Measurement and analysis of capital, productivity and economic growth

Erumban, Abdul Azeez

Chapter 4

Lifetimes of Machinery and Equipment: Evidence from Dutch Manufacturing*

4.1 Introduction

A crucial assumption underlying the empirical analysis in the previous chapters and in most international comparisons is that of constant depreciation rates of capital assets across countries. This would mean that the age-price profiles of capital assets are the same across countries, which is obviously a less realistic assumption. This is necessitated by the scarce empirical evidence on depreciation patterns. Geometric depreciation[1] rates have been derived in the literature either by using information on used-asset prices (Statistics Canada, 2007) or on asset lifetimes (Hulten and Wykoff, 1981; Fraumeni, 1997; Hulten and Wykoff, 1981). Hulten and Wykoff (1981) have demonstrated how one can estimate depreciation using information on market prices (of used-assets), based on microeconomics foundations.[2] Nevertheless, this approach is feasible only if there is substantial amount of information available on used-asset prices. This is not true in most countries, with possible exceptions of the United States and Canada. Therefore, researchers and national statistical institutes (NSIs) rely on a short-cut method based on estimates of asset lifetimes to derive depreciation rates. In this approach, the depreciation rate is derived as a ratio of assumed declining balance rate to the average lifetime of the asset, where the former determines the extent to which the value of an asset wears out (Fraumeni, 1997).

However, even this short-cut is often not feasible as it is hard to find estimates of service lives based on statistical information. Service life estimates require data on asset

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[1] For a detailed discussion on various forms of depreciation patterns, see OECD (2001).

[2] The idea behind using used-asset price models is that the component unit cost associated with the aging of assets, i.e. the depreciation, can be isolated by comparing prices of assets of different ages. Also see Hwang (2003) and Statistics Canada (2007) for two recent studies in this line and Jorgenson (1996) for a summary of studies on economic depreciation.

discards of firms. But firms do not have any incentive to keep record of their asset discard[3], which makes it difficult to arrive at reliable estimates of asset lifetimes (West, 1998). Accountants often consider it bad practice to include discarded assets in balance sheets, as it may appear like fraud. Instead, the general practice of NSIs is to rely on expert advice, information form tax authorities, or company records (OECD, 2001). These sources, however, may provide biased estimates of lifetimes. For instance, it is quite possible that the lifetimes and depreciation measures allowed for by tax authorities are set deliberately high for stimulating investment. Instead, one would need data on asset purchases and discards to derive expected service lives of assets.

This chapter aims to analyze the discard pattern of capital assets to estimate lifetimes in the Netherlands, using information on directly observed capital stock and discard patterns.[4] Note that discards and depreciation are distinct concepts. The former is useful in deriving the actual number of years an asset survived in the capital stock but provides no information on the decline in the price of asset as it ages, which is measured by depreciation. Statistics Netherlands (CBS) is one of the few statistical agencies in the world which used to collect data on capital stock and discards on a continuous basis (Smeets and van den Hove, 1997; Meinen, 1998). These two databases — capital stock and discard — are used in combination to estimate the lifetimes for three asset types — transport equipment, computers and machinery — in different industrial sectors. The estimated lifetimes for the Netherlands are presented in comparison with estimates for the United States, Canada and Japan.

It may be noted that there have been attempts in the past to estimate the service lifetimes of capital assets in the Dutch manufacturing sector, utilizing the capital stock and discard data (Meinen et al., 1998; Meinen 1998; van den Bergen et al., 2005). The present chapter is an addition to these existing studies and differs from earlier work in its methodology. We feed more discard information into the estimation of lifetimes than before and hence provide better estimates. To be more specific we monitor the discard pattern of each vintage over three consecutive years, and consider the average pattern over three different vintages for a given age (see section 3 for more detailed discussion). Earlier studies on Dutch manufacturing have considered only one vintage for a given age. Considering a single vintage as representative for a given age for all vintages may

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[3] Discards are also known as disinvestments, scrapping, retirements or the withdrawal of assets from the production process. We use the concept "discard" throughout this chapter.

[4] Estimates of retirement distributions are often examined for specific asset types such as computers (see Oliner, 1993). However, such attempts for a wider range of assets are rare.

result in biased estimates if the selected vintage is not sufficiently representative. Moreover, like investments, firm-level discards often follow a spiky pattern with positive discards in one year, followed by zero discards in subsequent years. Therefore, a single discard year may not necessarily provide a good representation of actual discard pattern. This problem is eased, to some extent, in this study by analyzing more vintages for a single age, including discard data for up to three years, rather than one (see Figure 4.1 and the following discussion in section 4.3). Indeed, we observe that the estimated survival function fits better to actual data when we incorporate more discard information, thereby providing better parameter estimates than previous studies.

The chapter is organized in five sections. Section 2 presents the methodology used in the present study in estimating lifetimes of assets. Section 3 provides a discussion on data and variables and section 4 provides the empirical results. The last section concludes the chapter.

4.2 Estimating Survival Functions and Asset Lifetimes: The Methodology

We estimate service lifetime of assets using actual information on capital stock and discard. Note that the most straightforward way to derive service lifetime would be by monitoring the life time of various vintages — the difference between the purchase year and discard year for each vintage will provide the life time of that particular vintage and an average across various vintages for a given asset will provide the mean service life for any given asset. However, given the nature of our dataset, it is not possible to follow such an approach, as it requires information on the year in which the asset is included and the year in which it is fully scrapped. Our data provides only the portion of each cohort of a particular vintage that is scrapped in a particular year; hence we need to estimate lifetimes using information on survival probability function. In order to derive consistent estimates of lifetime of capital assets, we analyze the discard pattern of these assets, which gives insights into the survival function. The survival function is the cumulative distribution of the probability that an asset survives until a given age and it helps us derive the average service life of the capital asset.

While estimating the survival distribution, one faces the problem of selecting an appropriate functional form.[5] Earlier studies have emphasized that survival functions with a longer tail like the Weibull or delayed linear are more realistic (Meinen et al., 1998; OECD 2001). In line with earlier studies (Meinen, 1998; van den Bergen et al., 2005; Nomura 2005) we assume a Weibull distribution to describe the survival pattern. It is a more general and flexible form of an exponential distribution. For instance, when the lifetime is assumed to be distributed according to the exponential distribution, then the hazard rate is a constant, independent of time. A constant hazard rate implies that the probability of discarding during the next time interval does not depend upon the duration spent in the initial state (Verbeek, 2004). The Weibull distribution, on the other hand, does not assume a constant hazard rate (see Pitman, 1992);[6] it is a parametric distribution which includes decreasing, constant and increasing hazard rates. The Weibull specification requires only two parameters, and it can capture distributions that are skewed. The lifetime distribution or the probability density (mortality) function, *f(x),* of the Weibull can be written as:

$$f(x) = \frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1} e^{-\left(\frac{x}{\beta}\right)^{\alpha}} \quad \text{for } x \geq 0, \tag{4.1}$$

where x is the age of the asset. The parameter α is the shape parameter and β is the scale parameter. This function is helpful in calculating the percentage of asset of a given vintage that is discarded at different ages. The exponential distribution is a special case of Weibull where α takes the value 1, hence a single parameter distribution with constant retirement. Thus Weibull is the exponential distribution of the power transformed age,

[5] For instance, there have been a number of approaches suggested in the literature on duration models to analyze mortality and survival functions. However, OECD (2001) has shown that most mortality distributions except delayed linear and bell-shaped distributions are clearly unrealistic. Other distributions include simultaneous exit and linear. While the former assumes all the assets to be retired from capital stock at the moment they reach their average service life, the latter assumes that the surviving assets are reduced by a constant amount each year. The delayed linear is a variant of linear one in that it also assumes retirement of assets in equal parts until the entire vintage is fully scrapped, but the retirement starts later than in the linear case and finish sooner. The bell-shaped distributions, on the other hand, assumes a gradual retirement which starts some years after the year of installation, reaches the maximum around its average service life, and then starts lowering some years after average lifetime. It also allows similar assets to be discarded at different ages.

[6] Also see Bekker (1991) for detailed discussion on the properties of Weibull distribution and Mudholkar et al (1996) for a generalized Weibull family of distributions for survival studies.

and is therefore more flexible than the exponential. From (4.1) the survival function *S(x)* — the probability that an asset of any vintage survives until the age x — can be written as *1-F(x)*, where *F(x)* is the cumulative density function, i.e. the cumulative distribution of lifetime distribution *f(x), i.e.*

$$F(x) = \int_0^x f(y)dy = 1 - e^{-\left(\frac{x}{\beta}\right)^{\alpha}} \tag{4.2}$$

and the survival function S(x) is,

$$S(x) = 1 - F(x) = e^{-\left(\frac{x}{\beta}\right)^{\alpha}} \tag{4.3}$$

where S(0)=1, S(∝)=0 and S(β])=e^{-1}, independently of the value of α.

