A Note on Bias Adjustment of the Time Dummy Hedonic Index

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Abstract: In this note, I derive an bias adjustment term for the Time Dummy Hedonic price index, which is slightly smaller than the adjustment term proposed in the academic literature. I also argue that these bias adjustment terms are inappropriate from a survey sampling perspective when all the items sold are observed and the prices (unit values) are measured without error.

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1. Introduction

The standard Time Dummy Hedonic (TDH) regression model, where the exponent of the parameter for the time dummy variables defines a quality-adjusted price index, has been frequently applied by academic researchers. The estimated index is biased because exponentiation is a nonlinear operation, and a bias adjustment term can be found in the literature. In this note, I review the bias adjustment.

After describing the hedonic model, section 2 derives an alternative adjustment term. Section 3 looks at the bias issue from a survey sampling rather than econometric perspective and focuses on the case when all the items sold are observed and the prices are measured without error. Section 4 concludes.

2. Bias adjustment

The TDH model explains the price of each item *i*, p_i^t, in terms of its characteristics z_{ik} $(k = 1,..., K)$ and time *t* $(t = 0,...,T)$. While time is continuous, prices and quantities are observed in discrete time periods. For some period *t*, the multiplicative TDH model can be expressed as

$$p_i^t = \exp(¢^t)\exp\left[\sum_{k=1}^{K} {}_k z_{ik}\right], \tag{1}$$

where $\exp(¢^t)$ measures the effect of time and $\exp[\sum_{k=1}^{K} {}_k z_{ik}]$ measures the combined effect of the characteristics; the characteristics parameters ${}_k$ are assumed fixed across time. For later use, both effects have been written in exponential form. Our interest lies in $\exp(¢^t)$ as this defines the quality-adjusted price index $P_{TDH}^{0t} = \exp(¢^t) = p_i^t / p_i^0$.

Equation (1) is deterministic, which is obviously unrealistic. One option to turn it into a stochastic model would be to add multiplicative errors u_i^t with $E(u_i^t) = 1$, where $E(.)$ is the expectation operator:[1]

$$p_i^t = \exp(¢^t)\exp\left[\sum_{k=1}^{K} {}_k z_{ik}\right]u_i^t. \tag{2}$$

The quality-adjusted index is now given by $P_{TDH}^{0t} = \exp(¢^t) = E(p_i^t)/E(p_i^0)$. Taking the (natural) logarithm of (2) yields

[1] Strictly speaking, it should be referred to as the expectation conditional on the design matrix.

$$\ln p_i^t = \delta^t + \sum_{k=1}^{K} \beta_k z_{ik} + \varepsilon_i^t . \tag{3}$$

The expected value of the error terms $\varepsilon_i^t = \ln(u_i^t)$ in (3) can be approximated as follows. The second-order Taylor series expansion of $\ln(u_i^t)$ at 1 is

$$\ln u_i^t \simeq \left[u_i^t - 1\right] - \frac{1}{2}\left[u_i^t - 1\right]^2 , \tag{4}$$

and taking expectations of (4) gives

$$E(\varepsilon_i^t) = E(\ln u_i^t) \simeq E\left[u_i^t - 1\right] - \frac{1}{2} E\left[(u_i^t - 1)^2\right] = -\operatorname{var}(u_i^t)/2 , \tag{5}$$

where $\operatorname{var}(u_i^t) = E[(u_i^t - 1)^2]$ denotes the variance of u_i^t. I will return to the implications of the non-zero expected value of the errors ε_i^t below.

