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An Application to PPI Microprocessors

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Hedonic Price Indexes under Static Pricing: An Application to PPI Microprocessors

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Abstract

Price change for microprocessors largely coincides with product turnover. This static pricing challenges some price index methods and makes accounting for quality change paramount in designing price indexes. We evaluate the performance of several hedonic methods of quality adjustment under static pricing. We find the relative performance of these methods depends on sample size. For the small product samples feasible for microprocessors, the low variance of time-dummy hedonics gives them an advantage over less simple specifications, but with the potential downside of being more biased.

1. Introduction

A matched-model price index uses prices on the same set of products every period to separate changes in price from changes in the average quality of the product set. Product turnover complicates this. Discontinued products and new products often differ in quality from continuing products, making a sample of continuing products unrepresentative of all products. This causes the well-documented "quality bias" in matched-model price indexes (National Research Council, 2002, chapter 4).

The limitations of matched-model indexes are especially pronounced for microprocessors because price changes seldom happen during a product's life. Instead, sellers change prices with the introduction of new products or the retirement of old products. Adhering to a strict matched-model index methodology would yield constant price levels, no matter how drastically prices or product qualities differ for new models.

Price indexes instead often employ some form of quality adjustment. One class of quality adjustment is based on hedonic regression, regressing price on observed product characteristics. (See Groshen et al (2017) for an overview of quality adjustment practices at U.S. statistical agencies.)

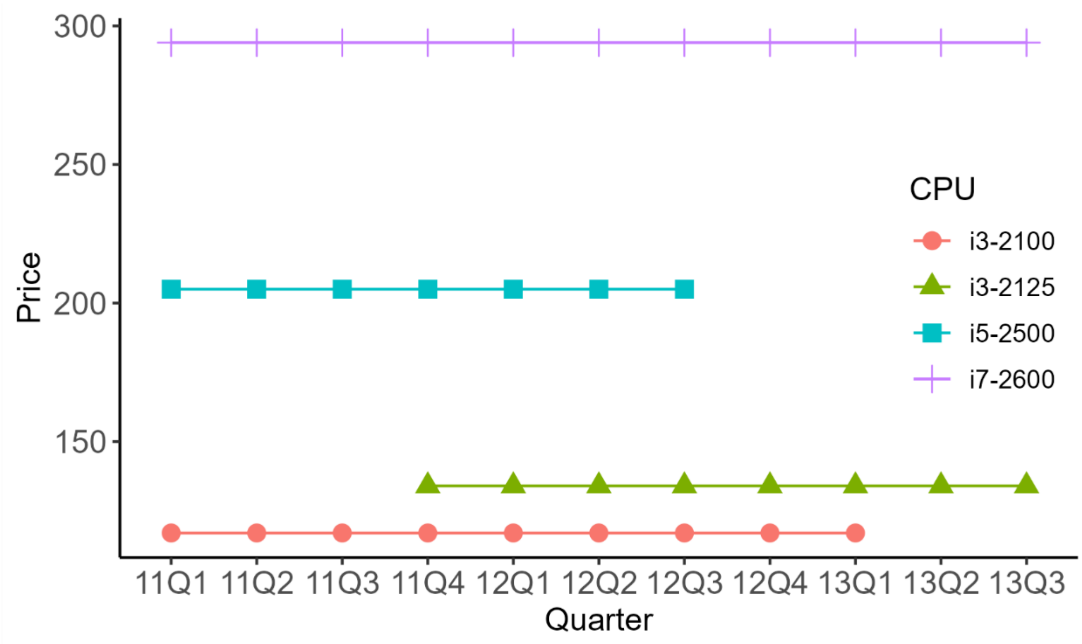
A variety of hedonic approaches are extant in price index methodology, and theory does not provide clear guidance on which would perform best. Empirical comparisons of the performance of different hedonics methods are rare in any setting and were previously missing for settings with static pricing.[1] We explore how different hedonic approaches behave under static pricing by running simulations. Specifically, we repeatedly generate product characteristics and prices, using real data to inform the distributions of random variables we use. We calculate several hedonic price indexes in each simulation.

By comparing the price index results across simulations, we can find the distribution of price index estimates under each hedonic approach. Unlike typical Monte Carlo simulations that assume one model or data generating process, our Monte Carlo simulations assume prices for entering, exiting, and continuing microprocessors are governed by separate data generating processes. These separate data generating processes allow us to reflect the pattern of unchanging prices for continuing goods, a pattern

[1] Many studies compare the results of different price index formulae to each other. McClelland (1996) and Adams and Klayman (2018) are among the few that simulate indexes and compare them to a trusted benchmark.

that Section 0 documents as prevalent in microprocessor pricing and one that is illustrated in Figure 1, where four microprocessors have the same price from their introductions until they are discontinued.

Figure 1. Prices for Select Microprocessors



Section 3 includes descriptions of the data and methodology and hedonic model specifications tests. The data generating processes, sample sizes, and other parameters of the Monte Carlo simulations are calibrated to wholesale semiconductor data from the United States. Section 3.1 details the generation of simulated data. Section 3.2 describes the hedonic specifications we test and the benchmarks to which we compare them. We calculate hedonic indexes on samples from this simulated population and measure differences from simulated population benchmarks. We use a time-dummy hedonic model with added exit and entry indicators to attempt to account for the three separate cohorts in the data generating process.