For notational simplicity assume λ=1/β. Then introducing an additive error term u with standard assumptions, one can specify an estimable non-linear equation, where survival function[7] is a function of age, as

$$S(x) = e^{-(\lambda x)^{\alpha}} + u \tag{4.4}$$

Given the Weibull distribution parameters, α and λ, the n^{th} moment of Weibull probability density function is given by

$$\mu_n = \left(\frac{1}{\lambda}\right)^n \Gamma\left(1 + \frac{n}{\alpha}\right) \tag{4.5}$$

[7] Some previous studies have used hazard function instead of survival function to derive asset lifetimes (e.g. Meinen, 1998). Survival function and hazard rate are closely related concepts, the latter is nothing but a simple transformation of the former. The hazard function can be expressed as $h(x) = f(x)/S(x)$, where f(x) is the lifetime distribution, and S(x) is the survival function. The hazard function describes the conditional probability that the asset is scrapped at a given age, given that it has survived up to that age. For the Weibull it can be derived as $h(x) = \frac{\alpha\lambda(\lambda x)^{\alpha-1} e^{-(\lambda x)^{\alpha}}}{e^{-(\lambda x)^{\alpha}}} = \alpha\lambda(\lambda x)^{\alpha-1}$.

where $\Gamma(n)$ is the Gamma function of the shape parameter n, $\Gamma(n) = \int_0^\infty y^{n-1} e^{-y} dy$

Following (4.5) the first moment or the mean of the two-parameter Weibull, which is by definition the expected average service life (Bekker, 1991; Nomura, 2005), *E(x)*, is given by,[8]

$$\mu_1 = E(x) = \frac{1}{\lambda}\Gamma\left(1 + \frac{1}{\alpha}\right) \tag{4.6}$$

The values of α and λ estimated using equation (4.4) are inserted in equation (4.6) to obtain the expected lifetime estimates of assets.

4.3 Data and Variables

Data Sources

The survival function and asset lifetime estimation in this chapter are conducted for 22 two-digit manufacturing industries in the Netherlands. Table 4.1 presents the list of industries considered along with the corresponding ISIC codes. In some cases several two-digit industries are clubbed together, based on the technology/product characteristics of such industries. For instance, different two-digit groups under textile products are combined into one. This was done in order to ensure sufficient numbers of observations to perform the regression analysis. Two exceptions are wood & wood products and medical & optical equipments. Due to very low number of observations in these industries, we had to club them with other industries group despite having no common technological/ product characteristics. Effectively, we have 15 industry groups in the final sample.

Though the final lifetime estimates are made for two-digit industries, the data used to estimate survival functions are based on the firm level data obtained from two surveys conducted by the Statistics Netherlands (CBS) — the capital stock survey and the discard survey. Therefore, it was essential to link these two to construct a comparable database.[9]

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[8] The median and mode are respectively $1/\lambda[(\ln(2))^{1/\alpha}]$ and $1/\lambda[(1-(1/\alpha))^{1/\alpha}]$. See Bekker (1991) for detailed discussion on the properties of Weibull distribution.

[9] See van den Bergen et al (2005) and Meinen (1998) for previous studies that have used these surveys in combination.

We use firm level data as it is the only source where from we can obtain data on capital stock and discards with vintage information. We discuss these two surveys below in short.

Table 4.1: Industries considered in the study

ISIC	Industry
15-16	Food, beverages & tobacco
17-19	Textile & leather pdts.
20+33+36	Wood & wood pdcts, medical & optical eqpt & Other mfg.
21	Paper and paper products
22	Publishing and printing
23	Petroleum products; cokes, and nuclear fuel
24	Basic chemicals and man-made fibers
25	Rubber and plastic products
26	Other non-metallic mineral products
27	Basic metals
28	Fabricated metal products
29	Machinery and equipment n.e.c.
30+32	Office machinery & computers, radio, TV & communication eqpt.
31	Electrical machinery n.e.c.
34-35	Transport equipment

The capital stock surveys have been conducted on a rolling basis since 1993 in such a way that each 2 digit industry will be surveyed once in five years. The survey contains information on all fixed assets that are used by enterprises in their production process, whether the assets are owned, rented or obtained through a leasing contract. More importantly, it provides the vintage year of each asset.[10] Because of the rolling nature of the survey, one or two benchmarks are available for each two-digit industry during the

[10] In some cases, especially for very older vintages, the exact year in which the asset was purchased is not available. But there is an average range of period available for such vintages, and hence the mid year is selected as the vintage year. Also, it is not clear whether the vintage years reported by firms for assets which are leased or purchased in the second-hand market are exact vintage years. For instance, they could be the year in which the firm has bought the asset in the second-hand market. Nevertheless, the presence of such cases might be significant only in asset type transport equipment (see Appendix Table 4.7 and the discussions in page 100).

period 1993-2001. Therefore it was essential to consider one benchmark year for each industry and match it with subsequent discard years.

The data on discards in the manufacturing industry has been collected since 1992 in the Netherlands (see Smeets and van den Hove, 1997). The survey provides information on all fixed assets which are no longer used in the production process. That is, it comprises all capital goods removed from the production process during the course of a particular year. However, this data is quite limiting due to the low response rate to this survey, as the information is gathered through mailed questionnaires.[11] The information available includes the value of asset withdrawn from the production process both in historic and current prices and the destination to which the withdrawn asset goes to, i.e. whether the asset is completely scrapped, sold in the second-hand market or returned to the lease company (the last option was added only recently).

Both capital stock and discard surveys cover only firms with 100 employees or more[12]. They provide firm level information on these variables in historic price at different vintages for eight asset types (see Appendix 4.1), among which we consider three — external transport equipments, machinery and equipments including internal means of transport (excluding computers), and computers and associated equipments (data processing machines that are freely programmable including peripheral devices; computers printers etc).

Appendix Tables 4.1 and 4.2 provide the number of firms reported to various benchmark capital stock surveys and annual discard surveys during 1993-2001. There are 1354 manufacturing firms that have responded to at least one benchmark capital stock survey and a maximum of 1245 firms that have responded to various discard surveys during 1994-2001. Nevertheless, we have not included all these firms in our final dataset as we had to delete a number of firms during the cleaning process. Since our methodology to estimate asset lifetimes includes the use of both capital stock and discard data, we have made a combined dataset, consisting of firms reported to capital stock and discard surveys.

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[11] Nevertheless, the data is quite reliable as the reported information is subjected to further scrutiny and reconfirmation in cases unbelievable or extreme information is found.

[12] Firms employing 100 or more employees constitute almost 69 percent of total employment, 80 percent of total sales and output and 78 percent of total value added in 2000, and therefore it is a fair sample of total manufacturing.

The historic value of capital stock in year *t-1* (as on 31 December) is linked to the historic value of discards in years *t*, *t+1* and *t+2* for each firm. Earlier studies have linked the benchmark capital stock in year *t-1* to only one discard year, say *t*, as they have used only single year discard information in the estimation of lifetimes (van den Bergen et al., 2005). As mentioned before, the present study incorporates more discard information into the estimation of lifetimes. Hence the benchmark capital stock data is linked to three discard years. The data is linked for each asset type and vintage year. That is the capital stock data for a particular asset bought in a particular year is linked to the same firm's discard data for the same asset type of the same vintage.

In the next step, we have deleted all the firms that have not reported to capital stock surveys, but to the discard surveys. This is because, since our analysis requires estimates of survival rates, which are the percentage of capital survived over years, it is meaningful only to include those firms that have reported to capital stock surveys. Also all those firms that have not reported discard value for at least one vintage are dropped from the sample. That is even if a firm has reported discards only in *n* vintages with reported capital stock in more than *n* vintages it is included in the sample. For the reported vintages, the actual discard values are used, while for the non-reported vintages, the discard is assumed to be zero. This assumption is based on the premise that there is no reason for a firm to report discard in certain vintages while not report discard in other vintages, other than not having a discard in that particular vintage. Those firms, that have no reported discard value in any vintage, are dropped, as we do not have any idea whether they have made any positive discard or not. Their inclusion may result in an exaggeration of capital stock, if we attribute zero discards to such firms. Such an attempt is seen to produce strange results, exaggerating the lifetimes of capital assets.

