The Treatment of Quality Change for Computer Price Indexes

~ A Review of Current and Proposed Practices ~

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1.0 Introduction[1]

Over the last decade, computers, along with other high-tech goods, have been unique from a prices perspective in that their general price levels have not kept pace with improvements in quality and performance. Unlike traditional commodities (e.g. wood, cars, steel), technological change in computers has been rapid and continuous, resulting in ever-increasing improvements and advances in output for a corresponding price level.

Given the importance of this commodity to the Canadian economy, Prices Division has been producing a computer price index series using distributor pricing information for almost ten years. This series has served as an input into the office machinery and equipment component of the Machinery and Equipment Price Index as well as a source of price movement for the computer equipment and supplies component of the Consumer Price Index.

This study has three general purposes, the most important being a discussion and evaluation of the current quality adjustment technique used for computers, the matched sample with the hedonic replacement method, along with a proposed alternative for a direct hedonic index and one based on the overlapping matched sample approach. A second objective of this paper is to recommended a methodology for the future of the index series. Finally, to better carry out this discussion, it is important that a backdrop or historical context of the computer market be provided, so a brief synopsis of the more recent trends and developments is included.

2.0 Data Source

Since 1996, Prices Division has been using the monthly data supplied by the International Data Corporation of Canada (IDC) to produce its own microcomputer price index. The data for this study come from the database used to produce the computer index series, which represent the prices for desktop computers sold to the commercial and government sectors and spans the period of March 1996 to June 2000. The models contained in the database are of the Intel chip variety that are being shipped by the dominant market share vendors (e.g. Compaq, IBM, HP, Dell), reflecting the market reality that to date, most commercial PC systems are equipped with Intel chips, while the other processor vendors (i.e. AMD, Cyrix) have had a very tough time gaining entry to this market segment.

As Figure I.1 shows, the number of monthly observations has grown from just over 100 models in 1996 to over 500 in June 2000. In terms of model variety, the average number of models per CPU class has doubled from approximately 10 in 1996 to just over 20 in 2000. This underlines the growth in the market in relation to the number and scope of models being offered by the dominant vendors.

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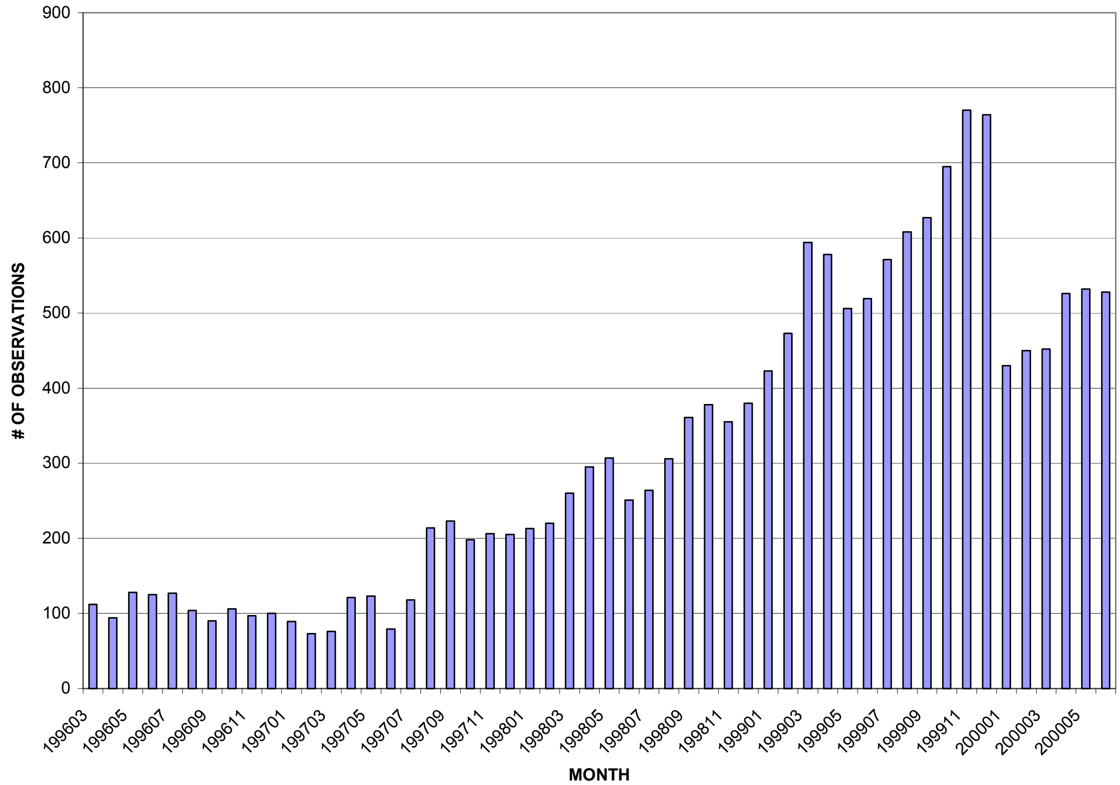
[1] *This paper should not be quoted without the explicit permission of the authors. The authors would like to express their gratitude to Andy Baldwin, Robin Lowe, Marc Prud'homme, and Kam Yu of Prices Division as well as Erwin Diewert, Jack Triplett and Ralph Turvey for their helpful comments and suggestions. Any views expressed are those of the authors and do not necessarily represent the opinions of Prices Division or Statistics Canada.*

Figure I.1- MONTHLY IDC PRICING DATA



3.0 Organisation of Study

This study is organised into four chapters. Chapter 1 provides an overview of computer prices and their performance over the last five years. Chapters 2 and 3 describe and evaluate the overlapping matched sample and the hedonic methodologies for dealing with quality change in computers. Chapter 4 compares these methodologies and, based on the results of this study, outlines recommendations for the future methodology of the computer price index.

CHAPTER 1 – Historical Analysis

1.1 Introduction

In this chapter, a historical review of computer prices and performance is provided. The trends in price and performance (as measured by key components such as processor class, random access memory, etc.) are identified and discussed. The objective is to show that the average price of a computer, before quality adjustment, has remained stable (or even declined), while computer performance has been increasing. If this is the case, then in the context of price index construction, the issue of quality change greatly overshadows the issue of price change, making the treatment of quality change the key focus in the production of a computer price index.

1.2 Key Variables

The key variables discussed in this chapter are computer prices, random access memory (RAM), central processing unit (CPU) or processor/chip class, hard drive size (HD) and extended cache (CACHE). The dependent variable is the computer price, which is represented by the average street price for a computer model or system. The average street price, while not exactly a transaction price, is a close estimate. In explaining this point, it is important to note that currently, Prices Division receives two prices for a given model, a *list price* and an *average street price*.

The *list price* corresponds to the vendor's (e.g. IBM or Dell) suggested selling price. The *average street price* is calculated by firstly, obtaining an average reseller cost per system through a survey of the various points and contacts in the distribution channel (i.e. resellers and distributors). Then, the average reseller cost is marked up or down to obtain an average Canadian street price. Street prices do not include taxes or shipping and handling charges.

In some instances, the list and street prices will be equal, and in others they will not. In the case of commercial sales of computer systems to governments and to medium and large businesses, computers are purchased primarily in bulk with certain performance specifications and requirements. Furthermore, these purchases are generally written up in a contract. Transaction prices under such circumstances are not readily discernible (i.e. there is no bill of sale like there would be with a home computer bought from a local retailer, so scanner data do not apply here), as these contracts often include service, warranties and various other "extras" such as software packages. Finally, in the case of government purchases, prices quoted in the Standing Offer usually remain in effect for one year.[2] So more often than not, the average street price will represent the actual transaction price for this sector.

[2] *These purchases refer to the Canadian federal government in particular.*

In the past, the major vendors typically set their list price as a "do-not-exceed price", which represented an upper maximum price to be respected by the resellers and distributors. However, with the advent of direct vendors (namely Dell), this has changed. The recent growth of web pricing (i.e. IBM and Compaq have joined the fray, as have others) has diminished the role of list pricing, so the difference between a list price and a street price is zero or almost zero in most circumstances.

Of the key variables mentioned earlier, the most influential are the RAM and CPU. RAM is essentially the amount of information a computer system can retain and the number of instructions it can carry out. This amount is measured in megabytes (MB). In this study, the CPU is represented by a performance score, which is a figure given to all processors or chips based on industry-wide benchmark performance tests.[3] The CPU score is important because it allows quality adjustments to be assessed when new generations of computer chips emerge. Another key characteristic of computer prices is the HD size (also measured in megabytes), which determines how many components and applications a system can store and handle. Finally, CACHE, which is the reservoir of memory where the system stores frequently accessed instructions and data, completes the list of basic components to a computer system (measured in kilobytes or KB). For the purposes of presenting a historical analysis, monthly averages for each variable were used to represent their movement.

1.3 Other Variables

Naturally, given their importance, the key variables are present throughout the entire study period. However, there are several additional variables that have had an influence (albeit relatively minor) on price differences across models at different times during this period. They are mentioned in Table A where prior to August 1997, components such as video memory cards, number of slots and drive bays were included as additional model descriptors in the pricing data. After 1997, these components were replaced by other model characteristics such as modems, sound and network cards and CD drives which have grown in importance. The latter components are covered in subsequent chapters of this study.

Table A – Additional Explanatory Variables

Period	Variables
March 1996 to July 1997	Video memory card, slots, drive bays, case type and software component
August 1997 to June 2000	Modem, sound card, network card, CD drive and Small Computer System Interface (SCSI) Centre

[3] *The CPU performance scores were obtained from the web site www.cpuscorecard.com. From the dialogue between the authors of this study and Intel—the main world-wide computer chip manufacturing company at present—the best representation of comparative performance across generations of processors is the use of weighted benchmark results to obtain a performance score, such as the source used in this study. These scores are updated frequently to ensure comparability of emerging models. The scores used for this analysis are presented in Appendix I, and date as of July 17, 2000.*

1.4 Historical Comparison

Price

Based on the data, the average price of a desktop computer typically purchased by the business or government sector has remained in the $2,500–$4,500 range for this study period, with the overall average for the entire set of observations being $3,057.

As Figure 1.1 shows, the average monthly price of a computer has been decreasing from March 1996 to June 2000. Fitting a trend line to the natural logarithm of the price results in a monthly rate of decrease of 0.5%. While the overall decline is not steep, there are noticeable sub-periods where the movements are more pronounced. For instance, the downward trends in average price are stronger for 1996, 1999 and the first half of 2000, while an upward trend in the average price occurs in 1997 and smoothes out in 1998. In explaining these movements, it is necessary to take into account two important phenomena: the introduction of new generations of CPU technology (i.e. Pentium, Pentium II and Pentium III processors mainly) and their weighting in the pricing data as they pass through their respective product life cycles. Figure 1.2 provides the movement in average prices for the various families of processor-based machines, along with the total average price, while Figure 1.3 indicates how the sample proportions for each of these machines change over the period.

Beginning in March 1996, there is a very strong downward trend in the average price of computers (see Figure 1.4) with monthly desktop prices declining by roughly 4%.[4] Referring back to Figure 1.3, we see that the entire sample is composed of Pentium machines for this particular period, which by then had become the mainstay of the business computer world, displacing the 486 machine. In this time, the average price fell by about $1,200, dropping from $4,188 to $3,023. This decrease is due to several events that transpired in the industry. Firstly, Intel cut the price of its processor chips several times to maintain their almost complete market domination and to ensure high future demand for its products. Coupled with this was the declining cost of memory (RAM and HD). In addition, leading vendors were slashing prices on many desktop models, often by over 20%, citing lower component costs, better inventory control and increased competition as they strategically lowered prices to improve or defend their market share.[5] The industry belief at the time was that suppliers would be forced to sell off old products to make way for the new, resulting in discount pricing.[6] Intel's Pentium 200 introduction in June 1996 confirmed this belief, offering more options to the existing selection, forcing prices for models with ranging speeds of 100–166Mhz to decline steadily.[7] These factors, combined with the anticipated release of MMX technology in early 1997, caused the drastic reductions in computer prices experienced during this period.

[4] *The monthly growth rate (here and throughout the rest of this study) represents the slope coefficient obtained by regressing the natural logarithm of the dependent variable (price, price index, RAM, etc.) against time.*

[5] *See www.newscan.com* ***The Kitchener-Waterloo Record*** *release June 10, 1996.*

[6] *See www.newscan.com* ***The Kitchener-Waterloo Record*** *release June 10, 1996.*

[7] *See www.intel.com pressroom news release dated June 10, 1996 entitled* ***Intel Introduces 200-MHz Pentium Processor****.*

For 1997, the trend in the average price of computers revealed increases of about 1.3% on a monthly basis (see Figure 1.5). This movement was largely attributable to the emergence of two new processor chips in the market. The first price increase came immediately in January when Intel finally introduced its MMX processor.[8] This increase was only slight however (the average price rose by only $125), due to industry speculation that the best was yet to come, with Pentium II technology on the horizon.[9] This prediction proved to be true and following its release in May 1997, Intel's Pentium II processor caused the largest price increase encountered for the entire period.[10] From its introduction until the fall of 1997, the average computer price rose by $827. Soon after the Pentium II machines entered the market, their average price reached a maximum of approximately $5,800, with the price eventually falling below the $4,000 mark in early 1998 (refer to Figure 1.2). Pentium II machines also gained a substantial portion of the sample quite quickly, rising to just under 40% of all systems in only six months. Demand for these machines was strong with the average RAM and HD more than doubling in order to accommodate this new generation of technology. CACHE levels also jumped on average by 180 KB. As is common in this industry, the price increases wore off soon after the Pentium II machines became mainstream systems and their prices returned to their normal declining tendency. Suppliers were changing their operational views and preferred to increase their volume and deflate prices, hoping the demand increase would offset low profit margins. This proved to be a burden for new competitors, but provided excellent value to consumers.[11]

In 1998 there was no real trend in price movement, replaced instead by some volatility as the average price bounced up and down, remaining on average in the $3,100 range (see Figure 1.6). Several factors caused the average price to hover during this year. Firstly, the Pentium II systems began to overtake the increasingly obsolete Pentiums as the computer system of choice among purchasers, representing a higher proportion of the models priced in the data. Even with the price declines occurring in 1998, the Pentium II machines still cost substantially more than the Pentiums they were replacing (nearly double in price), dampening the effect of falling Pentium prices.[12] Secondly, the introduction of the lower-priced Celeron systems into the pricing data in July 1998 had little impact on the overall average price since the Pentium II models still occupied the lion's share of systems sold commercially. The only noticeable price increase occurred as a result of the release of the Pentium II 400 MHz machines and the introduction of the new Xeon series class of chips for workstations.[13]

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[8] *See www.intel.com pressroom archives Jan. 8, 1997.*

[9] *See www.pcworld.com/hardware/desktop articles Feb. 1997.*

[10] *See www.intel.com pressroom archives May 7, 1997.*

[11] *See www.newscan.com* ***The Toronto Star*** *release April 1997.*

[12] *For 1998, the average monthly price of a Pentium system was $1,884, a Pentium II was $3,862 and a Celeron system was $1,662.*

[13] *See www.pcworld.com June 1998. One will note the substantially higher average price for the Xeon machines (the average price is in the $7,600 range). These are very high powered machines (i.e. workstations with average RAM of 200 MB) for specialized users and as such currently occupy a relatively small share of the sample. See www.smartcomputing.com,* ***Buying Computers - Desktop Systems****, September 1999, Vol. 7 Issue 9.*

Figure 1.7 shows the trend from the beginning of 1999 to June 2000, where the general movement in prices has been downward, even with the introduction of the Pentium III generation of machines. By the time the Pentium III processor had arrived in January 1999, purchasers were getting wise, realizing that high-end models accompanied by their high price tags, would eventually come down.[14] Distributors were battling long-running price declines with the net effect of the Pentium III release producing only a minor average price increase of $100. This lasted only a few months and by the summer of 1999, average desktops were selling below $3,000, where they have since remained. Analysts believe that these industry trends do not show signs of changing direction, as prices are expected to continue falling, due mainly to the mounting speculation over the upcoming Pentium IV technology.[15]

RAM

Undoubtedly, RAM is one of the independent variables having the most influence on the price of a computer. According to the data, the average level of RAM offered in models has been rising by approximately 4.2% on a monthly basis (see Figure 1.8). In 1996, the average RAM level was around 16 MB, while in the first two quarters of 2000, the level had increased eightfold to approximately 128 MB. In general, there were two forces at work. Firstly, with the advent of the Pentium II and Pentium III processors, a higher base level of RAM was required to run the new chips, and secondly, the cost of RAM fell dramatically during this study period.[16] In early 2000, the sharp jump in average RAM reflects the switch from Pentium II machines to Pentium III models as the technology of choice for businesses and government. The quality of desktop systems has been constantly rising, due to the impact of this increased accessible memory on a computer's speed.

CPU

In addition to RAM, the CPU is key when considering price discrimination across computer models. As in the case of RAM, we see a strong upward trend in the average monthly performance score for CPU, with the average level of performance rising at an estimated monthly rate of 3.9% (see Figure 1.9).[17] This steady rise in computer performance reflects the evolution in technology from Pentium to Pentium II and then to Pentium III-based systems. Interestingly, the trend in CPU performance appears to be following *Moore's Law*, doubling every 18 months or so.[18]

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[14] *See www.intel.com/wire/story technology news February 12, 1999.*

[15] *See **Ottawa Citizen** August 22, 2000.*

[16] *In early 1996, the price for 4MB of RAM dropped from $170 to $70 and was still falling. For more details, see www.newscan.com **Toronto Star** release May 2, 1996. By March 1999, the price of RAM in Canadian dollars (as quoted on the Internet) was in the neighbourhood of $3 per MB, excluding installation charges and taxes.*

[17] *For the benefit of the reader, the y-axis in Figure 1.9 uses the corresponding CPU chip class rather than the actual performance score.*

[18] *Loosely defined, Moore's Law states that CPU computing power or performance is expected to double every 18 months. This industry rule of thumb is attributable to the statements made by Gordon Moore, co-founder of Intel Corporation. Based on the data, the average performance scores for the three 18-month increments are 288.36, 572.17 and 1095.67, representing changes in growth of 198% and 191%. See www.smartcomputing.com, **Ram - Need More? Then Buy More**, March 1998, Vol. 9, Issue 3.*

HD

Besides the RAM and CPU, the hard drive storage capacity is also an influential factor when considering price differences across computer systems. Similar to these components, the amount of hard drive disk storage rose consistently over the study period, averaging a monthly rate of increase of 4.4% (see Figure 1.10). Consequently, the average size of a hard drive in June 2000 was 10.9 gigabytes (GB), up from 1.3 GB in March 1996.