By pooling the data of all the time periods $0,...,T$, the estimating equation for the TDH model becomes

$$\ln p_i^t = \alpha + \sum_{t=1}^{T} \delta^t D_i^t + \sum_{k=1}^{K} \beta_k z_{ik} + \varepsilon_i^t , \tag{6}$$

where the time dummy variable D_i^t has the value 1 if the price observation pertains to period *t* and 0 otherwise. As usual, an intercept term has been included in (6), and the dummy variable for period 0 has been left out to identify the model. I assume that (6) is estimated by Ordinary Least Squares (OLS) regression, yielding coefficients $\hat{\alpha}$, $\hat{\delta}^t$ and $\hat{\beta}_k$. The standard estimator of $\exp(\delta^t)$ is given by

$$\hat{P}_{TDH}^{0t} = \exp(\hat{\delta}^t) = \frac{\hat{p}_i^t}{\hat{p}_i^0} , \tag{7}$$

where $\hat{p}_i^0 = \exp(\hat{\alpha})\exp(\sum_{k=1}^{K} \hat{\beta}_k z_{ik})$ and $\hat{p}_i^t = \exp(\hat{\alpha})\exp(\hat{\delta}^t)\exp(\sum_{k=1}^{K} \hat{\beta}_k z_{ik})$ define the predicted prices.

For two reasons, $\hat{P}_{TDH}^{0t}$ is not an unbiased estimator of $\exp(\delta^t)$. Firstly, because $E(\varepsilon_i^t) \neq 0$, the OLS parameter estimators, including $\hat{\delta}^t$, are generally biased. Secondly, because taking the antilogarithm is a nonlinear operation, $\exp[E(\hat{\delta}^t)]$ will differ from $E[\exp(\hat{\delta}^t)]$. To obtain an approximation for the expected value of $\hat{P}_{TDH}^{0t}$, I will proceed as follows.

The difference between $\hat{\delta}^t$ and $E(\hat{\delta}^t)$ is likely to be small. The second-order Taylor series expansion of $\exp[\hat{\delta}^t - E(\hat{\delta}^t)]$ at 0 is

$$\exp\left[\hat{¢}^t - E(\hat{¢}^t)\right] \simeq 1 + \left[\hat{¢}^t - E(\hat{¢}^t)\right] + \frac{1}{2}\left[\hat{¢}^t - E(\hat{¢}^t)\right]^2. \quad (8)$$

Taking expectations of (8) yields

$$E\left[\exp\left[\hat{¢}^t - E(\hat{¢}^t)\right]\right] \simeq 1 + E\left[\hat{¢}^t - E(\hat{¢}^t)\right] + \frac{1}{2}E\left[\left[\hat{¢}^t - E(\hat{¢}^t)\right]^2\right]. \quad (9)$$

Thus, the expected value of $\hat{P}^{0t}_{TDH}$ can be approximated by

$$E(\hat{P}^{0t}_{TDH}) = E\left[\exp(\hat{¢}^t)\right] \simeq \exp\left[E(\hat{¢}^t)\right]\left[1 + \text{var}(\hat{¢}^t)/2\right], \quad (10)$$

with $\text{var}(\hat{¢}^t) = E[(\hat{¢}^t - E(\hat{¢}^t))^2]$. Writing $E(\hat{¢}^t)$ as $¢^t + [E(\hat{¢}^t) - ¢^t]$, where $E(\hat{¢}^t) - ¢^t$ is the bias of $\hat{¢}^t$, gives

$$E(\hat{P}^{0t}_{TDH}) \simeq \exp(¢^t)\left[1 + \text{var}(\hat{¢}^t)/2\right]\exp\left[E(\hat{¢}^t) - ¢^t\right]. \quad (11)$$

Equation (11) provides an approximate decomposition of the expected value of the standard TDH index $\hat{P}^{0t}_{TDH}$ into the "true" index $\exp(¢^t)$ and two bias components. The first bias component, $1 + \text{var}(\hat{¢}^t)/2$, is strictly greater than 1 because $\text{var}(\hat{¢}^t) > 0$. This component decreases as the sample size increases; it is a form of "small-sample bias". Whether the second bias component, $\exp[E(\hat{¢}^t) - ¢^t]$, is greater or smaller than 1 depends on the distribution of the (multiplicative) errors u_i^t in (3).

