A.Collins
A.E. Scorcu
R.Zanola

Sample Selection Bias and Time Instability of Hedonic Art Price Indexes

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Abstract: The uniqueness of art objects need to be taken into account in the construction of any art market price index. Yet the most widely used methods typically rely on biased samples, discarding a very large proportion of the information available (the repeated sales approach) and/or require strong assumptions regarding the structure and time stability of the market (the hedonic regression approach). In this paper a refined hedonic index is developed that explicitly addresses these problems. An empirical illustration comparing these methods is presented using a dataset of symbolist paintings appearing at auction over the period 1990-2001.

A.Collins - Department of Economics,
University of Portsmouth Business School,
Portland Street, Portsmouth P01 3DE, England,
e-mail: alan.collins@port.ac.uk

A.E. Scorcu - Department of Economics,
University of Bologna,
Strada Maggiore 45, 40125 Bologna, Italy,
e-mail: scorcu@spbo.unibo.it

R.Zanola - Department of Public Policy and Public Choice,
University of Eastern Piedmont,
Corso Borsalino 83, 15100 Alessandria, Italy,
e-mail: zanola@sp.unipmn.it

1. Introduction

A key and distinctive characteristic of the art market is the uniqueness of the art works. This feature contributes to the emergence of important differences in market exchanges characteristics, some of which are typified by very high transaction costs. Owing to such uniqueness, individual prices cannot easily be aggregated into sufficiently large homogeneous groups and the price of a specific art work can only rarely be observed, even over very long periods of time, often spanning decades. Thus in order to construct a price index for the art market, it is necessary to control for the non-temporal idiosyncratic determinants of price variations. The two most important empirical approaches that address these issues are the repeat-sales method (RSM) and the hedonic price method (HPM).[1] Yet these approaches have been subject to fierce criticism, principally because of their treatment of two key modelling problems, namely sample selection bias and time instability in the index.

It is thus timely and logical to consider whether methods which directly address these issues could actually lead to more reliable and significantly different numerical results in comparison with standard approaches. In particular, the purpose of this paper is to develop a hedonic price index that explicitly takes into account the time instability in the coefficients of hedonic regressions and also the problem of sample selection bias. Further, the paper compares the price indexes based on this refined approach with a standard hedonic index. An empirical illustration is made in the context of a dataset of Symbolist painters' work, sold worldwide during the period 1990-2001 by the major auction houses.

The rest of the paper is structured as follows. Section 2 provides a brief overview of the econometric concerns with the (hitherto) dominant approaches in the context of the relevant empirical literature. Section 3 details the methodology of a hedonic index that explicitly addresses the sample selection and time instability issues. Section 4 briefly describes the data and the key prior expectations for the illustrative model being estimated. Results are reported in Section 5. Some concluding remarks are then offered in Section 6.

2. Art Market Price Indexes: A Critical Appraisal of the Empirical Literature

In this section the two most widely used methods for the construction of art market price indices are outlined and their main methodological shortcomings highlighted. The RSM controls for uniqueness by using the transacted prices of the same item in different time periods. Provided that

[1] Alternative methods for computing an art price index include the representative painting method (Candela and Scorcu, 1997) and the hybrid method (Locatelli Biey and Zanola, 2005).

the idiosyncratic hedonic characteristics (and their implicit prices) do not change between sales, the price differences can be explained via time dummies and the price index can be obtained directly from the corresponding estimated time coefficients (Ginsburgh, Mei and Moses, 2006)

Nevertheless, the method has some major drawbacks. By its very nature, the sample of art objects sold, at least twice, at auction is non-random. The decision to put the item on sale for the second time is endogenous and depends upon idiosyncratic seller characteristics (which influences the level of her reserve price), on market conditions and the probability of a sale being achieved. Moreover, repeated sales represent only a small (and possibly biased) fraction of all the transactions that have occurred. In large part this is due to (i) the efficiency of the auction mechanism in assigning the object of the bidder with the highest reservation price and the assumed persistence in individual preference structure, because of collectors' strong habits (Case *et al.*, 1991; Wallace and Meece, 1997)[2] and (ii) the existence of significant transaction costs in the form of auction house fees. Moreover, the processing of new information about the repeated sales of a given period influences the estimated coefficients (and therefore the price index) of that particular period and also of the previous periods included in the sample. The revisions in the indexes due to the inclusion of updated information can be significant, particularly in small samples, as is often the case in art market studies. As a consequence, this approach has often been criticised for its inefficiency and the emergence of a significant sample selection bias.

