}, z_i, \delta_t)} \right) \quad (1)$$

Here p_{it} denotes the price in periods $t = 1, 2, \ldots, T$ for item $i \in I_{t,t+1}$. $I_{t,t+1}$ is the index set of all the matched items in periods t and $t + 1$. We explicitly note that prices depend upon 3 factors; (i) the state of the life cycle (l_{it}), (ii) item characteristics (z_i), and (iii) a purely inflationary component (δ_t). In practice, however—because of cost burden or capacity—the entire set of items cannot be included in the index. Instead a sample, $I^*_{t,t+1} \subset I_{t,t+1}$, is taken and used to construct the index[1],

$$\ln P^*_{st} = \frac{1}{|I^*_{t,t+1}|} \sum_{i \in I^*_{t,t+1}} \ln \left(\frac{p_{it+1}(l_{it+1}, z_i, \delta_{t+1})}{p_{it}(l_{it}, z_i, \delta_t)} \right) \tag{2}$$

As can readily be seen, if price trends vary across the product life cycle then there will be differences between (1) and (2). Potentially the differences will be significant. While the target index (1) records average price change across all items observed in periods t and $t+1$ the index (2) is highly dependent upon the nature of the sample $I^*_{t,t+1}$ and how it relates to $I_{t,t+1}$.

Note an assumption implicit in the derivation above; we suppose that the effects of product ageing should be included in the index and hence that the ageing process itself does not impact on quality. We argue this will certainly be the case for the products we examine in our empirical application, and probably for most product-types. However, we note that this is not always the case. For example, for certain products—such as clothing items, which are influenced by seasonal fashions, for products which decay, such as fruit and vegetables, or even for certain durable goods such as cars (see Pashigian, Bowen and Gould, 1995)—the age may be a utility yielding quality characteristic. Were this to be the case then this reorients our objective somewhat but much of our analysis we undertake below is likely still relevant as it remains necessary to account for the ageing effect in indexes.

The most common approach to price index survey sampling is to take a sample at some initial point and follow these same items through time (see for example, ILO, 2004, Chp. 7). As sampled items disappear from the market, and hence from the sample, they are replaced by other items in order to ensure the sample size does not change. This approach keeps the index sample as fixed as possible across time. While this limits the costs of continually refreshing the sample, and minimises problems with quality adjustment, it also may mean that measured price change for items in the sample will be different from that in the market. A key reason for this is that, on average, if this approach is followed, items in the sample are likely to be older than items in the market. In index (1) new items are automatically included in the index as soon as a price is observed in both periods t and $t+1$. However, they are much less likely to be included in (2). Hence, if there are systematic differences in price trends for 'young' and 'old' products then these two indexes are likely to differ.

To develop a framework for the measurement of this bias we propose a decomposition

[1] In practice, while weighting information may not be explicitly available to statistical agencies it may be possible to infer something about the importance of a particular item—perhaps because of the amount of shelf space it is devoted. Hence it may be the case that there is a degree of purposive sampling of items such that there is some implicit weighing. However, these practices vary and are hard to emulate hence we suppose that the sample is unweighted.

of price into three components. Our hedonic price model is,

$$\ln p_{it} = \alpha_i + f(l_{it}) + \delta_t + e_{it} \tag{3}$$

Here α_i is a dummy variable for each item i and represents a very flexible way of quantifying the impact of the characteristics, z_i, on price. The effect of time on price is assumed to be the same for all items and is represented by δ_t. We also include an effect for the stage of the product life cycle, $f(l_{it})$, which we discuss further below. This model is fundamentally similar to the widely used country-product-dummy regression approach (see for example, Rao, 2004; Diewert, 2005; de Haan and Krsinich, 2014) and is also related to the hedonic time-dummy approach, as in de Haan and Hendriks (2013).[2]

This hedonic model allows us to decompose the differences between the target index (1) and the sample index (2). If we substitute the price function (3) into both equations and compare their relative magnitudes we show in the Appendix that the bias can be written as,

$$\text{bias}_{t,t+1} = \frac{1}{|I^*_{t,t+1}|} \sum_{i \in I^*_{t,t+1}} [f(l_{it+1}) - f(l_{it})] - \frac{1}{|I_{t,t+1}|} \sum_{i \in I_{t,t+1}} [f(l_{it+1}) - f(l_{it})] \tag{4}$$

Clearly the bias is driven by the extent of life cycle pricing. If the life cycle function has a small impact on price then there is unlikely to be any bias. We investigate the size of the bias in section 4 but first turn to examining whether the life cycle component, $f(l_{it})$, is indeed significant.

3 Empirical Estimation of Life Cycle Price Effects

The hedonic equation in (3) illustrates our approach to modelling prices. However, the key question is; what form should the life cycle function, $f(l_{it})$, take?

We argue that summarizing the product life cycle necessarily requires two variables. Product age is clearly a pertinent characteristic of the life cycle. This relates the current period to the time at which a product was 'born' or first appeared on the market. However, product death, or when an item disappears from the market, is also a key feature of the product life cycle. This can be measured equivalently to age by what we call 'reverse age'—the number of time periods from the current period to product death. The third key feature of the life cycle is the length of a product's life. Together these three variables

[2] This model suits our purposes, which is to focus on the impact of the life cycle on prices while controlling very flexibly for product quality via a dummy variable. In practice, however, it may be that it is important to try as best as possible to include all items in the index even when no price is matched. In this case a hedonic model which includes item characteristics—such as, size, flavour, brand, etc.—might be more relevant as it would enable the imputation of the 'missing' prices.

completely summarize the state of the life cycle. In fact we have: life length = age + reverse age. A comprehensive life cycle modelling framework needs to incorporate at least two of these factors—the other can be obtained from the identity above. However, because of this identity, and the inclusion of product dummy variables in model (3), some care must be taken in constructing a estimable model that avoids collinearity. As we discuss below, we avoid this problem by taking nonlinear transformations of the life cycle variables and also using a nonlinear regression method.