Section 4 reports results. Hedonic methods differ in the expected values of their inflation rates. Thus, if one model is considered the true measurement objective, then the others would be considered biased. We find that the performance of the different hedonics varies based on sample size and which hedonic is chosen as a benchmark. Yet, for small samples, a simple time-dummy hedonic more closely tracks all the simulated population benchmarks we calculate. On small samples, it even outperforms indexes that share their index formula with the benchmarks.

Section 5 concludes by identifying implications of applying the results into the Producer Price Index (PPI). Critical considerations are the size of samples and an understanding of the underlying data generating process. More broadly, Monte Carlo simulations are a valuable tool to show the properties of different hedonic methods and model specifications.

2. Data

We parameterize Monte Carlo simulations with prices and characteristics data for wholesale microprocessors from Intel, the same data source used by Sawyer and So (2018) and Byrne et. al (2018). The data downloaded from their website include a price for a 1,000-chip direct shipment and seven product characteristics: number of cores, number of threads, thermal design power, base frequency, turbo frequency, cache size, and graphical processing execution units (for semiconductors with an integrated graphics processing unit). In addition, we use the PassMark performance score for each microprocessor.[2]

We highlight one pair of quarters in the Monte Carlo simulations, 2017 Q3 - 2017 Q4. We then check the robustness of our results with parameters from 2015 Q3 – 2015 Q4, 2014 Q2 – 2014 Q3, and 2012 Q3 – 2012 Q4. Running the simulations on multiple pairs of quarters allows us to see if the performance of the different indexes remains consistent on different data. Thus, we can reduce the chance that the performance of an index comes from the idiosyncrasies of one pair of quarters. The pool of data we chose from was between 2010 and 2020. The four pairs of quarters we selected each have at least five microprocessors exiting and entering. This fact is important because price change comes from entry and exit and many pairs of quarters had little to no exit or entry. Quarters without exit and entry have little price change, and any price change could be measured with a matched-model index. The quarters we selected also spanned the range of available quarters, which would help show the performance of different indexes with respect to any changes in technology or market conditions over time.

Our pool of data covers a period where the pricing behavior for microprocessors changed. Prior to 2010, the prices of existing microprocessors would fall when a new microprocessor was introduced (Flamm, 2017). Still, Aizcorbe (2005) estimates adjustments for quality improvements contributed more to declines in microprocessor price indexes than price movements. After 2010, the prices of existing microprocessors would tend to remain the same when a new microprocessor was introduced. Byrne et al (2017) noted that all microprocessors introduced in 2000 and 2001, had price changes within four quarters; yet, only 20 percent of microprocessors introduced from 2010 to 2013 saw a price change. This behavior is not unique to microprocessors; price changes largely coinciding with product turnover have been identified in cloud computing services (Sawyer and O'Bryan, 2023) and mobile phones (Aizcorbe et al, 2020). High degrees of price rigidity, if not fully static pricing, have been documented more widely. Carlton (1986) identified broad sectors in which the average price duration exceeds one year. Subsequent studies, reviewed in Alvarez (2008), find less frequent than annual price changes in a substantial fraction of products in a variety of countries and periods.

The number of continuing microprocessors with price changes trended downward (see Table 1). For 2009 Q1 – 2009 Q2 through 2012 Q4 – 2013 Q1, 75 percent of pairs of quarters had at least one continuing microprocessor with a price change. For 2013 Q1 – 2013 Q2 through 2015 Q4 – 2016 Q1, it was 50 percent. For 2016 Q1 – 2016 Q2 through 2019 Q3 – 2019 Q4, it was 27 percent.

Table 1. Microprocessor Vintage Counts

Interval	Exiting products	Entering products	Continuing products	Continuing products with price changes

[2] For more details on the PassMark performance score, see Sawyer and So (2018)

2009 Q1 – 2009 Q2	5	1	24	1
2009 Q2- 2009 Q3	2	5	23	8
2009 Q3 – 2009 Q4	3	7	25	1
2009 Q4 – 2010 Q1	0	13	32	3
2010 Q1 – 2010 Q2	9	4	36	0
2010 Q2 – 2010 Q3	3	8	37	4
2010 Q3 – 2010 Q4	3	4	42	4
2010 Q4 – 2011 Q1	3	17	43	2
2011 Q1 – 2011 Q2	0	0	60	0
2011 Q2 – 2011 Q3	17	7	43	0
2011 Q3 – 2011 Q4	0	13	50	8
2011 Q4 – 2012 Q1	35	7	28	0
2012 Q1 – 2012 Q2	0	0	35	2
2012 Q2 – 2012 Q3	0	21	35	3
2012 Q3 – 2012 Q4	17	15	39	3
2012 Q4 – 2013 Q1	1	9	53	1
2013 Q1 – 2013 Q2	26	0	36	0
2013 Q2 – 2013 Q3	0	23	36	4
2013 Q3 – 2013 Q4	0	20	59	1
2013 Q4 – 2014 Q1	3	3	76	4
2014 Q1 – 2014 Q2	0	26	79	0
2014 Q2 – 2014 Q3	23	14	82	2
2014 Q3 – 2014 Q4	0	3	96	2
2014 Q4 – 2015 Q1	0	0	99	0
2015 Q1 – 2015 Q2	0	8	99	2
2015 Q2 – 2015 Q3	0	5	107	0
2015 Q3 – 2015 Q4	21	20	91	0
2015 Q4 – 2016 Q1	0	8	111	0
2016 Q1 – 2016 Q2	0	0	119	0
2016 Q2 – 2016 Q3	0	4	119	0
2016 Q3 – 2016 Q4	0	2	123	0
2016 Q4 – 2017 Q1	0	23	125	0
2017 Q1 – 2017 Q2	60	0	88	0
2017 Q2 – 2017 Q3	1	5	87	0
2017 Q3 – 2017 Q4	13	12	79	0
2017 Q4 – 2018 Q1	0	0	91	0
2018 Q1 – 2018 Q2	18	18	73	1
2018 Q2 – 2018 Q3	4	1	87	1
2018 Q3 – 2018 Q4	24	3	64	0
2018 Q4 – 2019 Q1	1	12	66	0
2019 Q1 – 2019 Q2	0	18	78	3
2019 Q2 – 2019 Q3	12	2	84	0
2019 Q3 – 2019 Q4	0	0	86	8