The hedonic price method represents the main alternative method in the construction of an art price index (Ginsburgh, Mei and Moses, 2006). Hedonic regression estimates the implicit price to each of the time-invariant and time-varying characteristics of the item. The price index is then computed from the series of time dummies coefficients for a single regression equation.

Although large numbers of observations are typically available in art market datasets as compared to those used in repeat sales models, the recent literature on hedonic price indexes has also featured concern about some enduring issues. These are the instability of the estimated coefficients in hedonic regressions and the reliability and the interpretation of the time dummies (Berndt and Rappaport, 2001; Munneke and Slade, 2000; Pakes, 2003). In this context a time dummy is usually considered the price of a 'standard' painting, having controlled for all other hedonic characteristics. The approach requires strong assumptions. Even if the (unobservable) idiosyncratic effects are independent of the observable variables included in the regression equation and the functional form is adequate, market conditions change over time. Further, the estimation of a single hedonic regression equation for many time periods can bias the estimates of the time dummies (Chanel et al., 1996). A further issue is (again) the presence of sample-selection bias,

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[2] Usually it is assumed that the preference structure of the typical collector changes only slowly over time, possibly because of the existence of habits formation, with the exceptions of the so called 3Ds (Death, Debit and Departure).

particularly as the relevant information set used in the model estimation typically comprises only the transactions actually carried out, i.e. neglecting buy-ins which consist of unsold items whose hammer prices have not met the sellers' reserve prices (Beggs and Graddy, 2006)[3].

3. A Refined Hedonic Price Index: Methodology

The crucial importance of buy-ins is widely known in the art market. There are a high proportion of unsold items in the auction process due to reservation prices not being met. As a consequence, price indexes can suffer from non-randomness in the data used. A sample based only on sold art objects systematically excludes the 'less fashionable' art objects, inducing a bias in the sample price dynamics (Goetzmann, 1996). Accordingly, they may not represent the whole relevant art market.

To address this problem, it is possible to apply the Heckman two-stage procedure. In this context, it requires the estimation of a probit model to predict whether an art object is sold or remains unsold. Probit estimates are then used to evaluate the presence of, and to correct for, any sample-selection bias.[4] More formally, suppose that two latent variables are generated by:

$$P_i^* = X_i^{'}\beta + \varepsilon_i \tag{1}$$

$$Y_i^* = Z_i^{'}\gamma + \eta_i \tag{2}$$

where the dependent variable P_i* is the (logged) auction price of item i which is observed only for the items actually sold at auction; X_i is the set of relevant time-invariant characteristics; β is the vector of the shadow prices of the characteristics of the art object; ε_{i} is the error term; Y_i* is the unobserved propensity to select into sample; Z_i is the vectors of regressors containing common components with X_i; and the errors ε_i and η_i are, conditional on X_i and Z_i, jointly normal, $E[\varepsilon_i]=E[\eta_i]=0$, $E[\varepsilon_i^2]= \sigma^2$, $E[\eta_i^2]=1$, $E[\varepsilon_i\eta_i]=\rho\sigma$, and are independent of X_i. The variable Y_i* itself is not always observable; however, we can observe its sign. In particular, Y_i* is unobservable if $Y_i \leq 0$, and $Y_i = P_i$ if $Y_i > 0$. Under this assumption, the regression function for the observed dependent variable Y_i can be written as:

$$E\left[P_i \mid Z_i = P_i*, Y_i = 1\right] = [X_i^{'}\beta \mid Y_i* > 0] + E\left[\varepsilon_i \mid Z_i, Y_i* > 0\right] = X_i^{'}\beta + E\left[\varepsilon_i \mid \eta_i > -Z_i^{'}\gamma\right] = X_i^{'}\beta + \rho\sigma\lambda(\varepsilon_i) \tag{3}$$

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[3] Buy-in effects can be persistent, as an unsold artwork is not (always) put on sale again.