In our simulation below, one of the goals of the exercise will be to impute the life cycle function for products which live longer than we observe in our data. Given this we model the life cycle as a function of two variables; age stage = age/life and the log of life length. This fulfils the requirements of including two of the three features of the life cycle. The use of age stage, the fraction of product's life which has passed, is likely to be useful because it allows long- and short-lived products to have similar dynamics over their life but either stretched or compressed based upon the length of their life. We include life length in log form. This models log price changes as a function of the proportional change in life. While intuitively appealing—the impact of life length gets more modest as it gets larger—it also means that imputation of long-lived products is likely to be more robust because the logarithmic transformation reduces the scale of life length. These nonlinear transformations of the life cycle variables also have the advantage that they help to identify the model as they are not linearly related unlike; age, reverse age and life length.

Our approach, of using both age stage and life length, is different from many others, for example Bils (2009), who only includes product age in the life cycle function. A key challenge, however, is that we do not have strong a priori expectations about what this function should look like. Hence, a further requirement of the model is that the functional relationship between life cycle and price should be flexible.

A function which fits this criteria is a bivariate smoothing spline in age stage and life length. A smoothing spline approach imposes very little structure on the relationship between the two variables, only that it is a smooth differentiable function. It is estimated by solving the following optimisation problem,

$$\min{}_{\alpha,f,\delta} \sum_{i=1}^{I} \sum_{t=1}^{T} [\ln p_{it} - \alpha_i - f(l_{it}) - \delta_t]^2 + \lambda \iint [f''(v,u)]^2 dv du \tag{5}$$

Here there are two key criteria in the optimisation. First, to choose the parameters and life cycle function such that the model fits the data as closely as possible. Second, to make sure the life cycle function is reasonably smooth by penalizing its second derivative. The relative weight given to smoothness and fidelity—that is λ in equation (5)—is determined endogenously during the estimation and is dictated by minimizing the generalized cross validation (GCV) function (Craven and Wahba, 1979). Further details regarding the use of such models—termed generalized additive models or GAMs—can be found in Wood (2006).[3] This approach extends the work of Melser and Syed (2016) who used one dimensional additive smoothing splines in age and reverse age separately to model the product life cycle. The smoothing spline estimation method, which does not impose a linear relationship between the age variables, also helps to identify the life cycle pricing effects.

We apply these hedonic models to the academic scanner data set for the US made available by IRI (Bronnenberg, Kruger and Mela, 2008). The data we have available to us includes point-of-sale prices by UPC (i.e. barcode) for a large number of items and supermarkets across a range of cites in the US. In our analysis we define an item as a unique UPC/barcode. In this regard we aggregate across stores. We construct prices as unit values—that is value-weighted average prices—for each month. A monthly frequency is used because this is the most commonly used calculation frequency for CPIs. Importantly for our purposes the data spans more than a decade, from 2001-12. This is vital as the time span is long enough so that there are sufficient items for which we observe both their birth and death. In cases where we do not observe both it is not possible to precisely define the stage of the life cycle hence we cannot use these items to estimate our models. The 12-year span of our data means that a lesser number of items need to be discarded for this reason. We focus on 6 product categories from this data—beer, carbonated beverages, cigarettes, coffee, soup and toothpaste—and 6 cities—Atlanta, Dallas, Detroit, Los Angeles, New York and Washington DC. The data is summarized in Table 1.

⟨⟨ *Insert Table 1 here* ⟩⟩

The table shows the statistics for both included products—the products for which we observe both the product birth and death—and excluded products, where this is not the case. Before calculating these statistics we also dropped all products where the observed life was less than 6 months. These products are likely to be somewhat atypical and hence we exclude them from our analysis. In identifying the products to include we were in fact quite conservative in requiring that an item's birth and death be observed at least 3 months after our data starts or before it finishes. This is because prices can be missing for short periods for various reasons, such as non-sale.

For most included products the mean life length is around 30 months while the median life is closer to 25 months. The average life length tends to be relatively shorter for toothpaste—which has an average life length across cities of 27.43 months—compared with cigarette products which are relatively long-lived with an average life of 33.16 months. The fact that the median life length is lower than the mean indicates that there are a small

[3] The smoothing spline estimation is implemented using the approach of Wood (2004, 2006, 2011) reflected in the `mgcv` package in R.

number of long-lived products which skew the distribution. The table indicates that the number of observations for use in the smoothing spline estimation is ample. The smallest data set is for cigarettes in Detroit, but even here we have 9,803 observations. Across all city-product combinations the average number of observations is large at 28,756.

The contrast between the included and excluded items is significant. We investigate this in two ways. First, we calculate the mean and median life for the excluded items based on the observed data. This will underestimate their true value because the data is censored. Second, we suppose that life length follows a log-normal distribution and estimate the parameters of this distribution taking account of the censoring and obtain the mean and median life length. Clearly the sample of included products is skewed towards shorter-lived items than the population because of the censoring. This is important to note but an inevitable feature of the data we face. However, importantly the price level between the included and excluded items is not too different for most products and cities—implying that the characteristics of the included and excluded items are similar.

⟨⟨ *Insert Table 2 here* ⟩⟩

Using the included data we estimate smoothing spline hedonic regression functions for each city and product. The estimation results are shown in Table 2. Each of the models incorporates item dummy variables, time dummy variables and the 2-dimensional life cycle smoothing spline function as in (3). The models generally fit very well. The lowest R^2 we obtain is for toothpaste in Los Angeles but this is still a very impressive 0.8952. The model fits appear particularly good for cigarettes with the model for Atlanta having an R^2 of 0.9925. The tight model fits reflect the large number of dummy variable controls for time and item—this can be seen in the large number of parameters estimated—as well the flexible life cycle function. But is the life cycle function important in explaining price? The answer is unequivocally yes. We present an F-test of the significance of the spline function in Table 2. These are significant at the 1% level in all cases indicating that the life cycle effect is an important driver of price movements.