An assumption I am happy to make is that the variance of the errors u_i^t in (3) is the same for all items *i* and constant across all periods *t*, i.e. $\text{var}(u_i^t) = ±^2$. In this case we have $E(£_i^t) \simeq -±^2/2$ for the errors in the estimating equation (6). Since $-±^2/2$ is a "constant" term, estimating (6) by OLS regression will produce approximately unbiased parameter estimates – except of course for the intercept $\sim$, but that is not relevant for our purpose – and the second bias component in (11) will be approximately equal to 1. I therefore propose the following estimator of $P^{0t}_{TDH} = \exp(¢^t)$:

$$\tilde{P}^{0t}_{TDH} = \frac{\hat{P}^{0t}_{TDH}}{\left[1 + \text{var}(\hat{¢}^t)/2\right]}. \quad (12)$$

The derivation of (12) was based on the stochastic model specification (3). The same result is found if we first took the logarithm of (1) and then added (additive) errors $£_i^t$ with $E(£_i^t) = 0$, in which case $P^{0t}_{TDH} = \exp(¢^t) = \exp[E(\ln p_i^t)]/\exp[E(\ln p_i^0)]$. This is actually the usual approach. Estimating (6) by OLS now provides unbiased estimators $\hat{¢}^t$, albeit not necessarily with minimal variance, and so the second bias component of

(11) vanishes. We cannot check which assumption regarding the errors in equations (3) and (6) is "best", but I prefer the usual assumption $E(\text{£}_i^t) = 0$.

The proposed adjustment differs from the adjustment in the academic literature. Drawing on Goldberger (1968), Kennedy (1981) proposed the following estimator of $P_{TDH}^{0t} = \exp(\text{¢}^t)$:

$$\widehat{P}_{TDH}^{0t} = \exp\left[\hat{\text{¢}}^t - \mathrm{var}(\hat{\text{¢}}^t)/2\right] = \frac{\exp(\hat{\text{¢}}^t)}{\exp\left[\mathrm{var}(\hat{\text{¢}}^t)/2\right]} = \frac{\hat{P}_{TDH}^{0t}}{\exp\left[\mathrm{var}(\hat{\text{¢}}^t)/2\right]}. \qquad (13)$$

Given that $1 + \mathrm{var}(\hat{\text{¢}}^t)/2 < \exp[\mathrm{var}(\hat{\text{¢}}^t)/2]$, my bias adjustment turns out to be smaller than Kennedy's (1981) proposal, hence $\tilde{P}_{TDH}^{0t} > \widehat{P}_{TDH}^{0t}$.

Note that the second-order Taylor series approximation of $\exp[\mathrm{var}(\hat{\text{¢}}^t)/2)]$ is equal to $1 + \mathrm{var}(\hat{\text{¢}}^t)/2 + [\mathrm{var}(\hat{\text{¢}}^t)]^2/4$. Since the quadratic term will be extremely small, the first-order approximation $\exp[\mathrm{var}(\hat{\text{¢}}^t)/2)] \simeq 1 + \mathrm{var}(\hat{\text{¢}}^t)/2$ most likely holds true so that the two bias adjustments are approximately equal and should in practice produce very similar results. Anyway, the bias problem is of little practical importance: there is abundant empirical evidence indicating that, unless the sample is extraordinary small, we can ignore the bias of the standard estimator $\hat{P}_{TDH}^{0t}$.

Table 1: Results from a pooled OLS TDH regression for TVs

	TD coefficient	Standard error	TDH index	exp(variance/2)	1+ variance/2
Feb 2015	-0.0148648	0.0319951	0.9852451	1.0005120	1.0005118
Mar 2015	-0.0241579	0.0317302	0.9761316	1.0005035	1.0005034
Apr 2015	0.0473072	0.0305772	1.0484440	1.0004676	1.0004675
May 2015	0.0519111	0.0295949	1.0532821	1.0004380	1.0004379
Jun 2015	0.0612632	0.0294647	1.0631788	1.0004342	1.0004341
Jul 2015	0.0338776	0.0284843	1.0344580	1.0004058	1.0004057
Aug 2015	0.0355484	0.0280608	1.0361878	1.0003938	1.0003937
Sep 2015	0.0227978	0.0280583	1.0230597	1.0003937	1.0003936
Oct 2015	0.0028196	0.0279725	1.0028236	1.0003913	1.0003912
Nov 2015	-0.0335770	0.0276054	0.9669805	1.0003811	1.0003810
Dec 2015	-0.0879583	0.0274085	0.9157991	1.0003757	1.0003756
Jan 2016	-0.1874503	0.0275679	0.8290703	1.0003801	1.0003800
Feb 2016	-0.1500560	0.0278548	0.8606598	1.0003880	1.0003880
Mar 2016	-0.1390535	0.0287470	0.8701815	1.0004133	1.0004132
Apr 2016	-0.1485559	0.0282679	0.8619518	1.0003996	1.0003995
May 2016	-0.1026757	0.0281376	0.9024196	1.0003959	1.0003959
Jun 2016	-0.1152131	0.0402686	0.8911762	1.0008111	1.0008108