While price changes for continuing microprocessors were becoming less common, the quality of microprocessors continued to improve. For example, Intel introduced its i3-2100 in 2011 Q1 and discontinued it in 2013Q1, when it introduced the i3-3210. Both the i3-2100 and i3-3210 featured 2 cores and 3 MB of cache, but the newer i3-3210 was faster (with a base frequency of 3.20 GHz instead of 3.10 GHz) and drew less power (with a thermal design power of 55 W instead of 65 W). The i3-2100 was listed at $120 from its introduction until its discontinuation. The i3-3210 then entered at a lower price, $117.

As another example, Intel introduced the i5-6400 in 2015 Q3 at a price of $182. In 2017 Q1, it introduced its replacement, the i5-7400, at the same price. Yet, the i5-7400 was faster (with a base frequency 3.0 GHz instead of 2.7 GHz turbo frequency of 3.5 GHz instead of 3.3GHz), while remaining a 4-core processor with the same cache (6 MB) and thermal design power (65 W).

Such product improvements within a set price level were widespread. The mean PassMark score for Intel's product offering rose from 3,484 in 2009 Q1 to 11,221 in 2019 Q4 for microprocessors priced between $200 and $299. For microprocessors between $300 and $399, the mean PassMark score rose from 4,221 to 13,712.

The eight product characteristics have a high degree of explanatory power for price. Table 2 presents regression results of log characteristics on log price in 2017 Q3 and 2017 Q4. Column 1 of Table 2 includes a time dummy indicating the second period (2017 Q4). Column 2 adds indicators for products in their first quarter and products in their last quarter. In both specifications, logged values of the number of cores, number of threads, cache per core, and turbo frequency are highly significant. All product characteristics except the PassMark score have coefficients with the expected sign. In the time-dummy specification (presented in Column 1), the negative time-dummy indicates price deflation. When entry and exit indicators are added in Column 2, the time-dummy measures price change among continuing products, which is zero, as prices and characteristics are static for continuing products.

The regression presented in Column 1 of Table 2 approximates the regression used to calculate the U.S. Producer Price Index for Microprocessors, but the U.S. PPI selects a subset of regressors similar to Sawyer and So (2018) and excludes microprocessors more than 15 months old.

Table 2. Time Dummy Hedonic Regression using full sample, 2017 Q3 - 2017 Q4

	Dependent variable:	
	Log price	
	(1)	(2)
Log PassMark	-0.195	-0.354**
Standard error	(0.173)	(0.171)
Log base frequency	0.228	0.262
Standard error	(0.221)	(0.214)
Log turbo frequency	0.213***	0.234***
Standard error	(0.077)	(0.074)
Log threads	0.567***	0.625***
Standard error	(0.101)	(0.098)

Log cores	1.105***	1.225***
Standard error	(0.137)	(0.134)
Log (cache/cores)	0.609***	0.632***
Standard error	(0.088)	(0.085)
Log TDP	-0.130	-0.057
Standard error	(0.088)	(0.087)
Log graphics	0.052*	0.081***
Standard error	(0.030)	(0.030)
Time dummy	-0.026	-0.000
Standard error	(0.036)	(0.037)
Enter dummy		-0.315***
Standard error		(0.077)
Exit dummy		-0.068
Standard error		(0.072)
Constant	4.322***	5.062***
Standard error	(0.927)	(0.911)
Observations	183	183
R^2	0.921	0.928
Adjusted R^2	0.917	0.924
Residual Std. Error	0.240 (df = 173)	0.229 (df = 171)
F Statistic	223.584*** (df = 9; 173)	201.111*** (df = 11; 171)

*p<0.1; **p<0.05; ***p<0.01

3. Methods

3.1. Simulated Data Generating Processes

Consider a two-period model in which some products exit after the first period, some enter for the second period, and some continue in the market in both periods. Let products be indexed by $i \in I$. Let *A* denote the set of exiting products, *B* the entering products, and *C* the continuing products. Together A, B, and C partition I. Each product i has unchanging, observable characteristics X_i.

We simulate populations and samples for exiting, continuing, and entering products separately. Multivariate normal distributions generate the populations and samples. The parameters of the distributions are the means of the prices and characteristics, and the covariances of the prices and characteristics of the actual data.