The shape of the smoothing spline functions are innately complex—being a function of both age stage and log life length. In Table 2 we report the percentage change in price from the start to the end of a product's life that lives for 24 months (2 years) and for 96 months (8 years) after removing any temporal price effects. In most cases the price change is negative for products that live for 24 months—i.e. prices fall as product's age—just 4 of the 36 product-city combinations exhibit price rises over their life. Some of these life cycle effects are quite large—particularly for coffee and soup in certain cities—while for other products—such as carbonated beverages—the effects are fairly modest. The life cycle price trends are different for city-products that live for 96 months. Of the 36 city-product combinations 26 show price rises over their life. The rises are particularly large for toothpaste and soup products in certain cities. The contrast between the shorter and longer-lived products is interesting and concords with intuition. Shorter-lived products are likely to be so because they tend to exhibit price falls, and lower unit revenues, compared with their longer-lived counterparts.

⟨⟨ *Insert Figure 1 here* ⟩⟩

Examples of the estimated general smoothing spline functions are illustrated in Figure 1 for beer. These figures show the log life cycle price function, denoted by the degree of shading, plotted against age stage and life length. In these diagrams the product life cycle is reflected in a movement from right—for a certain life length—to left—as age stage moves from zero to one. While the life cycle functions are quite diverse one notable feature is that for a number of cities the peak price level is often at the end of life for a long-lived product. Also, there is generally more price volatility for short-lived products, such as in Figure 1a for Atlanta. The magnitude of the effects also varies, they are quite large for Dallas and Los Angeles—Figures 1b and 1d—and smaller for the other cities.

A key feature for our purposes is the degree of curvature in the life cycle pricing function. Table 2 provides an estimate of this for a product that lives for 24 and 96 months. The table provides the price change recorded in the first and second halves of life. This sums to the total price change in each case. If there was limited curvature in the life cycle function—that is prices evolved linearly over the course of their life—then we would expect these two price changes to be roughly equal. In fact in a number of cases they are quite different indicating curvature in the pricing function. For the products that live for 24 months, one pattern that seems quite common is for prices to rise somewhat in the first half of life—or to decline only modestly—and then to fall much more precipitously in latter life. For the products that live for 96 months there also appears to be curvature, but the patterns are more diverse. The fact that there appears to be curvature—whatever its nature—is important because this is likely to lead to bias in indexes which disproportionately sample from either old or new products. We now turn to the extent of this bias.

4 Estimating Life Cycle Sampling Bias Using Simulation

In the previous section we found significant evidence of life cycle pricing effects. However, it is not clear from this either that there is a life cycle sampling bias in price indexes or the magnitude of it. From (4) what is required for life cycle representativity bias to exist is; (i) significant life cycle price dynamics, and (ii) differences in the rate (second derivative) of these price changes over the life cycle. While we have confirmed the former and found some evidence of the latter it is difficult to get a clear idea of the extent of the bias by inspection alone.

Our basic approach to addressing this question is to construct simulations which mimic the index construction process as closely as possible and look at the impact of different sampling approaches. Two different simulation approaches are taken.

The first approach uses all the actual price data. This includes for products where the life cycle characteristics might not be fully observed because we do not know the birth or death date. We then randomly select an initial sample for the first periods, that is $I^*_{t,t+1}$ for $t = 1$ in equation (2), and follow these through time. If items disappear from the market then we suppose they are replaced by randomly selecting an item which is currently available in the market. So the sample size always stays the same. In addition we consider various frequencies at which the sample is completely re-selected. The frequencies of re-sampling—that is the length of time between which the sample is completely updated—we consider are; (i) never, (ii) every 5 years, (iii) every 2 years, and (iv) every year. This gives different ways in which $I^*_{t,t+1}$ evolves through time. These indexes are compared with index (1) where the sample is that for all matched products in the data. This provides an estimate of (4).

The second approach is broadly similar but creates an synthetic market of products and uses hedonic imputations to derive the price index. In constructing the market of products we want to ensure that the distribution of life lengths is representative of what actually exists. To do this we make use of the previously estimated log-normal distribution of life length for each city and product. We randomly sample life lengths from this distribution. Because this distribution is estimated taking account of the censoring in our data we will include very long-lived products in our market. Each product is then randomly allocated a birth date. The birth date can be as late as the last time period of our data but as early as x periods prior to the start of our data. Where x is the estimated median life length from the log-normal distribution. We start items' lives before the beginning of our data to ensure that there is a representative mix of product lives at the start of the sample when the indexes are first calculated. Prices are then imputed from our hedonic model for these items. For the duration of our data, that is for 12 years, we estimate indexes with the re-sampling frequencies outlined above.

The hedonic imputations approach has the advantage, over that using the actual data, that we abstract from any price change which is not related to the life cycle and we just use products for which know the life cycle characteristics. Of course, compared with using the actual data, we rely on the accuracy of the hedonic imputations. In both cases, for each product category in each city, we undertake 100 replications of these simulations and average the resulting differences from the ideal reference index calculated using all matched products in the market. The differences, in terms of annual average bias, are shown in Table 3.

⟨⟨ *Insert Tables 3 here* ⟩⟩

The results show the life cycle bias, for both the simulation using actual prices and using hedonically imputed prices, is in general non-trivial. First to the results for actual prices. When the index is never updated over a period of 12 years the bias, across all cities and products, averages 0.88 percentage points. Of the 36 product-city cases only 6 have negative biases. Hence positive bias tends to dominate. The largest bias is generally for coffee. In the case of Atlanta the bias is as much as 2.58 percentage points per year. The average bias for coffee is 1.92 percentage points. For the hedonic imputations simulation the results are similar though a little less extreme. The overall bias, when the sample is never fully updated, is 0.37 percentage points per annum, again reflecting the fact that for most product-city cases the bias is positive. The correlation of results at the product-city level for the two simulation approaches, for the never re-sampled case, is 0.3970 (with a p-value of 0.0052), which shows they are broadly consistent. While the bias is mostly positive it is not in all cases. Because of this perhaps a better measure of the error, if our focus is on the accuracy at the individual product-city level, is the absolute bias. Using actual prices this is 0.94 percentage points while using hedonic imputations it is 0.59.