CACHE

Unlike the components just discussed, CACHE has experienced a weaker trend in growth. While Figure 1.11 indicates a monthly increase of 1%, this trend is not as strong as with the other three components, showing more fluctuation around the trend. This is mainly due to the fact that the progression has been largely in two blocks or chunks, with the dominant categories being 256KB and 512KB. Basically, up until mid to late 1997, over 50% of the pricing observations indicate a CACHE level of 256KB, whereas from that point on over 50% of all the observations contain a CACHE level of 512KB.

1.5 Conclusion

Over the last five years, the computer industry has seen two diverging trends emerge—one of price decline and the other of ever-increasing performance. Perhaps the best way to summarize the historical analysis presented in this chapter is to compare a representative computer system for the beginning period of the study (March 1996) with the one for the ending period (June 2000), where these representative systems are based on the averages of the variables discussed.[19] Doing so results in the following two systems presented in Table B, and by comparing the differences in the two computers it is evident that the hypothesis mentioned earlier holds true—price and quality have been moving in opposite directions, with sizeable improvements in quality eclipsing the decline in average price in absolute value. Thus, the treatment of quality change is a critical issue that must be addressed when developing a price index for computers, and possibly for other high-tech goods with similar behaviour.

Table B – Composite Average Systems

Main Components	March 1996	June 2000	% change
CPU	Pentium 133 MHz	Pentium III 600 MHz	+571.8[20]
RAM	16 MB	128 MB	+700.0
Hard drive size	1.3 GB	10.9 GB	+738.5
Extended cache	256 KB	512 KB	+100.0
Price	$4,188	$2,727	-34.8

19 *The average systems presented in this table are* ***composites*** *of the average monthly values of price, RAM, CPU, HD and CACHE (for RAM and CACHE, the averages have been rounded to the nearest increment).*

20 *Based on comparing the average CPU scores for these two months.*

Figure 1.1 - Average Price (chart in semi-logarithmic form)

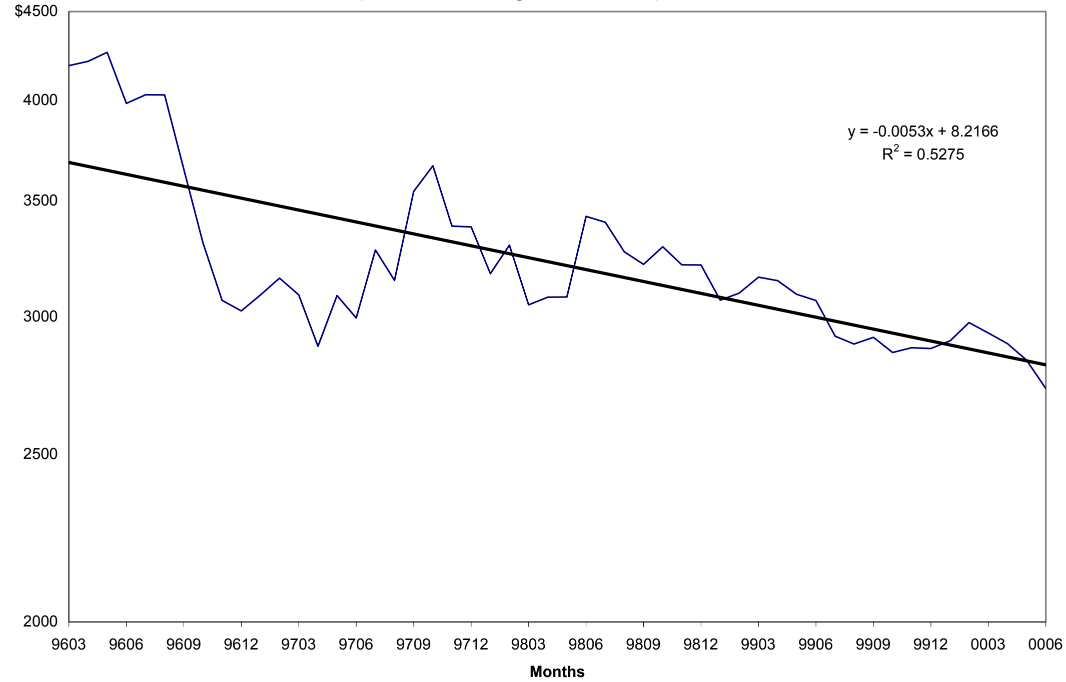


Figure 1.2 - Average Price For Pentiums, Pentium IIs, Pentium IIIs and Celerons

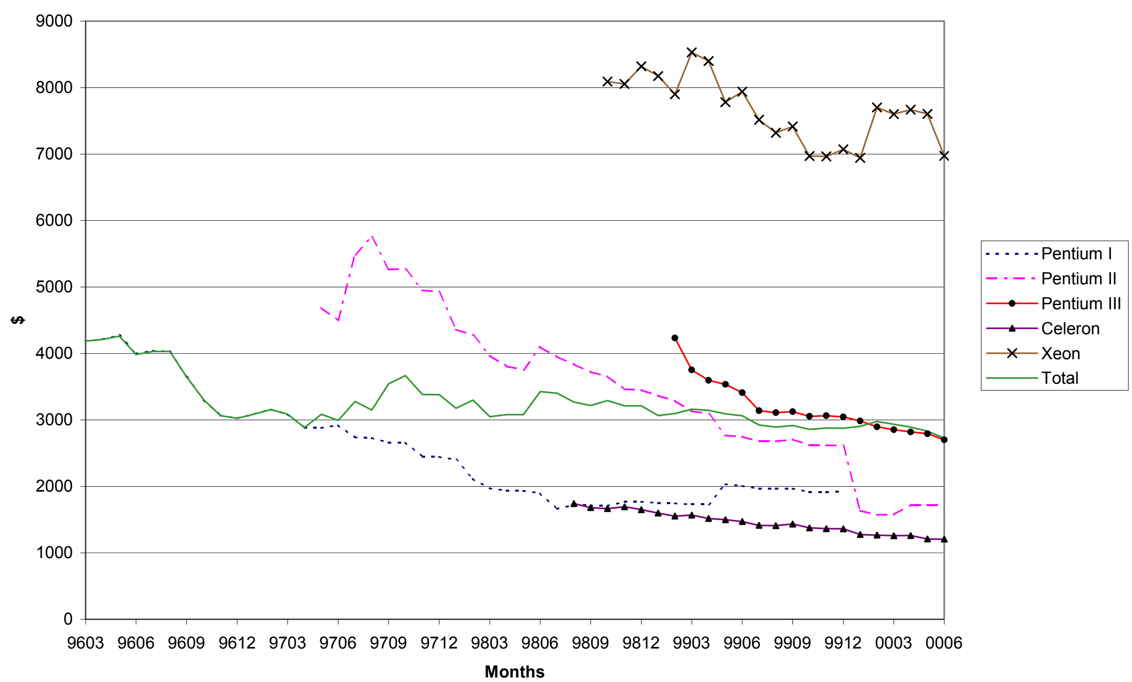


Figure 1.3 - Processor Class as a % of Monthly Sample

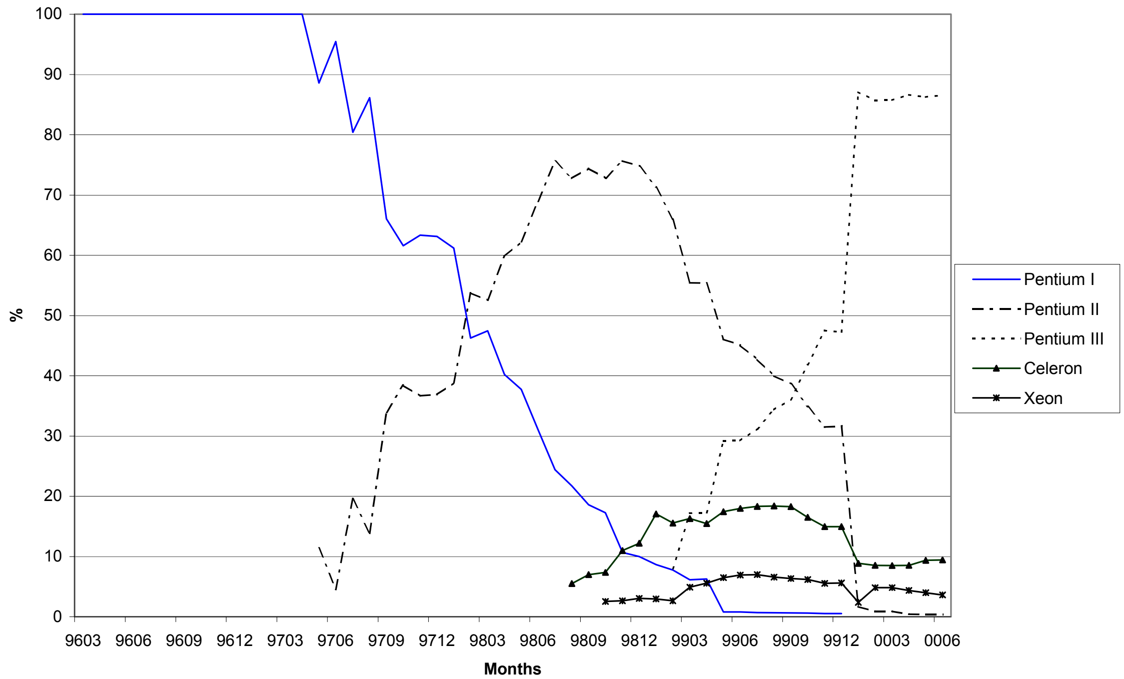


Figure 1.4 - Average Price - 1996
(chart in semi-logarithmic form)

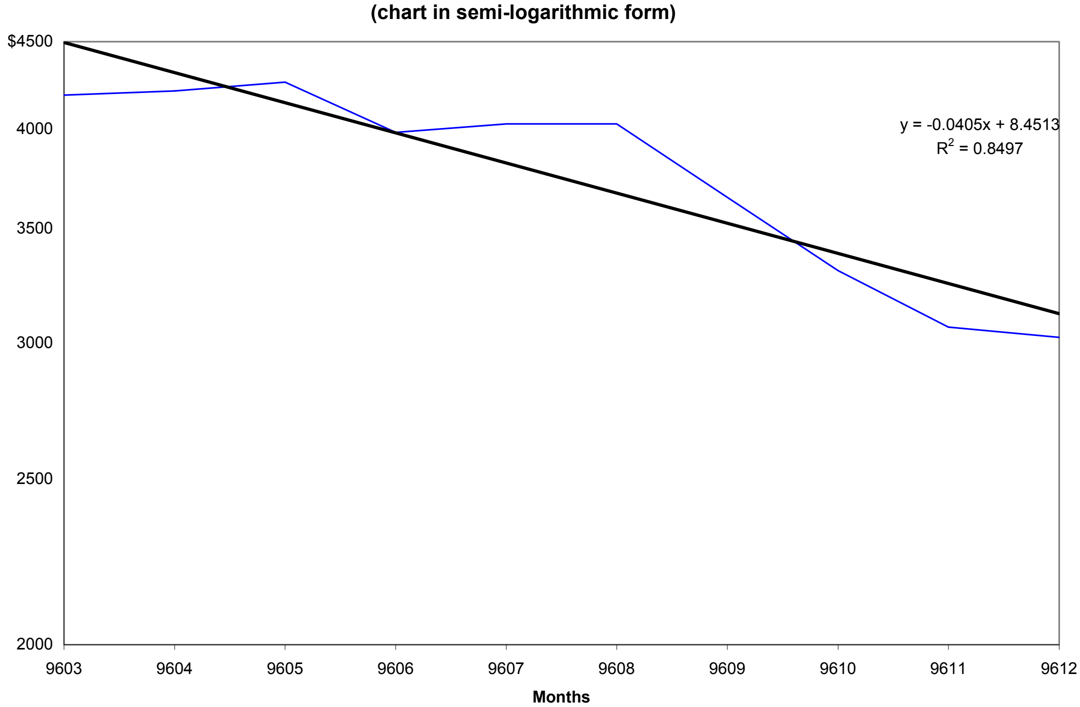


Figure 1.5 - Average Price - 1997
(chart in semi-logarithmic form)

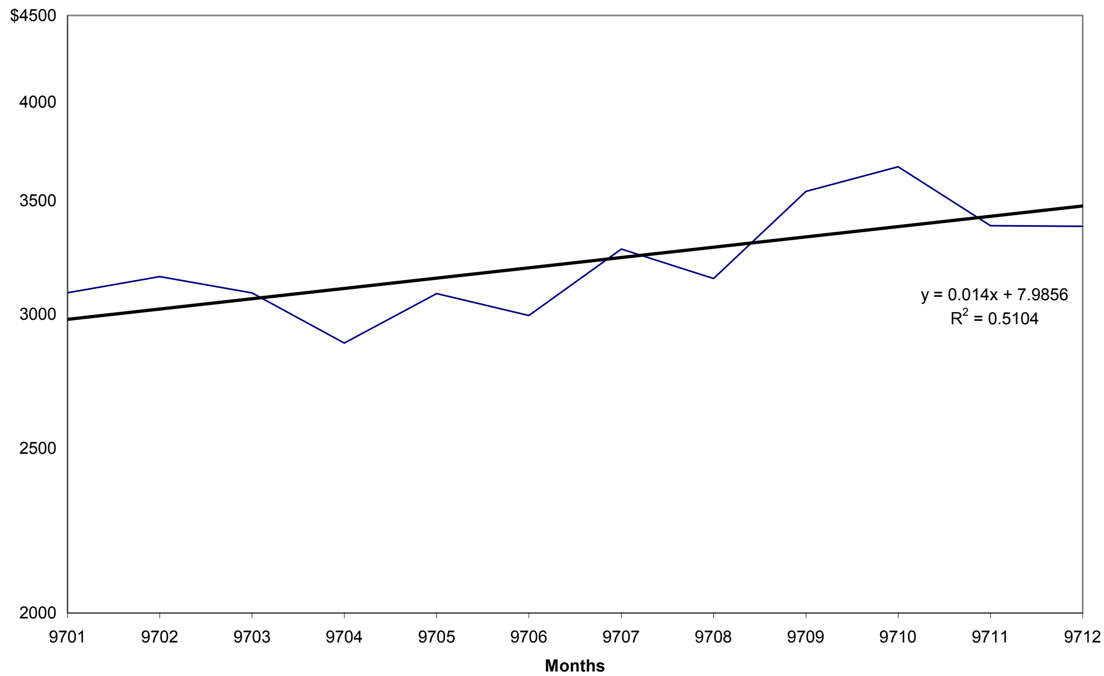


Figure 1.6 - Average Price - 1998
(chart in semi-logarithmic form)

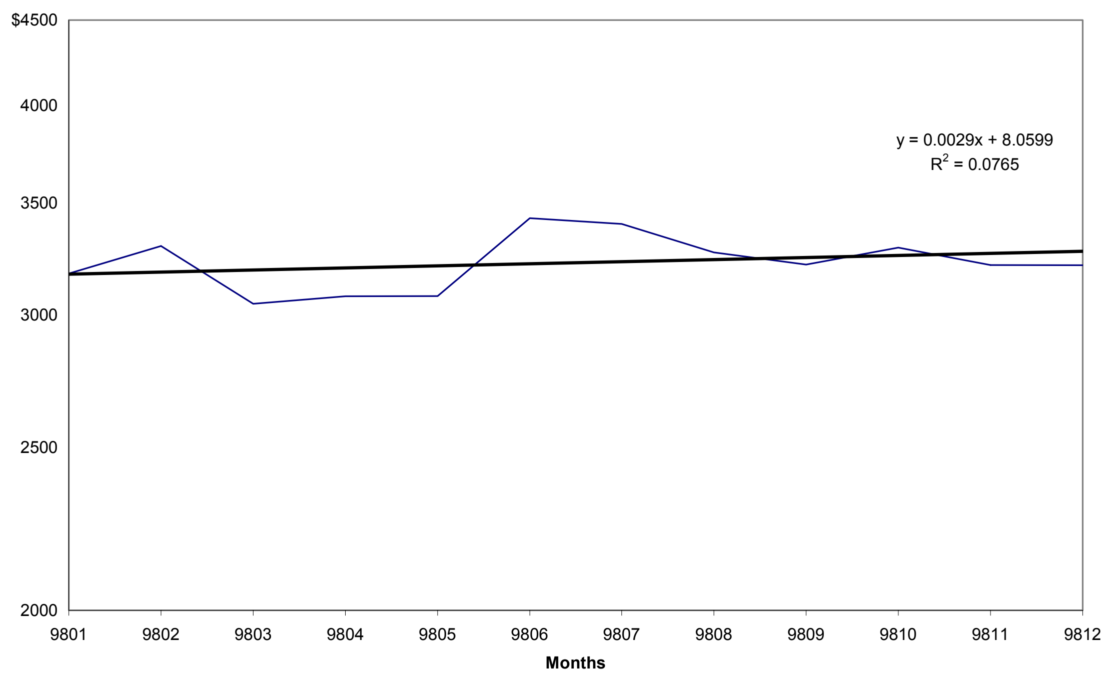


Figure 1.7 - Average Price - 1999 to June 2000
(chart in semi-logarithmic form)

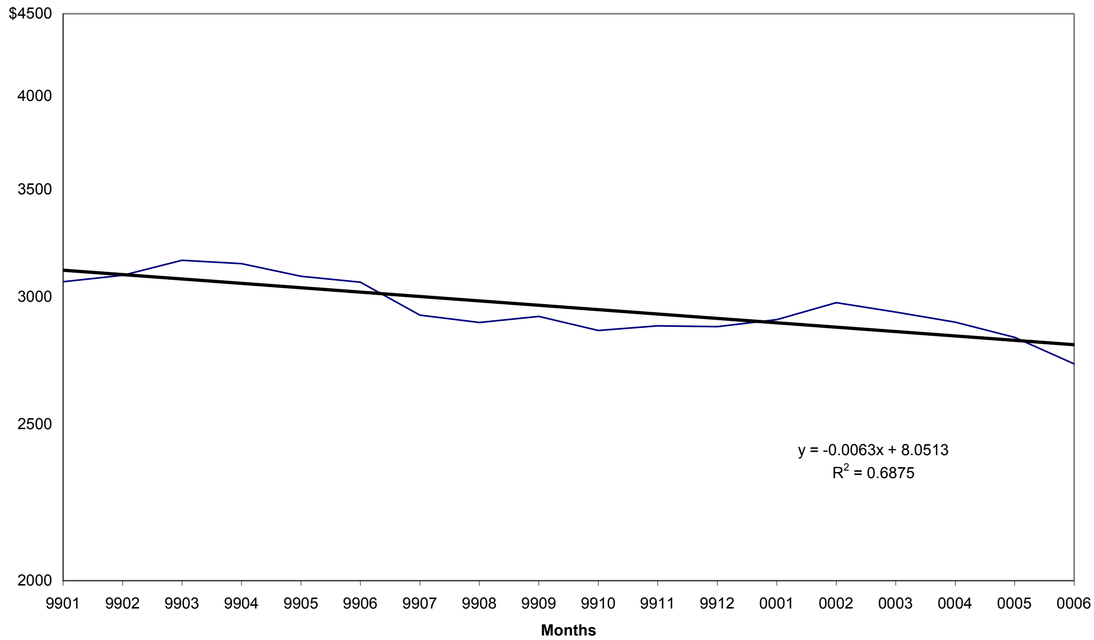


Figure 1.8 - Average RAM
(chart in semi-logarithmic form)

