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Measurement and analysis of capital, productivity and economic growth

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Document Version

Publisher's PDF, also known as Version of record

Publication date:
2008

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Erumban, A. A. (2008). *Measurement and analysis of capital, productivity and economic growth*. [Thesis fully internal (DIV), University of Groningen]. PrintPartners Ipskamp B.V., Enschede, The Netherlands.

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Chapter 5

Innovation, Obsolescence and Retirement: An Exploration Using Data for Dutch Manufacturing Firms

5.1 Introduction

In the previous chapter we have shown that the service lifetimes of capital assets vary across asset types, industries and countries. Those assets which are subject to high rates of discard will have low lifetimes. Therefore, it is imperative to look into the factors that determine the discard rates of capital assets. Firms may discard their assets due to obsolescence, physical wear-and-tear or simply decline in efficiency due to age. Many previous studies have argued that it is an endogenous decision of firms whether to discard an asset or not (Feldstein and Foot, 1971; Feldstein and Rothschild, 1974; Cooper and Haltiwanger, 1993; Caballero and Hammour, 1994, 1996; Cooley et al., 1997; Goolsbee, 1998). Physical wear-and-tear and efficiency decline lead to a situation in which the capital is no longer profitable to use in the production process (see Salter, 1960). Discard can also occur due to technological obsolescence, in which case capital assets are discarded well before the end of their physical lifetime. This has important implications for the measurement of capital, output and productivity growth rates. This point has been made most forcefully by Howitt (1998), who claims that a faster pace of technical change will tend to reduce the net rate of capital accumulation by causing both physical and human capital to become obsolete more quickly. With a given rate of investment, higher depreciation due to obsolescence will result in lower net rates of capital accumulation. Also in the context of the recent ICT revolution, many studies have argued that conventional growth accounting results might be biased if capital obsolescence is not taken into account (Gort and Wall 1998, Whelan 2002).¹ Thus the

¹ However, we do not maintain that the prevalence of embodied technical progress and obsolescence invalidates growth accounting as a tool for understanding the growth process, as claimed by Scott (1989). Rather, it stresses the need to find good price and depreciation measures in the capital input calculations. See Oulton (1995) for a defense of growth accounting, and Hulten (1992) and Dekle (2001) for applications with vintage capital. Also see Musso (2004).

discard behaviour of firms will have macro consequences and it is therefore important to examine the factors that determine this behaviour. This chapter empirically explores the factors that determine the firm level decision to discard as well as the magnitude of discards with special reference to the impact of technological innovations on these decisions.

Differences in discard patterns can have implications for differences in productivity growth rates between firms, industries and countries. For instance, Salter (1960) suggested that the measured UK productivity was lower than in the US due to a more intense process of capital destruction in the latter economy. Similarly, Oulton (1990) observed that capital scrapping explains the cross-industry productivity differences between 1960s and 1970s substantially, while comparing US-UK productivity differences. Despite its importance for patterns of economic growth, there is surprisingly little evidence on the empirical discard process, as stressed among others by Berndt (1991), Griliches (1994) and Hulten and Wykoff (1996). This is true of academic work as well as studies by statistical institutes. The standard practice in productivity literature is to assume a constant discard rate (e.g. Jorgenson, 1963; Jorgenson and Griliches, 1967; Jorgenson, 1974).² The assumption of a constant discard rate does not take into account that scrapping decisions are economic choices of firms owing to a number of factors. Thereby it excludes a priori what may be an important explanatory factor for variation in productivity growth rates (Feldstein and Rothshield, 1974; Hulten, 1990).

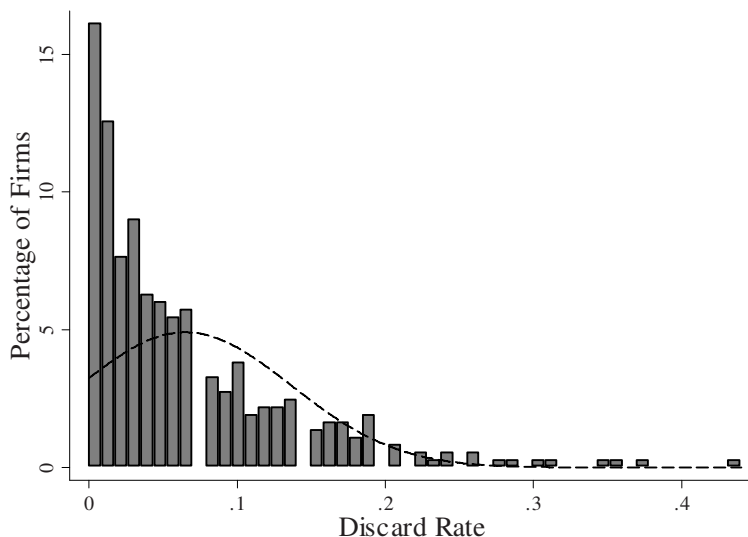
However, there have been some attempts to consider the endogeneity of discard decisions in economic modelling. In the vintage models in the tradition of Salter (1960), such as Bourcekkine et al (1998), Hendricks (2000), Greenwood and Jovanovich (2001), Whelan (2002) and Musso (2004) or in evolutionary models of growth (Silverberg, 1991; Schuette, 1994) discards of capital goods is modelled as an endogenous decision which determines slowdowns and accelerations in GDP and productivity growth. Nevertheless, empirical evidence is limited. At the micro level, using dynamic discrete choice models, asset case studies such as Das (1992) on cement kilns, Cockburn and Frank (1992) on oil tankers and Goolsbee (1998) on airplanes strongly support the view that capital discards is fundamentally an economic decision.³ But so far, survey-based studies which have a

² Also see Powers (1988) for a discussion.

³ Also see Cramer (1958), Walker (1968) and White (1971) for earlier studies that examined scrapping decisions.

wider range of asset types and firms are hard to find. A main bottleneck is the limited availability of large-scale longitudinal surveys on discard behaviour of firms.

Figure 5.1: Frequency distribution of firm level discard rates: Dutch manufacturing



Note: Average discard rates (discard/capital stock) across three asset types, machinery computers and transport equipments

The aim of this chapter is to add to the scanty evidence on patterns of obsolescence and depreciation by exploiting the unique firm-level database on discard decisions of medium and large manufacturing firms compiled by Statistics Netherlands. Nowadays, the National Statistical Offices of Canada, Japan and the Netherlands are three of the few statistical offices in the world which actually collect data on scrapping on a wide scale. We will use the data from Statistics Netherlands to study the determinants of the scrapping decision. Our analysis is different from earlier studies in this line as this is the first study that tries to model the firm level discard behaviour of a wide set of assets. In Figure 5.1 we depict the distribution of discard rates across manufacturing firms in the Netherlands. The picture clearly shows a large cross-firm variation in discard rates, suggesting the importance of examining the determinants of these differences.

The chapter is organised in six sections. The second section provides an overview of the modelling and measurement of the scrapping decision and the methodology adopted in the present study. This is important, as there is hardly any theoretical model that

explains the scrapping behaviour of firms. Therefore, it is essential to compile the odds and ends of the literature to form an eclectic view on the discard decisions of firms and the factors that nurture such decisions. It helps us derive a number of hypotheses regarding the potential determinants of discard decisions. The methodology used to examine the determinants of discard behaviour is discussed in section three. The fourth section presents the data construction and sources. Section five provides empirical results and section six concludes the chapter.