[4] Obviously, this does not implies that a two-step hedonic index refers only to the (stable) fundamentals; the index reflects bubbles and fads like any other index based only on actual transactions data.

where $\lambda(\varepsilon_i)=\phi(Z_i'\gamma)/\Phi(Z_i'\gamma)$ is the inverse Mills ratio, with ϕ and Φ the density and distribution functions of the standard normal, respectively. A consistent estimate of β can be therefore obtained using the selected sample by an OLS regression of P_i on X_i and $\lambda(\varepsilon_i)$, if γ is known. In the two step Heckman procedure the first step is given by the estimation of a Probit model, in order to obtain a consistent estimate of γ. Having obtained the estimates of the inverse Mills ratios, in the second step, equation (3) is estimated by OLS for those observations with $Y_i > 0$.

The potential time instability of price indexes is the second key issue analyzed in this paper. In the time dummy approach to hedonic modeling, art prices are regressed on a set of time-varying and time-invariant variables, as well as on a series of time dummies – the period t dummy is equal to one if the item is sold in period t and zero otherwise. The coefficients associated with the time dummy variables set are interpreted as the prices of the hedonic characteristic-free item and are used to construct the price index. This requires time stability in the hedonic regression parameters, constraining them to be constant over time. However, if the assumption does not hold, the estimated time dummy coefficients and the price indexes based upon them may be biased (Berndt and Rappaport, 2001; Pakes, 2003)5. For this reason, the approach set out in this paper adopts a refinement of the hedonic method - the chained Fisher index based on (one-period) sectional hedonic regressions[6].

The antilog of the time dummy coefficient is typically used to produce a quality-adjusted price index. The implicit assumption is that over time the additional sales included in the set of observations do not impact on the stability of asymptotic characteristics of the index. Index stability is often overlooked as a desirable characteristic (Clapham et al., 2006). However, since the stability of price indexes over time seems to be a questionable assumption in the art market, the Fisher price index for the *j*-characteristics at time *t+1* is employed. This can be defined as the geometric mean of the Laspeyres and Paasche price indexes where the weights are represented by the quantities of characteristics rather than quantities of goods. The Fisher price index is based on a series of sectional regressions that use all available characteristics of the items, while allowing both item characteristics and their implicit prices to change over time. More formally, it is defined as:

$$F_{t+1} = \left\{ \left[\sum \beta_{j,t+1} q_{j,t} / \sum \beta_{j,t} q_{j,t} \right] \left[\sum \beta_{j,t+1} q_{j,t+1} / \sum \beta_{j,t} q_{j,t+1} \right] \right\}^{\frac{1}{2}} \tag{4}$$

[5] The standard omitted variable argument, however, suggests that the estimated coefficients are unbiased in the case of lack of correlation between the omitted hedonic characteristics and the time effects.

[6] This index has other names: the price-of-characteristics index, the direct characteristics method, the alternative direct measure of the price change, the single period method and the characteristics price index.

where q are the weights normalized to one for each class of characteristics (i.e., media, salerooms, etc.). Using equation (4), it is possible to chain Fisher indexes across time such that $I_{t+1} = I_t F_{t+1}$, with $I_t = 100$ for $t = 1$. In particular, two different indexes can be developed when discerning whether or not sample selection bias is present. These are the Heckman chained Fisher price index (HCFPI) or the chained Fisher price index (CFPI). In the former, the coefficients associated with the characteristics are calculated from equation (3). In the latter, only sold items are considered in the computation of the β-coefficients.