The source of the bias can be most clearly seen by examining the last columns of Table 3 for the imputations simulation. Because we know the age of each item in this case we can calculate the difference in age between items in the target index and the sample index. The index which is never fully updated on average includes items which are around 30.50 months older than the target index. The 5-yearly, 2-yearly and annually updated indexes become increasingly similar to the target index in terms of their average ages. The annually updated index differs by only 3.88 months on average in terms of the difference in sample age from the target index.

As noted, the sign of the bias varies across product categories and cities. The primary reason for this is the diverse nature of the life cycle pricing functions. The most clear cut results are those for coffee, soup and toothpaste. Here the bias is invariably positive. These indexes place greater weight on older products than does the target index calculated across all products. The impact of this can be inferred from Table 2. Here we saw that it was generally the case for these three product categories that the longer-lived product, which lived for 96 months, increased more in price than the shorter-lived products. Thus these indexes tend to over-represent price rises relative to the market and hence have an upward bias. For the other product categories the results are more mixed. They reflect the way in which the prices of older products change relative to younger products and how longer-lived products change relative to shorter-lived items. Because the life cycle pricing functions are more complex for the other three products so are the bias results.

In Table 3 we report our simulation results for four different matched-model indexes based upon the frequency with which the sample is updated. These indexes have significantly different age profiles as was noted. The bias is clearly largest for the index which never updates the sample. That is products are followed until they die and are only then replaced. One of the key implications of our results is that updating the matched model sample frequently is a good idea as it significantly reduces the level of bias. Resampling every 5 years reduces the average absolute bias from 0.94 to 0.61 percentage points using the actual data while it falls from 0.59 to 0.36 for the hedonic imputations case. Updating every 2 years further lowers if further while for annual updating the average absolute annual bias is just 0.34 and 0.10 respectively, between one-third and on-sixth of what it was from never updating. While the extent to which the bias declines depends upon the particular shape of the life cycle function it is clear that more frequent re-sampling significant attenuates the life cycle representativity bias.

5 Conclusion

Official price indexes are usually constructed using samples of products rather than a census. In particular the standard approach is to select a sample in some base period and follow the items through time until they disappear from the market, in which case they are replaced. What this means is that the sample will tend to have a different—and older—age composition than the set of items available in the market. As has been noted, such as ILO (2004), this leaves these indexes open to bias if there are systematic changes in prices related to the age of products. We have shown that life cycle price trends are important for a range of products and importantly, that the prices do not change at the same rate across the life cycle. This means that the age of the sample is important for measured price change. We found that across all 6 products and 6 cities we examined in our data that the average absolute bias was between 0.59 and 0.94 percentage points per annum in fixed sample indexes depending upon simulation methodology. This is non-trivial. We explored various updating frequencies and the clear implication of this was that more frequent sample updating leads to less bias. The average absolute bias fell to 0.10 and 0.34 percentage points respectively for annually updated samples. This emphasises that attention needs to be paid to the construction of samples for elementary price indexes and ideally they should be updated as frequently as is practicable.

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Appendix

The derivation of (4) proceeds as follows,

$$\ln\left(\frac{P^*_{t,t+1}}{P_{t,t+1}}\right) = \frac{1}{|I^*_{t,t+1}|}\sum_{i\in I^*_{t,t+1}} \ln\left(\frac{p_{it+1}(l_{it+1}, z_i, \delta_{t+1})}{p_{it}(l_{it}, z_i, \delta_t)}\right) - \frac{1}{|I_{t,t+1}|}\sum_{i\in I_{t,t+1}} \ln\left(\frac{p_{it+1}(l_{it+1}, z_i, \delta_{t+1})}{p_{it}(l_{it}, z_i, \delta_t)}\right) \tag{6}$$

$$= \frac{1}{|I^*_{t,t+1}|}\sum_{i\in I^*_{t,t+1}} \Big([\alpha_i + f(l_{it+1}) + \delta_{t+1} + e_{it+1}] - [\alpha_i + f(l_{it}) + \delta_t + e_{it}] \Big) - \frac{1}{|I_{t,t+1}|}\sum_{i\in I_{t,t+1}} \Big([\alpha_i + f(l_{it+1}) + \delta_{t+1} + e_{it+1}] - [\alpha_i + f(l_{it}) + \delta_t + e_{it}] \Big) \tag{7}$$

$$= \frac{1}{|I^*_{t,t+1}|}\sum_{i\in I^*_{t,t+1}} \Big([f(l_{it+1}) + e_{it+1}] - [f(l_{it}) + e_{it}] \Big) - \frac{1}{|I_{t,t+1}|}\sum_{i\in I_{t,t+1}} \Big([f(l_{it+1}) + e_{it+1}] - [f(l_{it}) + e_{it}] \Big) \tag{8}$$

$$= \frac{1}{|I^*_{t,t+1}|}\sum_{i\in I^*_{t,t+1}} [f(l_{it+1}) - f(l_{it})] - \frac{1}{|I_{t,t+1}|}\sum_{i\in I_{t,t+1}} [f(l_{it+1}) - f(l_{it})] + \frac{1}{|I^*_{t,t+1}|}\sum_{i\in I^*_{t,t+1}} [e_{it+1} - e_{it}] - \frac{1}{|I_{t,t+1}|}\sum_{i\in I_{t,t+1}} [e_{it+1} - e_{it}] \tag{9}$$

The last line shows that the difference between the two indexes is due to; (i) the difference in life cycle price effects, and (ii) differences in random errors. Because the errors in (9) have a mean of zero and follow no systematic pattern their effect is likely to be negligible. Hence, we can quantify the systematic log bias between the two indexes as in (4).