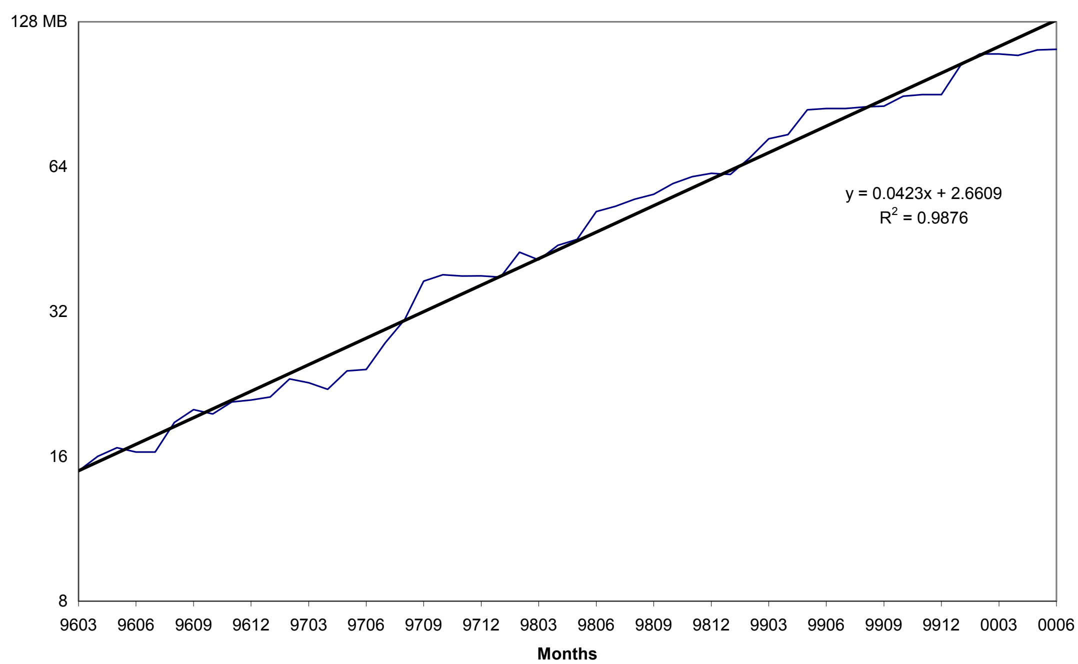


Figure 1.9 - Average CPU Score
(chart in semi-logarithmic form)

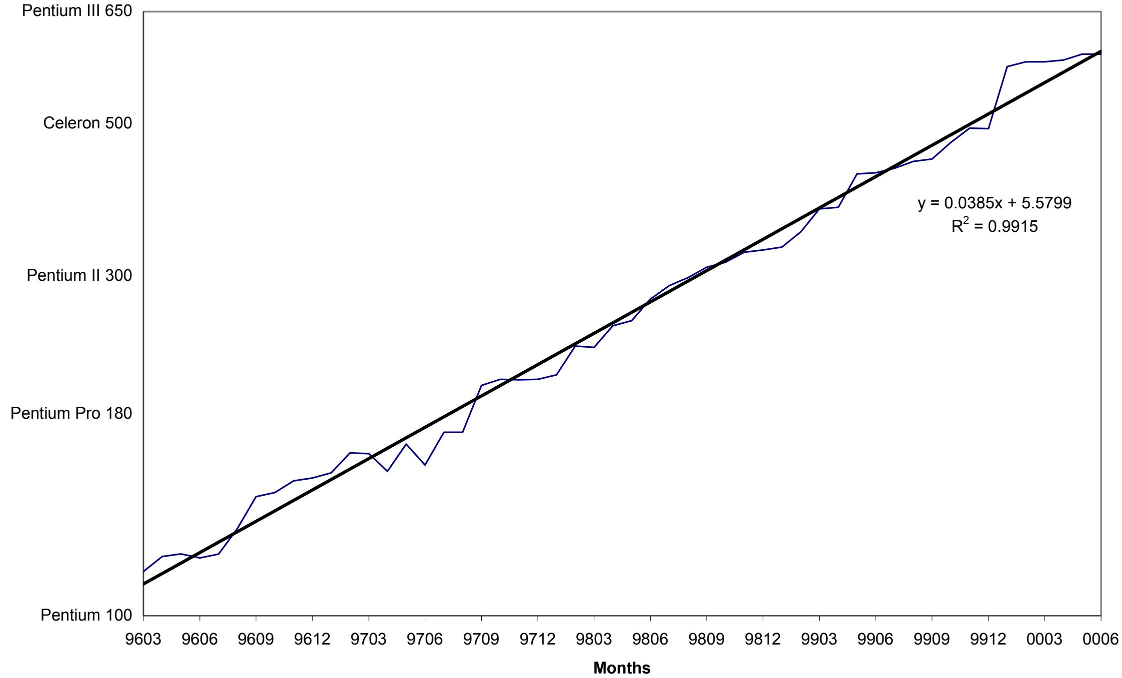


Figure 1.10 - Average Hard Drive
(chart in semi-logarithmic form)

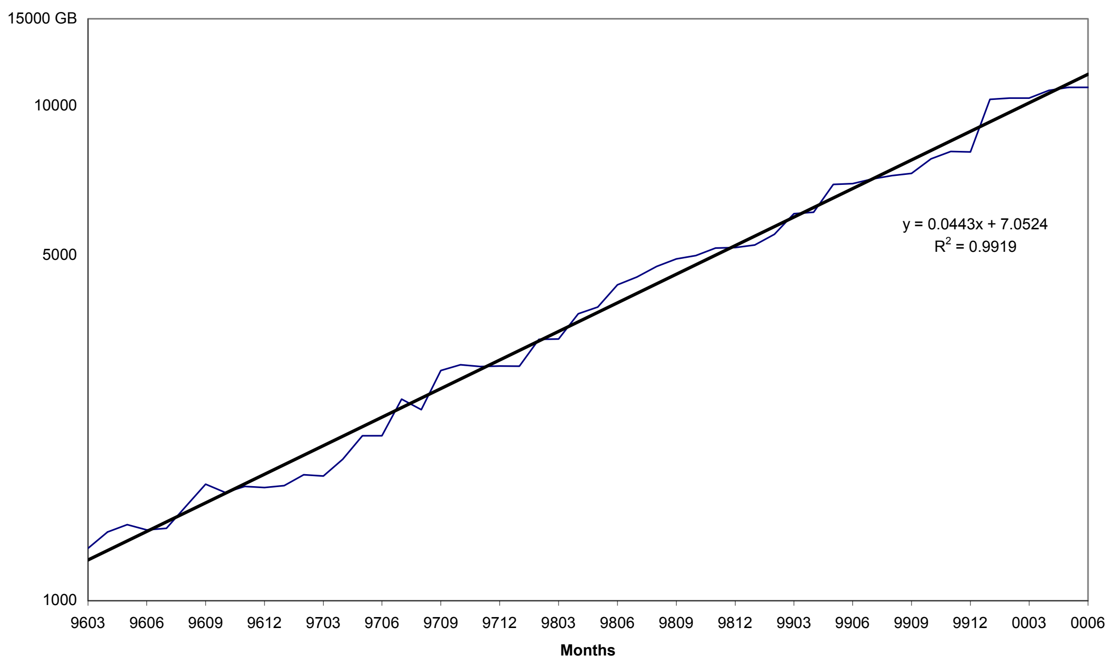
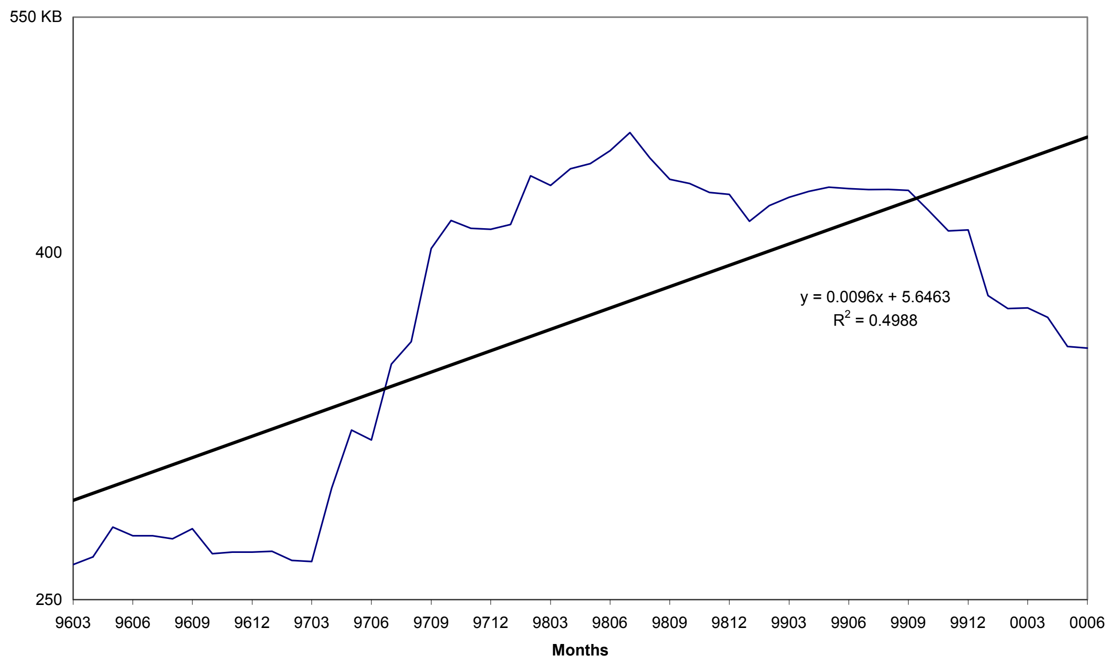


Figure 1.11 - Average CACHE (chart in semi-logarithmic form)



CHAPTER 2 – Overlapping Matched Sample Technique

2.1 Introduction

The objective of this chapter is to describe, use, and evaluate the method of overlapping matched sample pricing in the construction of a price index series for computers. The technique presents an alternative to the current methodology for producing the computer price index in Prices Division, which consists of a matched model sample with hedonic quality adjustments for replacements.[21]

Matched model sampling is a traditional method used for calculating price indexes in many statistical agencies for many products.[22] It is the process of comparing the ratio of prices between successive periods of time for the same model. Since the index is constructed solely on price ratios, matching models produces no change in the characteristics of the good and the product quality is held constant. This method performs best in the case of homogeneous products, where there is little change in the features of a product over time (e.g. raw materials such as diesel fuel).

However, the problem arises when models disappear, say due to obsolescence. At that point, one may choose either to accept the loss and continue on with the remaining price sample or to find a replacement model. Eventually, replacement models will have to be found somehow for the series to continue to exist.[23] The loss of models can be a minor issue for industries producing low-tech goods (e.g. lumber, hammers, tape), where the pace of obsolescence is slow and the replacement items are very close in quality anyway. Such is not the case with computers. This industry can best be described as *heterogeneous*, with product evolution coming at a very rapid pace and where the life span of the "typical" computer system or model is very short (sometimes only several months). Model replacement is no longer trivial.

So how does one introduce the new models? The next chapter looks at the hedonic method, where the price of the replacement model is quality adjusted. In this chapter, we look at the overlapping matched sample method, where the replacement models are simply linked in according to their availability in the overlapping sample periods. One of the main benefits to using this procedure is that it is simple to describe and carry out. Operationally, it accommodates new model characteristics more easily than in the case of the hedonic quality adjustment method. Also, the technique results in a continual updating of the pricing sample of models. However, the main criticism is that this procedure deals with quality change indirectly, relying instead on an implicit quality adjustment that may be insufficient in size and conditional on model prices declining.

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[21] *The procedure outlined and used in this study is based on the method suggested by Turvey (1999). The reader will note that the index series presented in this study are based on the geometric mean only, in order to avoid the dilemma of using the* ***average of the price relatives*** *versus the* ***relative of the average prices****. Since all series are produced this way, this has no impact on the comparison.*

[22] *See Triplett (2000).*

[23] *The choices include resampling, one-to-one replacement within a given sample frame, etc.*

For the remainder of this chapter, an overview of the overlapping matched sample technique is provided, followed by the estimated price index series, an analysis of the issues related to the methodology, and then the conclusions.

2.2 Overview of the Methodology

A summary of the overlapping matched sample method is presented in Table C. Assuming the series begins at month t, the total sample for any period can be defined as S_{t+n} and will be composed of matched (from the previous period $t+n-1$) and unmatched new models, M_{t+n} and nm_{t+n}. In turn, M_{t+n} can be broken down into matched new models and matched existing models, nm_{t+n-1} and em_{t+n-1}, less the disappearing new and existing models, dnm_{t+n-1} and dem_{t+n-1}.[24] Expressed algebraically,

$$M_{t+n} = nm_{t+n-1} + em_{t+n-1} - dnm_{t+n-1} - dem_{t+n-1}$$

where the models contained in M_{t+n} are used for calculating the price relatives between $t+n$ and $t+n-1$.[25]

Table C – Summary of Overlapping Matched Sample Method

Month	t	t+1	t+2,….	t+n
Total sample	S_t	S_{t+1}	S_{t+2}	S_{t+n}
Matched models	M_t	M_{t+1}	M_{t+2}	M_{t+n}
• Last month's new models	nm_{t-1}	nm_t	nm_{t+1}	nm_{t+n-1}
• Other existing models	em_{t-1}	em_t	em_{t+1}	em_{t+n-1}
• Disappearing new models	$-dnm_{t-1}$	$-dnm_t$	$-dnm_{t+1}$	$-dnm_{t+n-1}$
• Disappearing existing models	$-dem_{t-1}$	$-dem_t$	$-dem_{t+1}$	$-dem_{t+n-1}$
Unmatched new models	nm_t	nm_{t+1}	nm_{t+2}	nm_{t+n}

To illustrate, suppose that at t, there are four models in the sample and they are A, B, C and D. At $t+1$, the models available are now B, C, D, E and F, so that nm_t = A, B, C and D, while dnm_t = A and nm_{t+1} = E and F. Hence, $M_{t+1} = nm_t - dnm_t$ = B, C and D, and the price index for that period would be composed of the price relatives for these three models.

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24 *Disappearing new models are those new models from the preceding period, t+n-1, which remained unmatched at t+n.*

25 *Through the use of recursion, the formula for M_{t+n} can be defined as*

$$M_{t+n} = M_t + \sum_{i=0}^{n-1} nm_{t+i} - dnm_{t+i} - dem_{t+i}$$ *, for n>0 (note that when n=0, M_t reduces to nm_t).*

This definition expresses M_{t+n} in terms of the matched models for period t and the births and deaths of new and existing models since that time. At this point, the authors would like to acknowledge and thank Andy Baldwin of Prices Division at Statistics Canada for providing the basis for Table C and the formulae concerning M_{t+n} .

In the following period, $t+2$, the models available become B, C, E and G, so that nm_{t+1} = E and F, em_{t+1} = B, C, and D, dnm_{t+1} = F, dem_{t+1} = D, and nm_{t+2} = G. Therefore, $M_{t+2} = nm_{t+1} + em_{t+1} - dnm_{t+1} - dem_{t+1}$ = B, C and E, and the relatives for these models would be used to calculate the price index between $t+1$ and $t+2$. And so the process continues.

To summarize, the new models are only brought into the sample if they match during the overlapping period, which is composed of the current month and the preceding month. As the example illustrates, not all new models are necessarily used—they must be around for more than one period. The second step of this process is to calculate a price index using the models for the relevant period, as done for any typical price index. The results obtained by using this process follow.

2.3 Results

Index Series

Using the procedure described above, a price index series was calculated using the chained geometric means of the price relatives and is presented in Figure 2.1. Table D contains the estimated growth rates for the entire period as well as for the matching sub-periods discussed in Chapter 1. The index series exhibits a monthly rate of decrease of 2.85% for the entire study period, with the greatest decrease occurring in the first ten months of 1996.[26]

Table D – Rates of Growth

Period	Chained Relative of Geometric Mean (%)
Entire Study Period	-2.85
1996	-5.58
1997	-3.31
1998	-2.33
1999 to June 2000	-2.15

Changing Sample

One of the benefits of the overlapping method comes in the form of sample updating. For the statistician, there are really two issues here, sampling and quality change. These two issues *are not the same*, as shall be demonstrated below. From the sampling perspective, it is important for the sample to be representative—that mainstream computers are being priced at any point in time. The overlapping method, by virtue of its construction, guarantees sample renewal as new models appear. A drawback, though, is that this process is perhaps too objective—all models

[26] *This decrease corresponds to the introduction of new computer chips, which led to large declines in computer prices (see Chapter 1).*

appearing for a minimum of two periods will be included, even though they may not be representative. Of course, this can be remedied by giving greater weight to some models or selecting only those models deemed representative, but then the process begins to resemble more and more the current methodology used to calculate the index.[27]

As a result of calculating the index series presented in Figure 2.1, the observed average monthly matching rate is approximately 88%, meaning that from one month to the next, the index is calculated using 9 out of every 10 models available in the previous month (see Figure 2.2).[28] While this suggests that the continuity of the sample is strong, it must be kept in mind that this reflects a monthly matching rate, whereas the degree of model change would be more pronounced at the quarterly or annual frequencies. Nevertheless, it is important, even at this level. Figure 2.3 provides a summary of the number of new models expressed as a percentage of the total sample for each month. Though on average new models represent 11.5% of the sample for any given month, it is clear that in some circumstances this proportion is much higher. For example, from April to September 1997, the average is 51.7%.

As mentioned, the effect of sample decay is cumulative, as evidenced by the fact that when the sample for a month is compared with the same month one year later, the average 12-month rate of decay is 75.8% (see Appendix II). This means that 75.8% of the models have disappeared within a span of 12 months. One can see the important role that new models play. Clearly, the impact that these new models will have on the existing sample is *not* negligible.

From this, the main implications are: a) the sample used to produce the index will require frequent updating; and b) the rapid displacement of old models by new models must have an impact on the sample characteristics that define product quality and, hence, on the quality-adjusted price movement. The former is an important ramification no matter what technique is used, since it is part of the sampling strategy of any survey process. The issue of quality adjustment is examined more closely below.