4. Data

The methods outlined above were applied to a sample of the art works of painters that can be labeled Symbolists[7]. The data set features 1,915 paintings, 1,174 actual transactions and 741 buy-ins collected during the period 1990-2001. It comprises records of paintings sold at the world's major auctions, providing information on a number of variables - artist's name, nationality, title of the work, year of production, materials, date and city of sales, prices, pre-sale estimate (when available), dimensions, whether or not the work is signed, and further information. Prices are gross of the buyers' transaction fees paid to auction houses and are recorded in both local currencies and US dollars (USD). The historical exchange rate of the local currency against the USD has been used in the empirical application. No information is provided on provenance and the exhibition history of the art objects. The explanatory variables included in the study are:

- *Dimension*: the variable, *dim,* defines the surface of the print, in cm squared.
- *Exhibition*: a dummy variable, *exh*, which assumes value =1 if the art item has been already exhibited, *0* otherwise.
- *Expertise:* a dummy variable, *exp,* which assumes value =1 if an expertise exists for the art item, *0* otherwise.
- *Citation*: a dummy variable, *cit,* which assumes value =1 if citations exist for the art item in art books, *0* otherwise.
- *France*: a dummy variable, *fra,* which assumes value =1 if the creator of the art object was born in France, *0* otherwise.

[7] The painters included in the Symbolist dataset are G. Boldini, E.C. Burne-Jones, E. Carriere, A. Dadd, J. Delville, J. Ensor, I. H. Fantin-Latour, P. Gauguin, J.-J. Henner, F. Hodler, A. Hughes, E. R. Hughes, W. H. Hunt, F. Khnopff, G. Klimt, A.-M.Koester, H. von Merees, M. Maris, G. Moreau, A. Mucha, E. Munch, H. P. Picou, O. Redon, R. F. A. Rodin, G. A. Sartorio, J. W. Waterhouse, G. F. Watts and J. A. Weir. A subset of them can be considered as Symbolists for just a limited part of their production (allegories, mythological subjects, etc.), while other subjects (landscapes, portraits, still lives, etc.) are beyond this classification. However, in what follows these differences in artistic production are not considered. The data are drawn from the Gabrius dataset.

- *Painting:* a dummy variable, *paint,* which assumes value =1 if the art item is a painting, *0* otherwise.
- *Subject:* a dummy variable, *subj,* which assumes value =1 if the main focus is figurative or a portrait, *0* for all other subjects (among them, allegorical subjects, religious subjects, landscapes etc.).
- *Salerooms type and location*: Sotheby's and Christies are known to be the leading auction houses in this kind of transactions while the most important art auction markets are in New York and London. In order to take into account of the interactions between auction houses and the city environments in which the sales take place, we define the dummies *sothny,* for Sotheby's New York; *sothlon,* for Sotheby's London; *chriny*, for Christie's New York; *chrilon*, for Christie's London; *world,* all other salerooms and cities of sales (excluded variable).
- *Lotpos*: the variable, *lot,* defines the order of sale of the lot within each sale event.
- *Time*: a set of dummy variables, *dt,* with *t = 1990, ..., 2001*, which assume value = 1 if the painting has been put on sale in year *t*, *0* otherwise.

Table 1 reports the main descriptive statistics. As in several other econometric studies of art auction data it may be expected to observe positive price impacts for the *dim*, *exh*, *exp* and *cit* variables as well as the impact of the auction taking place at Sotheby's and Christies and the auctions taking place in New York and London. No prior expectations are assigned to the other variables aside from *lot* which might be expected to display a negative price impact.

[TABLE 1]

Certain features of the data set are particularly noteworthy. The distribution over time of the sales and buy-ins is relatively smooth over the 12 years considered. The New York and London markets are known to be the most important and they have a roughly similar share of auction sales. Similar results emerge with respect to the specific contributions of the Christies' and Sotheby's auction houses. It should also be noted that the (normalized) lot position of the items considered in the sample lies, on average, in the second half of the auction event.