5.2 Modelling the Scrapping Decision: An Overview

Measurement of capital and depreciation is fraught with difficulties and it is important to be clear about the concepts used. A machine is scrapped when it is withdrawn from the production process, or sold to another firm or dumped as waste. Depreciation is the loss in value of an asset as it ages. This will be due to both physical wear-and-tear during use and obsolescence. An asset becomes obsolete when it is no longer economical to keep it in production which will normally be long before the asset is physically worn out. Computers provide a good example of the difference between the two concepts. Whereas the older generations of computers are still capable of performing the same functions, as when they were new, newer models have made the older vintage obsolete and computers are scrapped (and replaced⁴) well before the end of their physical lifetime. Hence depreciation is caused both by declining physical efficiency and obsolescence (see e.g. Doms et al., 2004 for an application to personal computers). The relative importance of these two sources of depreciation will depend on the nature of the asset. Wear-and-tear will be more important for long-lasting assets, such as buildings, but obsolescence might be more important for machinery as argued by Scott (1989). Especially, for computers and software, obsolescence is argued to be the main driver of scrapping (Whelan, 2002). In this chapter we will focus on the determinants of scrapping of machinery and equipment, including computers, but excluding structures.

⁴ Note that the decision to discard an asset may coincide with the decision to replace it (see Salter, 1960; Parks, 1977). However, all discards need not be replaced by new. It is possible that firms discard assets without replacing them or exit from the market and consequently scrap their assets, or stop producing a particular product leading to scrapping of assets used in the production of that product. But a replacement decision is both a discard decision as well as an investment decision, and the fact that they are carried out simultaneously does not alter their individual characteristics (Salter, 1960) suggesting the importance of looking at the scrapping behaviour as different from investment. In particular, in the process of creative destruction, investment decision is simply the replacement decision (Benhabib and Rustichini, 1993; Boucekkine et al., 1997; Boucekkine et al., 1998). The decision to discard and replace also carries importance, as a large portion of investment is sunk costs with limited salvage value (Asplund, 2000).

In Table 5.1 we provide an overview of various scrapping models which have been proposed in the economic literature. Four stylized models have been selected: neoclassical models, vintage models (with perfect competition and monopolistic competition) and evolutionary models. For each model, we indicate the predictions for the relationship between a particular determinant of scrapping and the scrapping rate. A + (-) indicates a positive (negative) relation between change in the variable and the scrapping rate, while a 0 indicates no relationship. Many determinants have been suggested, but here we focus on two groups: economic and innovation variables. This is because these determinants have been suggested to be the most important ones, and can be measured within our dataset. The first consists of output quantity and factor input prices, such as wage rates. The second set of variables includes indicators of technological change: innovation within the firm itself and exogenous technological change embodied in capital goods available to a firm. The average age of capital is included as well for reasons discussed subsequently.

Table 5.1: Alternative scrapping models and the impact of variables on discards

<i>Model</i>	<i>Variables</i>	Output growth	Wage rate	Own innovation	Embod. tech. change	Averag. age of capital
Neo-classical		0	0	0	0	0
Vintage (perfect competition)		0	0	0	+	+
Vintage (monop. competition)		+	+	-/+	+	+
Evolutionary		0	+	0	+	+

Notes: + (-) indicates a positive (negative) relation between growth of the variable and the scrapping rate. A 0 indicates no relationship.

In contrast to investment models, scrapping models have not been studied intensively in the neo-classical literature. The mainstream neoclassical theory of investment⁵, proposed by Jorgenson (1967) was a *putty-putty* neoclassical model of

⁵ Other investment theories such as the Q theory (Brainard and Tobin, 1968; and Tobin, 1969, 1978) that addressed the issue of uncertainty within the neoclassical framework, and the real option theories (Pindyck, 1993; and Dixit and Pindyck, 1994) that considered the irreversibility and the option to delay the investment also make no explicit role for the decision to discard. Though under the real option theories the investment associated with the introduction of a new innovation may be considered as an option, there is hardly any specific role attributed to innovation in these models.

investment, where firms instantaneously adjust their capital stock without any cost. Gross investment consists of net (expansion) investment and replacement investment.⁶ Following Jorgenson (1963), where the firm's desired capital stock is derived from the neoclassical maximization principle, the common practice is to treat replacement investment as a fixed and constant proportion of the capital stock.⁷ Hence this literature concentrates on the determinants of net investment (Chirinko 1993). Thus by definition, growth of output and input prices (mainly rental prices), which feature prominently in the explanation of investment patterns, do not have any impact on the scrapping decision; it is just a physical necessity. By assuming a stationary technology, replacement investment consists of replacing old machines which have been worn out by new machines, which are identical to the old ones. Obviously, innovation does not play any role in this kind of models, either inside or outside the firm.

In contrast, the macroeconomic growth literature in the vintage capital tradition has explicitly dealt with the endogeneity of the scrapping process. In the vintage capital models, new vintage capital is the prime source of productivity growth, in that the latest vintages embody the latest technology.⁸ In contrast to the old vintage models (Johansen, 1959; Solow, 1962; Solow et al., 1966), where the source of technical progress embodied in the newest vintage was assumed to be exogenous, the recent endogenous growth models have allowed creative destruction or obsolescence of technologies to underlie the growth process (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1998).⁹ One of the earliest and explicit attempts that give specific importance to scrapping behaviour and its determinants in terms of economic and innovation variables is Salter (1960). Therefore, we consider Salter as the benchmark model in our subsequent discussion on vintage models, as it allows us to model firm level scrapping behaviour with reference to firm's innovation activities.

⁶ In order to keep the capital stock of a firm intact, it is essential to replace outmoded capital by new, which is called as replacement investment. Net investment, on the other hand, is an addition to the stock of existing capital, thereby is an expansion of the firm's capacity.

⁷ The assumption of constant rate of replacement investment has been challenged by many studies (see e.g. Eisner and Nadiri, 1968; Feldstein and Foot, 1971; Feldstein and Rothschild, 1974).

⁸ See Hercowitz (1998) for a review of embodiment literature, and Greenwood et al (1997) and De Long and Summers (1991) for studies that analyze the contribution of investment-specific technology to growth.

⁹ Also see Cooley et al (1997), Boucekkine et al (1998), Hendricks (2000), Whelan (2002) and Musso (2004).

In the seminal vintage model presented by Salter (1960), co-existence of different vintage machines is allowed¹⁰ where newer vintages embody higher level of technologies.¹¹ Hence the newest assets have the lowest unit input costs. The range of vintages in existence is defined by the condition that machines are scrapped when they cannot earn a positive quasi-rent anymore. Similar scrapping rules can be found in recent vintage capital models (see e.g. Hendricks, 2000; Greenwood and Jovanovich, 2001; Whelan, 2002; Musso, 2004). The basic Salter model is based on perfect competition in output markets. Therefore, output and input prices are exogenous and equal for all firms. They cannot be a cause for differences in scrapping behaviour. Instead, the main driver of scrapping decision is technical change in capital producing industries. The appearance of superior assets has a positive effect on scrapping rates. First, industry output is expanded until price falls to equality with the total costs of the new technology, including the initial investment costs. Second, some of the older existing assets are scrapped until the operating costs of the oldest asset equal the new level of best practice total costs. So, the higher the exogenous rate of innovation the lower the service life of assets.¹² Similarly, scrapping will be higher in firms with older vintage assets. This line of argument can be seen in many recent studies within the vintage capital framework that consider asset age as a determinant of productivity growth. For instance Wolff (1991) has implicitly argued that productivity growth is negatively associated with the average age, as newer vintage embody the latest technology (Also see Wolff, 1996; Boucekkine et al., 1998).