Table 1: Summary Statistics

		Included Items					Excluded Items					Cens. Log-Normal Dist.	
		No. Obs.	No. Prods.	Life Length		Price	No. Obs.	No. Prods.	Life Length		Price	Life Length	
Product	City		(% of Total)	Mean	Median	Mean		(% of Total)	Mean	Median	Mean	Mean	Median
Beer	Atlanta	13,118	547 (32.37)	30.76	24	8.53	69,255	1,143 (67.63)	69.64	56	8.49	477.24	128.80
	Dallas	13,253	588 (33.05)	30.12	24	8.50	71,935	1,191 (66.95)	69.10	55	8.30	445.03	122.95
	Detroit	12,282	494 (32.37)	31.78	23	8.60	57,014	1,032 (67.63)	66.32	56	8.97	467.63	123.71
	Los Angeles	15,954	622 (31.88)	34.17	27	8.58	70,265	1,329 (68.12)	62.07	45	9.02	317.35	113.54
	New York	18,214	959 (30.00)	29.87	24	7.89	116,141	2,238 (70.00)	62.98	57	7.63	479.82	131.99
	Washington, DC	16,580	715 (36.59)	31.85	24	8.56	74,487	1,239 (63.41)	70.58	62	8.30	371.09	107.75
Carbonated Beverages	Atlanta	32,784	1,223 (46.82)	32.55	24	2.26	70,655	1,389 (53.18)	57.58	46	2.11	136.85	61.89
	Dallas	43,992	1,881 (52.09)	27.94	18	1.96	88,071	1,730 (47.91)	57.76	46	2.04	111.72	49.96
	Detroit	32,605	1,316 (54.54)	31.69	25	2.21	62,899	1,097 (45.46)	64.21	53	2.29	113.28	52.85
	Los Angeles	33,383	1,344 (48.40)	28.83	21	2.03	74,406	1,433 (51.60)	58.65	43	2.22	126.56	56.40
	New York	61,574	2,407 (49.32)	30.09	23	1.79	139,017	2,473 (50.68)	63.06	49	1.98	131.32	58.59
	Washington, DC	53,805	2,164 (54.25)	29.07	22	1.80	91,537	1,825 (45.75)	56.25	38	2.13	94.17	47.12
Cigarettes	Atlanta	10,275	500 (30.62)	26.36	17	12.00	72,359	1,133 (69.38)	71.63	54	15.46	1,185.61	167.47
	Dallas	16,451	730 (38.91)	30.34	19	14.87	65,835	1,146 (61.09)	69.69	68	17.64	307.92	96.88
	Detroit	9,803	519 (35.62)	29.43	20	18.72	59,462	938 (64.38)	75.22	80	21.40	701.49	130.59
	Los Angeles	15,233	517 (36.95)	40.35	39	17.30	55,143	882 (63.05)	73.34	72	19.51	286.43	113.03
	New York	24,329	928 (43.57)	37.83	30	20.91	72,787	1,202 (56.43)	72.55	72	26.45	222.13	88.03
	Washington, DC	17,683	723 (38.05)	34.67	26	17.66	77,384	1,177 (61.95)	75.74	70	19.84	316.19	109.16
Coffee	Atlanta	24,294	919 (45.97)	31.12	24	5.94	52,903	1,080 (54.03)	54.23	46	5.39	121.87	59.87
	Dallas	38,261	1,394 (50.84)	31.74	25	5.75	57,508	1,348 (49.16)	46.82	33	5.45	86.72	48.40
	Detroit	31,085	1,038 (51.23)	34.04	26	6.15	46,391	988 (48.77)	51.73	43	6.03	94.43	52.79
	Los Angeles	36,078	1,287 (52.40)	31.56	25	6.70	52,448	1,169 (47.60)	48.34	33	6.33	86.11	47.56
	New York	52,208	1,936 (51.89)	31.73	27	6.20	80,851	1,795 (48.11)	50.78	39	6.12	90.65	49.53
	Washington, DC	40,901	1,462 (53.91)	31.33	25	6.11	54,423	1,250 (46.09)	47.47	34	5.75	79.41	45.48
Soup	Atlanta	26,225	928 (42.67)	33.22	28	2.13	73,207	1,247 (57.33)	64.12	66	2.08	159.85	76.54
	Dallas	34,807	1,319 (48.46)	30.29	27	1.99	77,135	1,403 (51.54)	59.45	64	1.96	116.47	59.45
	Detroit	28,776	1,072 (47.16)	30.92	27	2.08	67,326	1,201 (52.84)	61.12	66	2.03	142.03	64.05
	Los Angeles	52,281	1,605 (61.57)	35.42	31	2.39	64,236	1,002 (38.43)	68.14	72	2.34	93.56	50.06
	New York	68,050	2,099 (58.68)	36.21	34	2.30	95,748	1,478 (41.32)	67.69	72	2.15	98.59	53.86
	Washington, DC	42,450	1,509 (47.57)	32.09	29	2.15	94,755	1,663 (52.43)	60.26	65	2.12	126.87	62.94
Toothpaste	Atlanta	15,361	688 (58.70)	25.28	18	4.05	24,849	484 (41.30)	55.99	45	3.46	76.78	39.11
	Dallas	20,838	877 (59.42)	28.06	21	4.08	33,560	599 (40.58)	59.79	46	3.52	78.50	42.52
	Detroit	18,502	809 (62.04)	26.24	19	4.01	27,010	495 (37.96)	58.51	46	3.40	71.48	37.93
	Los Angeles	18,570	738 (56.94)	29.10	23	4.62	29,121	558 (43.06)	57.17	42	3.93	79.09	44.85
	New York	24,598	994 (57.03)	28.78	22	4.38	40,247	749 (42.97)	57.66	46	3.58	84.12	44.66
	Washington, DC	20,621	889 (60.23)	27.11	20	4.23	31,551	587 (39.77)	58.67	46	3.59	76.92	40.28
Average by Product Category													
Beer		14,900	654 -32.71	31.43	24.33	8.44	76,516	1,362 -67.29	66.78	55.17	8.45	426.36	121.46
Carbonated Beverages		43,024	1,723 -50.90	30.03	22.17	2.01	87,764	1,658 -49.10	59.59	45.83	2.13	118.98	54.47
Cigarettes		15,629	653 -37.29	33.16	25.17	16.91	67,162	1,080 -62.71	73.03	69.33	20.05	503.30	117.53
Coffee		37,138	1,339 -51.04	31.92	25.33	6.14	57,421	1,272 -48.96	49.90	38.00	5.85	93.20	50.61
Soup		42,098	1,422 -51.02	33.03	29.33	2.17	78,735	1,332 -48.98	63.46	67.50	2.11	122.90	61.15
Toothpaste		19,748	833 -59.06	27.43	20.50	4.23	31,056	579 -40.94	57.97	45.17	3.58	77.82	41.56