Table 2 provides a breakdown of the 1,915 observations in the dataset. The number of observations available in each year ranges from 106 in 1996 to 228 in 2001, and no clear time trend readily emerges from the data set. Nevertheless, the number of observations available in each year does permit estimation of yearly cross-sectional regression equations. In columns 2 and 3 the percentage of sold and unsold items are reported. Unsurprisingly, the market exhibits a certain cyclical variation. In the first part of the period under scrutiny in the aftermath of the bursting of the price bubble of the late Eighties', buy-ins are relatively high (with the maximum reached in 1993). In the second part of the recovery period there is an increasingly lower percentage of buy-ins, with the lowest value being reached in 1999.

[TABLE 2]

5. Empirical Results and Discussion

In this section the hedonic price indexes are presented for the group of Symbolist painters. Before turning to the Heckman chained Fisher Price Index (HFPI), a comparison is made of the standard hedonic Price Index (PI) with the Heckman selection Price Index (HPI), which only takes account of the sample selection bias. Although for the purposes of this study greater interest lies in the evaluation of the overall differences between indexes, it is interesting to also compare the empirical findings of these two specifications. The results for the two models are reported in Table 3 and which generally conform to prior expectations.

[TABLE 3]

The estimates of the PI model and the corresponding standard deviations are reported in columns 2 and 3. The coefficients and the standard deviations of the HPI model are displayed in columns 4 and 5. Standards errors and variance-covariance matrices of coefficients were computed applying the White heteroskedasticity-robust procedure due to some indications of heterosckedasticity. Whereas in the two models the differences between the estimated coefficients of the artistic variables (such as material, dimension and exhibition) are not great, those in the coefficients for the economic variables seem much stronger. Overall, sample selection bias was deemed to be significant (as indicated by the value found for the correction term) and thus pointing to a need for hedonic model estimates featuring a Heckman selection process. The PI and the HPI indexes were computed from the regression results reported in Table 4 and depicted in Figure 1.

[TABLE 4]

[FIGURE 1]

Figure 1 suggests some complex effects arise from auction buy-ins on the overall market price dynamic. An increase in buy-ins has a two-fold negative effect on the market price dynamics: a direct influence, since the hammer price of unsold items is relatively low with respect to the seller prior expectations, and an indirect influence, emerging from possible affiliation effects (between sold and unsold items) in a sequential auction. The HPI considers both such influences. The linear correlation coefficient between the buy in rate and the price index is therefore expected to be negative, and the effect should be stronger in the case of the HPI. The empirical evidence supports this prediction. Over the period under scrutiny, the correlation coefficients between the buy in and PI and HPI are -0.30 and -0.47, respectively[8].

While the main differences between the PI and the HPI dynamics have been shown to be related to sample selection bias, this analysis also explored the (in)stability of the indexes over time. To this end, Table 5 and Figure 2 show the FPI and the HFPI indexes computed from the regression results.

[TABLE 5]

[FIGURE 2]

Table 5 suggests that time instability effects in the estimation of the coefficients of the hedonic regressions can be important in modifying the market price dynamics. The linear correlation coefficients of the standard hedonic index PI and the corresponding time varying index FPI is positive but fairly low: 0.37. The correlation coefficient between the HPI and the corresponding time varying index HFPI drops to just 0.29. Specifically, the two sets of constant and time-varying coefficients in the price indexes exhibit different dynamics in the first half of the time frame, whereas the price dynamics appear to be more similar in the second half. In essence, the assumption of constant coefficients leads to misleading result particularly in respect of the early nineties.

Even if the sample selection bias and the restrictions on the hedonic coefficients are distinct issues, joint evaluation of their effect can seemingly lead to making substantial adjustments in the price index. This may be appreciated in respect of Figure 2, which presents a comparison between the time-varying and the Heckman time-varying index. It may be observed that for two years, the indexes suggest markedly different market dynamics.