In the first period, no products from B have yet entered. First-period log prices and characteristics for exiting and continuing goods are given by joint-normal distributions:

$$log(price_A), X_A = \mathcal{N}(\mu_A, \Sigma_A)$$

$$(1)$$

$$log(price_C), X_C = \mathcal{N}(\mu_C, \Sigma_C)$$

$$(2)$$

Prices for continuing goods remain the same in the second period. Products from A exited by the second period. Log prices and characteristics for entering goods are given by:

$$log(price_B), X_B = \mathcal{N}(\mu_B, \Sigma_B)$$

$$(3)$$

For 2017 Q3 – 2017 Q4 and 2015 Q3 – 2015 Q4, none of the continuing products have price change. For 2014 Q2 – 2014 Q3 and 2012 Q3 – 2012 Q4, we constrain the continuing products to have static prices by calculating the arithmetic mean of each continuing products price from each period, and having that mean be the price for each period.

3.2. Price Index Specifications

No single pricing function is dictated by model assumptions. Although Monte Carlo exercises can simulate the true pricing model, the "true" inflation rate depends on formula choice and weighting. An exact cost-of-living index would require assuming a demand model, for example. Likewise, specific production functions would need to be assumed to calculate a fixed-input output price index. Because products are entering and exiting the index, even a superlative index may not approximate any exact price index.

Nevertheless, the observational relationship between prices and characteristics can still be estimated. A hedonic index may be useful as a summary statistic, even if it lacks a clear structural interpretation. The usefulness of a particular hedonic index may depend on how well it can be estimated with the sample available. To investigate, we create a large population with our data generating process. We then create samples from that same data generating process and calculate several hedonic price indexes.

For any price index formula choice, we can calculate inflation rates in the large, simulated populations and in the small samples. (The data generation process was calibrated with real data, and the inflation rates in the large populations are near the inflation rates in the real data for all the formulae we investigate.) Each sample draw produces a different small sample and, therefore, a different inflation rate for a given formula. With repeated draws, we can estimate the variance of the inflation rates. We also can estimate the average difference from large-population inflation rate from that formula or from any other benchmark. We examine several price index formulae.

Because all the price index formulae we use estimate quality-adjusted price with the ratio of log prices, we must correct for the bias that is introduced from transforming log price ratios to price ratios. The first step of this process is to take the mean of the summation of exponentiated residuals:

$$\hat{\tau}_t = N_t^{-1} \sum_{i=1}^{N_t} e^{\in_{it}}$$

$$(4)$$

where $\in_{it}$ is the regression error for product i in time t and N_t is the number of products in a period. Taking equation *(4)*, the bias adjustment term is

$$\frac{\hat{\tau}_2}{\hat{\tau}_1}$$

(5)

The first index formula is a time-dummy index. This index is an OLS regression with product characteristics and a time-dummy variable for whether an observation is from period 1 or period 2; the time dummy gives a direct measure of price change between the periods and the product characteristics account for changes in the products. The regression model is

$$ln(p_{it}) = \alpha + \beta X_i + \delta I(t = 2) + \epsilon$$

(6)

The index change from period 1 to 2 is

$$(e^{\hat{\delta}} - 1) + \frac{\hat{\tau}_2}{\hat{\tau}_1}$$

(7)

This index is currently used for PPI Microprocessors. It constrains the characteristic coefficients to be the same for both periods. The exiting and continuing products have the same intercept and the continuing and entering products have the same intercept (the time dummy). Neither feature reflects the data generating process. The time-dummy index has the advantage of only having one model estimated on the dataset.

The second index formula is an OLS regression that includes time, exiting good, and entering good coefficients along with characteristic coefficients. The regression equation is

$$\ln(\mathrm{p_{it}}) = \alpha + \beta X_i + \gamma_{\mathrm{A}}\Pi(\mathrm{i} \in \mathrm{A}) + \gamma_{\mathrm{B}}\Pi(\mathrm{i} \in \mathrm{B}) + \delta\Pi(\mathrm{t} = 2) + \epsilon$$

(8)

The results of such a regression could produce price indexes in several ways. If the entry and exit indicators are proxies for unobserved characteristics, then when the continuing products have price change, it would be shown by the time-dummy coefficient. However, if none of the continuing products have price change, the time-dummy coefficient is zero. In this scenario, we would be able to measure constant quality price change from exit and entry of products, which is what we often observe with microprocessors.

Instead, we use the exit, time, and entry dummy coefficients to construct price relatives weighted by the proportion of exiting, entering, and continuing microprocessors. The index change from period 1 to 2 is

$$(e^{(\frac{\#A}{\#A+\#B+\#C}*\widehat{\delta}-\widehat{\gamma}_A)+(\frac{\#B}{\#A+\#B+\#C}*\widehat{\gamma}_B+\widehat{\delta})+(\frac{\#C}{\#A+\#B+\#C}*\widehat{\delta}))}-1)+\frac{\hat{\tau}_2}{\hat{\tau}_1}$$

(9)

Like the time-dummy index, the time-dummy with exit and entry indicators has the same characteristic coefficients for all products. Unlike the time-dummy index, however, the time-dummy with exit and entry indicators index has separate intercepts for exiting, continuing, and entering products.

The two-period hedonic imputation index estimates separate OLS regressions on period 1 and 2. The regressions are used to impute prices for all products in their respective time periods. The imputed log prices are used to make price ratios that are aggregated into a price index, in this case using a Jevons index.