All those cases where the reported discard values are higher than the value of capital in the given vintage are deleted from the sample.[13] All other cases are included in the sample. Thus finally we had a sample in which the number of firms is much lower than the actual number of responding firms. We end up with 969 firms (72 percent of total firms reported to various capital stock surveys) when we link the capital stock in year t-1

[13] While excluding such firms, we have allowed for a margin of error of 2 percent. That is even if the discard is greater than capital by 2 percent of capital at firm level, we have included them, assuming that it will be a reporting error. However, they are subjected to further scrutiny in that if the discard is greater than capital stock even after aggregating to industry level (for each vintage) we drop such cases from the original sample.

to the discard in year t. This further declined to 592 (44 percent) when added two more discard years (i.e. when we consider three discard years, t and t+1 and t+2). This decline is to be expected because, in the first case we include all those firms that have reported at least one vintage discard in the first year, however, in the second case, they are included in the sample only if they have responded to discard surveys in second and third years. This decline in the number of firms, however, is observed to have only marginal effect on the number of observation (vintages) in our regression analysis. The final sample consists of 53 percent of total firms reported to the first discard year survey and 52 percent of firms reported during three consecutive discard surveys. As previously mentioned, for most industries there are two benchmarks capital stock surveys available (see Appendix Table 4.1). However, we have considered only the first round benchmark surveys in the current analysis, as the second round will not allow us to include up to three discard years, as the discard data is not available since 2001. This is also the reason why we limit the number of discard years into three; the recent benchmarks do not allow us to use more than three discard years. Hence our estimates are based on the data for the mid and late 1990s only.

We have aggregated this linked dataset to the 2 digit industry level across each vintage for each asset separately. This aggregation is performed in order to ensure sufficient number of firms in the sample. This leaves us with the final dataset for each 2 digit industry, for different asset types and vintages. That means in our regression analysis, for each asset type, the degrees of freedom will be the number of vintages in that particular asset rather than the number of firms. Therefore, as mentioned before, the decline in the number of firms caused by the inclusion of more discard years into the model has only a negligible effect on the degrees of freedom in our regression model. For each industry we have a series of data on historic value of capital stock and discards across various vintage years, which are used to construct the variables entering to our regression equation in (4.4). In what follows we explain the construction of variables that enter equation (4.4).

Variables

Survival function (S): The dependent variable in our Weibull specification (4.4) is the survival function, which is calculated as the cumulative distribution of survival rate. It implies the probability that an asset is not discarded before the age x. In order to calculate the survival rate we exploit data on capital stock and discard. Capital stock is the historic value of asset i of vintage j for industry k, taken as such from the capital stock survey, and discard is the historic value of asset *i* of vintage *j* for industry *k*, taken from the discard survey. The survival rate for a particular asset of particular vintage *j* at time *t* (or at age *x* where *x* is measured as *t-j*), is calculated as the historic value of capital in year *t-1* minus historic value of discard in year *t* divided by historic value of capital in year *t-1*. Specifically, provided that the benchmark capital stock is available for the year *t-1* and discard data is available for the year *t*, the survival rate for an asset of age *x* in year *t* can be calculated as[14],

$$s_j^t(x) = \frac{K_{j,t-1} - D_{j,t}}{K_{j,t-1}} \qquad (4.7)$$

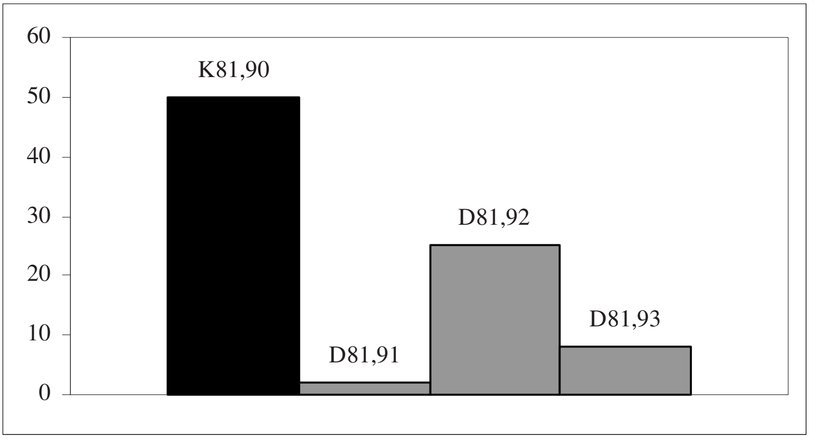
where $s_j^t(x)$ is the survival rate of an asset of vintage *j* at the age *x* at time *t*. *K* is the historic value of capital stock and *D* is the historic value of discard of an asset of j^{th} vintage in year *t*. The capital that is reported in year t-1 is assumed to be the capital as existed on December 31st in year t-1 and therefore, Dj for year t-1 in (4.7) is assumed to be zero. Since we use both capital stock and discard of same vintage to derive survival rates, we consider them in historic prices. The results will remain the same even if we use current or constant price figures, as both these variables will be inflated (deflated) by the same price indices, and as we take the ratios.

Assuming that the survival rate for an asset of all vintages are equal for a given age x, i.e. sj(x)=s(x), (4.7) provides us the probability that an asset of any vintage survives until the age x, under the condition that it has survived until the age x-1. This is a standard, but strong, assumption, needed to make empirical estimation possible with the available data. Otherwise, one requires obtaining the information on capital stock and discards in all vintages over a long span of time, which is not practically possible. Consider a simple example. Suppose a firm has machines of 3 vintages 1975, 1980 and 1985 existed in year 1990 (note that in practice firm can have even older vintages). In order to obtain the survival rate of each vintage at a given age, say 5, one would require information on capital stock and discard for each of these three vintages at age 5, i.e. capital stock and discard data for vintage 1975 in 1980, for vintage 1980 in 1985 and for vintage 1985 in 1990. However, it is hard to obtain such long series of data. Suppose we have

[14] For simplicity the industry index –*k*– is dropped.

information on capital stock and discard of all these vintages in 1990, then we could calculate the survival rate of vintage 1985 at age 5. Then we assume that this survival rate is applicable to other two vintages as well at the age 5 regardless of their vintage.

Figure 4.1: Benchmark capital stock (K) & annual discard series (D) of vintage *j* in year *t*



Note: K (D)*, ** = capital stock (Discard) of vintage * existed in year **.

However, the discard pattern was found to be lumpy in most cases, as is often observed in the investment pattern.[15] A typical example of lumpy discard is depicted in Figure 4.1. The first bar in the figure shows the capital stock of vintage 1981 existed in the year 1990 (that is of age 9), and the second, third and fourth bars respectively show the value of discarded capital of the same vintage in years 1991, 1992, and 1993 (that is at age 10, 11 and 12). It is obvious from the figure that the discard pattern is lumpy with almost no discard at age 10 and a large amount of discard at age 11. However, if we consider the total discard over the three consecutive years, we see that almost 70 percent of capital is discarded during the three years. According to the abovementioned methodology, the first two bars can be used to calculate the survival rate of an asset of age 10. And following the assumption sj(x) =s(x), the survival rate calculated using the first two bars can be considered representative of the survival rate of asset of any vintage

[15] Earlier studies have shown that investment takes place in bursts. See for e.g. Domes and Dunne (1998), in the case of US and Fennema et al (2006) for the Netherlands.

at the age 10. Hence, as we observe very low discard in the first year, which will result in a very high survival rate at the age 10, attributing the same survival rate calculated using a single year's discard information as in previous studies (see equation 4.7) for all vintages does not seem to be an appropriate one. Though the particular vintage, considered as the representative vintage for the given age, say 10, have shown such a tendency, it may not hold for all vintages. More over the same vintage has shown a bulky discard in the next year, indicating that considering a single discard pattern may result in biased estimate of survival rate. Therefore, if one considers the single year discard information, taking a single vintage as representative of a particular age may affect the estimated survival rate for that particular age for all vintages, if the representative vintage has shown a very large or small discard.