Table 2: Smoothing Spline Hedonic Regression Results

						Life Cycle Price Effects					
					F-Test	Life of 24 Months			Life of 96 Months		
Product	City	No. Obs	No. Parms.	R^2	of Spline†	1st Half	2nd Half	Total	1st Half	2nd Half	Total
Beer	Atlanta	13,118	693.16	0.9861	5.72***	-0.89	-1.49	-2.38	0.05	1.32	1.37
	Dallas	13,253	737.81	0.9833	16.54***	-1.02	-1.51	-2.52	4.85	6.10	10.95
	Detroit	12,282	642.66	0.9877	11.62***	-0.85	-1.81	-2.66	1.80	1.85	3.65
	Los Angeles	15,954	772.05	0.9606	15.56***	-2.65	-4.55	-7.21	4.59	12.09	16.69
	New York	18,214	1,108.95	0.9763	10.03***	1.18	-0.70	0.48	1.21	3.46	4.67
	Washington, DC	16,580	855.99	0.9857	5.58***	0.09	-1.88	-1.79	0.31	2.24	2.55
Carbonated Beverages	Atlanta	32,784	1,373.37	0.9620	8.93***	0.06	-2.28	-2.22	-1.67	-6.64	-8.31
	Dallas	43,992	2,029.31	0.9656	10.90***	0.43	-1.09	-0.67	-1.61	3.81	2.21
	Detroit	32,605	1,465.61	0.9660	12.34***	-0.08	-3.56	-3.64	-3.41	2.85	-0.56
	Los Angeles	33,383	1,494.21	0.9559	25.67***	-2.07	1.40	-0.67	6.40	-7.32	-0.93
	New York	61,574	2,556.97	0.9701	34.40***	-0.47	1.14	0.67	7.67	3.64	11.31
	Washington, DC	53,805	2,312.93	0.9622	42.89***	-0.68	-3.73	-4.42	-1.26	9.41	8.15
Cigarettes	Atlanta	10,275	650.64	0.9925	31.16***	-2.90	-0.38	-3.29	3.56	1.78	5.33
	Dallas	16,451	879.83	0.9847	7.61***	1.54	-3.81	-2.27	-1.50	-3.83	-5.33
	Detroit	9,803	669.88	0.9873	17.18***	-2.23	2.89	0.66	0.74	-4.46	-3.71
	Los Angeles	15,233	664.87	0.9810	28.46***	-2.20	-6.16	-8.36	-0.50	-6.24	-6.74
	New York	24,329	1,078.85	0.9896	67.64***	-1.54	-0.52	-2.06	3.16	-12.43	-9.27
	Washington, DC	17,683	872.43	0.9857	18.67***	3.96	-4.75	-0.79	-3.53	5.81	2.27
Coffee	Atlanta	24,294	1,069.95	0.9361	46.41***	-2.27	-13.72	-15.98	6.92	-1.89	5.03
	Dallas	38,261	1,544.65	0.9445	44.69***	-5.56	-7.86	-13.42	8.92	-1.96	6.95
	Detroit	31,085	1,188.92	0.9349	71.92***	-3.25	-12.13	-15.38	-0.16	0.13	-0.02
	Los Angeles	36,078	1,437.22	0.9154	36.45***	-2.78	-9.26	-12.04	-0.44	3.57	3.13
	New York	52,208	2,086.90	0.9471	58.52***	-1.59	-3.96	-5.56	7.88	-4.13	3.76
	Washington, DC	40,901	1,612.70	0.9533	33.05***	0.90	-6.82	-5.92	-2.00	-2.21	-4.21
Soup	Atlanta	26,225	1,078.83	0.9272	68.33***	-4.03	-11.75	-15.78	6.79	10.20	16.99
	Dallas	34,807	1,464.82	0.9282	52.47***	-4.77	-14.24	-19.01	18.86	8.96	27.82
	Detroit	28,776	1,217.75	0.9091	33.04***	-3.68	-13.40	-17.08	3.40	3.95	7.34
	Los Angeles	52,281	1,753.62	0.9208	75.40***	-7.61	-11.78	-19.39	10.46	1.48	11.94
	New York	68,050	2,247.70	0.9489	13.12***	-2.00	-1.31	-3.31	2.88	3.92	6.80
	Washington, DC	42,450	1,653.92	0.9121	35.81***	-3.67	-7.44	-11.11	5.99	3.06	9.05
Toothpaste	Atlanta	15,361	836.56	0.9239	74.76***	-3.54	-11.76	-15.31	8.10	25.28	33.38
	Dallas	20,838	1,025.58	0.9269	32.51***	-1.42	-5.15	-6.57	3.77	17.51	21.27
	Detroit	18,502	959.17	0.9265	46.41***	-1.72	-10.43	-12.14	4.69	31.63	36.31
	Los Angeles	18,570	885.50	0.8952	49.57***	-2.55	-3.55	-6.10	7.86	25.04	32.90
	New York	24,598	1,140.84	0.9502	3.10***	0.51	2.13	2.64	-0.87	-0.22	-1.09
	Washington, DC	20,621	1,039.44	0.9393	24.97***	-1.25	-0.95	-2.19	1.80	2.74	4.54

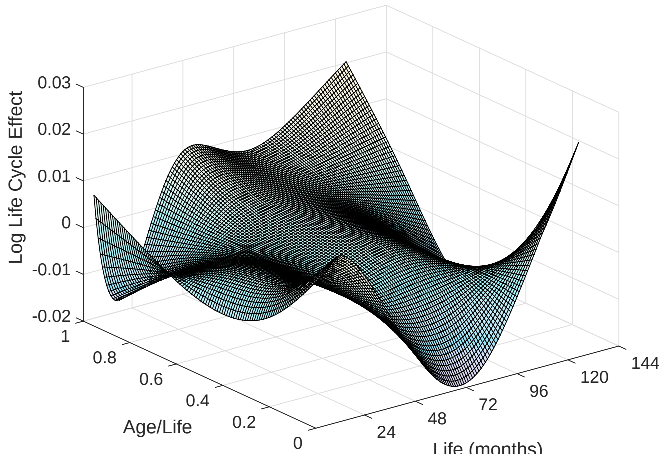
† Significance levels are: ***=1%, **=5%, *=10%.