Salter also sketches the contours of vintage models in imperfect competition environments in which innovation at the firm-level (implicitly) also plays a role. Particularly interesting is the case of monopolistic competition with emphasis on product differentiation and quality, rather than price.¹³ In a monopolistic environment, Salter

¹⁰ Note that we abstract from the complications which arise out of semi-independent machines within a plant. We assume that machines within a firm are independent. Salter (1960, chapter 7) provides a discussion, maintaining that the basic model is also valid in this more complex situation.

¹¹ This is due to innovation in capital producing industries. For instance a recent study by Sakellaris and Wilson (2004) shows that each newer vintage is about 12 percent more productive than its predecessor.

¹² Similar arguments have been made by Oliner (1996), where the adoption of a new technology capital (such as numerically controlled machines) reduces the lifetime of older capital.

¹³ Bardhan and Priale (1996) provide a theoretical model that considers the endogeneity of scrapping decisions, by allowing the coexistence of different vintages along with the endogeneity of technical progress, monopolistic competition and dynamic economies of scale. But it is a very abstract model with limited empirical applicability.

ventures the possibility that a firm with obsolete equipment moves away from competition of low-cost firms by producing ‘quality’ products buttressed with appeals to prestige and the age of the firm (Salter 1960, p. 93). Thus, innovation at the firm-level, in the form of new product development, might paradoxically lead to longer lifetimes of capital and to lower scrapping rates. Alternatively, when production of new products would require newer vintages of machines, scrapping might also accelerate (e.g. new software which is necessary to enable new internet services). Thus the impact of own innovation is unknown. Also under imperfect competition, output growth might be different across firms, and insofar demand is elastic, faster output growth is coupled with lower prices and hence higher scrapping according to Salter’s scrapping rule. Further the relative factor prices that may vary across firms will be crucial in deciding the degree of outmoded capital which is obsolete. As the relative wage goes up, the obsolescence standards are high and hence scrapping and replacement will also be high. Later models of the vintage tradition also came to similar views regarding wage rates (e.g. Cooley et al., 1997).¹⁴

In evolutionary models of growth (Silverberg, 1991; Schuette, 1994) retirement of capital goods is modelled as an endogenous decision which determines slowdowns and accelerations in GDP and productivity growth. Common to most vintage models (except, for instance, Salter’s monopolistic competition case) is the homogenous treatment of all firms in terms of their scrapping behaviour. In various evolutionary models, differences in scrapping behaviour are a central driver of industry and productivity developments such as in the arch-type models by Silverberg (1991) and Schuette (1994). Typically, production operations such as scrapping are assumed to be governed by a few simple rules of thumb such as a fixed asset life time or simple pay-back calculations. Importantly, these rules differ across firms, as in the model by Schuette (1994). As in the Salter model, firms with more recent asset vintages obtain a productivity advantage over other firms. If embodied technological change is high, these so-called aggressive firms will have a significant cost advantage and increase their market shares. But if it is low, these firms will loose demand. He shows that firm heterogeneity in replacement policies can have significant effects on both market structures and

¹⁴ Wage rate has been considered as determining factor in replacement decisions in the past literature also. For instance, Habakkuk (1962) has explained the differences in replacement policy in US and UK during the 1820s in terms of wage differences, which has been supported by Swan (1976). Also see Norris (1957) who shows that current or expected shortage of skilled labour (which will have an increasing effect on wages) may also favour replacement of old technology by new.

industry productivity growth. One reason for firms to hold on longer to older vintages than their competitors is in the anticipation of significant technological change in the near future. Or because the basic technologies currently in use are not compatible with the new best-practice machines. In the Schuette (1994) model, scrapping decisions are independent from economic variables. In the Silverberg (1991) model inputs costs do have an influence through the pay-back calculation. In both models, within –firm innovation processes are not taken into account so we presume that they do not have an impact on firm-level scrapping rates.

Determinants of Scrapping Decisions: Empirical Evidences

In the preceding discussion, we have shown that the literature have identified a set of variables that can play a crucial role in the discard decisions of firms. Hence, it is interesting to have an overview of the past empirical evidence that explicitly examines the determinants of scrapping. A summary of selected macro and micro studies in this regard is provided in Table 5.2. At the macro level previous studies within the vintage capital framework have observed that discards and/or replacements are negatively related to price of new capital (Whelan, 2002; Musso, 2004).¹⁵ The observed negative impact of price of new capital goods can be viewed as supportive of the positive effect of embodied technical change, as the decline in the relative price of capital goods is often viewed as an indicator of embodied technical change (Hulten, 1992; Hornstein and Krusell, 1996; Greenwood et al., 1997; Cummins and Violante, 2002). In addition, Oliner (1996) have observed that the alight of numerically controlled machines have caused substantial decline in economic life of conventional machines, thus implicitly indicating the effect of innovation on discard decisions. Evidences from investment literature shows that innovations necessitate new investment for their implementation (Lach and Schankerman, 1989; Lach and Rob, 1992), which may also indicate that if the investment takes place in the form of replacement, innovation affects discard decisions (also see Toivanen and Stoneman 1998). Swan (1976) shows that higher wages induce rapid replacement, as increasing wage rates will cause shrinking profits from older capital assets. Other macroeconomic studies that identify the endogeneity of discard decisions

¹⁵ Whelan (2002) allows capital retirement to be endogenous, by adding an additional support cost concept to the basic Solow type vintage model. In his formulation, retirement is endogenous in that once the marginal productivity of machine falls below the support cost, the machine will be discarded. Musso (2004) is an extension of Hendricks (2000) and Whelan (2002) in that it extends to a two sector model and provides some numerical investigation of the dynamic properties of the model, allowing retirement to vary over time.

have observed that retirement should be negatively related to business cycle and positively to average age of the asset (Cooper et al., 1999).¹⁶ The former is rationalized by the fact that retirements will be higher during recession, as the cost of reallocation is low during recession. It may also be noted that many previous macro studies that have examined the relationship between vintage effects on productivity implicitly came to the conclusion that older vintage capital should face faster scrapping and replacement as they embody older or outmoded technology (Driver, 1990; Wolff, 1991; Boucekkine, et al., 1998).

Table 5.2: Determinants of scrapping decisions: A summary of selected studies

<i>Study</i>	<i>Variables</i>	Wage rate	Embod. tech. change*	Averag. age of capital	Fuel prices	Business cycles
<i>Macro Studies</i>						
Musso (2004)			+			
Whelan (2002)			+			
Oliner (1996)			+			
Cooper et al (1999)				+		-
Mauer and Ott (1995)			+			
Swan (1976)		+				
<i>Micro Studies</i>						
Goolsbee (1998)					+	-
Das (1992)				+	+	
Cockburn and Frank (1992)				+	+	
Parks (1977)			+	+		

Note: *Most studies found a negative relationship between the price of new capital goods and retirement or replacement. This could be interpreted as an effect of embodied technical change (see text).