The period 1 regression model is

$$ln(p_{i1}) = \alpha_1 + \beta_1 X_{i1} + \epsilon_1$$

(10)

The period 2 regression model is

$$ln(p_{i2}) = \alpha_2 + \beta_2 X_{i2} + \epsilon_2$$

(11)

The index change from period 1 to 2 is

$$(e^{\left(\frac{\sum_{i=1}^{\#A+\#B+\#C} \widehat{log(p_{i2})}-\widehat{log(p_{i1})}}{\#A+\#B+\#C}\right)}-1)+\frac{\hat{\tau}_2}{\hat{\tau}_1}$$

(12)

The advantage of this method is that period 1 and period 2 have separate intercepts and coefficients. Also, there are enough degrees of freedom in periods 1 and 2 to support models with all 8 variables. The disadvantages are that the exiting and continuing products in period 1 have the same intercepts and coefficients and the continuing and entering products in period 2 have the same coefficients and intercepts.

The third, and last index is the two-period hedonic imputation with Exit and Entry indicators index. This index estimates separate OLS regressions on periods 1 and 2. The regressions are used to impute prices for all products in their respective time periods. The imputed prices are used to make price ratios that are aggregated into a price index. The period 1 regression has an exit indicator, and the period 2 regression has an entry indicator.

The period 1 regression model is

$$ln(p_{i1}) = \alpha_1 + \gamma_A + \beta_1 X_{i1} + \epsilon_1$$

(13)

The period 2 regression model is

$$ln(p_{i2}) = \alpha_2 + \gamma_B + \beta_2 X_{i2} + \epsilon_2 \tag{14}$$

The index change from period 1 to 2 is

$$(\mathrm{e}^{\left(\frac{\sum_{i=1}^{\#A+\#B+\#C} \widehat{ln(p_{i2})} - \widehat{ln(p_{i1})}}{\#A+\#B+\#C}\right)} - 1) + \frac{\hat{\tau}_2}{\hat{\tau}_1} \tag{15}$$

The advantage of this method is that period 1 and period 2 have separate intercepts and coefficients. Also, there are enough degrees of freedom in periods 1 and 2 to support models with all 8 variables. In the first period regression, the exiting products and continuing products have the same coefficients, but different intercepts. In the second period regression, the continuing products and entering products have the same coefficients but different intercepts. The weighting for the time-dummy with exit and entry indicators index and both two-period hedonic imputation indexes is the same.

We do not simulate the two-step method of Erickson and Pakes (2011). Although it is still one of the frontier methods for addressing unobserved quality change in price indexes, estimation in Erickson and Pakes (2011) relies on price change in continuing goods. Under static pricing, its two stages cancel each other exactly.

4. Monte Carlo Results

4.1. Simulated data the same size as the actual data

Our main simulation was run with parameters set to match microprocessors in 2017 Q3 - 2017 Q4. Thirteen microprocessor models exited the market after 2017 Q3, and 12 were introduced in 2017 Q4. We calibrate $\mu_A, \sum_A, \mu_B, \sum_B, \mu_C, \sum_C$ in equations 1-3 to the means and covariance matrices observed in the price and characteristics for exiting, entering, and continuing goods. We generate simulated populations 1,000 times larger than the actual number of observations using the data generating process. For all the price index formulae we examine, the calculated inflation rates are nearly identical in the simulated populations and raw data. We then sample these simulated populations to have the same number of observations as the actual data.

Each price index formula gives a different inflation rate, as shown in Table 3. All the indexes, except the matched-model index, show price decline. The target index for the time-dummy with exit and entry indicators shows the largest decline while the time-dummy target index shows the smallest decline. Entry and exit indicators give both the time-dummy and hedonically-imputed Jevons index a more negative inflation rate, which is consistent with the idea that the proxy for some otherwise unobserved quality that is higher in entering products and lower in exiting products. Yet, without assuming a utility function or production function, no formula has a special claim to giving the one true inflation rate.

Table 3. 2017 Q3 – 2017 Q4 Actual, Target, and Means of Simulation Indexes

Formula	Price change computed from: Actual data	Simulated population	Means of small-sample simulations
Matched-model	0.0000	0.0000	0.0000
Time dummy	-0.0166	-0.0163	-0.0159
Time dummy w/ exit and entry	-0.0211	-0.0208	-0.0218
Jevons index	-0.0186	-0.0178	-0.0186
Jevons w/ exit and entry	-0.0190	-0.0182	-0.0194

We take each formula's inflation rate (as calculated from the full simulated population) as a target and measure the difference with inflation rates in individual small-sample simulations using all the different formulae. We call this difference error, and we calculate root mean squared error (RMSE) for each pairing of a target index and an evaluated index. For all targets, the time-dummy index has the lowest RMSE, as shown in Table 4.