It can be argued that this lumpiness may disappear in some cases, when aggregating across vintages at two digit industry level. However, the problem of considering a single vintage as representative for all vintages at a given age still prevails. It is not necessary that all vintages have a similar discard behavior at any given age. That is, as mentioned earlier, the assumption of $s_j(x)=s(x)$ need not hold. For instance the survival pattern of an asset of age 10 of vintage 1997 may be different from an asset of age 10 of vintage 1999. However, in order to incorporate this heterogeneity completely into the model, as we stated before, we need to have discard information throughout the lifetime of each asset, which is not practically possible. Therefore, given the data constraints, we suggest examining more vintages for the same age and consider an aggregate or average discard behavior of these different vintages at any particular age. In doing this we have considered three discard years for each vintage, which will help us calculate the survival rate for a particular vintage at three different ages. For instance, take the previous example depicted in Figure 4.1. If we take into account only one year of discard data, our estimate of the survival rate at age 10 would be based only on the discards of vintage 1981 in year 1991. Suppose we have capital and discard information on two more vintages, say 1979 and 1980. This would allow us to calculate the survival rates of these two vintages also in years 1991, 1992 and 1993, respectively at age 12, 13 and 14 for vintage 1979 and at age 11, 12 and 13 for vintage 1980. This along with the information we have on vintage 1981, would mean that now we have survival rates of three vintages at age 12. We propose to take an average of these three survival rates for a given age, which contain information of three different vintages for a given age.[16]

More specifically, assuming that there is no second-hand investment in any particular asset of a given vintage, the survival rate for any particular asset of age *x* in years *t+1* and *t+ 2* are given by

$$s_{j+1}^{t+1}(x) = \frac{K_{j+1,t-1} - D_{j+1,t} - D_{j+1,t+1}}{K_{j+1,t-1} - D_{j+1,t}}$$

$$s_{j+2}^{t+2}(x) = \frac{K_{j+2,t-1} - D_{j+2,t} - D_{j+2,t+1} - D_{j+2,t+2}}{K_{j+2,t-1} - D_{j+2,t} - D_{j+2,t+1}} \quad (4.8)$$

As before, this average survival rate provides us the survival rate of an asset of a specific age regardless of its vintage. That is we assume that sj(x)=s(x) for all vintages. However, in the current approach, s(x) carries information on the survival rate of more vintages. Hence the generalization sj(x)=s(x) becomes more reliable. Thus, unlike the earlier studies (van den Bergen et al., 2005), which consider only the first year discard information, the present approach has the advantage of feeding more information on discard pattern of different vintages into the estimation of lifetime.

Once the survival rate is calculated, the survival function *(S)* is calculated as the cumulative distribution of survival rates. That is,

$$S(x) = \prod_{i=1}^{x} s(i) \quad (4.9)$$

Note that (4.8) assumes that there is no second-hand investment in the vintage *j*. This is because, only in the absence of second-hand investment capital stock in year *t* for

[16] We have also calculated the survival rate using the total capital stock in three years (t-1, t and t+1) and total discards in three years (t, t+1 and t+2). The total capital stock is calculated by summing the constant price capital stock at any given age, say x, existed during three years, where the annual capital stock is calculated as the difference between previous year's capital stock and current year's discard. Similarly the total discard at any given age is calculated by summing the three years constant price discard for the given age. Then the survival rate at age x is calculated as the total capital stock of age x during the three years (t-1, t and t+1) – total discards of age x during the three years (t, t+1 and t+2)/ total capital stock of age x during the three years (t-1, t and t+1). The results remain to be similar to the ones obtained using average survival rates.

any particular vintage *j* can be calculated using information on capital stock in year *t-1* and discard in year *t* as $K_{j,t-1}$ - $D_{j,t}$. If there exists second-hand investments in the given vintage *j*, the capital stock in year *t* will be $K_{j,t-1} - D_{j,t} + SK_{j,t}$, where $SK_{j,t}$ is the second-hand purchases of the same vintage *j*. Hence the survival rate will be higher than what is actually obtained assuming there is no second-hand investment. We do not attribute much significance to this problem, as it is expected to have only negligible effect on our results, as second-hand investments typically constitute a very tiny portion of total investment, especially in the asset types which we consider. For instance, from the recent investment surveys we gauge that the share of second-hand investment is only 1.5 percent in transport equipment, 0.3 percent in computers and 0.4 percent in machineries. This however varies across industries with a maximum of 4 percent in all the asset types, and a mode of 0 in computer and machinery and 2.5 in transport equipment. Hence, our assumption that its share is trivial is justified (see Appendix Table 4.3).

Age of the asset (x): The age of an asset of a particular vintage is calculated as the discard year (year when it was discarded) minus its vintage year (year when it was purchased); i.e. $x=t-j$.

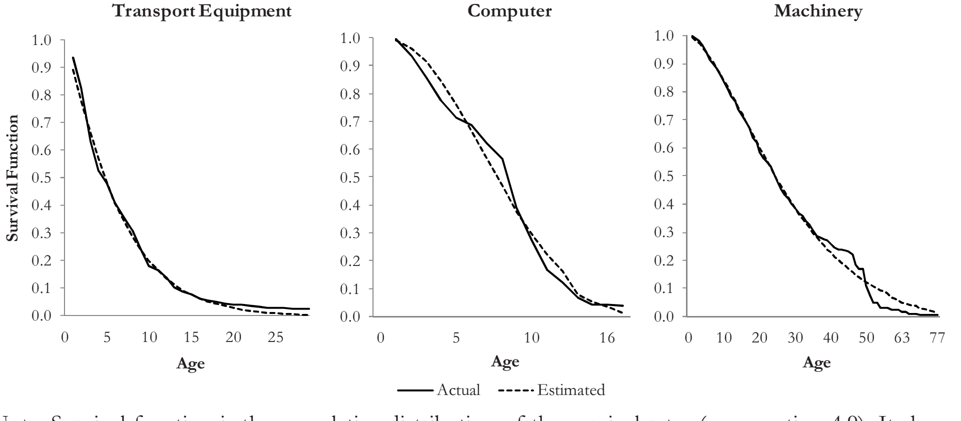
4.4 Empirical Results

We have estimated equation (4.4), where we regress the actual survival function, calculated using (4.9), on the age of the asset. Since the Weibull specification is non-linear in parameters, we have used a non-linear regression method. It is, however, also possible to estimate the equation using a linear model by transforming the data into log form (e.g. Meinen, 1998). Nevertheless, the non-linear estimation is assumed to be more realistic and robust. In the linear transformed model, the parameter values are determined in such a way that they minimize the squared residuals for the transformed function rather than the original function. Hence, the estimated parameters may not produce the best fit of the original function to the data. Comparisons of estimated survival function with actual survival data have shown that the non-linear results are more close to actual data, compared to the linear ones (see Appendix Figure 4.1). Hence, we opt for non-linear regression estimation using a sequential quadratic programming algorithm, as provided in SPSS. The estimation is performed both for single discard year as well as 3 discard years cases for purpose of comparison. In the former case, all firms that have reported at least one vintage in the first discard year are included in the sample, while in the latter case only firms that have reported zero or positive discard in at least one vintage in all the three years are included. The estimated parameters α and λ are then used to derive the expected service lifetimes of capital, using equation (4.6). While performing the regression, we have faced the problem of exaggerated tails on discard rates, caused by the continuous lack of discard reporting in some of the older vintages. Such long tails affect the variability of discard rates and hence the regression estimation. Therefore, we have excluded such large tails from our regression, after allowing for a maximum of three vintages after the oldest vintage with positive discard. In section 4.1 we discuss the regression results and in section 4.2 we present the lifetime estimates derived using the estimated coefficients.

Regression Results

Tables 4.2, 4.3 and 4.4 provide the estimated coefficients of nonlinear regression, using three year's discard information. The first four columns in each table provide the estimated α, its standard error and its lower and upper confidence intervals. The same for λ are provided in the next four columns. The last two columns provide R^2 and degrees of freedom.

Figure 4.2: Actual vs. estimated survival function, food, beverages & tobacco industries



Note: Survival function is the cumulative distribution of the survival rates (see equation 4.9). It shows the probability that an asset survives at a particular age.

In general, the estimated standard errors are small and the coefficients are significant at 1 per cent level in all industries and all assets. In all the cases, the 95 percent confidence intervals are generally quite narrow both for α and λ. The R^2 values are generally high. However, as discussed in the non-linear regression literature, one should not over rely on the R^2 statistic, but also look at the fitted lines. Hence, along with these statistics, we have also examined all the estimated regression lines along with the actual ones. Figure 4.2 provides the actual and estimated survival functions for three asset types in the food, tobacco & beverages industry. It can be seen that the estimated lines fit very well to the actual data in almost all the asset types. However, this story does not hold for all industries and asset types. Such cases, where the estimated line does not fit to the actual data very well, are excluded from our lifetime estimations.