Table 3: Simulated Estimates of Life Cycle Sample Representativity Bias (percentage points per year)

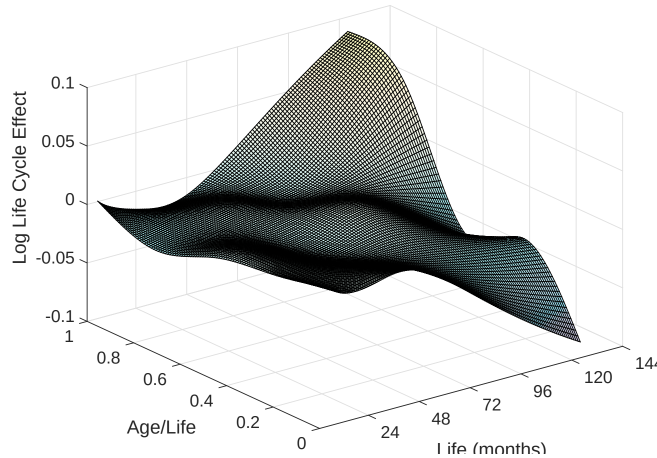
		Actual Prices				Hedonically Imputed Prices								
		Re-sampling Frequency				Re-sampling Frequency				Avg. Age of Target	Avg. Diff. in Age from Target Index by Re-sampling Frequency:			
Product	City	Never	5 Years	2 Years	1 Year	Never	5 Years	2 Years	1 Year	Index	Never	5 Years	2 Years	1 Year
Beer	Atlanta	0.34	0.32	0.18	0.19	0.25	0.12	0.04	0.02	84.93	35.21	16.72	7.26	3.93
	Dallas	0.87	0.57	0.34	0.28	-0.09	-0.11	-0.05	0.00	82.16	36.31	16.82	7.38	3.61
	Detroit	-0.12	-0.02	-0.16	-0.16	0.14	0.09	0.04	0.02	82.73	35.32	16.45	7.53	3.68
	Los Angeles	1.15	0.78	0.34	0.36	-0.79	-0.29	-0.11	-0.04	77.07	34.74	16.14	7.43	3.59
	New York	-0.27	-0.12	-0.25	-0.19	-0.28	-0.16	-0.05	-0.02	86.23	35.72	16.71	7.64	3.69
	Washington, DC	0.39	0.37	0.17	0.16	0.04	0.05	0.03	0.01	75.19	34.70	16.58	7.54	3.98
Carbonated Beverages	Atlanta	0.05	0.18	0.52	0.43	0.29	0.01	-0.01	-0.02	51.65	30.80	15.86	7.24	3.58
	Dallas	0.01	0.07	0.24	0.11	0.03	0.07	0.07	0.01	45.82	29.53	15.46	7.61	3.98
	Detroit	0.30	0.42	-0.16	-0.10	-0.01	0.04	-0.02	-0.03	46.97	29.30	15.54	7.65	3.86
	Los Angeles	0.06	0.54	0.37	-0.03	-0.78	-0.53	-0.15	-0.04	48.91	29.85	15.46	7.24	3.90
	New York	0.10	0.25	-0.05	0.11	-1.05	-0.37	-0.17	-0.01	50.23	30.28	15.78	7.60	4.02
	Washington, DC	0.61	0.61	0.45	0.39	-1.06	-0.13	-0.04	-0.03	43.36	27.73	15.03	7.78	4.07
Cigarettes	Atlanta	0.47	0.38	0.34	0.14	-0.59	-0.46	-0.18	-0.06	103.77	37.08	16.27	7.87	4.07
	Dallas	-0.45	-0.33	-0.25	-0.03	-1.01	-0.48	-0.17	-0.11	69.91	34.66	16.66	7.42	4.18
	Detroit	0.22	0.15	0.21	0.31	1.41	0.71	0.32	0.13	86.90	36.05	16.92	7.05	3.77
	Los Angeles	-0.15	-0.05	-0.04	-0.17	0.79	0.39	0.17	0.06	76.21	34.05	16.45	7.03	3.63
	New York	-1.20	-1.04	-0.88	-0.83	-0.80	0.06	0.12	0.02	64.75	33.36	15.71	7.40	4.05
	Washington, DC	-0.07	-0.02	-0.18	-0.20	-0.53	-0.38	-0.23	-0.16	75.01	34.65	16.40	6.83	4.04
Coffee	Atlanta	2.58	1.79	1.67	1.28	1.16	0.74	0.33	0.25	50.03	29.88	15.81	7.26	3.97
	Dallas	2.33	2.08	1.50	1.51	0.35	0.61	0.51	0.30	42.82	27.08	14.54	7.21	4.00
	Detroit	2.37	2.06	1.68	1.59	1.07	0.49	0.20	0.09	45.24	27.45	15.06	7.41	3.79
	Los Angeles	1.05	0.69	0.60	0.73	0.63	0.38	0.17	0.08	42.72	27.21	14.94	7.52	3.74
	New York	1.56	1.26	1.12	0.66	1.55	0.96	0.51	0.26	43.88	27.67	14.95	7.34	3.85
	Washington, DC	1.65	1.23	1.08	0.75	0.39	0.23	0.18	0.08	40.95	26.31	14.39	7.47	4.00
Soup	Atlanta	1.43	0.76	0.37	0.33	1.18	0.49	0.21	0.13	58.37	31.75	15.78	7.45	3.75
	Dallas	2.54	1.28	1.17	0.70	1.00	0.89	0.44	0.25	48.64	28.69	15.68	7.37	3.73
	Detroit	1.42	0.50	0.15	-0.19	0.76	0.65	0.37	0.24	51.93	30.49	15.89	6.89	3.70
	Los Angeles	2.04	0.97	0.84	0.64	0.98	0.95	0.54	0.37	44.53	27.40	15.37	7.19	3.99
	New York	1.30	0.53	0.65	0.49	0.47	0.32	0.18	0.12	46.02	28.39	15.04	7.49	3.82
	Washington, DC	1.93	0.68	0.58	0.35	-0.22	0.03	0.07	0.09	50.73	29.25	15.89	7.39	3.75
Toothpaste	Atlanta	2.14	0.89	-0.04	-0.08	1.66	0.92	0.38	0.15	38.94	26.20	14.71	7.48	3.94
	Dallas	0.56	0.03	-0.18	-0.27	1.00	0.52	0.24	0.07	40.27	26.21	14.87	7.68	3.99
	Detroit	2.37	1.59	0.23	0.09	2.21	1.41	0.70	0.35	37.89	25.42	14.73	7.44	4.02
	Los Angeles	0.45	-0.55	-0.91	-1.10	1.99	1.30	0.75	0.32	40.90	26.30	14.71	7.46	3.83
	New York	0.54	0.60	0.45	0.42	0.25	0.13	0.08	0.03	41.60	27.11	14.95	7.27	3.84
	Washington, DC	0.93	0.56	0.10	0.00	0.73	0.36	0.16	0.05	39.24	25.96	14.82	7.53	4.13
Average by Product Category														
Beer		0.39	0.32	0.10	0.11	-0.12	-0.05	-0.02	0.00	81.39	35.33	16.57	7.46	3.75
Carbonated Beverages		0.19	0.35	0.23	0.15	-0.43	-0.15	-0.05	-0.02	47.82	29.58	15.52	7.52	3.90
Cigarettes		-0.20	-0.15	-0.13	-0.13	-0.12	-0.03	0.01	-0.02	79.43	34.98	16.40	7.27	3.96
Coffee		1.92	1.52	1.28	1.09	0.86	0.57	0.32	0.18	44.27	27.60	14.95	7.37	3.89
Soup		1.78	0.79	0.63	0.39	0.70	0.56	0.30	0.20	50.04	29.33	15.61	7.30	3.79
Toothpaste		1.17	0.52	-0.06	-0.16	1.31	0.77	0.39	0.16	39.81	26.20	14.80	7.48	3.96
Average of All Product Categories														
Avg.		0.88	0.56	0.34	0.24	0.37	0.28	0.16	0.08	57.13	30.50	15.64	7.40	3.88
Avg. of Abs. Value		0.94	0.61	0.41	0.34	0.59	0.36	0.18	0.10	—	—	—	—	—