Table 4. 2017 Q3 – 2017 Q4 RMSE

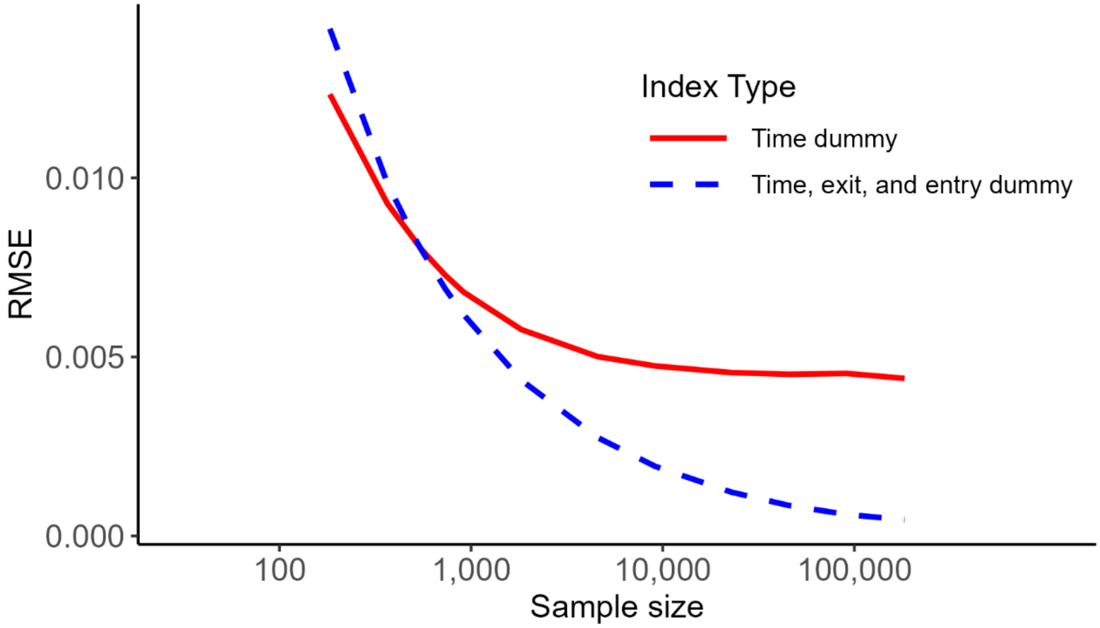
Target index	Evaluated Index: Matched-model	Time dummy	Time dummy w/exit & entry	Jevons index	Jevons w/exit & entry
Time dummy	0.0163	**0.0113**	0.0151	0.0146	0.0160
Time dummy w/exit & entry	0.0208	**0.0123**	0.0142	0.0146	0.0158
Jevons index	0.0178	**0.0115**	0.0147	0.0145	0.0158
Jevons index w/exit & entry	0.0182	**0.0116**	0.0146	0.0144	0.0158

Minimum in **Bold**

4.2. Simulated data with varying sample sizes

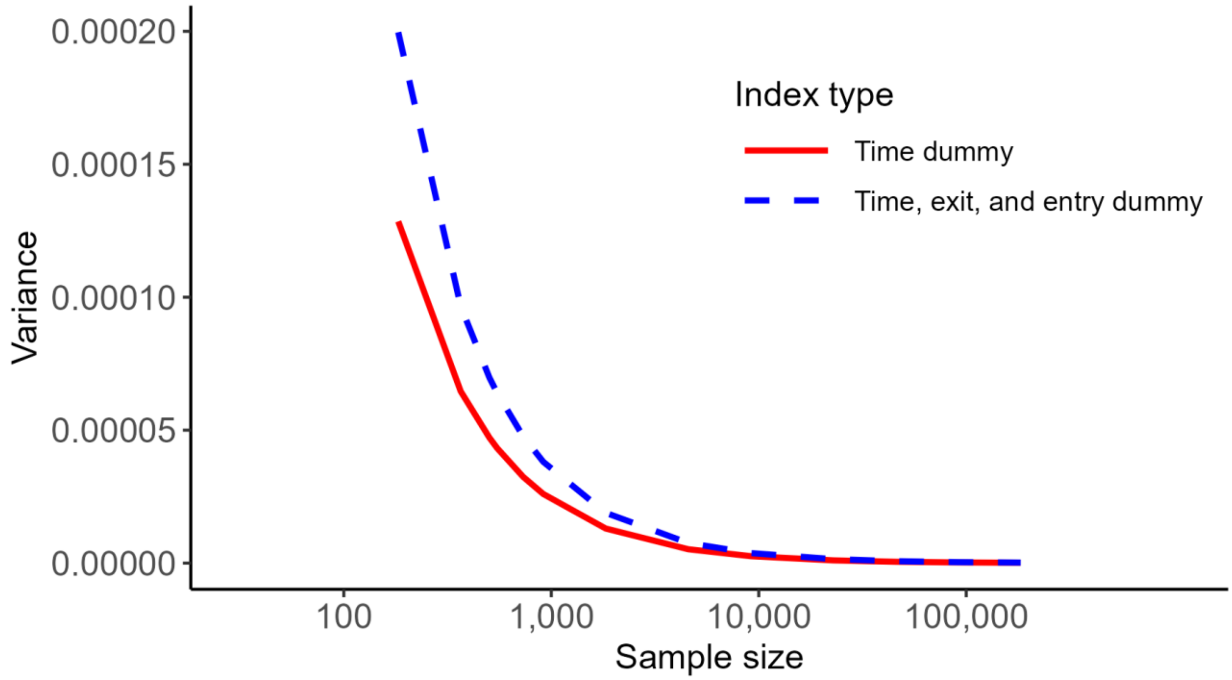
The time-dummy hedonic warrants greater attention because it is currently used in the PPI microprocessors index. To better understand why the time-dummy hedonic consistently outperforms the other hedonics, we created simulations of different sample sizes using 2017 Q3 – 2017 Q4 data to see how the variance and bias (and accordingly, the RMSE) change as the sample size changes. We also include the time-dummy with exit and entry indicators in this second set of simulations because this index shows greater price change than the time-dummy, but worse performance when measured by their respective RMSEs. This greater price change is consistent with the exit and entry indicators capturing quality adjusted price change missed by the time-dummy alone, as we would expect from the data generation process.