Quality Adjustment

Conceptually, one of the underlying assumptions at the micro level of constructing a price index is to keep the quality and/or the quantity of the good or service constant in order to provide pure price movements only, whether the comparison is temporal or spatial. Ideally, the statistician desires continuity of the good or service at the micro level. An apple in one period or place should be compared to the same type, quality and size of apple in another period or place, in order to be able to sensibly talk about the difference in price. Of course at higher levels of aggregation, basket compositions or weighting schemes are numerous, depending on the

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[27] See Chapter 4. One can choose to delay the entrance of new models until they become representative. However, the more subjective one makes the model inclusion process, the more one strays from the original overlapping matched sample procedure, which ultimately becomes no different than the current methodology, minus quality adjustment.

[28] Note that there are four months where no new models were matched.

intended use.[29] But the point remains that for meaningful comparisons to occur, a commodity must be defined and described in the same manner over time and space. Herein lies the difficulty for the statistician who must come to terms with the fact that almost all goods evolve over time (i.e. their quality improves), resulting in a situation where the current model or version of a good will eventually disappear and will have to be replaced with one of (usually) higher quality. If the sample is to be representative of the current period, then quality will change and some form of adjustment will be required.[30]

At this point the statistician has two choices: a) use a *direct adjustment method* (such as hedonic adjustment or option pricing) if a one-to-one replacement is being considered; or b) use an *indirect method* (such as an overlapping matched sample) if a many-to-many replacement is preferred. With a direct adjustment, the size of the quality change is known and its impact on the series can be evaluated easily. In the case of the overlapping matched sample method, the change in quality is not treated in any direct manner. Rather, it is an implicit change, relying on the market valuation of the quality associated with the new models, making it less visible than in the case of direct adjustment. However, as Turvey (2001) points out, one can estimate the quality change realized under the overlap method through the computation of an *Implicit Quality Index*, which is simply the ratio of an unadjusted (for quality) index to the actual index produced for the period, representing the pure price change. In the case of the geometric mean, this would be:

$$Q_{t/t-1} = \frac{P_{t/t-1}^{unadjusted}}{P_{t/t-1}^{actual}}$$

where

$$P_{t/t-1}^{unadjusted} = \frac{\prod_{i=1}^{n} (P_t^i)^{1/n}}{\prod_{j=1}^{m} (P_{t-1}^j)^{1/m}}, \quad P_{t/t-1}^{actual} = \prod_{i=1}^{n} \left(\frac{P_t^i}{P_{t-1}^i} \right)^{1/n}$$

which reduces to

$$Q_{t/t-1} = \frac{\prod_{i=1}^{n} \left(P_{t-1}^i\right)^{1/n}}{\prod_{j=1}^{m} \left(P_{t-1}^j\right)^{1/m}}$$

[29] *For aggregating different commodities to form an index, one can use fixed-weighted indexes, current-weighted indexes, Fisher indexes, etc.*

[30] *One always has the option of keeping the sample the same and continuing to price the same models, no matter how unrepresentative they may become. This avoids the quality change problem only temporarily though, since old models are eventually discontinued.*

In this case, $Q_{t/t-1} > 1$ when the prices of actual models are greater than those of the unadjusted sample in the same period. This signifies a quality improvement as the new models, under the assumption of higher price equals higher quality, replace the lower-priced disappearing models. However, if this price dynamic does not occur and the prices of the new models equal or are less than those of the disappearing models, then $Q_{t/t-1} \leq 1$, implying no quality improvement or quality deterioration. This may or may not be the case, depending on whether the assumption of higher price equals higher quality holds. As Turvey (2001) states, bias in the index will arise when the arrival of new, higher quality products does not cause price reductions in the disappearing models, or when the new models entering the market are priced higher, with little if no difference in quality.

In order to get some idea of the degree of actual quality adjustment under the overlap method, the Implicit Quality Index was calculated and then compared to the index series of the geometric means of RAM and CPU. The latter were obtained from the same models in the sample used to calculate the actual price index.[31] If the overlap method provides an adequate quality adjustment, then one would expect these three series to move together reasonably well, even after taking into account that other quality characteristics such as hard drive size and cache are not included in the analysis.

These index series are presented in Figure 2.4, where from the results one can see that there is an increasing divergence between the RAM and CPU indexes and the Implicit Quality Index. With the exception of the first month or two, the resulting quality level appears to be underestimated using the overlap method, with the problem becoming more serious over time. An explanation for this phenomenon can be found by looking at the behaviour of the new models on their own. If we construct and compare similar index series for the new models (see Figure 2.5), we see that this price index shows little in terms of trend movement in the upward direction, oscillating instead around an average value of 111.3. Meanwhile, the index series for RAM and CPU are increasing very strongly, reflecting the trends originally mentioned in Chapter 1. Over time, the prices of new models are not necessarily reflecting their changing quality level, leading to a downward bias in the measure of the quality adjustment.

New Models Versus Old Models

To further examine this bias, the new models entering the sample were compared to the old models leaving the sample on the basis of price, RAM and CPU. Under the overlap method, the ratio of the prices of the new or replacement models to the old or disappearing models should reflect the inherent difference in quality in the case of a many-to-many replacement. Taking this one step further, the percentage change between the average price of the new and old models should reflect the percentage change in their average quality. Therefore, with RAM and CPU as the main indicators of quality, one would expect to see similar values for these variables across the periods where new and old models are observed. For example, if the average price of new

[31] *These three index series are produced as chained index series. In addition, for the four months where no new models were introduced, the preceding month's values were used as a proxy in order to calculate the chained index series. This will not impact the analysis in any significant manner, since there is no change in the index movement for all three series during this period.*

models in a particular month is 10% higher than the old models being replaced, one should see corresponding increases in RAM and CPU of approximately the same magnitude. They will not be exact, and in fact the percentage differences should be lower in the case of RAM and CPU, since other quality characteristics are not considered in this case.[32]

These percentage changes were calculated using the geometric means of price, RAM and CPU of the new and old models, for the 38 months where both new and old models were observed. The results are presented in Figure 2.6.[33] In terms of movement, the percent change in price moves similarly to the percent changes in RAM and CPU for the most part.[34] However, the percent difference in price is actually less than those of RAM and CPU for the majority of months (27 and 26 months, or 71% and 68.4%). These differences are further presented in Figures 2.7 and 2.8, where their size and variation are shown. As these results indicate, the difference is mostly negative and can be substantial at times, reaching over -20% for 14 periods in the case of CPU (or 36.8%) and 42.1% for 16 periods in the case of RAM. Clearly, this implicit method of quality adjustment is underestimating the size of the quality change.

2.4 Conclusion

In summary, the main benefits of the overlapping matched sample method as presented in this study are—it is a simple method to implement, it updates the sample continuously and, though not discussed at any great length here, it accommodates new models with different characteristics much easier than the hedonic method.

Despite these advantages, it has a major conceptual weakness in that quality differences among models are not addressed in any direct manner. They are handled implicitly, and therefore, can lead to an underestimation of quality change. Furthermore, the method of sample selection inclusion is perhaps too objective. Are all these new models representative enough to be included so soon in the sample? Under this method the answer is yes. But given the size of this segment relative to the total sample, further consideration should be given as to when or if they should be included at all (perhaps by considering an extended overlap period). Finally, on the issue of new characteristics of replacements, the problem is not insurmountable in the case of hedonics, it merely requires more effort. Unfortunately, this point alone is not sufficient to recommend the overlapping matched sample method over the hedonic approach in the case of computer price indexes.

[32] *If the actual percentage changes for RAM and CPU were, for the sake of argument, both 7%, then one could say that the higher price change is overestimating the quality change. However, this may not be the case if the hard drive size or type has improved.*

[33] *Figures 2.6, 2.7 and 2.8 use periods rather than months to present the data, since the months where there were no new and old models have been removed.*

[34] *The estimated correlation coefficients between price and RAM and between price and CPU were 0.83856 and 0.63892 respectively.*

Figure 2.1 - Overlapping Matched Sample Index
(chart in semi-logarithmic form)

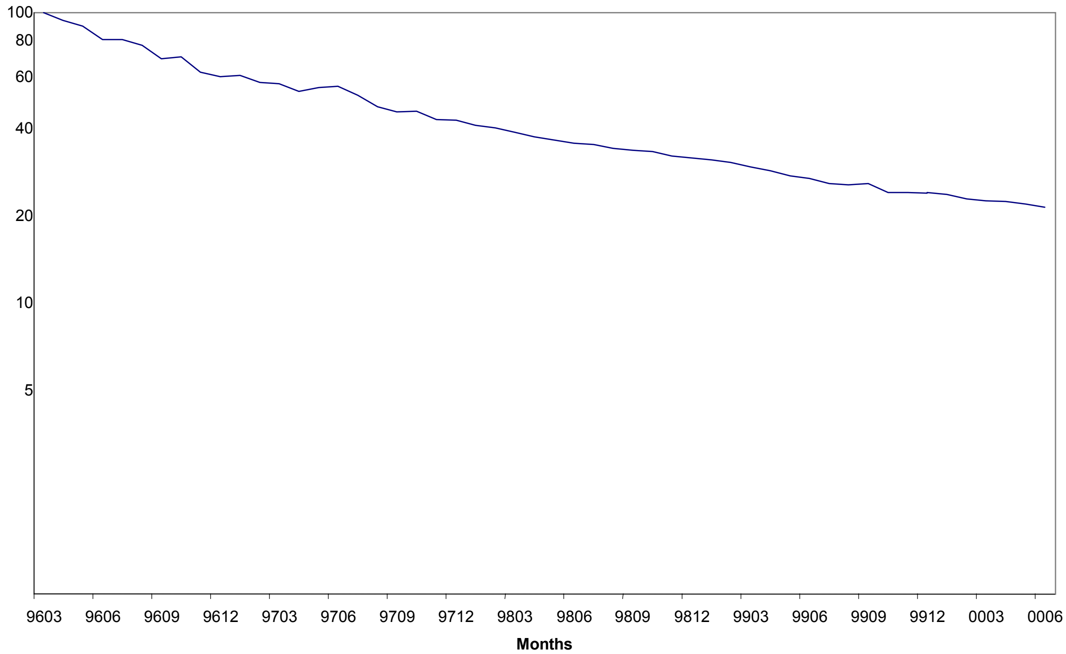


Figure 2.2 - Matching Results

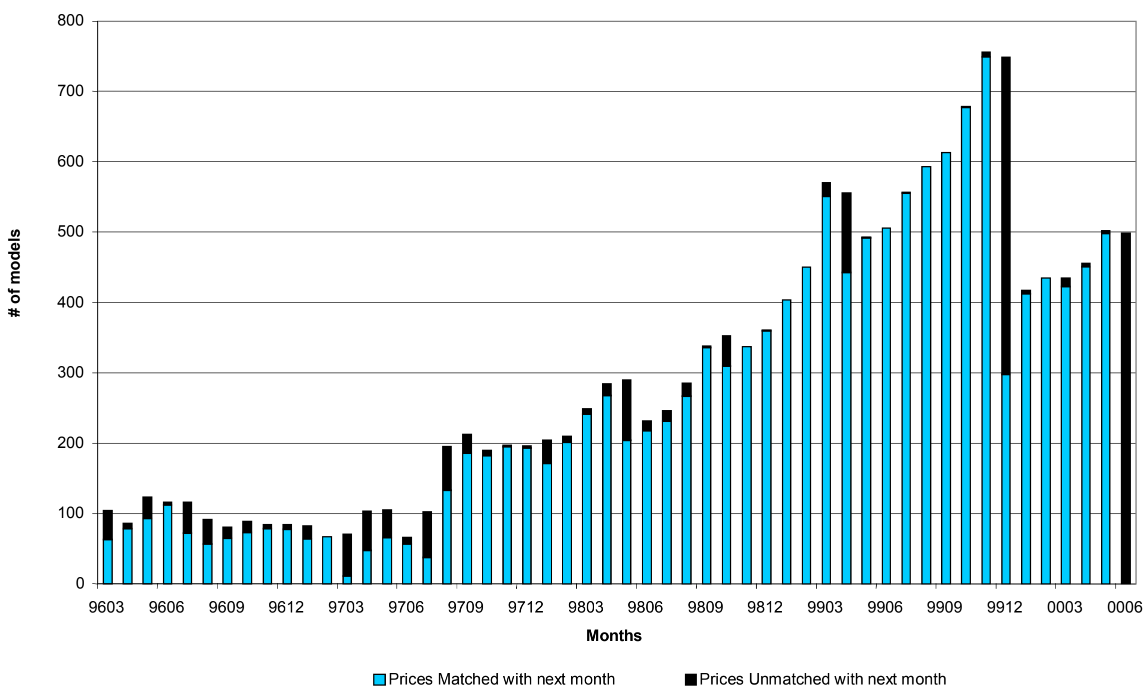


Figure 2.3 - New Models as a % of the Entire Monthly Sample

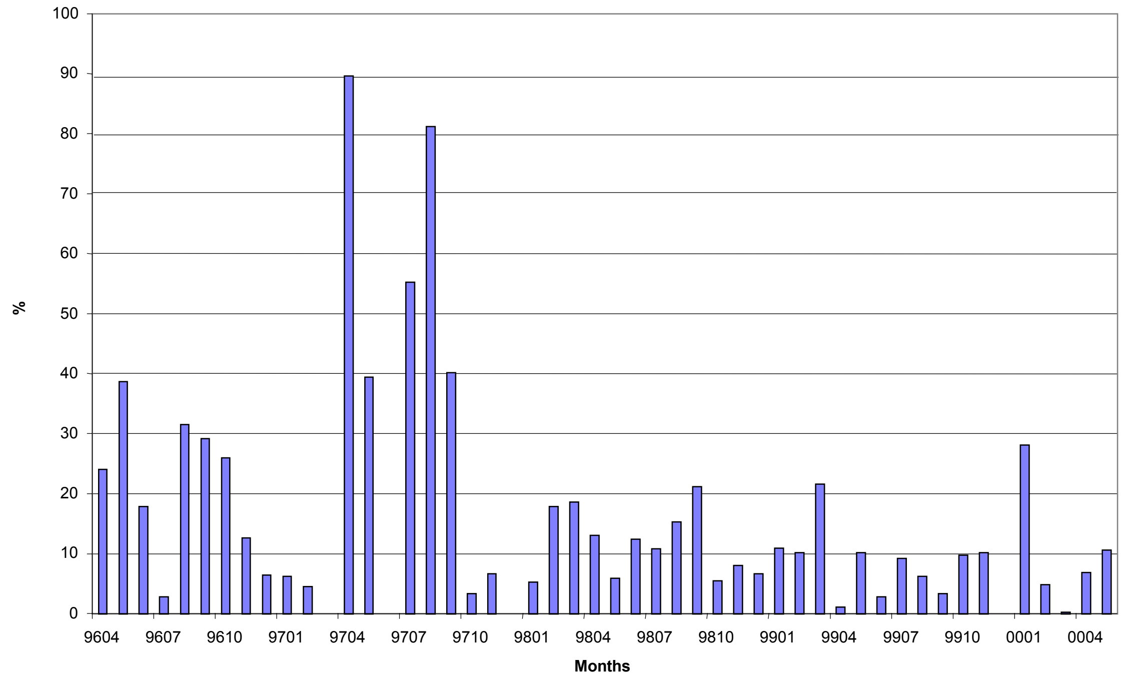


Figure 2.4 - Implicit Quality Index vs. RAM and CPU Indexes

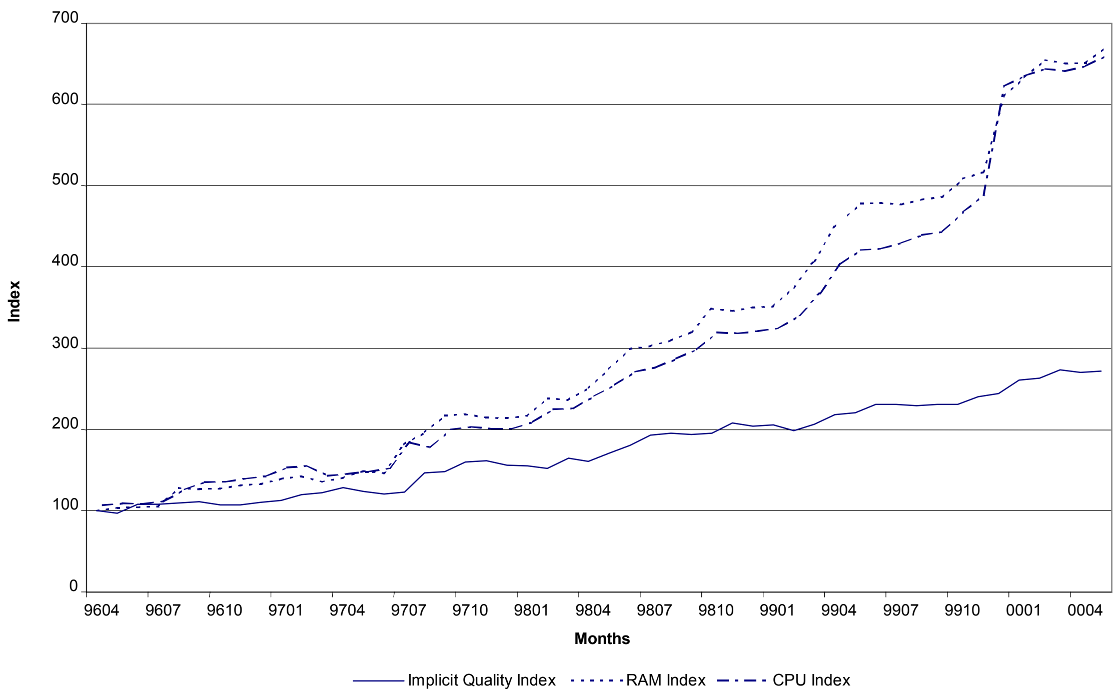


Figure 2.5 - Price Index vs RAM and CPU Indexes - New Models

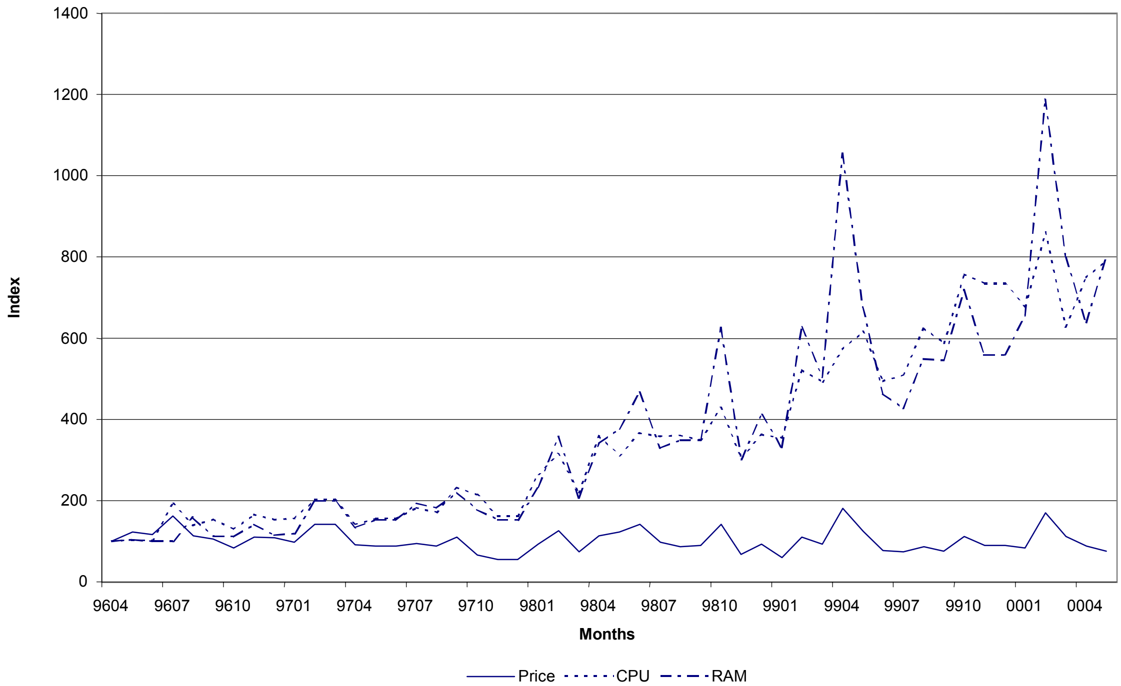


Figure 2.6 - Price, CPU and RAM of New/Old Models (as a %)