Table 4.2: Estimated regression coefficients — Transport equipment

	α				λ					
Industry	**Estimate**	**SE**	**LC**	**UC**	**Estimate**	**SE**	**LC**	**UC**	R^2	**DF**
15+16	1.14	0.03	1.08	1.21	0.15	0.00	0.15	0.16	0.99	28
17 to19	1.00	0.17	0.63	1.37	0.16	0.02	0.12	0.19	0.86	17
20+33+36	1.22	0.13	0.94	1.49	0.18	0.01	0.15	0.20	0.94	17
21	1.12	0.13	0.85	1.39	0.20	0.01	0.17	0.23	0.93	17
22	2.18	0.18	1.81	2.55	0.23	0.01	0.22	0.24	0.98	20
23	1.00	0.08	0.83	1.17	0.11	0.01	0.10	0.12	0.93	30
24	1.00	0.11	0.77	1.23	0.08	0.00	0.07	0.09	0.84	23
25	1.00	0.14	0.70	1.30	0.14	0.01	0.12	0.16	0.86	16
26	1.16	0.16	0.82	1.50	0.20	0.02	0.17	0.24	0.90	19
27	1.80	0.11	1.56	2.04	0.11	0.00	0.11	0.12	0.98	16
28	1.27	0.12	1.02	1.52	0.19	0.01	0.17	0.21	0.95	20
29	1.12	0.17	0.75	1.49	0.18	0.02	0.15	0.22	0.89	13
30+32	1.38	0.11	1.14	1.61	0.21	0.01	0.20	0.23	0.97	22
31	1.05	0.14	0.73	1.37	0.15	0.01	0.12	0.17	0.92	11
34+35	1.00	0.11	0.78	1.22	0.12	0.01	0.11	0.14	0.90	16

Notes: SE is the standard error of estimate. LC and UC are respectively lower and upper confidence interval at 95 percent and DF is the degrees of freedom. All the coefficients are significant at 1 percent. α is the parameter that determines the shape of the survival function and λ is the parameter that determines the scale or magnitude of the function.

We have also estimated the survival function using the standard single year discard rates for purpose of comparison. The results for single year discard cases are provided in Appendix Tables 4.4, 4.5, and 4.6. We observe that the number of observations (vintages) has increased in most industries on average by four observations in transport equipment, two in computers and five in machinery when we incorporate three discard years.[17] In addition, we observe that the incorporation of more discard years into the estimation improves the fitted curves in most cases (for e.g. see Appendix Figure 4.2). Hence, the estimates obtained in three years' discard approach are more reliable.

Table 4.3: Estimated regression coefficients — Computers

	α				λ					
Industry	**Estimate**	**SE**	**LC**	**UC**	**Estimate**	**SE**	**LC**	**UC**	R^2	**DF**
15+16	2.16	0.15	1.83	2.48	0.11	0.00	0.10	0.12	0.98	15
17 to19	2.98	0.41	2.09	3.88	0.10	0.00	0.09	0.11	0.97	14
20+33+36	1.88	0.36	1.10	2.67	0.13	0.01	0.11	0.15	0.89	13
21	1.46	0.14	1.15	1.76	0.13	0.01	0.12	0.14	0.96	13
22	1.67	0.13	1.39	1.96	0.09	0.00	0.09	0.10	0.97	16
23	1.00	0.08	0.82	1.18	0.10	0.00	0.09	0.10	0.94	14
24	1.53	0.06	1.40	1.65	0.10	0.00	0.10	0.11	0.99	15
25	3.04	0.62	1.69	4.38	0.10	0.00	0.09	0.11	0.89	14
26	4.60	0.69	2.90	6.30	0.11	0.00	0.11	0.12	0.96	7
27	2.13	0.13	1.87	2.39	0.06	0.00	0.06	0.06	0.98	24
28	1.97	0.06	1.84	2.10	0.12	0.00	0.11	0.12	1.00	15
29	2.06	0.09	1.86	2.25	0.13	0.00	0.12	0.13	0.99	14
30+32	1.44	0.04	1.36	1.51	0.12	0.00	0.11	0.12	1.00	18
31	1.91	0.22	1.44	2.39	0.10	0.00	0.09	0.11	0.95	15
34+35	2.56	0.13	2.28	2.84	0.13	0.00	0.12	0.13	0.99	13

Notes: As in Table 4.2

It may be noted that the shape of the survival function is determined by the value of α. Therefore, there are various possibilities regarding the survival rate and consequently the shape parameter α.[18] We observe that on average the α values are 1.2 for transport equipment, 2.2 for computers and 1.6 for machinery. This indicates that the chance of discard is highest in computers, followed by machinery and transport equipment. This is largely in consistency with earlier estimates for the Netherlands (e.g. Meinen, 1998; van den Bergen et al., 2005).[19] However, the values vary notably across industries. In

[17] This could happen if the same firm has discarded more vintages in the later discard years, as the number of observations in our analysis is the number of vintages.

[18] For instance a unitary α indicates a constant survival rate, an α lying between 1 and 2 indicates a regressively decreasing survival rate, an α taking the value 2 indicates linearly decreasing survival rate and an α greater than 2 indicates progressively declining survival rate (see OECD, 2001; Meinen, 1998; Bekker, 1991).

[19] The average values of α in Meinen (1998) are 1.3, 2.1 and 1.5 and in van den Bergen et al (2005) are 1.5, 1.7 and 1.8 respectively for transport equipment, computers and machinery. These are calculated from Table 3-1 of Meinen (1998) and Tables A2 to A4 of van den Bergen et al (2005).

transport equipment almost 6 industries have shown an α hovering around 1, indicating a constant risk of discard. In eight industries α lies between 1 and 2 indicating a near constant or regressively decreasing survival rate, and in one industry, publishing & printing (22), it is greater than 2 indicating a progressively increasing discard rate. In computers, there is only one industry with unitary α, i.e. the petroleum, cokes and nuclear fuel industry (23). The value of α lies between 1 and 2 in seven industries showing a regressively increasing chance of discard. Also in seven industries α is greater than 2, indicating a progressively decreasing survival rate, with the largest magnitude being in industries rubber & plastic products (25) and other non-metallic minerals (26). The story of machinery seems to be some what similar to that of transport equipment; there are 2 industries with α close to unity, 11 industries with α between 1 and 2 and only 2 industries with α greater than 2.

Table 4.4: Estimated regression coefficients — Machinery

	α				λ					
Industry	Estimate	SE	LC	UC	Estimate	SE	LC	UC	R^2	DF
15+16	1.54	0.03	1.48	1.60	0.03	0.00	0.03	0.03	0.99	69
17 to19	1.70	0.05	1.61	1.80	0.04	0.00	0.04	0.04	0.99	54
20+33+36	1.57	0.07	1.42	1.72	0.04	0.00	0.03	0.04	0.97	48
21	1.43	0.03	1.37	1.50	0.04	0.00	0.04	0.04	0.99	49
22	2.00	0.09	1.81	2.19	0.07	0.00	0.06	0.07	0.98	34
23	1.31	0.14	1.03	1.58	0.03	0.00	0.02	0.03	0.79	54
24	1.72	0.05	1.61	1.83	0.04	0.00	0.04	0.04	0.99	57
25	1.34	0.03	1.27	1.40	0.03	0.00	0.03	0.03	0.99	44
26	2.23	0.43	1.37	3.09	0.03	0.00	0.03	0.03	0.68	47
27	2.32	0.06	2.21	2.43	0.03	0.00	0.03	0.03	0.99	55
28	1.40	0.05	1.31	1.49	0.03	0.00	0.03	0.03	0.98	65
29	1.06	0.05	0.97	1.16	0.05	0.00	0.05	0.05	0.96	49
30+32	1.40	0.01	1.37	1.42	0.05	0.00	0.05	0.06	1.00	65
31	1.03	0.03	0.97	1.08	0.02	0.00	0.02	0.02	0.98	54
34+35	1.32	0.06	1.19	1.44	0.04	0.00	0.04	0.04	0.96	47

Notes: As in Table 4.2

Thus the number of industries with progressively increasing rate of discard is larger in computers compared to machinery and transport equipment. While the largest number of industries with constant survival rate is observed in transport equipment, the lowest is found in computers. These observations are intuitively appealing as one would expect the chance of discard to be higher in the asset type computers, which is subject to severe technological obsolescence. However, the intensity of discard risk, as visible from the magnitude of the coefficient, varies across industries, which may be due to the differences in composition of computer assets in various industries. For instance if the share of fast depreciating components are higher, then the discard rate in such industries may face an acceleration compared to other industries.

The value of λ, the scale parameter, does not affect the shape of the survival rate but the magnitude of the survival rate, independent of the value of α. There is a negative relationship between the value of λ and the magnitude of the survival rate; the lager the magnitude of λ, the smaller the magnitude of the survival rate. It can be seen from the tables that the magnitudes of λ are generally lower in asset type machinery, compared to computers and transport equipment. This indicates that, in general, the magnitude of survival rate (discard rate) is higher (lower) in machinery compared to computers and transport equipment.