At the micro level, there have been a few asset-specific empirical case studies that tried to model the decision to discard explicitly. Das (1992)’s simulation results shows that the decision to hold, operate or retire the cement kiln is predominantly sensitive to fuel prices and the age of the asset; these are positively related to retirement. Cockburn and Frank (1992) have also identified the role of fuel price along with the age of the asset, as they approached the problem with a special interest to understand the role of oil price hike in the 1970s (an exogenous shock) on discard of oil tankers, while Goolsbee

¹⁶ Also see Caballero and Hammour (1994, 1996)

(1998) has found evidence of the strong influence of, fuel price, capital cost and deregulation policies on airline retirement. While fuel prices have a positive impact, capital cost and business cycle have a negative impact on discard. Energy prices have a positive effect, as they will make the existing asset less valuable, and hence accelerate scrapping. Older planes are more fuel intensive and hence an increasing fuel price makes it relatively less productive inspiring firms to scrap and replace them.¹⁷ The cost of capital and business cycle are negatively related to retirement as the opportunity cost of reallocation delays is high in booms. Also an earlier study by Parks (1977), who has modelled the scrapping pattern of automobiles in post-war US observed that age is the main determinant of automobiles scrapping, while the price of new capital goods relative to the cost of repairs also has a negative impact. Following the endogenous vintage growth models, the observed impact of age in these micro studies, could be interpreted as an element of embodied technology. This issue will be further discussed subsequently. Repair costs have been highlighted as a factor in discard decision by Lambe (1974) and Quayle (1972) also under the assumption that increasing repair costs will make the older vintage relatively expensive, persuading the firm to replace (also see Clapham, 1957; Eilon et al., 1966). This literature considers repairs as an alternative to scrapping.

Thus the limited empirical evidence seems to support some of the theoretical hypotheses listed in Table 5.1. What is missing in studies of scrapping to date is the explicit role of innovation in determining cross-firm discard behaviour, and the consideration of a larger set of asset types, which is the primary focus of the present study.

5.3 Methodology

In the previous section we discussed some theoretical models and empirical studies of scrapping behaviour. Various models highlight alternative determinants of discard and there is no encompassing framework to study discard behaviour of firms. Therefore, deriving from the alternate viewpoints put forward in the literature (as seen in Table 5.1), we postulate the following eclectic relationship;

$$D = f(Y, P, AGE, INN) \tag{5.1}$$

¹⁷ Baily (1981) has also noted that the rising fuel prices can cause massive capital obsolescence; fuel inefficient vintages will be utilized less intense and scrapped earlier at times of fuel price increase. Also see Boucekkine and Pommeret (2004).

where D is the discard, Y is an output quantity variable, such as gross output or sales, P represents the input prices, AGE is the age of the asset and INN is the innovation variable. We estimate this model to find out the relative importance of each determinant. To estimate the parameters of relevant determining variables, we require an empirical model that specifies the functional form of the relationship between discard rates, innovation and other variables. Unfortunately there is no theoretical model that establishes a functional relationship. Previous micro studies have used a dynamic discrete-choice model (Das, 1992) or logit model (Cockburn and Frank, 1992) to specify the relationship between discard decision and selected variables. In the present study, we cannot do any kind of dynamic analysis such as time-series or panel models, for reasons of data availability. Therefore, we have opted to perform two estimation techniques. The first is a probit analysis,¹⁸ where we model the decision of the firm to discard or not. The second is to do a cross-section ordinary least squares (OLS) regression analysis across firms, where we relate the magnitude of observed discard rates to selected variables. In the first step, we estimate a probit model, where the dependent variable takes the value zero if the firm has reported no positive discards and one otherwise, irrespective of the magnitude of discard. Deriving from (1), we specify the following probit model,

$$\Pr(D_i) = \rho_0 + \rho_y YG_i + \rho_w WG_i + \rho_a AGE_i + \sum_{k=1}^K \rho_k INN_{ki} + \sum_{n=1}^N \rho_n IND_{ni} + v_i \quad (5.2)$$

where $\Pr(D_i)$ is defined as $\Pr(D_i) = 1$ if $D_i > 0$ and $\Pr(D_i) = 0$ if $D_i = 0$, where D_i is the discard rate in firm i . YG is the output growth rate, WG is the wage rate growth rate, AGE is the average age of the assets INN are K number of innovation variables and v is the random error term with standard assumptions. In our estimation, given the data availability, we approximate the input price variable by wage rate. Ideally, we would like to have wage-rental ratios instead of wage rates, as it would measure the relative price of labour better. But, as capital user cost calculations at the firm-level are hard to make, we follow the general literature by using wage rates as a proxy. The idea is that higher wage growth may induce firms to move towards labour-saving technology, hence accelerating scrapping and replacement. Notice that we have also included an industry dummy, IND ,

¹⁸ Both probit and logit models are extensions of generalized linear regression models, used to deal with dichotomous and categorical variables. The main difference between the two is that the linearization of dependent variable in the logit is achieved by natural log of the odds, while it is done by the inverse of the standard normal cumulative distribution in probit. In practice, this, however, provide not much difference in the final results.

in order to take account of industry heterogeneity. This is important as there is significant inter-industry variation in discard rates (see Appendix Table 5.1).¹⁹ Apart from the two digit industry dummies captured by IND, we have also estimated the model by dividing industries as high-tech and low-tech, following an OECD classification, in order to see whether the discard patterns differ between high-tech and low-tech industries.

It is important to note that the coefficients of the above specified probit model hardly have any direct interpretations, as they are not necessarily the marginal effects one usually obtains in ordinary least squares regression models (see Greene, 2002 for a discussion). Therefore, in order to interpret the quantitative implication of the results, we need to compute the marginal effects of the explanatory variables, for which the estimated coefficients can be utilized. The marginal effects, that is the change in the probability for an infinitesimal change in each explanatory continuous variable and the discrete change in the probability for dummy variables, for a probit model can be estimated as,

$$\frac{\partial E[y/x]}{\partial x} = \left\{ \frac{dF(\rho'x)}{d(\rho'x)} \right\} \rho \tag{5.3}$$

$$= f(\rho'x)\rho$$

where y is the dependent variable, x is the vector of explanatory variables and $f(\cdot)$ is the density function that corresponds to the cumulative distribution, $F(\cdot)$. Following this, in our probit specification the marginal effect for an independent variable, say YG, can be derived as $\phi(\rho'x)\rho_y$, where ϕ is the standard normal density. Note that though the derivatives of this conditional mean function are useful when the variable is continuous, they are less useful when the explanatory variables are dummy variables. In such cases, it would be useful to analyze the effect of range of $\rho'x$ (using the sample estimates) and with the two values of the binary variable (Greene, 2002, p 817).

Notice that in (5.2) we model the decision to discard. Nevertheless, our database also provides us with the actual magnitude of discard, i.e. how much of capital is being

¹⁹ Note that there is evidence that capital is very much sector-specific and hence it is important to account for this sectoral heterogeneity of capital (Boddy and Gort, 1971; Goolsbee and Gross, 1997).

discarded by the firm. Therefore, it would also be interesting to look at the effect of these explanatory factors on the *rate* at which the firms discard their assets. Therefore, we have also estimated a model where we relate the observed discard rates to the set of explanatory variables. Assuming a linear relationship, we specify (5.1) as:

$$\ln D_i = \alpha_0 + \alpha_y YG_i + \alpha_w WG_i + \alpha_a AGE_i + \sum_{k=1}^K \alpha_k INN_{ki} + \sum_{n=1}^N \alpha_n IND_{ni} + e_i \quad (5.4)$$

where $\ln D$ is the natural logarithm of discard rate D , e is the error term which is assumed to be independent and identically distributed and all other variables are as explained before.