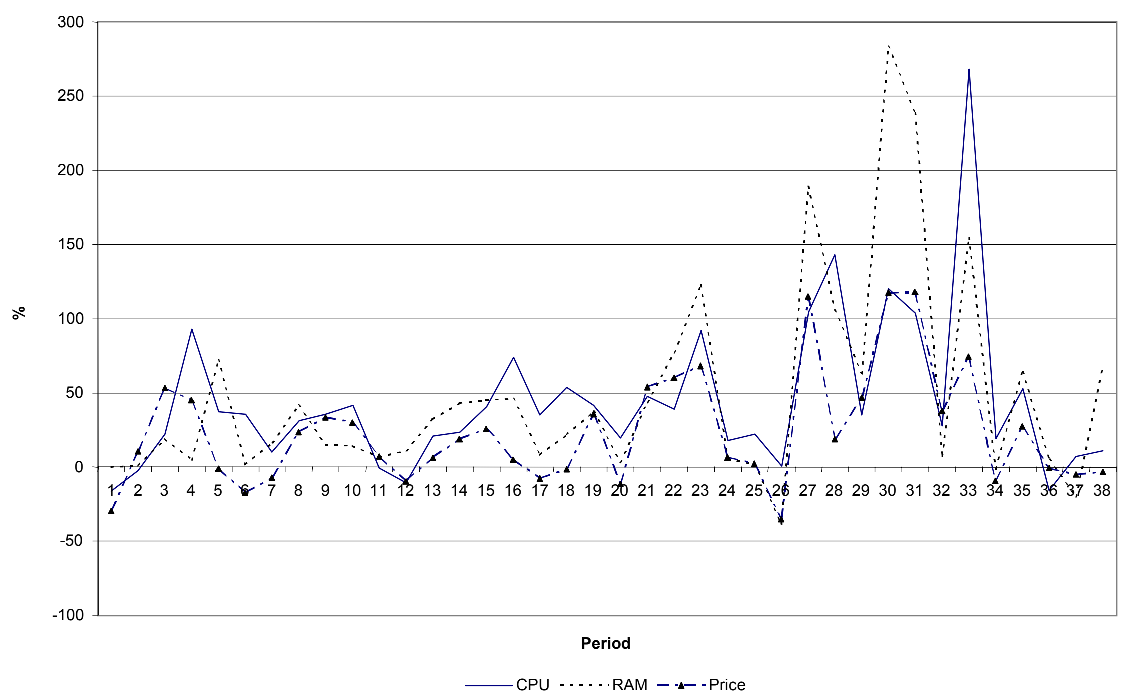


Figure 2.7 - Difference of New/Old Price (%) - New/Old RAM (%)

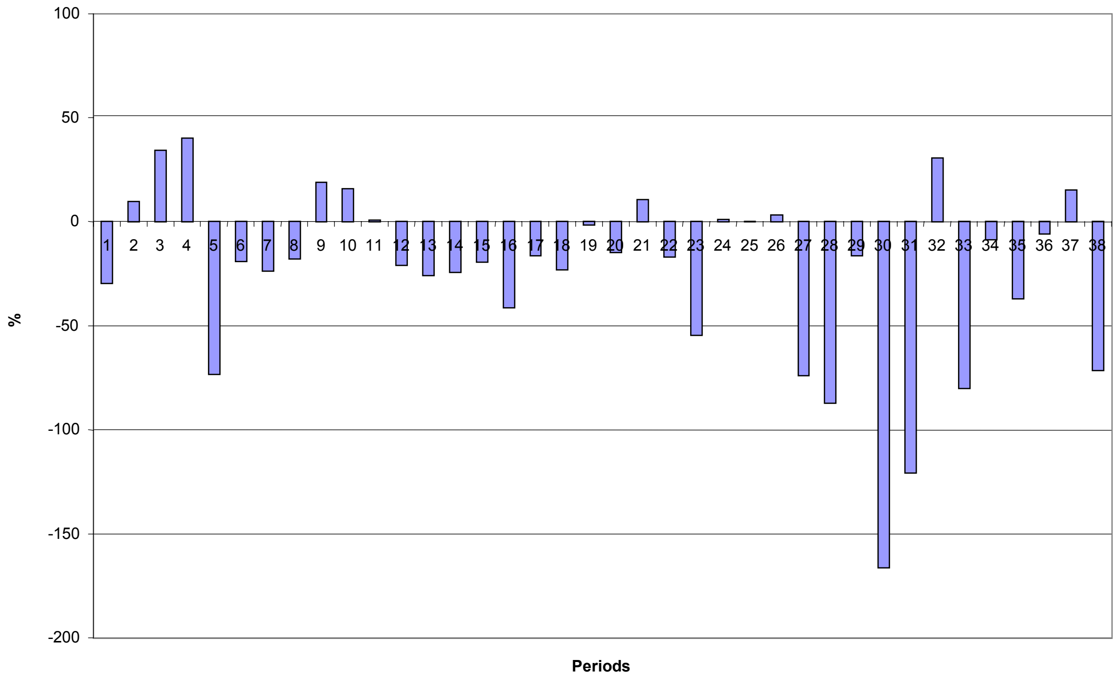
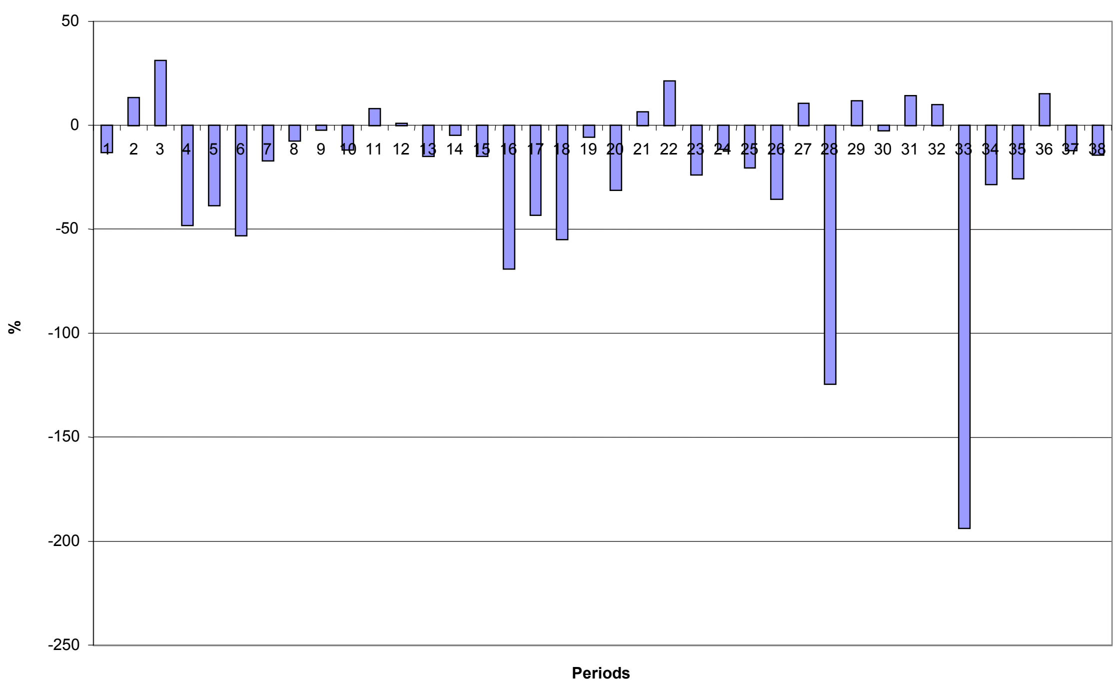


Figure 2.8 - Difference of New/Old Price (%) - New/Old CPU (%)



CHAPTER 3 – Hedonic Methodology

3.1 Introduction

This chapter examines the use of hedonic methodology in the treatment of quality changes for computers. The objective is to assess how well this process works, and how it impacts on the calculation of a price index for computers. The main questions to be answered are, how feasible is this quality treatment technique from a practical perspective, can it be used on a regular basis and if so, under what circumstances?

Generally speaking, the hedonic method attempts to explain the changes in the price for a good or service by relating them to changes in the characteristics of the good or service.[35] In the case of computers, the relationship is between their price and their various components or characteristics, such as RAM, CPU speed, hard drive size and a number of qualitative variables (vendor, presence of a compact disc or CD drive, modem, etc.). The main benefits of the hedonic approach are that it deals with the issue of quality change head-on and that it has theoretical underpinnings. Other techniques attempt to deal with quality changes indirectly (e.g. through sample adjustment) and are more procedural-based.[36] One of the major drawbacks of hedonic methods is the heavy reliance on high quality data with adequate numbers of observations to obtain statistically significant results. Related to this is the fact that since regression analysis methods are used to estimate the equations, one always runs the risk of getting poor or unusable results. In effect, the resources required to produce good results can be substantial when compared to other quality treatment options. Nevertheless, this methodology is either currently used or being considered by several other statistical agencies (the Bureau of Labor Statistics, the Bank of Japan, the Institut national de la statistique et des études économiques (INSEE), the Australian Bureau of Statistics, etc.).

While there are various ways of employing hedonic methodology in the case of quality change, they generally fall into one of two groups, direct hedonic indexes and indexes based on matched models with hedonic quality adjustments. Direct hedonic indexes are price index series calculated using the estimates taken directly from a regression equation. Under the matched model procedure, models are matched from period to period and only when models disappear from the sample are hedonic equations used to impute quality adjusted prices for replacement models. Prices Division at Statistics Canada currently uses this approach. Both hedonic methods are considered in this study.

In the remainder of this chapter, there is a general discussion of hedonics from the point of view of model-fitting results, then two methods of calculating a direct hedonic index are considered, followed by an illustration of the matched model approach and the construction of a hypothetical index using this procedure, ending with a conclusion.

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[35] *For an in-depth review of hedonic quality adjustments, the reader should consult **The Practice of Econometrics, Classic and Contemporary** by Ernst R. Berndt (1991), Chapter 4.*

[36] *One such technique, the **Overlapping Matched Sample Method**, was discussed in the previous chapter.*

3.2 Hedonic Methods – General Comments and Results

The real challenge associated with the hedonic method lies in the estimation of an appropriate model, that is, one that captures the price and component relationship to a high degree. The major problem pertaining to the estimation of hedonic equations is the choice of functional form, since this choice will determine the quality of the results (relevance, accuracy, reliability, plausibility, etc.). Typically, the choice of functional form is limited to linear, semi-log or double-log models or some variant of the double-log model (for example, where only one of the explanatory variables appears in log form), although forms requiring non-linear estimation have been suggested.[37] In order to discriminate between these choices, several criteria can be used including graphical analysis, signs and values of the estimated coefficients, log-likelihood statistics, adjusted R^2, formal test statistics such as the Double Length Artificial Regression test (or DLAR test) for functional form, results of Box Cox estimation and hypothetical test case results.[38]

For the purposes of this study, one of the principle objectives was to determine how difficult it would be to fit a model for each month of the period—could it be done and if so at what level of effort? Secondly, would these models provide usable results? By comparing the level of difficulty of using this methodology with the results it provides, we are really establishing the trade-offs associated with this hedonic method from a practical perspective.

Results

As mentioned, the first step was to try and fit an equation for each month of the data. Initially this was done using the two primary explanatory variables, RAM and CPU and various functional forms were estimated for the monthly equations (these being linear, semi-log, log-linear and double-log versions).[39] Models were then estimated using several additional influential variables to see if the fit could be improved. The second part of this evaluation was to use the resulting models to carry out a hypothetical quality change for each month, by using a realistic change in models. These quality changes were then assessed to determine how reasonable they were.

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[37] *See Triplett (1987).*

[38] *See Davidson and MacKinnon (1993).*

[39] *These functional forms are defined in the following manner:*

linear $$P_i = \beta_0 + \sum_{j=1}^{n} \beta_{ij} X_{ij}$$

semi-log $$\ln P_i = \beta_0 + \sum_{j=1}^{n} \beta_{ij} X_{ij} \text{ or } P_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ij}$$

log-linear $$\ln P_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ij} + \sum_{k=1}^{l} \gamma_k Z_{ik}$$

double-log $$\ln P_i = \beta_0 + \sum_{j=1}^{n} \beta_{ij} \ln X_{ij}$$

where Z_k represents a set of linear variables.

Model Fits Using RAM and CPU Only

The results from just using these two key variables are impressive. Not only was a model found for each of the 52 months of the data set, but the level of fit, as crudely measured by the adjusted R^2, is reasonably strong (see Figure 3.1).[40] The average monthly adjusted R^2 is 0.7282, with a minimum of 0.5491 and a maximum of 0.8782, indicating that at *worst*, just taking into account differences in RAM and CPU can explain 54.91% of the price differences across computer models for a particular month, while on average they account for 72.82%.

The distribution of functional forms chosen is presented in Table E, where the most prevalent functional form is the log-linear transformation, where price is transformed and then either RAM or CPU are transformed by taking the natural logarithm. This functional form accounts for 31 out of 52 months (or roughly 60%).

Table E – Functional Forms Using RAM and CPU

Functional Form	Months	As a %
Linear	7	13.5
Semi-log	5	9.6
Log-linear	31	59.6
Double-log	9	17.3
Total	52	100.0

Model Fits with Additional Variables

After fitting a model for each month using just RAM and CPU, additional variables were tried, mainly HD and CACHE, but also others such as vendor type, hard drive type, etc. A frequency of the models is presented in Table F. The most common number of variables was four, though some fit well with just three, and a few required up to six explanatory variables.[41] Naturally, the added variables improved the level of fit significantly (see Figure 3.2), as now the average adjusted R^2 is 0.8230, with the range being 0.7549 to 0.9066. Again, the log-linear version, where at least one of the influential variables is transformed, is the most often chosen, accounting for 43 out of 52 months (or 82.7%).

[40] *While categorizing the fit of a particular model is often subjective, it is reasonable to expect the signs of the estimated coefficients to match* ***a priori*** *expectations and the estimated equation to be able to explain at least a significant portion of the changes in the dependent variable. Whether* ***significant*** *translates to 50%, 60% or 80% of the variance in price is for the reader to decide.*

[41] *Only one model exceeded six explanatory variables, requiring eight.*

Table F – Functional Forms Using Additional Variables

Functional Form	Months	As a %
Linear	1	1.9
Semi-log	8	15.4
Log-linear	43	82.7
Double-log	0	0.0
Total	52	100.0

Quality Changes

Having found reasonably well-fitting models for each of the months, the next step was to evaluate just how realistic these results were. This was done by using the estimated equations to perform a hypothetical quality change for each of the months. The two models, original and replacement, were selected to represent a model change that would normally occur on a monthly basis, so the quality difference between the two would not be as great as say in the case where a model change was done annually. For the latter, one would expect a much greater difference in quality due to the rapidity of technological change.

The results of the hypothetical quality change are presented in Table G. This table contains the variables or characteristics that change between the original model and the new or replacement model, along with the original model price, the new model price, the quality adjusted price for the new model and the percentage changes between the new and old models and between the new and quality adjusted new models. As is evident from the results, using the quality adjusted prices results in a larger price decline—or a smaller price increase—than in the case where the quality change was simply ignored. On average, the price change is -5.8% for the entire period with quality adjustment, but without quality adjustment the average is 34.5%—two very different movements. Considering several individual model changes for illustrative purposes, we see that an increase in RAM, CPU and the number of drive bays for the month of August 1996 results in a quality adjusted price increase of 0.7%, which is much smaller when compared to a face value increase of 86.5%. Likewise, a change in CPU, HD and vendor type for June 1997 results in a quality adjusted price decrease of 32.7%, greater than the face value decrease of 13.4%. While the magnitude of the difference for these two examples may seem large (85.8% and 19.3% respectively), they must be considered in light of the fact that several key model characteristics have also changed, making them sensible adjustments. As a final example of this point, when only the CPU changes for a model replacement in April 1997, the difference is much smaller, a decrease of 0.6% when compared to a 5.8% increase, for a total difference of 6.4%. Overall, the results obtained using these models are as expected, with the magnitude and direction of the quality changes varying directly with the importance and size of change in the characteristics, which is not surprising given the models' level of fit in the first place.