Estimated Lifetimes

The estimated α and λ are used to derive average service lifetime estimates using equation (4.6). The resulting lifetime estimates for the three asset types are presented in tables 4.5, 4.6 and 4.7. We provide estimates based on one year discards (see equation 4.7) and three years discards (see equation 4.8). Our preferred estimates are the latter ones and therefore, the discussion in the following section is based on these estimates. The results based on single year discards are provided for purpose of comparison, and will be discussed subsequently.

Transport Equipment

The estimated lifetimes for transport equipment are presented in Table 4.5. It can be discerned from the table that transport equipment has shown an average service life of 6 years. In four industries the estimated regression line had no good fit to actual data. These are industries basic chemicals, rubber & plastic products, other non metallic mineral products and electrical machinery. The lifetime varies across industries, say from 3.8 years in printing & publishing to 9 years in petroleum, cokes & nuclear fuel industry. The industries publishing & printing and office machinery, computers, radio TV & communication equipment sectors have shown the lowest estimates of average lifetimes. Interestingly, as mentioned before, these are among the industries that have shown relatively high value for α. The industries basic chemicals and petroleum, cokes & nuclear fuel have shown the highest lifetime for transport equipment.

Table 4.5: Estimates of expected average service lifetimes, transport equipment

Industry	Single Discard	3Years Discard
Food, beverages & tobacco	8.1	6.3
Textile & leather pdts.	-	6.4
Wood& wood pdcts, med.& opt. eqpt & Other mfg.	6.1	5.4
Paper and paper products	5.3	4.8
Publishing and printing	4.1	3.8
Petroleum products; cokes, and nuclear fuel	-	9.0
Basic chemicals and man-made fibers	-	-
Rubber and plastic products	-	-
Other non-metallic mineral products	-	-
Basic metals	-	7.8
Fabricated metal products	7.5	5.0
Machinery and equipment n.e.c.	7.6	5.2
Office mach. & computers, radio, TV & communi eqpt.	-	4.3
Electrical machinery n.e.c.	-	-
Transport equipment	-	8.3
Average	***6.5***	***6.0***

Notes: Single Discard refers to the lifetimes estimated using only one year's discard information and 3 Years Discard refers to the ones estimated using 3 years discard information. A – sign indicates that fitted curve is not close to actual function hence the results are not reported.

The lease and second-hand sales effect on the lifetime of transport equipment

It may be noted that our lifetime estimates for transport equipment can be influenced by the high share of leased assets and second-hand sales. The discard data makes a distinction between final destinations of discards, whether they are scrapped, sold in the second-hand market or returned back to the leasing company. It is seen that the second-hand sales and returns to leasing company are more prominent in the asset type transport equipment (see Appendix Table 4.7). The share of total discard value in transport equipment going back to the leasing company is as high as 56 percent in 2000. Also 35 percent of total transport equipment was sold in the second-hand market, with almost 50 percent of industries registering a second-hand sale of more than 30 percent. Only 2.5 percent of transport equipment was fully scrapped. This suggests the strong presence of leased assets and a large second-hand market for the asset type transport equipment. In almost all the industries with lower lifetime estimates for transport equipment, we observe that the share of assets going back to lease company and second-hand sale is more than 80 percent.

This pattern is typical for transport equipment but not for other assets. The story is quite different in the case of computers and machinery. On average 53 percent of computers are fully scrapped, while 17 percent are sold in the second-hand market and only 1.5 per cent is returned to leasing company. Similarly, machinery has shown almost 52 percent scrap, while 13 percent is sold in the second-hand market and less than 1 percent returned to leasing company.

The average duration of a lease contract is probably shorter than the average age of owned transport equipment, which will therefore cause to result a shorter lifetime estimate (van den Bergen et al., 2005). This is because the rental price of an asset is directly observable, if there is an active lease market, which is not the case with an owned asset. As argued by Salter (1960), a firm will discard its assets when the quasi-rent earned by an asset becomes zero. However, in the case of leased asset, since the firm has no sunk cost, it may return the asset back to the lease company, once the profit earned by the asset falls below the ones that could be earned by a new asset. For a firm that owns the asset, however, it will have to recover the sunk cost, and therefore will opt to keep the asset until its quasi-rent becomes zero. Therefore, a competitive firm with leased assets may discard its assets faster than a firm with own assets. The firm should be able to arrange the lease contract, on the basis of observed rental prices, and the forecasted returns. This argument would naturally raise the question why should a competitive firm ever go for an own transport equipment, if there is an active rental market, as it might hamper its competitiveness. This could happen if firms require specialized transport equipments, such as refrigerated mobile cold storages that could be used in food industry, which may often not be available in the rental market.

Similarly, the larger share of second-hand sale indicates that the asset is sold for reuse and hence not used by the firm until the end of its actual service life, which will also reduce the lifetime estimate. In the presence of an active second-hand market, the firm could salvage the sunk-cost by selling the asset in the second-hand market. Nevertheless, we make no adjustment for the presence of second-hand market and leased assets in our study. As we have mentioned before, discard in our analysis is defined to include any withdrawal of an asset from the production process. Since the discard of an asset implies that it is no more profitable to keep (or efficiently usable) it in the production process in that particular industry, it is reasonable to expect that no competitive firm will be willing to use an asset discarded by another firm in the same industry, as it might adversely affect its efficiency and hence competitiveness. Similarly, as regard to the return to lease company, we assume that the economic life of that asset to this particular industry is over, and hence it is being discarded from that industry. Since most of the leased assets are found to be in transport assets, this assumption may be valid, as most discarded automobiles (or sold in the second-hand market) are generally going to final consumers.

Computers

The estimated lifetimes for computers are provided in Table 4.6. Here, one should keep in mind that the asset type computers include not only personal computers, but also mainframe computers and computer associated equipments such as printers. Therefore, this is not an estimate of lifetime for computers per se, rather an average estimate for computer and related equipments. On average, the computers show a lifetime hovering around 9 years with the highest registered in industry basic metals. There are two industries, textile & leather products and rubber & plastic products, which have obtained a relatively bad fit for the estimated regression line. The estimated lifetimes vary across industries, but not substantially. We observe a minimum of 7 years in wood & wood products, paper & paper products, machinery & equipment and transport equipment industries and a maximum of 15 years in basic metals. Most other industries have shown a lifetime of around 8 years.

Table 4.6: Estimates of expected average lifetimes, computers

Industry	Single Discard	3Years Discard
Food, beverages & tobacco	19.0	8.1
Textile & leather pdts.	-	-
Wood& wood pdcts, med.& opt. eqpt & Other mfg.	-	6.9
Paper and paper products	-	6.9
Publishing and printing	16.8	9.7
Petroleum products; cokes, and nuclear fuel	-	10.4
Basic chemicals and man-made fibers	28.1	8.7
Rubber and plastic products	-	-
Other non-metallic mineral products	-	8.0
Basic metals	-	15.0
Fabricated metal products	9.0	7.6
Machinery and equipment n.e.c.	13.7	6.9
Office mach. & computers, radio, TV & communi eqpt.	6.8	7.8
Electrical machinery n.e.c.	-	8.9
Transport equipment	9.8	6.9
Average	***14.7***	***8.6***

Notes: as in Table 4.5.

Machinery

For the asset type machinery on average the estimated lifetime is 26 years (Table 4.7). The industries publishing & printing, office machinery, radio & TV manufacturing and machinery & equipment have shown the lowest lifetimes. The highest lifetime is registered in industries electrical machinery n.e.c., and basic metals. For the industry petroleum products we did not find a good fit for the estimated model. The lower rates observed for the industry office machinery, radio & television manufacturing is rather appealing as one would expect the service life in such a highly dynamic industry which is subject to severe technological advancement to have a relatively higher discard rate compared to high sunk-cost industries such as basic metals.

Table 4.7: Estimates of expected average lifetimes, machinery

Industry	Single Discard	3Years Discard
Food, beverages & tobacco	31.2	27.9
Textile & leather pdts.	28.4	22.8
Wood& wood pdcts, med.& opt. eqpt & Other mfg.	34.7	24.9
Paper and paper products	-	22.5
Publishing and printing	22.6	13.6
Petroleum products; cokes, and nuclear fuel	-	-
Basic chemicals and man-made fibers	30.0	24.7
Rubber and plastic products	34.7	29.5
Other non-metallic mineral products	35.8	28.7
Basic metals	-	33.0
Fabricated metal products	28.5	29.2
Machinery and equipment n.e.c.	24.5	19.6
Office mach. & computers, radio, TV & communi eqpt.	13.6	16.7
Electrical machinery n.e.c.	-	41.0
Transport equipment	39.9	23.7
Average	***29.4***	***25.5***

Notes: as in Table 4.5.