Equation (5.4) has a practical problem that it can not incorporate those cases with zero discards, as the log transformation is not possible in such cases. One option is to exclude such cases from the sample and estimate the above model. However, that may create sample-selection bias, and therefore, we have opted to transform the dependent variable to $1+D$ and hence the final model will be

$$\ln(1+D_i) = \beta_0 + \beta_y YG_i + \beta_w WG_i + \beta_a AGE_i + \sum_{k=1}^K \beta_k INN_{ki} + \sum_{n=1}^N \beta_n IND_{ni} + u_i \quad (5.5)$$

Note that the above models abstract from any time-series effects. It may be mentioned that earlier studies both on investment as well as discard behaviour have been based on either time-series or panel-data analysis, as these decisions are also functions of time. Due to data limitations, however, we were not able to do any dynamic modelling, and therefore, have specified the above set of models for cross-section analysis.²⁰ We do not have time series data on this issue to test any discrete time varying models.

²⁰ It may be noted that the variables identified by the macro economics literature such as user cost may be less relevant for cross firm variation in investment and discard, as it is rational to assume that user costs do not vary much across firms, particularly in countries with flexible capital market. See Hall et al (1998) for a review of firm level investment studies that subdue user cost term due to this reason. Also see Hubbard (1998) for a review of studies that incorporates user cost in explaining cross firm investment behavior, due the relevance of other variables in user cost such as taxes

Another important feature of our model is of a more parsimonious nature in that we had to exclude some important variables that are identified in the literature. For instance maintenance costs (Quayle, 1972) and repair costs (Lambe, 1974; Parks, 1977) are often considered as major determinants of firm's decision to discard its assets. This literature also frequently acknowledges the role of obsolescence, quality deterioration, rate of return and taxation in influencing firm's discard decision. It is practically difficult to compile data on repair costs when dealing with a composite asset group, as is the case with our analysis. Two old studies in these lines (Clapham, 1957; Eilon et al., 1966), that tried to determine the optimal age for replacing an asset, assume that repair costs increase linearly over time. This implies that, to some extent, higher age of the asset also reflects the higher repair costs associated with the asset. Similarly, the technology changes in asset-producing industries as mentioned by Salter (e.g. computer industry), fuel price shocks (Cockburn and Frank, 1992), and industry heterogeneity in terms of technological differences can also be important. And institutional factors such as industry regulations (Goolsbee, 1998) like safety and environmental standards, tax regulation, including financial accounting rules and tax incentives such as depreciation allowances, might also be important in influencing firms' discard decisions.

Nevertheless, typically, the variables such as repair costs, regulations, and external price and technology shocks are not firm-specific, and hence may have the same effect on all firms in an industry. As such they are not expected to be important for cross-firm based estimation. However, if they are dominant, one would not expect to find a clear relationship between discard rates and economic or technology variables. The issue of industry heterogeneity has been accommodated to a large extent by including industry dummies. Since the innovation measures used in this study (to be discussed in the next section) are indicators of innovation implemented by the firm (*ex post*), to some extent, they may capture the changes in asset-producing sector, if the innovation is not taken place within the firm.²¹ For instance, the firm might have introduced a new production process, not developed by the firm, but outside.

5.4 Data and Variables

Our objective in this chapter is to examine the relationship between a firm's capital discard rates and decisions and their innovative behaviour. In doing this we consider

²¹ Since the innovation dummies are indicators of *ex post* realized innovation, the only information we have is that the firm has implemented the innovation.

three different types of assets, for which we had sufficient data on capital discards: computers, machinery and transport equipment. We exploit firm-level data on relevant variables, available through various micro-economic surveys conducted by the Statistics Netherlands (CBS). We utilize data from five surveys: production statistics (PS), capital stock surveys, capital discard surveys, investment surveys and community innovation surveys (CiS). Therefore, it was essential to link these different surveys, to construct a comparable database. A detailed description of the linking procedure is provided in Appendix 1. Basically, the investment, capital stock and discard surveys were used to calculate the discard rates (note that the last two surveys were explained in detail in the previous chapter). PS and CIS were used for the explanatory variables. An important choice to be made is the time-period of analysis. Variables in the CIS are not available annually, but cover a period, e.g. CIS 3, which is used in this study, covers the period 1998-2000. That is, for instance, it asks the question whether the firm has introduced a new production process during 1998-2000. Also, as noted in the previous chapter, discards in the discard surveys are found to be missing or zero and lumpy, in many years. Therefore we decided to do a cross-section analysis for the period 1998-2001, assuming that innovation in the period 1998-2000 has an impact on discards during the period 1999-2001 allowing for a one-year lag.

We have first linked the discard survey to the capital stock surveys and then to the investment survey and further to the PS and CIS.²² We obtained a final dataset of 357 firms which discarded computers, 366 firms for machinery and 226 firms for transport equipment for which all necessary variables were available.²³ This constituted 30.6 per cent (computers), 31.4 per cent (machinery) and 19.4 per cent (transport equipment) of all firms responding to discard surveys during 1999-2001. Also it covers 32.2 percent (computers), 33 per cent (machinery) and 20.4 per cent (transport equipment) of total firms reported to various capital stock benchmarks. The number of firms reported to capital stock and various discard surveys are listed in Appendix Tables 4.1 and 4.2 and to production, investment and innovation surveys are provided in Appendix Table 5.2. In what follows we explain each of the variables used in the study and their construction.

²² See Klomp and van Leeuwen (2001) for a study that links surveys on innovation (CiS2) and output while analyzing the impact of innovation on economic performance.

²³ While linking capital stock to discard and investment, we have excluded all those firms which have not reported at least one benchmark capital stock, and at least one discard year during 1998-2001. See Appendix 1 for more a detailed explanation of cleansing rules used.

Discard rate (D): The dependent variable in (4) is the discard rate, which is calculated as the discard value in year t divided by capital stock in year t-1 for each firm, averaged across 1999-2001, i.e.

$$D_{i,j,1999-2001} = \frac{\sum_{t=1999}^{2001} (D_{i,j,t} / K_{i,j,t-1})}{3} \quad (5.6)$$

where t, i and j respectively represent year, firm and asset, D is the constant-price discard value and K is the constant-price capital stock. Note that this is different from the way we derived survival rates in the previous chapter, where the unit of analysis was vintages rather than firms. Therefore, the survival rate of each vintage was calculated as against the discard rates of assets (aggregated across vintages) in each firm in this chapter. The series of gross capital stock in constant prices at firm-level are derived as:

$$K_{i,j,t} = K_{i,j,t-1} - D_{i,j,t} + I_{i,j,t} \quad (5.7)$$

where I is investment in asset j in firm i during the year t measured in constant prices.²⁴ Then the dependent variable in (5) is calculated as $\ln(1 + D_{i,j,1999-2001})$.

Output growth (YG): The growth rate of output, measured as $\ln(Y_t / Y_{t-1})$, where Y is the real output calculated by deflating nominal output by industry-specific output deflators, for each firm averaged for the period 1998-2000 is used. The value of output for this purpose is taken from the production survey which is conducted every year for all the firms in the Netherlands. Output growth is likely to have a positive effect under Salter's vintage model with monopolistic competition, while all other models listed in Table 5.1 attribute no relationship between discard and output growth.