Table G – Summary of Hypothetical Quality Changes

	Changes in Variables for Old vs. New Models					Price for Old Model	Price for New Model	% Change New vs. Old	Quality Adj. Price for New Model	% Change New vs. Quality Adj.
Date	CPU	RAM	CACHE	HD	Other Variables					
199603				x		4,258	3,596	-15.5	4,336	-17.1
199604	x			x		3,754	3,456	-7.9	4,271	-19.1
199605	x		x			2,767	4,078	47.4	3,619	12.7
199606	x	x				3,547	5,947	67.7	5,782	2.9
199607	x		x			5,570	7,272	30.6	8,165	-10.9
199608	x	x			# of drive bays	3,406	6,353	86.5	6,306	0.7
199609	x				# of drive bays	2,643	2,632	-0.4	3,241	-18.8
199610	x	x				3,597	3,585	-0.3	4,454	-19.5
199611	x	x				2,850	3,561	24.9	3,782	-5.8
199612	x	x				2,131	3,023	41.9	2,905	4.1
199701	x	x			HD type	2,935	5,799	97.6	4,884	18.7
199702	x	x				3,430	3,893	13.5	4,563	-14.7
199703	x	x				2,867	3,884	35.5	3,864	0.5
199704	x					3,267	3,455	5.8	3,477	-0.6
199705	x		x			1,812	2,711	49.6	2,471	9.7
199706	x			x	vendor	3,975	3,443	-13.4	5,117	-32.7
199707	x			x	vendor	2,813	2,875	2.2	3,443	-16.5
199708	x	x				2,233	3,327	49.0	3,603	-7.6
199709	x				modem	2,111	3,318	57.2	2,905	14.2
199710	x			x		1,819	2,449	34.6	2,228	9.9
199711	x	x		x	modem	1,836	4,741	158.2	3,628	30.7
199712	x			x	modem	1,848	3,822	106.8	3,215	18.9
199801	x			x		1,519	2,199	44.8	1,826	20.4
199802	x	x				1,826	3,536	93.6	2,707	30.6
199803	x		x		modem, HD type	1,621	2,442	50.6	3,222	-24.2
199804	x				modem	2,230	3,606	61.7	3,483	3.5
199805	x		x			5,981	6,311	5.5	7,671	-17.7
199806	x	x				2,630	3,965	50.8	3,769	5.2
199807	x	x			HD type	2,423	2,552	5.3	3,685	-30.7
199808	x		x			1,866	2,351	26.0	2,668	-11.9
199809	x	x	x		HD type	1,799	2,513	39.7	3,005	-16.4
199810	x	x				2,533	3,661	44.5	3,658	0.1
199811	x	x				7,568	8,875	17.3	10,827	-18.0
199812	x	x				1,806	2,112	16.9	2,591	-18.5
199901	x		x			1,684	2,316	37.5	2,194	5.5
199902	x		x			1,644	2,128	29.4	2,158	-1.4
199903	x	x			HD type	1,741	2,939	68.8	2,672	9.9
199904	x	x				2,058	2,053	-0.2	2,839	-27.7
199905	x	x				2,997	4,652	55.2	4,077	14.1
199906	x				HD type	3,918	4,639	18.4	5,637	-17.7
199907	x	x				1,108	1,275	15.1	1,501	-15.1
199908	x	x	x			2,793	3,266	16.9	4,939	-33.9
199909	x		x			6,574	10,086	53.4	9,762	3.3
199910	x	x				1,779	1,734	-2.5	2,537	-31.7
199911	x				vendor	1,889	1,547	-18.1	2,259	-31.5
199912	x	x				1,554	2,121	36.5	2,165	-2.1
200001	x		x			2,066	2,150	4.1	2,297	-6.4
200002	x	x	x			1,606	2,646	64.8	2,566	3.1
200003	x	x				2,186	2,314	5.9	3,241	-28.6
200004	x		x			1,984	2,336	17.7	2,511	-7.0
200005	x				HD type	3,251	4,233	30.2	4,784	-11.5

3.3 Direct Hedonic Indexes

Dummy Variable Method – Pooled Approach

The most direct way of producing a quality adjusted price index centres on the estimation of a price index series through the use of econometric methods. There are several methods of doing so, one of the earliest being the Dummy Variable Method. Under this approach, one estimates a model such as:

$$\ln P_{it} = \alpha_0 + \sum_{t-1}^{T} \delta_t D_t + \sum_{k=1}^{n} \beta_{ki} X_{ki} + u_i \ .$$

In this representation, P_{it} is the price of the i^{th} model in period t, while D_t is a time dummy variable equal to 1 in period t and 0 otherwise and X_{ki} represents the various characteristics of a computer such as RAM, CPU, hard drive capacity, etc. The coefficient δ_t represents the percentage change in price across time periods holding quality constant. Under the pooled approach, D_t will consist of several subsequent periods (i.e. months, quarters or years), all grouped together under one estimation. One then takes the antilog of the estimated values for the various δ_t to construct the quality adjusted price index.

As an option, the pooled approach does offer the benefit of maximising the sample size, however, two main drawbacks centre on the stability of the coefficients and the impracticality of using this approach for continuous price index construction. To begin with, the pooled approach is based on the assumption that the coefficients for the various X_{ki} are stable throughout the observation period. This is highly unlikely as the period T increases for two reasons. First, as time passes we are more likely to see a dissimilarity of characteristics as products evolve and new characteristics are introduced. Second, the fact that over a sufficiently long period of time, changing relationships between price and the different X_{ki} are expected, which are mainly due to the evolution and behaviour of secondary markets for inputs such as RAM and CPU.[42] Finally, from a practical perspective, using such a method to produce an ongoing price index series would result in continual revisions to the entire series, due to the re-estimation of the original equation as the pooled set of data grows.

Dummy Variable Method – Adjacent Period Approach

An alternative to the pooled approach is to use adjacent period regressions. Instead of grouping all the periods at once and estimating one equation, only two adjacent periods are pooled at a time. The resulting estimates are then used to produce a chained price index multiplying out the series of antilog estimates for δ_t (Berndt [1991]). Under this time-varying hedonic method, the assumption of coefficient stability is relaxed and coefficients are allowed to vary over time, particularly in the case of monthly data. As well, the problem of having to revise the entire index series after each estimation is eliminated. Based on these reasons, a direct hedonic index was calculated using the adjacent period.

[42] *In their study, Berndt, Dulberger, and Rappaport (2000) have found this to be the case.*

The results are presented in Figure 3.3, along with the index series obtained using the overlapping matched sample method for comparative purposes. As the graph shows, the adjacent period dummy variable index is decreasing more rapidly than its counterpart. The average monthly rate of change is -4.23%, a difference of 1.38% (in absolute terms) when compared to the overlap series.

Prud'homme-Yu Approach

There exist numerous alternatives to the dummy variable approach for calculating direct hedonic indexes. One recent method suggested by Prud'homme and Yu (2001) uses predicted values from adjacent periods to construct simple price relatives.[43] To construct a price relative between t and $t+1$ (or $p_{t/t+1}$), the first step is to estimate two hedonic models, one for each. Next, the observations from both periods are pooled to form one data set and this pooled set of data is then used to produce two sets of predicted values, one from each equation. That is,

$$\hat{p}_k^t = f(X_i^t, X_j^{t+1}, \hat{\beta}^t)$$

$$\hat{p}_k^{t+1} = f(X_i^t, X_j^{t+1}, \hat{\beta}^{t+1})$$

where $k = i + j$ (i.e. the pooled data).[44] Each model in the pooled data set now has predicted prices for t and $t+1$. These prices can now be used to calculate the index base on the arithmetic mean of the price relatives, the price relative of the arithmetic means, or the geometric mean. It would seem that the main benefit of this method over the dummy variable approach is that the Prud'homme-Yu method does use the matched model approach, albeit in weak form as prices are imputed for missing models—in fact, *all* prices are imputed.

Results

The results using this procedure are presented in Figure 3.4, where the index was produced by calculating the price relatives using the geometric mean and then chaining them together. The estimated rate of monthly change for this index is -4.07%. Included for comparison is the price index series calculated using the dummy variable method and the overlap method. Not surprisingly, the series produced using the dummy variable and Prud'homme-Yu methods are the most similar of the three, though the former declines at a slightly quicker pace.[45]

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43 *Actually, the Prud'homme-Yu method used in this study is not really a direct hedonic method in the truest sense. However, given the important role that regression estimates play in the construction of indexes, it is closer to a direct method than it is to an indirect method.*

44 *This is just a re-formulation of the original description set out in Prud'homme and Yu (2001).*

45 *The difference in the estimated monthly rates of decrease between the Prud'homme-Yu method and the dummy variable method is -0.16%, while between the Prud'homme-Yu and the overlapping matched model series it is 1.41%.*

Direct Hedonic Indexes – Comments

From a practical perspective, there are some concerns to using these direct hedonic methods—the major one being a greater degree of intervention in the calculation of the index. With the adjacent period dummy variable method, estimates of δ_t can be affected by factors typically associated with any regression estimation (poor model fits, existence of severe multicollinearity, omitted variables, etc.), which in turn could affect the robustness of the index series. Coupled with this is the fact that the results presented in this chapter employ all observations for a given month, whether they are representative or not.[46] This too may impart some bias in the calculation of the index, particularly in months where model turnover is not great. The reader will recall from the previous chapter that approximately 9 out of 10 models are matched from one month to the next, so that one tends to see a small degree of model change at the monthly frequency. With such a high rate of matching, one questions the need to employ a direct hedonic index when actual prices are available (granted the change is cumulative, so some form of adjustment is required).

Similarly, in the case of the Prud'homme-Yu approach where all prices are imputed, the level of bias could be greater than when actual or direct prices for matched models are used. Again, the degree of bias will depend on the level of fit of the estimated model, as determined by the choice of explanatory variables, functional form and so on, from where it follows that poorly fitting models will produce poorly imputed prices. One other difficulty occurs when the fitted hedonic models change slightly from month to month in the case of qualitative (i.e. dummy) variable definitions.[47] In such a case, common definitions spanning the two periods must be imposed, which occur at the expense of a lower degree of fit for one of the two (or both) models.

3.4 Current Methodology – Matched Sample with Hedonic Adjustments

The method used presently by Statistics Canada to produce a computer price index is analogous to the one practised by the Bureau of Labor Statistics (BLS), in that a matched sample process is followed, with hedonic equations being used to adjust reported prices as model characteristics change (see Holdway [2000]).

Basically, cross-sectional models are estimated on a regular basis. Then, the most recent results are used to calculate a quality adjusted price for a replacement model in the pricing sample by applying the differences in the characteristics between the old model and the replacement model.[48]

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46 *The issue of sample composition is addressed in the following chapter.*

47 *In the case of hard drive type, for example, the number and definition of the dummy variables representing this characteristic differed between two particular months. The result being that the price relative calculated was clearly non-representative. To resolve this problem, the data were pooled and then a new model was fitted. Using the variables contained in the pooled data set, the models were then re-estimated for each month and predicted prices were obtained. The resulting price relatives were more in line with the remaining series. While this problem occurred a few times, it was not prevalent in this analysis.*

48 *The BLS has been updating its equations on a quarterly basis, whereas in the case of Statistics Canada this process has been less frequent. At the time of this study, there have been two annual updates to the equations. Prior to this, the updates were carried out on an occasional basis (see Barzyk [1999]).*

Consider the hypothetical example provided in Table H, where the new model available in May is about to replace the original model available up to April. At face value, the difference in price between the two models is $450, and if the new model replaces the original model in May without any consideration for a change in quality, the resulting price relative would be 1.286, or a price increase of 28.6%. Clearly, the models are not directly comparable since they differ across the key performance attributes. Using a hedonic equation that captures the contribution of these components to explain differences in computer prices, one uses the change in the model characteristics in order to arrive at a shadow price for the new model had it existed in April.

Table H – Hypothetical Change in Computer Models

Model Characteristics	Original Model in April	Replacement Model in May
CPU processor	Compaq Pentium III Deskpro EP 500 MHz	Compaq Pentium III Deskpro EP 600 MHz
Memory	64 MB RAM	128 MB RAM
Extended cache	128K CACHE	256K CACHE
Hard drive storage capacity or size	6.4 GB hard drive	10.0 GB hard drive
Inclusion of Ethernet card	No Ethernet (or network) card	Ethernet (or network) card included
Price	$1,573	$2,023
Shadow price of new model in April		$2,847

For the purpose of illustration, let us assume that such an equation existed and using it resulted in a shadow price for the new model of $2,847 for the month of April. This price would then be compared to the actual price of the replacement model ($2,023). The resulting price change is a decrease from $2,847 to $2,023, or -28.9%. The quality change amount is calculated as the difference between the shadow price and the price of the original model, or $2,847-$1,573= $1,274 (or an increase of 81% from the original model). The resulting price relative would show a *decline* of 28.9% from April to May, and not the increase of 28.6% originally calculated.[49]

This approach represents a compromise between the two extremes of the overlapping matched model and the direct hedonic index approaches. As such, it has the benefit of being grounded in the matched model approach, which is ideally what the price index strives to measure. If no model change occurs, then the issue of quality change disappears and all methodologies should reduce to a simple matched model index. However, because there is a model change, the hedonic method is used to adjust the quality of the replacement models, so

[49] *Under the current practice for calculating a quality adjustment in the industrial price indexes program of Prices Division, the price difference between April and May would be calculated for the* ***new*** *model and not the old one.*

that the quality differences are handled in a direct manner, which is a second major benefit of this approach. From a historical perspective, it should be mentioned that one of the main reasons for establishing and using this methodology over the calculation of a direct hedonic index was the lack of data necessary to produce a direct index. This is no longer an issue, since the current database provides an ample source from which to draw observations.

Under the matched sample with hedonic adjustments approach, however, sample management becomes an important element in the production of an index. With any matched sample process, choosing and maintaining a sample that is representative is paramount in order to produce a robust series. Having described in general this approach to index construction, we now turn to the construction of a hypothetical index series based on this method.

Matched Sample Hedonic Price Index Series

As mentioned, the methodology used to calculate the hypothetical price index draws mainly from the methodology already in place. Essentially, price relatives are calculated for a matched sample of models from one month to the next. Models are replaced using the hedonic method to account for quality change. The specifics are provided below.

Sample Selection Process

The series begins in March 1996. In this month and for approximately the next 18 months, the monthly sample size consists of about 100 models. An initial group of 30 models was selected, where the intention was to represent the mainstream group of CPUs (roughly the middle 50% of the sample). As the number of models available grew, the sample size was increased by 15 models twice throughout this period, once in October 1997 and then again in March 1998 to bring the total sample to 60 models. The selection of these additional models was spread evenly across the entire mainstream bracket, in order to reflect the prevailing distribution of models at that time and to avoid introducing any bias into the sample. Finally, vendors were weighted in the sample based on the proportion of models each vendor accounted for in the total month's data set. Meaning that if a vendor's models represented 20% of all the models for a month, then their models made up 20% of the sample for the month.[50]

Replacement of Models

Model replacements were carried out as determined by the sample (i.e. forced replacements) and linked in using the hedonic quality adjustment method. When a middle- or lower-end mainstream model was lost, a replacement model was selected from the highest end of the mainstream group, and if none was found then the selection process proceeded downward through the CPU categories until an appropriate replacement was found. If a high-end model was discontinued, then a replacement was chosen from the same grouping, and if still no model was found, then the mainstream bracket was extended to the next highest CPU class and so forth

[50] *This is more an artifact of the exercise and not necessarily a benefit. Throughout the production of the price index for computers, much use is made of timely market intelligence and research in determining the sample composition. For the purposes of this study, a more objective approach was tried. This point will be discussed more fully in the next chapter.*

until a replacement was found. In effect, choosing a replacement model represented a trade-off between its longevity in the sample and the size of the corresponding quality adjustment. This trade-off can be explained in the following manner. For the most part, models which are lost in a given month belong to a CPU class or classes which embody older, outdated technology—basically these CPU classes are on their way out anyway. Therefore, replacing a model with one in the same or similar CPU class usually means more frequent model replacements, since the replacement models are likely to disappear soon as well. However, because the replacement models are similar in technology, the differences in quality will be small. At the other extreme, choosing replacement models from the CPU classes representing cutting-edge technology all but guarantees that they will be in the sample for a longer period of time, since these models are just entering the market. As a result, the quality changes will be less frequent, but of a larger magnitude, because now the differences in quality will be big (different technology). In this study, the compromise was to choose replacement models from the high end of the *mainstream* models, so that the benefits and costs of reflected in each extreme were realized and balanced off to some extent.

Quality Adjustment Process

The hedonic equations estimated earlier in this chapter were used to provide the quality adjustments for the replacement models. This was done on a quarterly basis, meaning the equation for the first month of a quarter (March 1996, June 1996, September 1996, etc.) was used for a period of three months before being replaced. While monthly equations are available for this study, quarterly model changes represent a good trade-off between model timeliness and resource constraints that will be faced in the actual production of the index. In the case where no variable existed in the hedonic equation for a unique characteristic of the replacement model, a similar model was sought and if none was found, the change was ignored.[51]

Results

The resulting index series is presented in Figure 3.5, alongside the other two hedonic indexes. The estimated monthly rate of change for this index is -4.49%, very similar to the -4.29% and -4.07% obtained for the dummy variable and Prud'homme-Yu series.

Model Changes

Over the 52-month period of the index series, 307 models in total were used in the production of the index. Accounting for the original 30 models plus the two 15-model increments, leaves 247 model replacements that were required over a period of 51 months, an average of approximately 5 model changes per month.

[51] *For the purposes of this study, no option price was pursued since the historical pricing was limited. In practice, when such a situation occurs, an option price is relatively easy to find.*

Quality Adjustments

Out of the 247 replacements, all were carried out using the hedonic equation applicable for the period. However, for 89 of the replacements (or 36%), there was a change in at least one additional computer component which was not represented in the hedonic equation. A summary of the changes is provided in Table I, where the major proportion of these changes applies to only one additional variable (61 out of 89 or 68.5%). For most of these replacements, the variable difference was kept as small as possible, given the availability of models. In fact, 61 of these 89 model changes occurred in the first two years of the series (1996, 1997) when the sample was the smallest and replacements were limited. Notably, the components in question are of the type for which option pricing is generally available. Finally, the average adjusted R^2 for the hedonic models used in producing this series was 0.8270. This indicates that on average, these models accounted for 82.7% of the variability in price, signifying that the impact these additional variables had on the calculations was minimal at best. These results support the point made earlier in this chapter regarding the issue of additional characteristics and hedonic equations, namely that it poses no significant impediment to using this method of quality treatment.

Table I – Summary of Quality Adjustments

Category	Number	% Distribution
Total Quality Changes	247	100.0%
1. Model changes entirely accounted for by hedonic equation	158	64.0%
2. Model changes with additional characteristics not accounted for by hedonic equation and composed of:	89	36.0%
2a) Changes in just one variable,	61	24.7%
- hard drive size	36	14.6%
- cache	10	4.0%
- hard drive type	15	6.1%
2b) Changes in more than one variable	28	11.3%

3.5 Conclusion

The conclusions in this chapter are limited to general comments on the hedonic approach. A more formal comparison of the series calculated using the various approaches discussed so far will be carried out in the next chapter.

This having been said, one of main criticisms against using the hedonic method has been in the form of operational constraints, namely the data availability and resources required to estimate the models. To obtain robust and usable results, a good data source is essential both in terms of quality and quantity. Afterwards, the model fitting process can prove an arduous task. The whole reasoning behind the hedonic method is to relate the differences in prices to the differences in key components across computer models. Poorly fitting models would seem to indicate that, at best, the relationship is spurious or random.

From this exercise, however, the experience is such that with a relatively minimal amount of effort, reasonably good fitting models were found which produced realistic and usable results. The database used in this study lends itself to this type of estimation very well. Besides prices, model-specific information (RAM, CPU, etc.) is tracked in a standardised format over time as well, which facilitates this type of analysis.