Figure 1: Life Cycle Pricing Functions for Beer

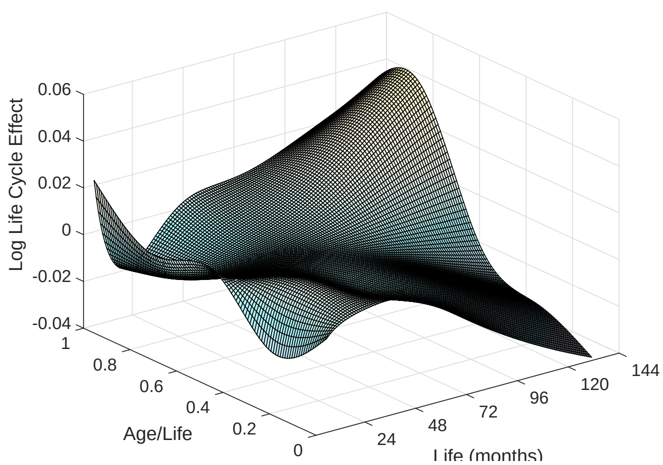
(a) Atlanta



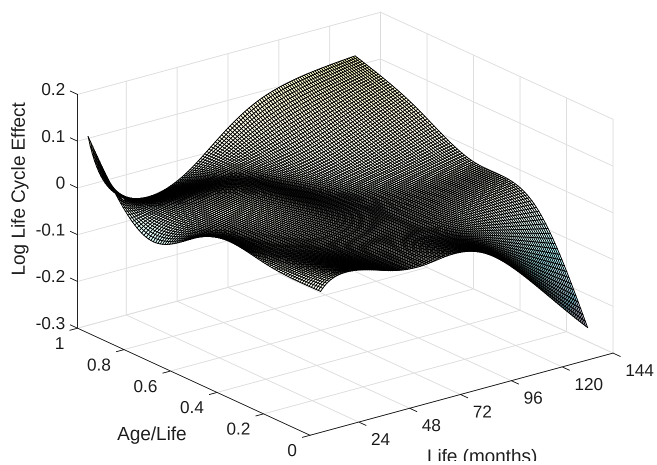
(b) Dallas



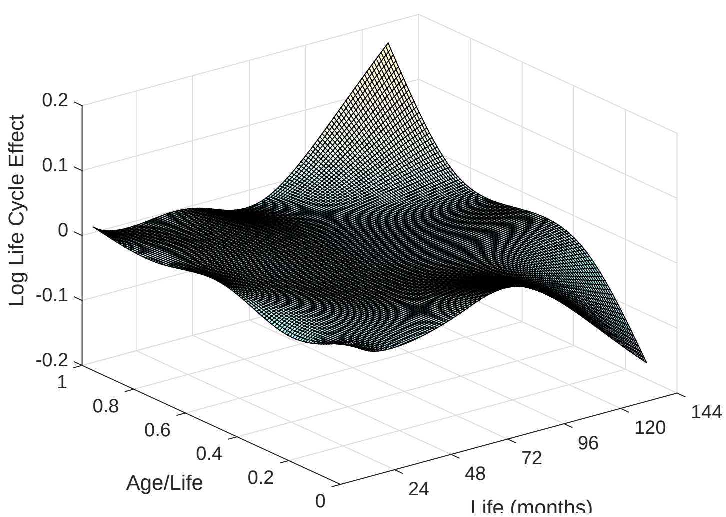
(c) Detroit



(d) Los Angeles



(e) New York



(f) Washington, DC