Wage rate (WG): The growth rate of total wages divided by total persons employed, i.e. $\ln[(W_t / L_t) / (W_{t-1} / L_{t-1})]$, where W is the total compensation and L is the number of employees, averaged for the period 1998-2000. The data is taken from production statistics. Wage growth proxies changes in the relative price of capital to labour and is expected to have a positive effect on discard both in monopolistic competition model

²⁴ See Appendix 1 for a detailed description of this approach.

and in evolutionary models. This is because an increase in the wage rate will reduce the relative marginal productivity of older vintage capital and hence induce firms to replace.

Average Age (AGE): As in the previous chapter the age of any given asset type of a particular vintage is calculated as the discard year (t) minus its vintage year (v). However this is possible only at vintage level, not at firm-level for aggregate capital stock (of any asset). But our analysis is at the firm-level and we need the average age of all assets of a particular type of different age at any point in time. We take a weighted average of the ages of various vintages of an asset active in the capital stock, where the weights being the share of each vintage of same asset in the total asset stock for a given year in the given firm, i.e.²⁵

$$AGE_{i,j,t} = (t - v)_{i,j,t} \frac{K_{i,j,t,v}}{\sum_{v=0}^t K_{i,j,t,v}} \quad (5.8)$$

The idea here is that the larger the share of a vintage asset in total capital stock of that asset (across all vintages), the larger its weight in average age. This corresponds to Nelson (1964), where average age of capital is assumed to be lower, when the new vintage investment relative to total capital stock is higher (p.585). McHuge and Lane (1987) also use a similar approach, but they have adjusted the capital stock for capacity utilization,²⁶ hence their measure is utilized age of capital. Age is an indicator of efficiency loss; older capital goods become less and less efficient over time, and therefore age is expected to have a positive effect on discard.

Innovation (INN): An important issue in the context of the present analysis is the measurement of technological change at the firm-level. For example in their study of the impact of innovation on investment, Toivanen and Stoneman (1998) use the firm's own R&D as an indicator but admit that this is not a very good indicator as much of the technological opportunities may arise from R&D of other firms, public research

²⁵This is important because an un-weighted average will produce a very high average age if there is large number of older vintages existing in a firm, even if the share of such older vintages in total capital stock is very small. For example, if the firm has one unit of capital stock of vintage 1940, and 100 units of the same asset of vintage 1990, the average age in 1991 will be 26, though the share of capital to be scrapped due to this age is quite marginal, say only one per cent of total capital stock. Therefore it is important to consider a weighted average of age, where the weights could be the share of each vintage asset in total capital stock.

²⁶ See Erumban (2001 and 2005) for discussions on capital stock and capacity utilisation.

institutes etc. Moreover, there is not a clear link between R&D expenditures and innovation at the firm-level. First, the lag between R&D expenditure and innovative output is unsure. More importantly, it is increasingly acknowledged that measures which only refer to (cumulated) innovation investment might give an incomplete picture of the innovation processes within the firm. Firm-level innovation is the result of interaction between both internal and external knowledge databases (Cohen and Levinthal, 1989). Utilising the technological environment, e.g. through R&D cooperation, patent licensing or more informal mechanisms, will contribute to innovation output directly, alongside internal investment.

Other alternative measures of innovation would be to use patent data (Griliches, 1979). But data on patents will only capture the process of invention and miss out most of the more incremental innovation output. Therefore, innovation in this chapter is represented by a set of alternative variables. This is because of the multi-faceted character of the innovation process and its outcomes. CIS3 contains several quantitative and qualitative variables which measure the innovation outcomes directly. Cis3 is conducted for the period 1998-2000 covering all firms²⁷ in the Netherlands. All the quantitative variables in the surveys are for the year 2000, while the qualitative information is collected for a period of three years, 1998-2000.²⁸

We define a firm to be innovative, only if it has introduced either a new or substantially improved product or process during the survey period.²⁹ All the variables created are based on this definition, and are listed in Table 5.3.

²⁷ For firms with 10-50 employees a sampling procedure is adopted. However, since our capital stock and discard data are only for firms employing 100 and more employees, we consider only such firms in our analysis.

²⁸ The survey provides a myriad of information on innovation variables such as innovation investment, innovation output and qualitative variables associated with technological environment. Innovation is defined as new or substantially improved product, service, or process for the firm, which is assumed to be 'the result of developing and/or applying new or recent technologies'. Hence, it could either be a product-innovation or a process-innovation. While the former is defined as a good or service, which is either new or improved with respect to basic characteristics, technical specifications, intended use or user friendliness, the latter is defined as new and improved production technology, methods of supplying services and delivering products. In both cases the innovation is new to the relevant firm, not necessarily new to the market; it doesn't matter it was developed by the firm itself or by some other firm.

²⁹ Cefis and Marsili (2005) have also used a similar definition.

Table 5.3: Alternative innovation indicators used in the regression analysis

Variable	Description	Definition	Type
INNOV	Total Innovation	Indicates whether the firm has undertaken some kind of innovation (either product or process-innovation) during the period 1998-2000.	Dummy (takes 1 if innovative and 0 otherwise)
PDTIN	Product-innovation	Indicates whether the firm has introduced any new or significantly improved products	Dummy (takes 1 if introduced a new product and 0 otherwise)
PCSIN	Process-innovation	Indicates whether the firm has introduced any new or significantly improved production processes	Dummy (takes 1 if introduced a new process and 0 otherwise)
TURN	Turnover share	The share of turnover caused by new or significantly improved products (goods or services), i.e. due to product-innovation, introduced during the period 1998-2000. ³⁰	Continuous
RDN	Intramural R&D spending	All creative work undertaken within the firm aiming to increase the stock of knowledge, and the use of this stock of knowledge to devise new application, such as a new and improved product or process	Continuous (intensity measured as R&D spending/ total turnover)
RDX	Extramural R&D spending	The same kind of activities as in RDN, but performed by other companies, for this firm.	

Industry dummies (IND): In order to capture industry-specific effects, we have included a set of industry dummies to control for industry heterogeneity. A set of dummies is created based on the 2 digit Dutch industry classification (SBI). The dummy takes the value 1 if the firm belongs to a particular 2 digit industry and zero otherwise. Also, we have estimated the model by replacing these two digit dummies by an OECD

³⁰ CiS3 asks the firm to estimate the distribution of total turnover between newly introduced (or improved) products introduced during 1998-2000 and unchanged or old products.

classification of industries as high-tech and low-tech. The classification of industries is provided in Appendix Table 5.3. Dummy (HTEK) takes the value of one if the firm falls in high-tech category and zero otherwise. We expect a positive coefficient for technology-intensive industries, because these industries are more prone to faster changes in technology and hence to keep their competitive positions they may need to move to the best-practice technology faster leading to accelerated replacement of older assets.

Table 5.4: Descriptive statistics

Variable	<i>Computer</i>		<i>Machinery</i>		<i>Transport Eq.</i>	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
D	0.05	0.10	0.04	0.07	0.14	0.19
ln(1+D)	0.04	0.08	0.04	0.06	0.12	0.15
YG	0.02	0.21	0.02	0.21	0.04	0.13
WG	0.04	0.05	0.04	0.05	0.04	0.05
AGE	6.26	2.61	15.26	6.04	5.27	3.11
TURN	0.23	0.25	0.23	0.25	0.22	0.25
RDX	0.00	0.01	0.00	0.01	0.00	0.01
RDN	0.02	0.03	0.02	0.03	0.01	0.03
No. firms.	357		366		226	

Note: Mean and standard deviations (Std. Dev.) are computed for each asset type across firms.