6. Concluding Remarks

This study has focused on two key drawbacks associated with applications of hedonic regression for the construction of price indexes in art markets: the instability of coefficients in hedonic regressions

8 Further, the correlation coefficients between the lag of the buy in rate and the PI and HPI (relevant in the case of a delayed effect on the former variable on art prices) are negative.

and sample selection bias. Due to the former, it is difficult to give any structural interpretation for the hedonic regression coefficients. The latter problem arises because the effect of auction buy-ins is systematically neglected in the construction of a price equation even in typical cases where such buy-ins may comprise 30-40 percent of the available data. These two problems are closely intertwined though conceptually distinct. Confusing or neglecting their distinctive root causes is likely to reduce the reliability of price indexes in the art market.

Correcting for these effects can be, however, a fairly straightforward task. It requires the application of the characteristics price index and of the two step Heckman estimation procedure.

An empirical illustration is provided in the context of the auction sales of paintings by a group of symbolist artists (over the period 1990-2001) on the most important international markets. The empirical evidence strongly suggest that (i) neglecting buy-ins and even more importantly (ii) instability of time coefficients, represents a serious source of bias in the computation of any art price index.

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TABLE 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Price	223,954.800	990,598.600	1,281.38	2.15e+07
Dim	3122.855	4638.634	0.00	72298.84
Exh	0.753	1.432	0.00	17.00
Exp	0.512	0.756	0.00	3.00
Cit	0.983	1.668	0.00	28.00
Fra	0.413	0.492	0.00	1.00
Paint	0.585	0.493	0.00	1.00
Subj	0.263	0.440	0.00	1.00
Sothny	0.198	0.398	0.00	1.00
Sothlon	0.182	0.386	0.00	1.00
Chriny	0.179	0.383	0.00	1.00
Chrinlon	0.203	0.402	0.00	1.00
Lot	0.686	0.336	0.00	1.00
d90	0.094	0.291	0.00	1.00
d91	0.089	0.285	0.00	1.00
d92	0.059	0.235	0.00	1.00
d93	0.072	0.258	0.00	1.00
d94	0.086	0.280	0.00	1.00
d95	0.084	0.277	0.00	1.00
d96	0.053	0.224	0.00	1.00
d97	0.083	0.277	0.00	1.00
d98	0.100	0.300	0.00	1.00
d99	0.098	0.298	0.00	1.00
d00	0.072	0.259	0.00	1.00
d01	0.110	0.313	0.00	1.00

TABLE 2. Total number of observations, actual transactions, and buy-ins

Year	Number of obs.	Sold items (%)	Buy-ins (%)
1990	180	50,56	49,44
1991	162	56,79	43,21
1992	107	52,34	47,66
1993	130	44,62	55,38
1994	158	55,70	44,30
1995	163	60,12	39,88
1996	106	61,32	38,68
1997	163	47,24	52,76
1998	199	58,29	41,71
1999	180	62,78	37,22
2000	139	60,43	39,57
2001	228	60,53	39,47

TABLE 3. Estimates PI and HPI

	PI		HPI	
Variable (1)	**Coef. (2)**	**Std. Err. (3)**	**Coef. (4)**	**Std. Err. (5)**
Dim	0.00007*	0.00002	0.00006*	0.00001
Exh	0.22034*	0.02984	0.21728*	0.02718
Exp	0.58826*	0.06437	0.55901*	0.06745
Cit	0.21278*	0.03804	0.19389*	0.03627
Fra	0.10680	0.10262	0.12149	0.11150
Paint	0.68690*	0.09104	0.72677*	0.09724
Subj	-0.26808*	0.09584	-0.24460*	0.08868
Sothny	0.64586*	0.11998	0.58035*	0.11887
Sothlon	0.68872*	0.12810	0.588897*	0.12984
Chriny	0.49477*	0.13469	0.39206*	0.13421
Chrinlon	0.38423*	0.12286	0.30794*	0.12715
Lot	-0.49955*	0.12579	-0.54377*	0.11704
Constant	9.35316*	0.21999	8.32883*	0.22864
Time dummies	(11)		(11)	

	F(23,1047)	30.07	Wald chi2(23)	454.45
	R-squared	0.41	Log pseudo likelihood	-3060.81
	Ramsey RESET	8.53	Wald test of indep. eqns (rho = 0)	38.00

Note. *,**,***, significance at 1%, 5%, 10%, respectively.