Lifetime estimates: Single year versus three year discard approaches

Since we have incorporated more discard information into our empirical model, it is worth comparing the results of the standard approach with that of ours. In Tables 4.5, 4.6 and 4.7 we have also provided the estimates based on single year discards information. As is evident from the tables, we could estimate lifetime for more industries when we incorporate more discard information, as it provides better model fit. In most industries the single discard year estimates tend to produce significantly higher lifetimes compared to the three discard year estimates. This is particularly true in asset type computers.

In Table 4.8 we compare our estimates of lifetimes for different two digit industries with two earlier studies based on single year discard rates conducted for the Dutch manufacturing, i.e. Meinen (1998) and van den Bergen et al (2005). While the former study has used a somewhat similar methodology as ours (but with one year of discard data), the latter has used a hazard function to estimate lifetimes. The table provides only results that are comparable. For instance, van den Bergen et al (2005) also provides results for more industries, which are however not based on actual information on capital stock and discard. Rather they have taken them from other industries or derived based on expert guesses, as they could not obtain robust results for these industries. Such estimates are not reported in Table 4.8.

Table 4.8: Comparison of asset lifetime estimates with earlier studies for the Netherlands (industry wise)

	van den Bergen et al			Meinen		New Estimates*		
Industry	*Tran-sport*	*Comp-uter*	*Mach-inery*	*Comp-uter*	*Mach-inery*	*Tran-sport*	*Comp-uter*	*Mach-inery*
Food, beverages & tobacco	6	12	27	13	43	6	8	28
Textile & leather pdts. [1]	5	14	35	15	28	6	-	23
Paper & paper products	5	6	-	10	27	5	7	22
Publishing & printing	5	8	35	-	-	4	10	14
Petroleum pdts; cokes, & nuclear fuel	5	8	-	10	-	9	10	-
Basic chemicals & man-made fibres	-	12	30	13	38	-	9	25
Other nonmetallic mineral pdcts	-	-	30	-	-	-	-	29
Basic metals [2]	7	-	-	16	36	8	15	33
Fabricated metal products	5	8	33	-	-	5	8	29
Machinery & equipment n.e.c.	5	12	-	-	-	5	7	-
Office mach. & computers, radio, TV& comm.eqpt.[3]	-	-	20	-	-	-	-	17
Transport equipment [4]	-	5	30	-	-	-	7	24
Average*	***5***	***9***	***30***	***13***	***34***	***6***	***8(10)***	***24(26)***

Notes: In Meinen (1998) industry wise estimates for transport equipment are not available.
In some cases the industry estimates are averages across several industry groups. They are in Meinen, 1) only textiles; 2) basic metal and fabricated products together; and in van den Bergen et al., 3) average for office machinery & computers and radio, TV etc.; and 4) the average for cars & trailers and other transport equipment.
**Un-weighted averages across industries. * Averages (in parentheses) are calculated for those industries for which there are lifetime estimates in van den Bergen et al (in Meinen).

The table shows that our estimates are generally slightly higher than that of van den Bergen et al for transport equipment[20] with a few exceptions. In computers, the new estimates are lower than that of van den Bergen et al in three out of eight industries, same in one industry, fabricated metal products and 1 to 2 years higher in other industries. The new estimate for computers is the same as that of Meinen's estimate in petroleum products industry, while in all other industries they are lower, say by 1 to 5 years. The lifetime estimates for machinery in both previous studies are generally higher than the new estimates. In particular in all industries the new estimates are considerably lower than Meinen's estimates, while slightly lower in seven out of ten industries compared to van den Bergen et al. The observed differences are substantial in some industries while trivial in others. For instance our estimates are 21 years lower than van den Bergen et al in industry printing and publishing and 12 years lower in textiles. Similarly the new estimates are lower by 13 years in basic chemicals and by 15 years in food, beverages and tobacco, compared to Meinen.

The observed differences may largely due to the methodological differences. In addition, our approach also differs from van den Bergen et al (2005), particularly in the way the data has been used. For instance, we have excluded all those firms that have not reported zero or positive discard in at least one vintage (i.e. those firms with missing observations throughout all the vintages in the data) from the sample. van den Bergen et al (2005) however have included all such firms assuming zero discards under the presumption that these are not real missing cases. Unfortunately, there is no way to verify the validity of this underlying assumption. The problem is that if this assumption is not realistic, i.e. if it is a real missing case, its inclusion will overestimate capital stock (underestimate discards). Hence we opt to exclude such firms both from capital stock and discard data. Further, we exclude all those cases where the discard values are higher

[20] It may, however, be noted that in order to deal with the problem of leased assets, van den Bergen et al (2005) have raised their estimates for transport equipment by 0.712, which they have obtained from the relationship between life times estimated including and excluding leased asset types for food and tobacco manufacturing. Such an analysis was possible only for food and tobacco manufacturing as the information on return to lease company is available only since 1999 and the only industry for which there is meaningful number of data after 1999 is food and tobacco. We, however, did not opt to make such an adjustment because, the share of leased asset varies significantly across industries (see Appendix Table 4.7), and it may not be appropriate to use a common factor across industries. We also observed that if the leased transport equipments are excluded from the analysis, the life time for food and tobacco manufacturing increases by almost 1.3 years.

than capital stock, as it is an impossible situation. However, they have corrected the data in these cases by attributing such discard cases to a nearby vintage year. But, there is no criterion by which one can decide which vintage it can be attributed to, other than arbitrary selection. In any case, this is not a severe problem, as the number of such cases is quite negligible in all the three asset types we have considered. The treatment of discard has also been different, at least in asset type machinery. They do not consider second-hand sales and return to leasing company (the share of latter is quite marginal though) as discards, while we do. And in transport equipments, they have raised the lifetime estimate for all industries, using a factor which they have calculated for transport equipment in food products, beverages and tobacco industries by excluding leased assets from the sample. In our regression analysis we allow only three exaggerated tails, while they have included up to five. Finally they have used two bench marks in most cases, and selected the results that appear to be reasonable. Since our methodology incorporates three years' discard information, it was not possible for us to consider the second benchmarks due to lack of adequate data to include more discard information. These differences may also cause the observed differences in Table 4.8.

Lifetime estimates: Comparison with other countries

In Table 4.9 we compare our estimates with available estimates for the United States, Japan and Canada for aggregate manufacturing. For the U.S., the estimates are taken from the Bureau of Labor Statistics (BLS)[21], where they are provided for three asset types, namely metal working machinery, special industry machinery n.e.c., and general industrial equipment including materials handling. We have considered an un-weighted average of these three asset types, as the estimate for machinery. We also provide US estimates obtained from Bureau of Economic Analysis (BEA). For Canada the lifetime estimates are taken from OECD (2001a) and Statistics Canada (2007). In the former case, we take an un-weighted average for machinery across industries, and in the latter case an un-weighted average across various asset types used in manufacturing sector. For Japan the estimates are taken from Nomura (2005) averaged across various asset types.

[21] The data is downloaded from the BLS website http://www.bls.gov/mfp/mprcaptl.htm on June 06 2006.

Table 4.9: Comparison of asset lifetime estimates with earlier studies (Total manufacturing)

Country (Source)	Transport	Machinery	Computers
Canada (OECD)*	-	12	-
Canada (Statistics Canada)**#	11(7)	14(12)	10(9)
US (BLS)*	10	21	6
US (BEA)**	9	18	7
Japan (Nomura)**	14	13	7
Netherlands (our estimates)*	6	26	9

Notes: *Simple average across various industries; ** Simple average across various asset types; *** Estimate for total manufacturing; N.A Not Available; # Figures in parenthesis are *ex ante* estimates. The US estimates for computers from BEA (Bureau of Economic Analysis, 2003) are for office and computing equipment and from the BLS are the average across mainframe computers, personal computers, storage devices, printers, terminals, tape drivers and other office and computing equipments. It is not clear whether it is an estimate for the manufacturing sector alone. Also the US estimates for transport equipments are for trucks, buses and trailers, excluding those used in passenger services and other service industries.