Note: "variance" is estimated by the squared standard error of the TD coefficient; # observations is 2,447; *R* squared is 0.936. The parameter estimates for the characteristics can be found in the Appendix.

To illustrate these points, I ran a pooled (OLS) TDH regression on scanner data for TVs from a Dutch retail chain, covering the period January 2015 to June 2016 (with January 2015 as the base period). Table 1 contains the relevant regression results, i.e. the estimated time dummy parameters and the standard errors as well as the unadjusted TDH index and the bias adjustments. As expected, the two bias adjustments are tiny and very similar, the adjustment I proposed being marginally smaller than the adjustment proposed by Kennedy (1981).[2]

3. A survey sampling perspective

I assume that (3) with $E(\varepsilon_i^t) = 0$ is the appropriate hedonic model. We then have

$$P_{TDH}^{0t} = \exp(\delta^t) = \exp\left[E(\ln p_i^t) - E(\ln p_i^0)\right] = \frac{\exp\left[E(\ln p_i^t)\right]}{\exp\left[E(\ln p_i^0)\right]}. \tag{14}$$

In econometrics, modelling is viewed as a data generating process; prices in the hedonic model (3) are treated as random variables. It is typically assumed that the model applies to an almost infinite population, or "superpopulation", and that the observed products pertain to a sample drawn from this (super)population. Sampling introduces additional randomness. The distribution of the error terms is thought to capture both sources of stochastics.

In this section, I look at the bias issue from a survey sampling or "statistical" perspective. I assume that *i*) prices are measured without error, and *ii*) the population of items sold within a product category is finite and observed in its entirety. Initially, I also assume that *iii*) there are no new and disappearing products; the finite population U is fixed over time. The finite population counterpart to the "superpopulation-based" price index (14) is

$$P^{0t} = \frac{\exp\left[\sum_{i \in U} \ln p_i^t / N\right]}{\exp\left[\sum_{i \in U} \ln p_i^0 / N\right]} = \frac{\prod_{i \in U} (p_i^t)^{\frac{1}{N}}}{\prod_{i \in U} (p_i^0)^{\frac{1}{N}}} = \prod_{i \in U} \left(\frac{p_i^t}{p_i^0}\right)^{\frac{1}{N}}, \tag{15}$$

[2] I have to admit that I find Kennedy's (1981) derivation and the related literature on the bias adjustment, including e.g. van Garderen and Sha (2002) and van Dalen and Bode (2004), difficult to follow. I also got confused because both the CPI manual (ILO et al., 2004) and Triplett (2006) (erroneously) mention that half the variance of $\hat{\delta}^t$ should be *added* to $\hat{\delta}^t$ before exponentiation when using Kennedy's adjustment. I thank Kevin Fox for drawing my attention to this error in the literature.

where *N* denotes the size of *U*, i.e. the number of products sold. From a survey sampling perspective, there are no stochastics involved, and the price index defined by (15) will be completely deterministic.

Let us now relax assumption *iii*) to allow for new and disappearing products. U^0 and U^t, with sizes N^0 and N^t, denote the populations of products sold in periods 0 and *t*. We have $U^0 = U_M^{0t} \cup U_D^{0(t)}$, where U_M^{0t} is the sub-population of matched products sold in both period 0 and period *t*, and $U_D^{0(t)}$ is the sub-population of disappearing products sold in period 0 but not in period *t*; similarly, $U^t = U_M^{0t} \cup U_N^{t(0)}$, where $U_N^{t(0)}$ is the sub-population of new products sold in period *t* but not in period 0.