TABLE 4. The PI and the HPI Indices

	PI	HPI
d90	100.00	100.00
d91	77.60	83.30
d92	75.11	79.70
d93	62.75	61.26
d94	83.59	90.78
d95	94.18	101.38
d96	60.71	68.38
d97	97.06	96.60
d98	102.84	108.27
d99	101.09	113.29
d00	133.23	133.55
d01	88.27	95.88

FIGURE 1. Comparison of the PI (Hedonic) and HPI (Heckman) Indexes

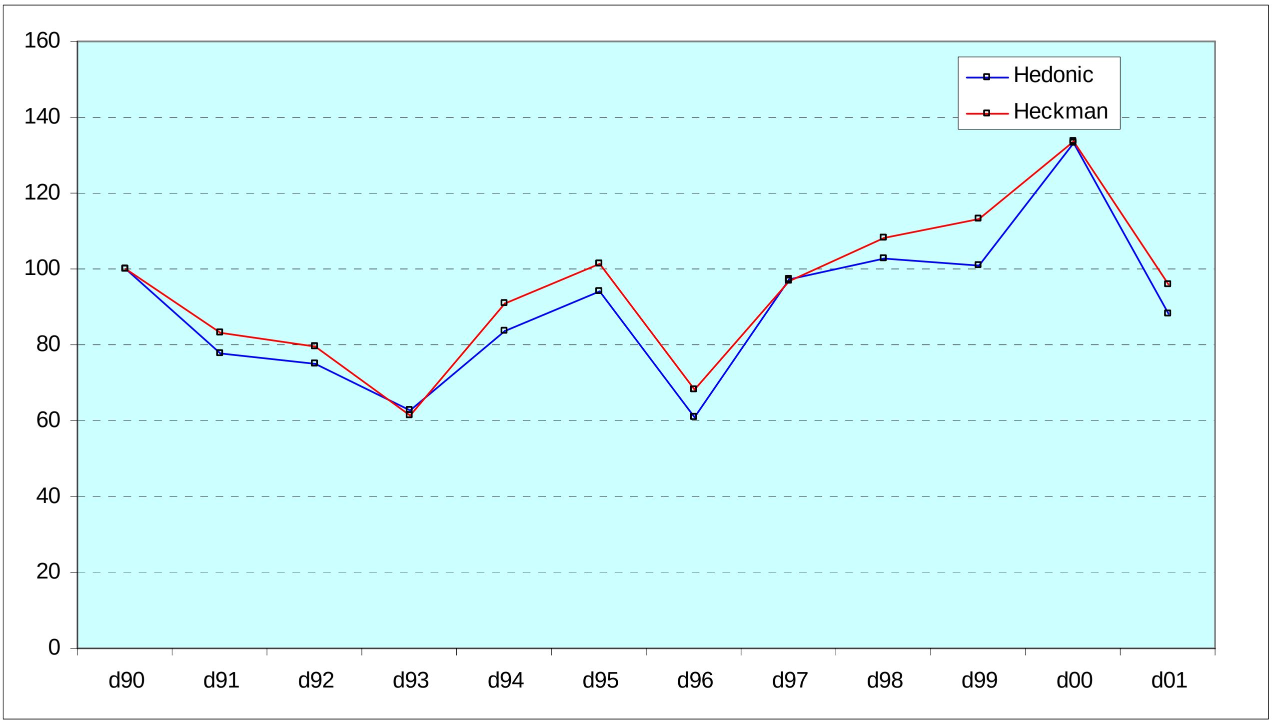

TABLE 5. The FPI and the HFPI Indices

	FPI	HFPI
d90	100	100
d91	88.40	110.37
d92	98.89	85.3
d93	106.53	97.07
d94	107.36	128.37
d95	95.18	84
d96	88.82	92.37
d97	113.64	101.77
d98	96.45	109.11
d99	97.37	96.59
d00	108.33	113.93
d01	98.10	103.46

FIGURE 2. Comparison of the FPI and HFPI Indices