A summary of the variables in our data set is provided in Table 5.4. It shows that on average, the discard rate (D) in computers was almost 5 per cent, in machinery 4 per cent and in transport equipment 14 per cent with a high variance across firms. This discard rate, which varied across assets, indicates the possible differences in the expected asset lifetime across different asset types (see also chapter 3). The average age of the computer capital stock for the whole sample is 6.3 years, for machinery 15.3 years and for transport equipment 5.3 years. Importantly, firms differ notably in their scrapping behaviour (see Figure 5.2). This large variance in discard rate testifies the importance of having a better understanding of the determinants of the discard behaviour. As shown in Figure 5.2, a large number of firms are found at the left tail of the distribution in all the three assets, having very low rates of discard, attaining a low average discard rate.

Figure 5.2: Frequency distribution of firm level discard rates (by asset)

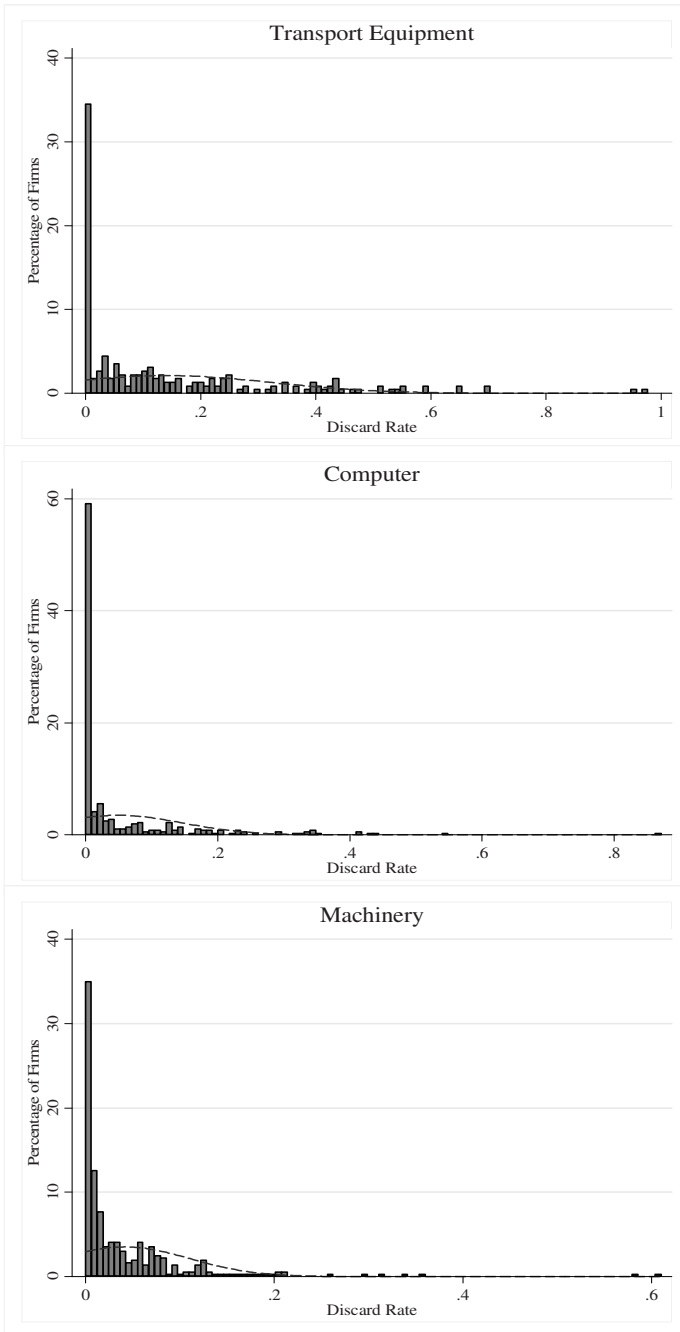


Table 5.5: Number of innovative and non-innovative firms in the sample (by asset)

	<i>No. of Firms in the sample that reported discard of</i>		
	Computer	Machinery	Transport Eq.
Innovative Firms*	292	299	182
Product-innovation	266	272	166
Process-innovation	232	236	148
Non-innovative firms	65	67	44
Total	357	366	226

Note:* Innovative firms are those which have introduced a new product/ process or both.

It can also be seen in Table 5.5 that almost 80 per cent of firms in the sample are innovative in the sense that they have either introduced a new product or process during 1998-2000. Moreover, more than 70 per cent of firms have reported to have product-innovation and almost 65 per cent have reported to have process-innovation. Also almost 35 per cent of firms belong to high- or medium-tech industries.

5.5 Empirical Results

The results of the Probit analysis and the OLS analysis are discussed respectively in sections 5.5.1 and 5.5.2. It may be noted that all the OLS estimates are adjusted for heteroscedasticity, and there is no severe serial correlation among our independent variables entered in different equations in all the three asset types (see Appendix Table 5.4). Total innovation (INNOV) is found to be correlated with product- and process-innovation indicators. Similarly, product-innovation indicator is correlated with turnover share. This is to be expected, as these measures possess somewhat the same information. This, however, does not affect the robustness of our regression results as these variables do not enter the equations simultaneously.

Determinants of Discard Decisions: The Probit Results

We estimate equation (5.2), where the probability of an asset to be discarded is modelled as a function of innovation, economic and age variables. Note that we have used alternative innovation measures, as described in the data section. Therefore, we have estimated equation (5.2) under six alternative specifications ranging from M1 to M6, replacing/dropping some (innovation) variables. The first model is the basic model with only economic variables: output growth and wage rate growth. In the second model, the average age of capital in a firm and the total innovation dummy are included. Subsequently, in Model 3 we replace the total innovation dummy by product- and

process-innovation dummies, in order to capture the product/process specificities of innovation. In Model 4 we have process-innovation dummy to represent the process-innovation and the share of turnover caused by product-innovation to represent the product-innovation rather than a dummy. In Model 5, innovation dummies are replaced by two measures of R&D expenditure, the internal R&D and external R&D. All the above models are estimated with industry dummies, and the final model, Model 6, is the same as Model 4 except that the 2 digit industry dummies are replaced by high-tech dummies. In what follows we list these six specifications used in the probit analysis, where the subscripts 1,..., 6 stands for six estimated probit models.

$$M1: \Pr(D_i) = \rho_{1,0} + \rho_{1,y} YG_i + \rho_{1,w} WG_i + v_{1,i}$$

$$M2: \Pr(D_i) = \rho_{2,0} + \rho_{2,y} YG_i + \rho_{2,w} WG_i + \rho_{2,a} AGE_i + \rho_{2,n} INNOV_i + v_{2,i}$$

$$M3: \Pr(D_i) = \rho_{3,0} + \rho_{3,y} YG_i + \rho_{3,w} WG_i + \rho_{3,a} AGE_i + \rho_{3,d} PDTIN_i + \rho_{3,s} PCSIN_i + v_{3,i}$$

$$M4: \Pr(D_i) = \rho_{4,0} + \rho_{4,y} YG_i + \rho_{4,w} WG_i + \rho_{4,a} AGE_i + \rho_{4,tr} TURN_i + \rho_{4,s} PCSIN_i + v_{4,i}$$

$$M5: \Pr(D_i) = \rho_{5,0} + \rho_{5,y} YG_i + \rho_{5,w} WG_i + \rho_{5,a} AGE_i + \rho_{5,rx} RDX_i + \rho_{5,rm} RDN_i + v_{5,i}$$

$$M6: \Pr(D_i) = \rho_{6,0} + \rho_{6,y} YG_i + \rho_{6,w} WG_i + \rho_{6,a} AGE_i + \rho_{6,tr} TURN_i + \rho_{6,s} PCSIN_i \\ + \rho_{6,h} HITEK_i + v_{6,i}$$