One other issue that has not been discussed much is—what if a characteristic that is not part of the hedonic equation changes? For example, what if a sound card is included in the replacement model (not offered in the original model) and there is no representation of this quality change in our estimated hedonic equation? Well, in fact, the statistician has a few options: a) choose another replacement model where this characteristic remains unchanged; b) use some other form of information to estimate the cost for this quality characteristic (e.g. option pricing); or c) ignore the quality change if it is not significant (i.e. if it is not a key variable, the impact should be minimal). If the model fits well and the crucial variables are represented (RAM, CPU, hard drive, etc.), then other model changes should be looked upon as minor and treated as such. Suffice it to say that this problem does not hamper the usefulness of the hedonic method in addressing the issue of quality change to any significant degree.

Lastly, we offer a commentary on the obsolescence of the hedonic model estimates. While no formal study regarding the longevity of these estimated models was conducted, the resulting distribution of functional forms, combined with the experience of Prices Division in using these models, leads one to infer that their degree of effectiveness hinges primarily on the frequency with which they are updated. The more stale these estimates become, the less representative the results. Ultimately, this is more critical than the problem of missing variables, for when presented as a trade-off, it would seem far better to estimate simple models more frequently (i.e. models with only the key variables included) than it would to estimate perfectly fitting models only occasionally, with long periods between model updates. As demonstrated in this study so far, the bulk of quality change comes from a few key components and capturing this dynamic should be the real goal behind this methodology.

Figure 3.1 - Adjusted R^2 for Models with RAM and CPU Only

Figure 3.2 - Adjusted R^2 for Models with Additional Variables

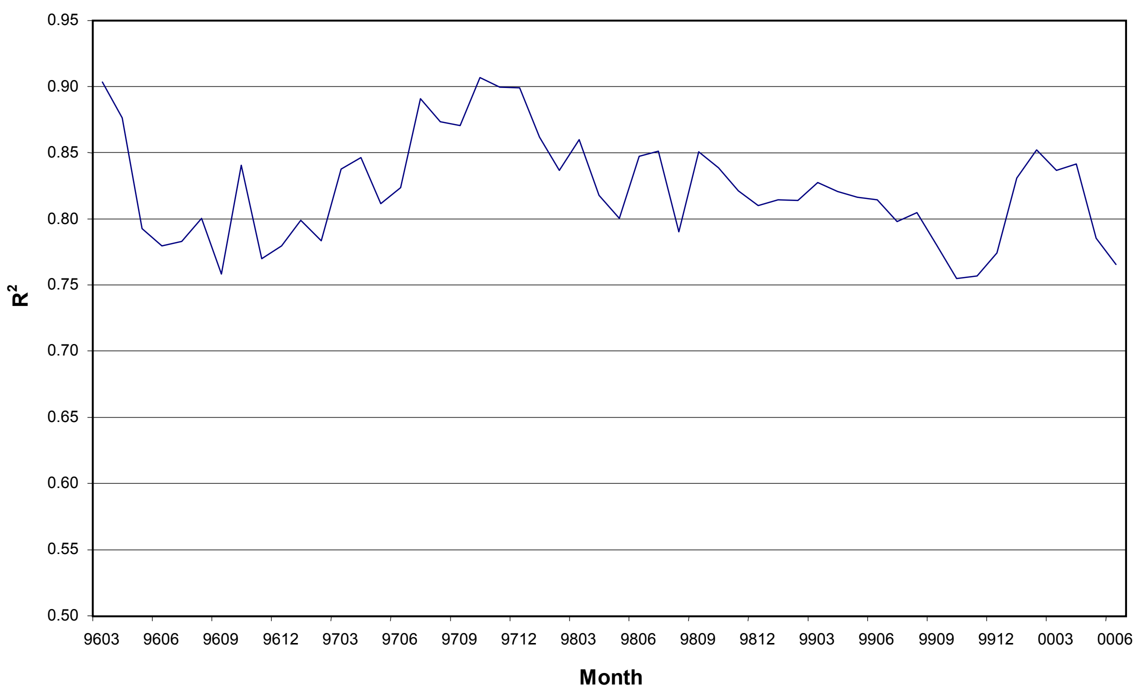


Figure 3.3 - Adjacent Period Dummy Variable Price Index vs. Overlap Price Index (chart in semi-logarithmic form)

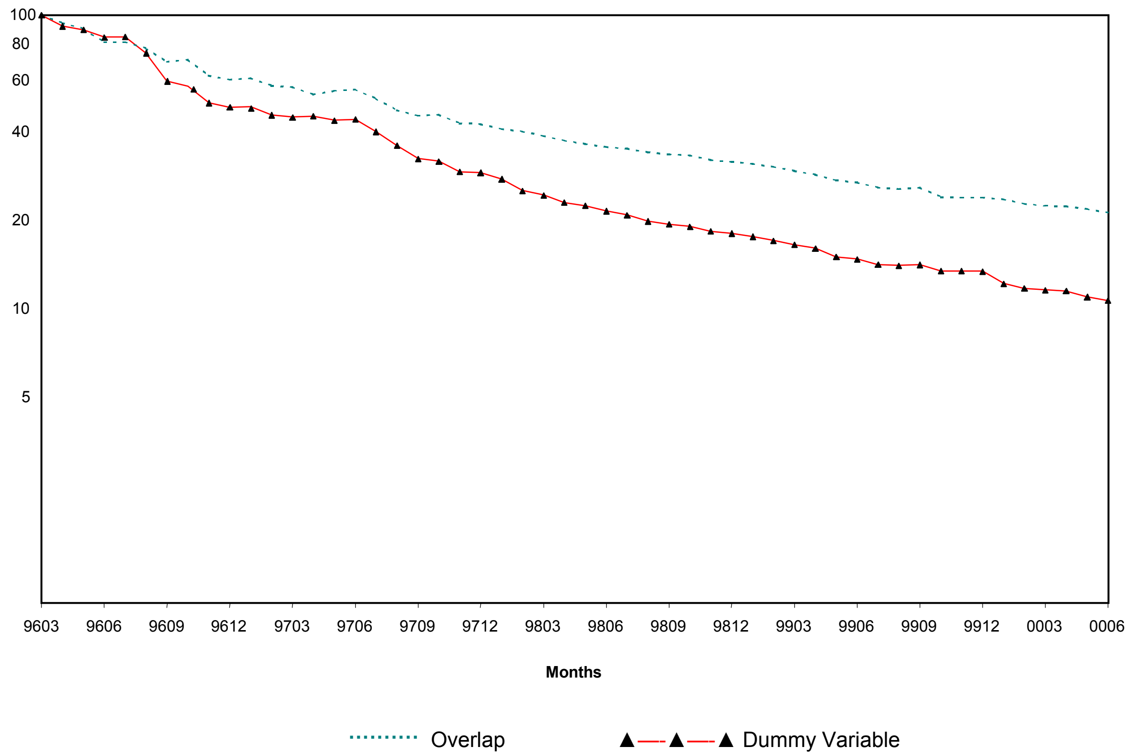


Figure 3.4 - Overlap, Adjacent Period Dummy Variable and Prud'homme-Yu Price Indexes (chart in semi-logarithmic form)

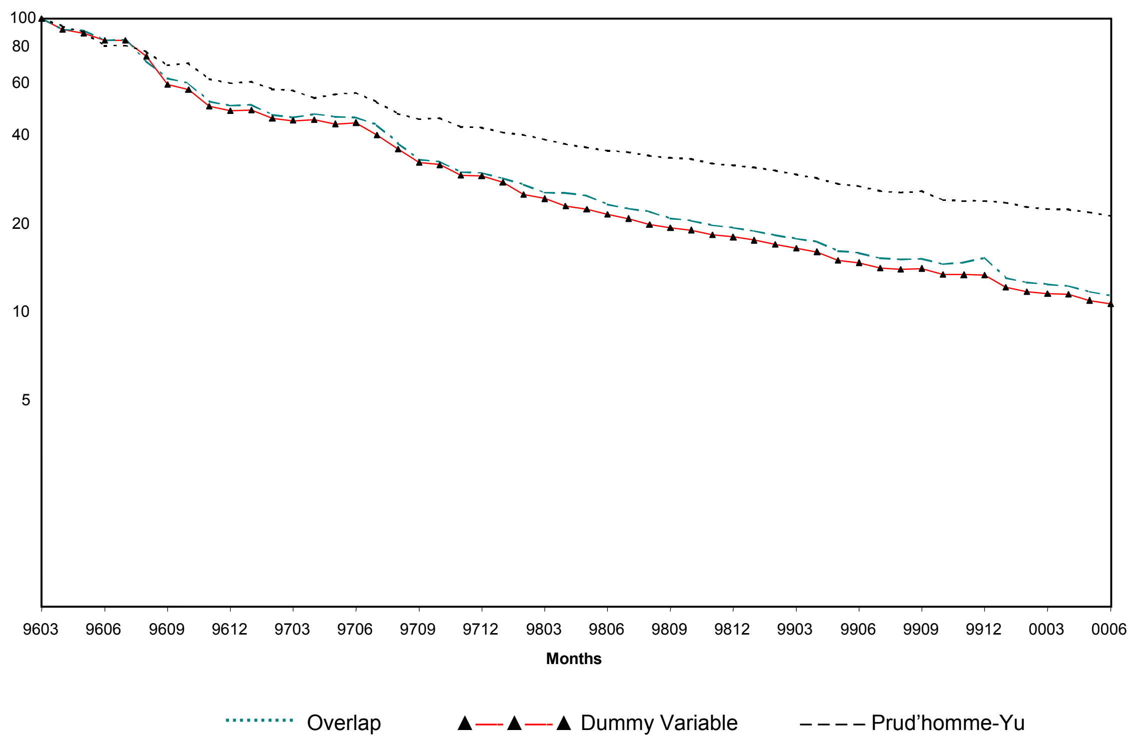
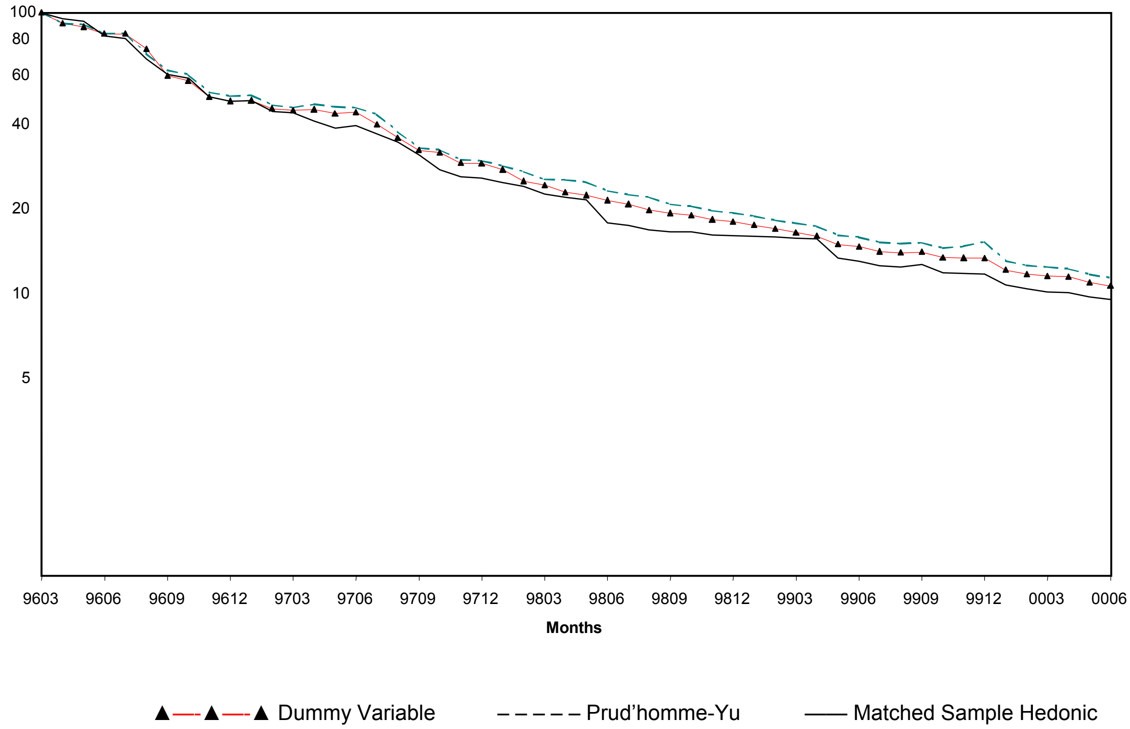


Figure 3.5 - Adjacent Period Dummy Variable, Prud'homme-Yu and Matched Sample Hedonic Price Indexes (chart in semi-logarithmic form)



CHAPTER 4 - Series Comparison and Proposed Methodology

4.1 Introduction

This chapter has two main objectives, the first being to compare the various price index series produced so far in this study, namely the overlapping matched sample, dummy variable, Prud'homme-Yu and matched sample hedonic series. The second objective is to arrive at a recommended methodology for producing the current price index for computers as well as for several recently proposed series in Prices Division.[52] The suggested methodology is a result of the various comparisons and analyses presented in this study, combined with the accumulated knowledge and experience of having produced a price index for computers for nearly ten years.

4.2 Comparison of Series

Original Series

The first step was to compare the four index series mentioned above at the general level, noting the difference in movements and average monthly rates of change. By "general level", what is meant is the original series as presented in the earlier chapters of this study as they would be carried out in a regular methodology. These versions are presented in Figure 4.1, from where it can be seen that the three hedonic series are virtually identical, certainly much closer in value and movement than the overlapping matched sample series. This result is borne out even further through a comparison of the average monthly rate of change for the four series provided in Table J (Rows A and B), where the matched sample hedonic index was used as the point of comparison. The difference between the three hedonic-based indexes is small, (0.26% and 0.42% in absolute values) but much bigger in the case of the overlap index (1.64% in absolute value). Clearly, the hedonic indexes are declining at a faster pace than the overlap series.

[52] *As mentioned previously in this study, the current price index series for computers are produced using data for desktops and portables that are intended for purchase by the commercial and government sectors. It is the intention of Prices Division to begin producing an equivalent series for the household sector. More of this is discussed in the second portion of this chapter.*

Table J – Comparison of Average Monthly Rates of Change

Category	Overlap Matched Sample Index	Dummy Variable Index	Prud'homme-Yu Index	Matched Sample Hedonic Index
A) Average rate of change for original series	-2.85%	-4.23%	-4.07%	-4.49%
B) Difference in rates between each original series and Matched Sample Hedonic series	-1.64%	-0.26%	-0.42%	0.00%
C) Average rate of change for series produced using models from Matched Sample Hedonic series	-2.32%	-3.94%	-4.26%	-4.49%
D) Difference due to *Quality Change Effect* = (Matched Sample Hedonic Series) – (Series in Row C)	-2.17%	-0.55%	-0.23%	0.00%
E) Difference due to *Sampling Effect* = (Series in Row B) – (Series in Row D)	0.53%	0.29%	-0.19%	0.00%

Series Using Matched Sample Hedonic Data

Given the different methodologies, these results are not surprising. Essentially, there are two effects at work—a *sampling effect* and a *quality change effect*. In the first instance, a portion of the difference between the series can be attributed to the fact that different samples will be chosen and used under the different methodologies, and these will naturally have different impacts on the index—a *sampling effect*. In the case of the *quality change effect*, even after holding the sample constant for all series, differences will arise out of how the quality change is treated in terms of scope and type of adjustment (direct versus indirect).

To isolate these two effects, the overlapping matched sample, the dummy variable and the Prud'homme-Yu series were re-calculated with the same models (or sample) as were used in the calculation of the matched sample hedonic index. These re-calculated series are presented in Figure 4.2. As well, Table J contains the corresponding average monthly rates of change for both the original and the re-calculated series (Rows A and C respectively). Row D in Table J presents the estimated degree of the *quality change effect*, calculated as the difference between the average monthly rate of change for the matched sample hedonic index minus the average monthly rate of change for each of the other re-calculated indexes. Finally, the *sampling effect* can be calculated residually as the difference in the original series (Row B) minus the difference due to the *quality change effect* (Row D).

From the results presented in Figure 4.2 and Table J, the main observations are: 1) that the Prud'homme-Yu and matched sample hedonic series are even closer in value and movement than before; and 2) that the divergence between the overlap and the matched sample hedonic series—and more interestingly—between the dummy variable and the matched sample hedonic series, have both increased. These findings are presented in the third row of Table J.

Overlapping Matched Sample Series

The estimated quality change effect in the case of the overlap series is -2.17%, which is quite large when compared to the other series. Given the results presented in Chapter 2, however, this result is not surprising. The reader will recall from that chapter that it was shown that the quality change treatment associated with the overlap procedure is upwardly biased, so one expects the hedonic series to decline faster. What is interesting to note is that the sampling effect is positive (0.53%), helping to offset the overall difference between the matched sample hedonic index. It would appear that when the entire sample is used, models are added where price declines are more pronounced, making the original overlap and matched sample hedonic series closer in value.

Dummy Variable Series

For the dummy variable index, the direction of the sampling and quality change effects is similar, though smaller in magnitude when compared to the overlap procedure. The quality change effect is -0.55%, while the sampling effect is 0.29%. Both effects likely stem from the fact that the estimate of δ_t is now based on a much smaller number of observations, reducing the average level of fit for the models and the robustness of the estimates. This is shown to some extent in Figure 4.3, which compares the adjusted R^2 values for the original series and the series using the models from the matched sample hedonic index. As one can see, the level of fit is much lower in the second case (for the entire period, the average adjusted R^2 is 0.6802 compared to 0.8092 for the original series). This difference is more pronounced early on in the series, where from March 1996 to March 1998 the average adjusted R^2 is 0.6076 for the re-calculated series and 0.8092 for the original series. For the remainder of the period, the levels of fit are much closer in value (the average adjusted R^2 values are now 0.7447 and 0.8161 respectively).

Prud'homme-Yu Series

The quality change effect is much smaller in the case of the Prud'homme-Yu index (-0.23%). Nevertheless, this difference is likely due to the fact that the degree of imputation is much higher, as *all* prices are imputed both *forwards* and *backwards* under this method. Even though the hedonic models generally fit well, they do not fit perfectly, so the imputation could have a dampening effect on the observed price movements. Meanwhile, the difference from the sampling effect is -0.19%, which would stem from the fact that all models are being used in the Prud'homme-Yu approach and given that the prices for these additional models are all imputed, once again the dampening effect has to be taken into account.

4.3 Recommendations

From the results of this study, it is recommended that Prices Division continue to produce its index series for computers using the methodology developed almost ten years ago. Clearly, the overlapping matched sample approach offers a viable alternative when hedonic methods cannot be employed, but as shown in this study, there appears to be an upward bias associated with this type of implicit quality adjustment. In addition, the problem of missing characteristics can be overcome with the use of option pricing.