We observe that our results for transport equipment are closer to the *ex ante* estimates[22] provided by Statistics Canada (2007), while they are considerably lower than Nomura (2005)'s estimates for Japan.[23] For computers, our estimates are similar to the Canadian estimates, but higher than the U.S. and the Japanese estimates. The U.S. estimates for computer is lower than our estimates, but it is not clear whether these are estimates only for manufacturing. This is very important as it is also possible that the share of personal computers which are subjected to more rapid technological obsolescence is lower in manufacturing industries compared to service sectors. In the manufacturing sector computer equipments may largely consists of mainframe computers or highly customized numerically controlled machines, which may not be replaced as quick as personal computers may. Our estimate for machinery is almost double the Japanese and Canadian estimates though relatively closer to the BLS estimates for the U.S. The cross-country differences are larger in machinery, while it is lower in computers. These differences could either be due to the differences in asset composition, or due to the differences in the factors that determine the discard behaviour of firms. They could also be due to the differences in industry composition. We compare the estimates for two-digit industries in Table 4.10.

[22] These are survey estimates of the expected life of assets.
[23] Both Statistics Canada and Nomura have employed a survival analysis to derive lifetimes.

Table 4.10: Comparison of machinery lifetime estimates with earlier studies (industry wise)

Industry	Canada	U S (BLS)	Netherlands
Food, beverages & tobacco [1]	11	24	28
Textile & leather pdts. [2]	10	18	23
Wood& wood pdcts, med.& opt. eqpt & Other mfg. [3]	11	17	25
Paper & paper products	18	19	22
Publishing & printing	-	18	14
Petroleum pdts; cokes, & nuclear fuel	16	25	-
Basic chemicals & man-made fibres	13	19	25
Rubber & plastic products [4]	12	16	29
Other nonmetallic mineral pdcts [5]	13	22	29
Basic metals	-	31	33
Fabricated metal products	10	28	29
Machinery & equipment n.e.c. [6]	8	29	20
Office mach. & computers, radio, TV & communi eqpt. [7]	8	-	17
Electrical machinery n.e.c. [8]	-	16	41
Transport equipment [9]	9	18	24
Average	***12***	***21***	***26***

Notes: The figures for Canada are taken from OECD capital manual, and the figures for US are the revised estimates available at the Bureau of Labor Statistics website, http://www.bls.gov/mfp/mprcaptl.htm. For the US the estimates are simple average across three asset types, say metal working machinery, special industry machinery, n.e.c., and general industrial equipment including materials handling.
In some cases the industry estimates are averages across several industry groups. They are 1) For Canada, the average for food & beverages and tobacco, and for the US the average for food & kindered products and tobacco; 2) For Canada, the average for leather and textiles, and for the US, the average for textile & mill products, apparel & other textiles products and leather & leather products; 3) For Canada, the average for wood and other manufacturing industries, and for the US the average for lumber & wood products, furniture & fixtures, instruments & related products and miscellaneous manufacturing; 4) For Canada, the average for rubber & plastic products; 5) For the US, Stone, clay & glass products; 6) For Canada, machinery industries, and for the US industrial machinery and equipment; 7) For Canada, electrical and electronic products; and For the US 8) electronic and other electrical equipment and 9) average for motor vehicles & equipment and other transport equipment.

The industry level comparison was possible only for machinery, as industry wise estimates for the U.S. and Canada were not available for transport equipment and computers. For the US the estimates are from BLS and for Canada, they are taken from OECD capital manual. However, in the latter case we have no information about the components of machinery (more importantly whether transport equipments are included or not). This is important because a comparison is meaningful only if the same combination of assets is included in all the estimates. Nevertheless, we do compare them as we do not have a better estimate to compare with.

Interestingly the Canadian estimates are much smaller than both the U.S. and the new estimates for the Netherlands in all industries. This is surprising. For instance, the U.S. and the Canada share not only geographical proximity, but also many economic characteristics, which make it less probable to have such huge differences in their asset lives. Hence, it may be an indication of differences in asset composition. Of course, one could argue that the discard decision and consequently the lifetimes of asset depends on many factors including tax policy, innovation, output growth and input prices, among others, which can vary across countries leading to differences in lifetimes. This is an issue that warrants further research, though. However, even if one gives allowance for such issues, one would not expect to have such huge lifetime differences, especially between countries of similar economic conditions. When comparing the U.S. figures with the Dutch estimates, it is seen that the machinery in the Netherlands lives longer than in the U.S. in almost all industries except in publishing & printing and machinery & equipment, where it is less respectively by 4 and 9 years. The difference between the estimates, on average is 5 years with the largest difference being in electrical machinery n.e.c. These differences may either be real, or a reflection of the asset composition or due to measurement error.

4.5 Concluding Remarks

In this chapter we present estimates of average service life for three different asset types — transport equipment, computers, and machinery — for the manufacturing industries in the Netherlands. For this purpose, we exploit a unique firm level dataset on directly observed capital stock and discards of these asset types. A Weibull distribution function is estimated using a non-linear regression estimation procedure, where the survival function of select asset is regressed on its age. The Weibull parameters are then used to calculate the expected service life of the assets. In the measurement of lifetimes, unlike earlier studies, we have incorporated more information on discard pattern of each vintage and hence provide better approximation of survival rates. The new lifetime estimates can be used, *inter alia,* to derive depreciation rates using a declining balance approach (see Fraumeni, 1997).[24]

The estimated regression coefficients are found to have a good fit in general, and it has further improved when we incorporate more discard information into estimation. Moreover, the number of observation has increased in most industries when more discard years are added into the model. On average the transport equipment have shown a lifetime of 6 years while the machinery and computers have respectively shown 26 and 9 years. A comparison of our estimates with that of earlier estimates for the Netherlands, where single year discard information is used, indicates that the new estimates are slightly higher than the previous estimates for transport equipment and lower for machinery and computers.

We also compare our results with estimates available for the US, Japan and Canada. While our estimates for transport equipments are quite close to estimates for Canada, they are significantly lower than that of Japan. In general, the transport equipment seems to show a lower lifetime in our results (than the average observed for other countries), at least in some industries. This may be attributed to the large share of leased assets and second-hand sale in transport equipment component, with possibly lower length of lease contract. This point, however, needs further substantiation looking at the share of these factors in other countries for which relevant data could be gathered, like Japan for instance. For machinery, our estimates are larger than both Japan and Canada, but to some extend closer to that of the U.S. In particular, the machinery lifetime differences in some industries, particularly between US and the Netherlands are lower than the differences observed at the aggregate level. These differences could either be due to compositional differences or due to differences in determinants of capital discard across countries. In the latter case, it warrants further research unearthing the determinants of discard behaviour of firms. Computers, however, have shown a lifetime that is almost same as Canadian estimates, but slightly higher than the U.S. and Japanese estimates. Given the possible errors in measurement and data, this may indicate that the assumption

[24] The depreciation rates in this approach can be measured as the ratio of an assumed declining balance rate to the average service lifetime. This could be done under different assumptions on declining balance such as double declining balance, or a rate which is based on a pre-determined rate of initial value of the capital that remains at the end of life time (see OECD 2001a for a discussion). For instance in the double declining balance approach, depreciation may be approximated by twice the inverse of the asset's lifetime.

of a common depreciation rate for computers, at least across developed countries, may be valid. But for machinery, they still show substantial difference.

It may be noted that there is wide variation in asset lifetimes across industries. The cross industry variation is seen to be decreasing as we incorporate more discard information. But it still does exist. The difference is observed despite the fact that we have considered a relatively high level of aggregation, where one might expect to have similar estimates. The difference is substantial in some cases. For instance the difference between minimum and maximum asset life in machinery is more than 20 years. Nevertheless, apart from the technological specificities, which may be countered by the high level of aggregation we have used, we have no explanation for this. The observed difference may either be a reality, or indicate noise. It is a worthwhile topic for future research.

Similarly, the observed cross-country differences in lifetimes may indicate that the assumption of a common depreciation rate in cross-country productivity studies may produce biased results on the relative roles of inspiration and perspiration in driving economic growth and cross-country growth differences. In particular, we observe differences in machinery lifetime between advanced countries, and the differences between developed and developing countries could be even more. Such international differences in asset lifetimes may exist due to a variety of reasons including differences in the composition of capital stock, tax incentives, maintenance cost, under maintenance or technological change (OECD, 2001; Blades, 1993; Van Ark and Timmer, 2000; Summers and Heston, 1995; Bu, 2004; Pritchett, 2000). If the observed difference is a reality, it is important to examine the factors that induce firms to discard their capital assets in different countries. This would help us understand why some firms discard their machines faster than others, which will have consequences for their productivity growth (Salter, 1960). This is particularly important from the perspective of the relationship between innovation and investment/discard behavior, particularly in the milieu of increasing technological obsolescence. In the next chapter, we try to unearth the factors that influence the discard behavior of firms, with special reference to technological change.