Figure 2. RMSE with Time, Exit, and Entry Dummy Target, 2017 Q3 – 2017 Q4



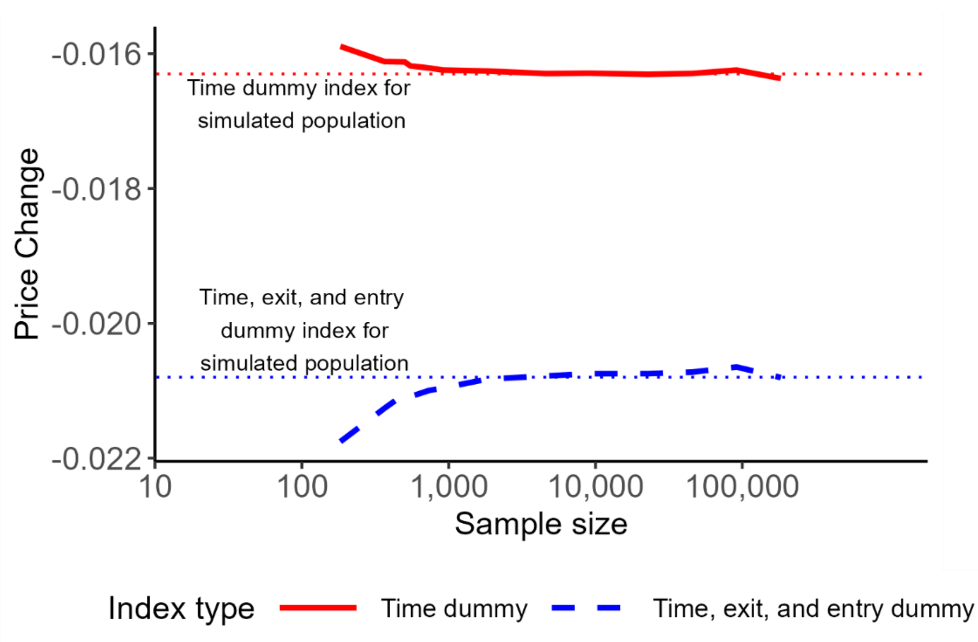
Starting with the time-dummy with exit and entry indicators as the target, Figure 2 shows the RMSE for both the time-dummy and time-dummy with exit and entry indicators rises as the sample size decreases, with the time-dummy with exit and entry indicators having better performance until about a sample size of 500 observations.

Figure 3. Comparison of Variance for Simulated Populations, 2017 Q3 – 2017 Q4



Looking at the variance for different sample sizes for the two types of indexes, Figure 3 shows the time-dummy always has a lower variance for a given sample size, and as sample size decreases, the variance of the time dummy with exit and entry indicators increases at a faster rate.

Figure 4. Comparison of Finite Sample Bias for Simulated Populations, 2017 Q3 – 2017 Q4



Both hedonics in Figure 4 show bias against their simulated population target as sample size decreases, but the size of the bias is relatively small.

The superior performance of the time dummy hedonic, even measured against target indexes produced by other hedonics, is because of the time dummy's relatively low variance. As sample size increases and variance decreases, this advantage disappears.

4.3. Simulations based on other periods

To verify the robustness of the above results, we repeated the simulations on three additional pairs of quarters. In 2015 Q3 – Q4, 2014 Q2 – Q3, and 2012 Q2 – Q3, similar patterns are found. Tables 5, 6, and 7 parallel Table 3 in giving price changes calculated by the various formulas on actual data, on a simulated population (calibrated as described in Section 3, like before), and on small samples drawn from the simulated population (as before).

Matched-model indexes register no price change when there are no prices change on continuing goods, as in 2015 Q3-Q4 (Table 5) and 2012 Q2-Q3 (Table 7). As mentioned in section 3.1, in 2014 Q2-Q3, two continuing products had price change, and so a matched model calculated actual data has a small decrease (leftmost column in Table 6). Because we evaluate static pricing scenarios, we replace the 2014 Q2 and 2014 Q3 prices for these products with their two-period mean price before calibrating the simulations.

Table 5. 2015 Q3 – 2015 Q4 Actual, Target, and Means of Simulation Indexes

	Price change computed from:		
Formula	Actual data	Simulated population	Means of small-sample simulations
Matched-model	0.0000	0.0000	0.0000
Time dummy	-0.0163	-0.0165	-0.0159
Time dummy w/ exit and entry	-0.0194	-0.0195	-0.0194
Jevons index	-0.0159	-0.0160	-0.0159
Jevons index w/ exit and entry	-0.0186	-0.0188	-0.0188

Table 6. 2014 Q2 – 2014 Q3 Actual, Target, and Means of Simulation Indexes

	Price change calculated from:		
Formula	Actual data	Simulated population	Means of small-sample simulations
Matched-model	-0.0026	0.0000	0.0000
Time dummy	-0.0108	-0.0083	-0.0078
Time dummy w/ exit and entry	-0.0112	-0.0092	-0.0093
Jevons index	-0.0122	-0.0111	-0.0112
Jevons index w/ exit and entry	-0.0112	-0.0100	-0.0103