For direct hedonic indexes, such as the adjacent period dummy variable and Prud'homme-Yu methods examined in this study, the results obtained are very similar to the matched sample hedonic approach, so there appears to be little difference between the three methods. However, this study has shown that a matched model approach is certainly feasible, since matching models from one month to the next yields generally good results. And if one agrees with the premise that the degree of imputation should be minimized whenever actual data exist for the calculation of a price relative, then a direct hedonic approach would be considered more utilitarian especially when a large proportion of the sample has disappeared and a high degree of imputation was required. Such would be the case for an annual index.

In summary, if one considered a grid such as the one presented in Figure 4.4, where the two criteria for evaluating these methodologies are theory (or desirability based on theoretical grounds) and practical considerations, then the placement of the various methods would have all the hedonic series falling into the upper left quadrant, while the overlapping matched sample would be placed in the upper right. In this representation, we see that the hedonic series would enjoy a higher level of theoretical desirability, while at the same time, the pragmatic considerations associated with this methodology would not differ by much, relative to the overlapping matched sample process. Of the three hedonic series, we consider the matched sample hedonic method as the most desirable, followed by the Prud'homme-Yu and the Dummy Variable approach. Again, this distinction occurs because the degree to which the matched sample concept is employed in the index decreases from one hedonic method to the next.

Nonetheless, the current methodology of producing a price index series does require some refining and standardization (e.g. more frequent updating of the hedonic equations, improved sampling procedures), so a proposed methodology has been developed and is presented in the remainder of this chapter. It is based largely on the methodology used in the construction of the matched sample hedonic index presented in Chapter 3. There are some concepts and procedures, however, which have been added based on the current availability of information.

4.4 Proposed Methodology for Computer Price Indexes

General Objectives

The general purpose behind the creation of a computer price index is to produce a comprehensive set of index series covering computers and computer-related equipment for several sectors in the economy—these being the household, government and commercial sectors.[53] The aim is to produce a group of indexes which is representative and theoretically robust.

Sampling Strategy

The sampling strategy has two components, sample selection and sample replacement.

Sample Selection

The main goal of the sampling strategy is to design, select and maintain a representative sample of computer models, given the available sources of information. Where possible, shipment values will be used to determine the relevant composition of vendors and processor model generations on a quarterly basis. Models will be chosen from a mainstream group representing the middle 50% to 60% of models currently supplied to Prices Division.

Sample Replacement

Models will be replaced as determined by the sample. Currently, the situation does not warrant forced replacements, where outdated or obsolete models are still being priced. The experience to date shows that these models are removed from the data source in a timely manner. As a middle- or lower-end mainstream model is lost, it will be replaced by one selected from the highest end of the mainstream group, and if none is found then the selection process will proceed downward through the CPU categories until a suitable replacement is found. When a high-end mainstream model is discontinued, a replacement will be chosen from the same grouping, unless there are none available, then the mainstream bracket will be extended by one CPU class at a time until a replacement is located.

Quality Adjustment

As models are replaced, the hedonic method will be used to incorporate the change in quality. The hedonic equations will be updated on a quarterly basis using the most current information. With each update, the process will entail checking for appropriate functional form and evaluating the fit of the models and the robustness of the results (inclusion of major independent variables, correct sign on coefficients, predicted values, etc.). When a replacement model features characteristics that are not represented in the hedonic equation, there are three options available:

[53] *In the terminology of the System of National Accounts, these three sectors correspond to* ***Persons and unincorporated businesses****, to* ***Governments*** *and to* ***Corporations and government business enterprises*** *respectively.*

(1) find a more suitable replacement model which does have represented characteristics
(2) use option pricing to estimate the values of the missing characteristics
(3) ignore these extra characteristics

Formulae and Weighting

Depending on the availability of weighting information, all attempts will be made to produce a set of indexes using fixed and current weights, as well as a geometric mean of the two (often referred to as the Laspeyres, Paasche and Fisher index formulae respectively).

Proposed Series

The series will consist of price indexes for desktop and portable computers for each of the three targeted sectors. These two series will be combined to form an aggregate index for each individual sector. Finally, the sectors will be combined to produce an overall index.

Dissemination

The periodicity of the series will be monthly and there will be a six-month revision period. These series will be published and made available to the public using the typical dissemination vehicles of Statistics Canada.

Figure 4.1 - Overlap, Dummy Variable, Prud'homme-Yu and Matched Sample Hedonic Indexes (chart in semi-logarithmic format)

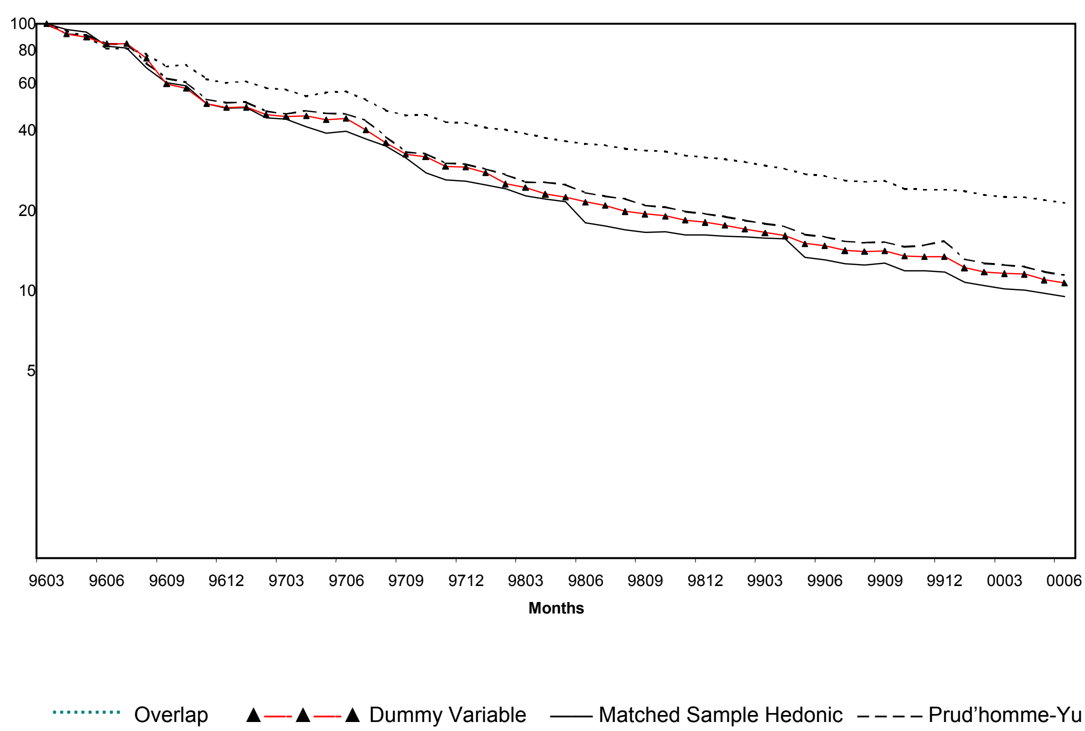


Figure 4.2 - Overlap, Dummy Variable, Prud'homme-Yu and Matched Sample Hedonic Indexes Using Matched Sample Hedonic Data (chart in semi-logarithmic format)

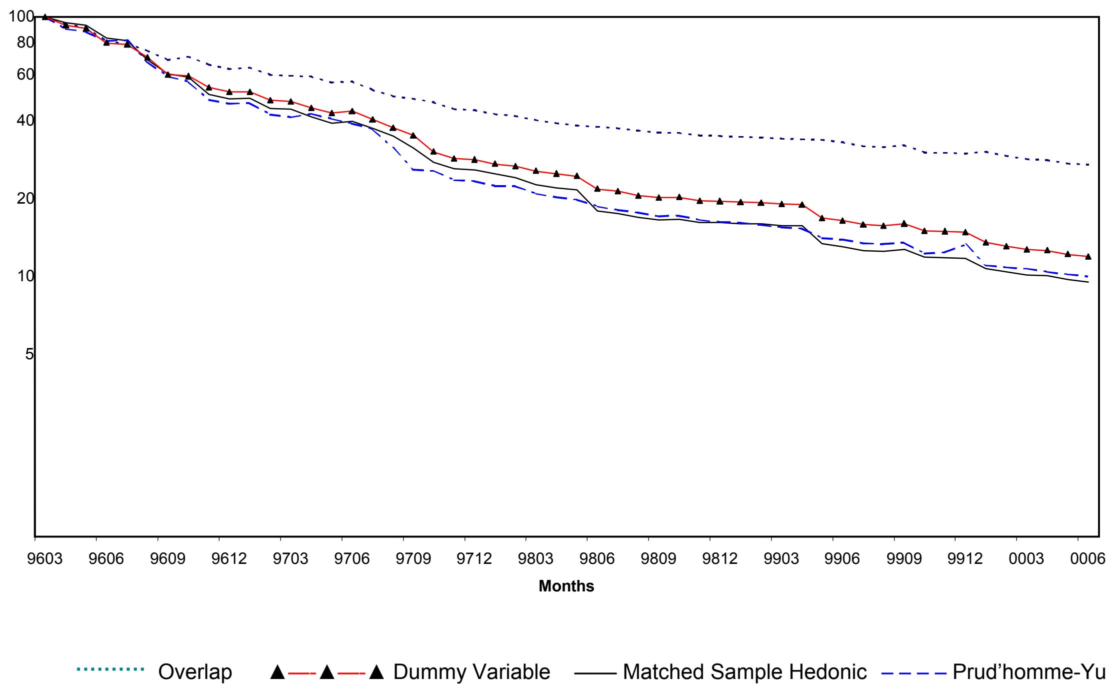


Figure 4.3 - Comparison of Adjusted R^2 Values Obtained for the Dummy Variable Original and Re-Calculated Series

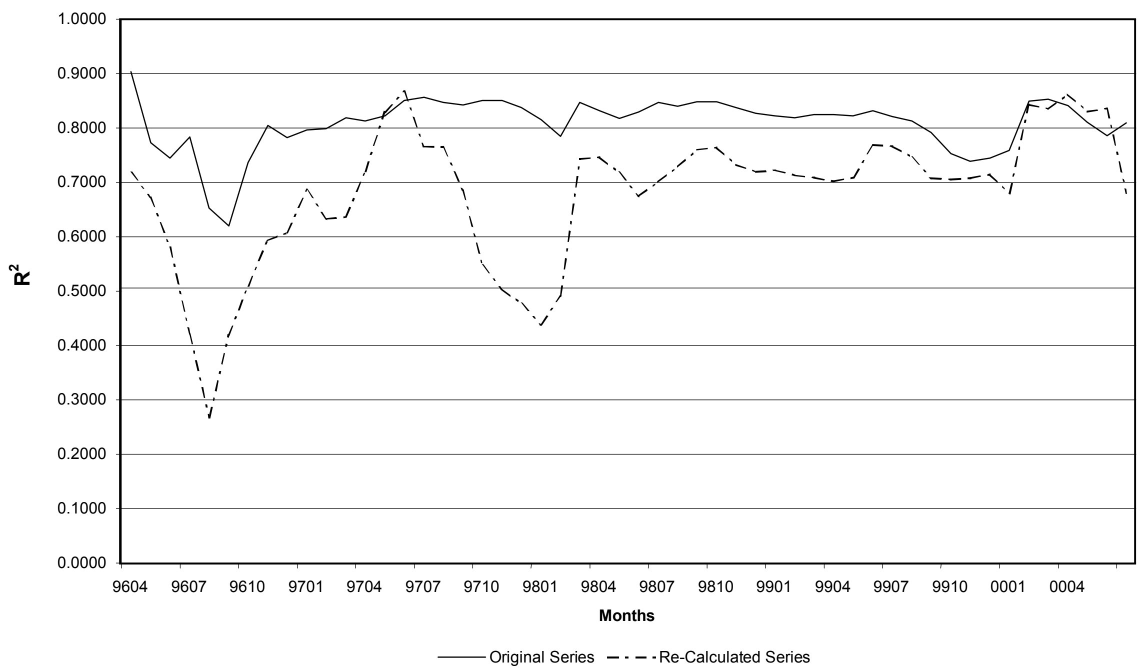
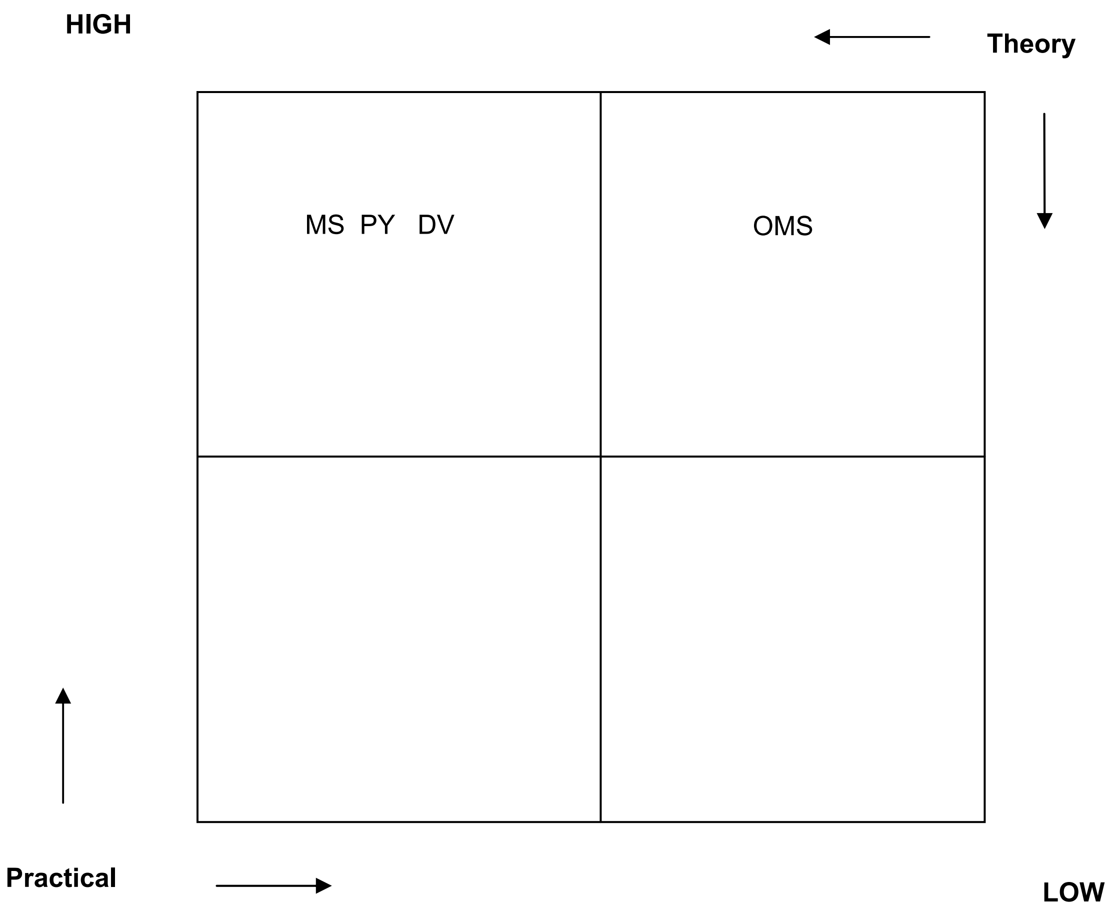


Figure 4.4 - Summary of Options from Statistic Canada's Perspective



Where:

MS - Matched Sample Hedonic index
PY - Prud'homme-Yu index
DV - Dummy Variable index
OMS - Overlapping Matched Sample index

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Appendix I - CPU Performance Scores

Processor Class	CPU Score as of 2000/07/17	Processor Class	CPU Score as of 2000/07/17
486DX4 / 100	118	Celeron 466	1373
Pentium / 75	186	Xeon II / 450 (512 KB)	1406
Pentium / 90	220	Xeon II / 450 (1 MB)	1420
Pentium / 100	245	Pentium III / 450	1500
Pentium / 120	270	Celeron 500	1502
Pentium / 133	298	Celeron 533	1628
Pentium / 150	306	Xeon III / 500 (512 KB)	1649
Pentium / 166	339	Pentium III / 500	1650
Pentium / 200	377	Xeon III / 500 (1024 KB)	1667
Pentium MMX / 166	422	Pentium III / 533	1752
Pentium Pro 150	459	Pentium III / 550	1780
Pentium MMX / 200	478	Xeon III / 550 (512 KB)	1827
Pentium Pro 180	516	Pentium III / 500E	1867
Pentium MMX / 233	531	Pentium III / 600	1930
Celeron 266	548	Pentium III / 533EB	1960
Pentium Pro 200	574	Pentium III / 600B	2036
Celeron 300	582	Pentium III / 600E	2110
Pentium II / 233	693	Pentium III / 600EB	2177
Celeron 300A	762	Xeon III / 667	2242
Pentium II / 266	784	Pentium III / 650	2270
Celeron 333	818	Pentium III / 667	2320
Pentium II / 300	857	Pentium III / 700	2420
Celeron 366	890	Xeon III / 733	2477
Pentium II / 333	940	Pentium III / 733	2510
Pentium II / 350	1000	Pentium III / 750	2540
Celeron 400	1011	Pentium III / 800	2690
Pentium II / 400	1130	Xeon III / 800	2714
Pentium II / 450	1240	Pentium III / 866	2890
Celeron 433	1248	Pentium III / 1GHZ	3280

Appendix II - Twelve-month Rates of Sample Decay

Reference Month	Beginning Sample Size	Number of Matches After 12 Months	% of Original Sample Lost
199603	104	6	94.2
199604	86	4	95.3
199605	123	4	96.7
199606	116	4	96.6
199607	116	4	96.6
199608	91	13	85.7
199609	80	7	91.3
199610	89	6	93.3
199611	84	4	95.2
199612	84	3	96.4
199701	82	4	95.1
199702	67	3	95.5
199703	71	3	95.8
199704	103	0	100.0
199705	105	4	96.2
199706	66	3	95.5
199707	102	7	93.1
199708	195	33	83.1
199709	212	75	64.6
199710	190	76	60.0
199711	197	56	71.6
199712	196	56	71.4
199801	204	61	70.1
199802	210	80	61.9
199803	249	97	61.0
199804	284	131	53.9
199805	290	42	85.5
199806	232	58	75.0
199807	246	73	70.3
199808	285	107	62.5
199809	338	166	50.9
199810	353	182	48.4
199811	337	205	39.2
199812	361	227	37.1
199901	404	2	99.5
199902	450	21	95.3
199903	570	66	88.4
199904	556	66	88.1
199905	493	98	80.1
199906	506	104	79.4
Average =	223.2	54.0	75.8