All the products sold in periods 0 and *t* should be considered when making price and quantity comparisons. Thus, the dynamic finite population counterpart to (15) must be defined on the *union* $U^{0t} = U^0 \cup U^t$ with size N^{0t} (see also de Haan, 2005), that is

$$P^{0t} = \frac{\prod_{i \in U^{0t}} (p_i^t)^{\frac{1}{N^{0t}}}}{\prod_{i \in U^{0t}} (p_i^0)^{\frac{1}{N^{0t}}}} = \prod_{i \in U^{0t}} \left(\frac{p_i^t}{p_i^0} \right)^{\frac{1}{N^{0t}}}. \tag{16}$$

Obviously, the period *t* prices for $i \in U_D^{0(t)}$ and period 0 prices for $i \in U_N^{t(0)}$ in (16) are unobservable, or “missing”, and they have to be imputed by $\hat{p}_i^t$ and $\hat{p}_i^0$. By writing U^{0t} as $U^t \cup U_D^{0(t)}$ in the numerator of the first expression of (16) and as $U^0 \cup U_N^{t(0)}$ in the denominator, the finite population index becomes

$$P^{0t} = \left[\frac{\prod_{i \in U^t} p_i^t}{\prod_{i \in U^0} p_i^0} \right]^{\frac{1}{N^{0t}}} \left[\frac{\prod_{i \in U_D^{0(t)}} \hat{p}_i^t}{\prod_{i \in U_N^{t(0)}} \hat{p}_i^0} \right]^{\frac{1}{N^{0t}}}. \tag{17}$$

I now make the additional assumption that *iv*) the populations U^0 and U^t, hence the union U^{0t} and its size N^{0t}, are non-stochastic. This assumption seems appropriate from a survey sampling perspective. In this case, the first component in (17) is also non-stochastic because the observed prices do not result from a stochastic process and are measured without error (assumption *i*)). This is different for the second component in (17) since modelling is required to predict the “missing” prices.

The estimating equation (6) is now viewed as a purely *descriptive* (rather than stochastic) model. The error terms, or actually the regression residuals, merely reflect that the model cannot perfectly describe the data. I assume that (6) is estimated by OLS regression on the pooled data of all periods $t = 0,...,T$, as before, and that the predicted values $\hat{p}_i^0 = \exp(\hat{\alpha})\exp(\sum_{k=1}^{K} \hat{\beta}_k z_{ik})$ and $\hat{p}_i^t = \exp(\hat{\alpha})\exp(\hat{\delta}^t)\exp(\sum_{k=1}^{K} \hat{\beta}_k z_{ik})$ will serve as imputed prices in (18). A number of points are worth noting.

First, the standard TDH index estimator $\hat{P}_{TDH}^{0t}$, given by equation (3), is equal to (17). This is due to the OLS orthogonality property that the regression residuals sum to zero in every time period; with $\sum_{i \in U^0} (\ln \hat{p}_i^0 - \ln p_i^0) = 0$ and $\sum_{i \in U^t} (\ln \hat{p}_i^t - \ln p_i^t) = 0$, we have $\prod_{i \in U^0} \hat{p}_i^0 = \prod_{i \in U^0} p_i^0$ and $\prod_{i \in U^t} \hat{p}_i^t = \prod_{i \in U^t} p_i^t$, so that equation (17) simplifies to $P^{0t} = \prod_{i \in U^{0t}} (\hat{p}_i^t / \hat{p}_i^0)^{1/N^{0t}} = \exp(\hat{\delta}^t) = \hat{P}_{TDH}^{0t}$.