Table 7. 2012 Q3 – 2012 Q4 Actual, Target, and Means of Simulation Indexes

	Price change calculated from:		
Formula	Actual data	Simulated population	Means of small-sample simulations
Matched-model	0.0000	0.0000	0.0000
Time dummy	-0.0391	-0.0390	-0.0356
Time dummy w/ exit and entry	-0.0414	-0.0410	-0.0402
Jevons index	-0.0352	-0.0359	-0.0348
Jevons index w/ exit and entry	-0.0361	-0.0365	-0.0358

The rest of the index formulae show price deflation, with magnitudes differing by a several tenths of a percentage point. In 2015 Q3-Q4, deflation measurements vary from -1.59 to -1.94 percent among the four hedonic indexes (Table 5). In 2012 Q2-Q3, deflation is steeper and measures diverge more, ranging from -3.52 to -4.14 percent (Table 7). The time dummy with exit and entry indicators indicates the steepest deflation in 2015 Q3-Q4 and 2014 Q2-Q3.

Simulations reveal how the imprecision of small sample estimates also varies between models. Tables 8, 9, and 10 parallel Table 4 in displaying the root mean square of difference between the inflation rate calculated by the target index formula on the full simulated population and rate calculated the evaluated index on a small sample. In the simulations based on 2015 data (displayed in Table 8) and 2012 data (displayed in Table 10) the simpler time dummy index has the lowest mean squared error for all target indexes. In all periods adding entry and exit indicators to our time-dummy index increased mean squared error, even for targets based on formulae with entry and exit indicators (compare the second and third columns in Tables 8, 9, and 10). In the 2015-based simulations, adding entry and exit indicators to the Jevons specification increases mean squared error no matter the target from which it is computed. In the 2014-based simulation (displayed in Table 9), deflation was small enough that the matched model, with its zero inflation, was sometimes closer to the full population rates than any of the small sample hedonic index estimates. Only when the target index was the full population Jevons index did one of the hedonic indexes have a lower mean squared error. That hedonic index was the simple time dummy rather than the small sample Jevons index itself. Thus, in all periods we analyzed the time dummy hedonic had the lowest squared error of any of the hedonics run on small samples.

Table 8. 2015 Q3 – 2015 Q4 RMSE

	Evaluated Index				
Target index	Matched-model	Time dummy	Time dummy w/exit & entry	Jevons index	Jevons index w/exit & entry
Time dummy	0.0165	**0.0076**	0.0101	0.0089	0.0103
Time dummy w/exit & entry	0.0195	**0.0084**	0.0096	0.0095	0.0101
Jevons index	0.0160	**0.0076**	0.0102	0.0089	0.0104
Jevons index w/exit & entry	0.0188	**0.0081**	0.0097	0.0093	0.0100

Minimum in **Bold**

Table 9. 2014 Q2 – 2014 Q3 RMSE

	Evaluated Index				
Target index	Matched-model	Time dummy	Time dummy w/exit & entry	Jevons index	Jevons index w/exit & entry
Time dummy	**0.0083**	0.0098	0.0118	0.0167	0.0156
Time dummy w/exit & entry	**0.0092**	0.0099	0.0117	0.0165	0.0155
Jevons index	0.0111	**0.0103**	0.0118	0.0164	0.0155
Jevons index w/exit & entry	**0.0100**	0.0101	0.0117	0.0165	0.0155

Minimum in **Bold**

Table 10. 2012 Q3 – 2012 Q4 RMSE

	Evaluated Index				
Target index	Matched-model	Time dummy	Time dummy w/exit & entry	Jevons index	Jevons index w/exit & entry
Time dummy	0.0390	**0.0154**	0.0160	0.0196	0.0194
Time dummy w/exit & entry	0.0410	**0.0159**	0.0159	0.0202	0.0198
Jevons index	0.0359	**0.0150**	0.0165	0.0192	0.0192
Jevons index w/exit & entry	0.0365	**0.0150**	0.0163	0.0193	0.0192

Minimum in **Bold**

5. Conclusion

Static pricing is a central feature of the microprocessor market we study. The lack of price changes on continuing products violates the assumptions of some common models. Instead, a data generating process that allows for static pricing is needed to evaluate price index performance.

For small sample sizes (like those often found in the PPI), the pure time-dummy hedonic has lower variance and lower MSE than other specifications, regardless of the population index benchmark from which that error is computed. If it is thought that entry and exit indicators control for unobserved quality changes, then the time dummy with entry and exit indicators calculated on the full simulated population might be the preferred benchmark. Such a benchmark reveals a bias-variance tradeoff. If that were the true inflation rate, then the pure time-dummy hedonic would be biased, but on small samples would give lower MSE than even the time-dummy with entry and exit itself.

With the multitude of different hedonic methods and potential combinations of variables, judgmental selection of a hedonic is difficult. Monte Carlo simulations can bring new facts to light and add transparency to the evaluation of different hedonic options. Simulations allow different hedonic methods and specifications to be evaluated against a range of target indexes. For microprocessors during this period, sample size affects performance of different specifications so greatly that even the choice of which formula's benchmark to target became secondary. In our case, a much larger sample would be needed for a time-dummy with entry and exit indicators to have lower MSE even if the model with entry and exit indicator is assumed to better fit the data generating process. Because the performance of hedonic index variations is so situationally specific, Monte Carlo simulations can be a valuable tool in evaluating and applying hedonics for price index analysts, such as those in the PPI.

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