Second, under assumptions *i*), *ii*) and *iv*), only the second component of equation (17) has uncertainty. This implies that the bias adjustments for $\hat{P}_{TDH}^{0t}$ discussed in section 2, which assume that the first component is stochastic, are inappropriate. Importantly, if there are no new and disappearing items, $\hat{P}_{TDH}^{0t}$ is non-stochastic from a survey sampling perspective. From an econometrics perspective, $\hat{P}_{TDH}^{0t}$ remains stochastic and adjusting for bias would still be required.

Third, the imputed prices are out-of-sample predictions, but it will be difficult to assess their accuracy. It does suggest that a parsimonious regression model, with only the most important price-determining characteristics included, is preferred over a model with many independent variables. The latter model could suffer from overfitting, which makes out-of-sample prediction problematic.

Fourth, because some prices are "missing", the prices data set is incomplete, and we can interpret the observed data set as a sample from the true underlying data set that includes the unobservable prices. Also, the imputations are model-dependent. So, even from a survey sampling perspective, the second component of (17) should be treated as stochastic. However, it will be difficult to measure the impact on the accuracy of $\hat{P}_{TDH}^{0t}$ in terms of its mean square error.

Fifth, assumption *i*) is crucial. The price for a homogeneous product is measured without error only if it is calculated as the unit value across the observation period, i.e. as the value divided by the quantity sold.[3] But if prices are measured at a single point in time during the observation periods, or as averages of a few price quotations, which is what statistical agencies have traditionally been doing, they do have measurement error (Balk, 2004). With sampling in time, prices must be treated as stochastic variables, and the proposed bias adjustment may or may not be useful.

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[3] For details, see ILO et al. (2004). Diewert, Fox and de Haan (2016) discuss the bias that arises when the frequency of calculating unit values does not align with the publication frequency.

4. Conclusion

In this note, I proposed an alternative bias adjustment term for the TDH index, which is smaller than the adjustment term proposed in the literature. I argued that they will lead to similar results in practice and also argued that if all the products sold are observed and the prices (unit values) are measured without error, like in most scanner data sets, then the econometrics-based bias adjustments are inappropriate from a survey sampling perspective. Anyway, the bias problem is of little practical importance; all the available empirical evidence, including the evidence presented in section 2, suggests that it is safe to ignore the bias.

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Appendix: Regression results

Table A.1 shows the OLS parameter estimates and standard errors for the characteristics included in the empirical regression model for TVs discussed in section 2.

Table A.1: Regression results, excluding time dummies

Variable	Coefficient	Standard error	t-statistic
Intercept	6.2264181	0.0351743	177.02
Brand			
'Low quality'	-0.1332732	0.0232081	-5.74
Philips	-0.0561047	0.0184054	-3.05
Panasonic	0.0647752	0.0279184	2.32
Samsung	0.0650328	0.0202745	3.21
Sony	0.1759336	0.0172706	10.19
Processor			
Single core	-0.0399569	0.0160967	-2.48
Quad core	0.0806517	0.0174920	4.61
Hexa/Octa core	0.2648286	0.0276823	9.57
Screen type			
OLED	0.7057137	0.0339220	20.80
Screen size			
<29	-0.2607026	0.0191251	-13.63
40	0.2750528	0.0199359	13.80
42-47	0.4343349	0.0213964	20.30
48-50	0.5978358	0.0201487	29.67
55	0.8588598	0.0224967	38.18
>55	1.3674641	0.0292151	46.81
Screen curvature			
Not curved	-0.2350841	0.0154377	-15.23
Resolution			
'Low'	0.0912865	0.0216240	4.22
3840x2160	0.3778351	0.0148433	25.45
Energy class			
A+	0.0163054	0.0121391	1.34
A++	-0.0152320	0.0229782	-0.66
B	-0.0288773	0.0163831	-1.76
Dlna			
No	0.0659904	0.0142359	4.64
3D			
No	-0.1368229	0.0118787	-11.52
Internet			
No	-0.1692378	0.0236574	-7.15
Video on Demand			
No	-0.0274138	0.0158212	-1.73
Satellite receiver			
No	-0.0670860	0.0141992	-4.72

Note: all the coefficients except Energy class and Video on Demand differ significantly from 0 at the 5%-level.