As we mentioned before, the coefficients of the probit model do not allow us to understand the marginal effects of these variables. Therefore, we have estimated the marginal effects of the estimated probit coefficients following (3), and the results along with their standard errors and model statistics are provided for each asset in Tables 5.6, 5.7 and 5.8. The likelihood ratio chi-square test tells us that all our models, except the basic model M1, are statistically significant for computers and transport equipment, as compared to a model with no predictors. For machinery discard those models are significant in which the process-innovation is included (M3, M4 and M6 in Table 5.6). The pseudo R² improves as we introduce innovation and age variables to the basic model

indicating an improvement in fit of the model that is due to the independent variables.³¹ The subsequent discussion of the results will be mostly based on Model 4, which is the most significant model for all asset types (with industry dummies). This choice, however, does not affect the interpretation of our results, as the estimated coefficients are almost stable across various models.

Table 5.6: Marginal coefficients: probit regression for machinery discards

Variable	M1	M2	M3	M4	M5	M6
YG	-0.262 (0.17)	-0.254 (0.167)	-0.316 * (0.165)	-0.309 * (0.169)	-0.246 (0.167)	-0.221 (0.136)
WG	-0.481 (0.377)	-0.526 (0.372)	-0.568 (0.367)	-0.561 (0.368)	-0.518 (0.372)	-0.52 (0.347)
AGE		0.006 ** (0.003)	0.006 ** (0.003)	0.006 ** (0.003)	0.007 ** (0.003)	0.007 *** (0.003)
INNOV		0.03 (0.048)				
PDTIN			-0.026 (0.041)			
PCSIN			0.101 ** (0.047)	0.089 ** (0.042)		0.079 ** (0.039)
TURN				-0.014 (0.081)		0.008 (0.071)
RDX					-0.843 (1.964)	
RDN					0.171 (0.719)	
HTEK						0.002 (0.036)
Pseudo R ²	0.05	0.07	0.09	0.08	0.07	0.06
Long likelihood	-127.3	-124.7	-122.1	-122.3	-124.8	-129.7
Chi ²	12.5	17.8	22.9 *	22.5 *	17.5	17.3 ***

Notes: *** indicates significance at 1 per cent, ** at 5 per cent and * at 10 per cent. Figures in parenthesis are standard errors. All the models, except M6, are estimated with industry dummies. In M6 industry dummies are replaced by High-Tech dummies, and therefore its degrees of freedom for Chi-square is lower.

³¹ Note that it is a pseudo R² because there is no direct equivalent of an R² (from OLS regression) in probit models.

Both in computers and transport equipment output growth and wage rate growth are found to be playing no significant role in a firm's decision to discard. However, the decision to discard machines seems to be negatively influenced by output growth rate in Models M3 and M4. This suggests that those firms which face high output growth tend to have a lower probability for discarding machinery. This result may be a consequence of a business cycle effect which is not captured in our model, as we do not have time elements in our data. As far as the wage rate is concerned, it is possible that firms respond to increase in wage rate by adjusting prices and output. Those firms which had relatively high wage rate increase might have opted to increase utilization of their labour force as well as machinery to obtain higher output growth. This however, contradicts with the possibility that increasing wage rate will induce firms to substitute labour by capital, moving towards more capital-intensive technology. Substitution, however, might be a long run process especially in the Netherlands as the less flexible hiring and firing rules in the Netherlands may make substitution less possible. A better interpretation of this result requires more dynamic time-series analysis.

Process-innovation is seen to play a significant positive role in a firm's decision to discard machinery but not in computer and transport equipment. This indicates that those firms which introduce a new production process may be replacing their old capital with new one as expected. The difference between process-innovative and non-innovative firms, as measured by the marginal coefficient is 0.09, indicating a 9 per cent higher discard probability in a process-innovative firm. For computers, product-innovation measured by turnover share has a positive and significant impact on discard decisions. The probability to discard is higher in those firms which enjoy a higher turnover due to the introduction of a new product, thus suggesting that it is not just the innovation introduced by the firm per se, but the realized turnover increase due to the implementation of the innovation that prompts the firm to discard and replace its computers. None of the innovation variable seems to play any role in the decision to discard by firms in transport equipment.

Table 5.7: Marginal coefficients: probit regression for computers discards

Variable	M1	M2	M3	M4	M5	M6
YG	-0.102 (0.209)	-0.096 (0.212)	-0.085 (0.211)	-0.132 (0.216)	-0.129 (0.217)	-0.024 (0.144)
WG	0.292 (0.54)	0.106 (0.55)	0.123 (0.555)	0.048 (0.556)	0.069 (0.554)	-0.008 (0.533)
AGE		0.045 *** (0.012)	0.045 *** (0.012)	0.044 *** (0.012)	0.043 *** (0.013)	0.049 *** (0.011)
INNOV		0.012 (0.075)				
PDTIN			0.059 (0.075)			
PCSIN			-0.066 (0.066)	-0.067 (0.061)		-0.067 (0.059)
TURN				0.198 * (0.121)		0.142 (0.122)
RDX					0.298 (3.604)	
RDN					2.193 (1.381)	
HTEK						0.116 * (0.059)
Pseudo R ²	0.07	0.09	0.10	0.10	0.10	0.06
Long likelihood	-228.9	-222.2	-221.6	-220.8	-220.1	-232.2
Chi ²	32.7 ***	46.2 ***	47.3 ***	49.0 ***	50.3 ***	30.0 ***

Notes: As in Table 5. 6.

Average age of the asset is found to play a positive and significant role in the discard decision, for all the three asset types. The magnitude of the estimated marginal effects on computer discard is on average 0.04, implying that a firm with 1 year higher average age will have a 4 per cent higher discard probability. In the machinery the marginal effect of age is around 0.006, while in transport equipment it is 0.07, suggesting respectively an approximate effect of 0.6 per cent and 7 per cent. This positive effect confirms the findings in earlier studies. It may be noted that average age of an asset is often considered as an indicator of embodied technical change (Nelson, 1964; Wolff, 1991; Bahk and Gort, 1993), which is in accordance with the embodiment hypotheses in the vintage capital models that older capital embodies older technology (Salter, 1960; Solow, 1960 and Solow et al., 1966 among others). Kendrick (1980) has used average age as an indicator of diffusion of new technology in his growth accounting exercise and Gittleman et al (2006) have translated age of the asset into a measure of obsolescence. Also some previous studies have assumed that repair costs increase linearly over time,

and hence age could also be a proxy for this (Clapham, 1957; Eilon et al., 1966). Thus, predominantly age is both a measure of efficiency decline as well as obsolescence, induced by the fact that newer vintage assets embody newer technology, particularly for machinery and computers. For the discard of transport equipment, age may also be a measure of the lease effect, as the share of leased equipment is quite large in this asset type (see Appendix Table 4.7 and the discussion in section 4.2 in the previous chapter). If the asset discards are defined as return to the lease company, the decision to discard will have hardly any influence by any variable other than the lease contract, which is perhaps defined in terms of a fixed number of years that may be captured by the age variable. Thus the observed positive impact of average age on machinery and computer discard may reflect the impact of technology embodied in the latest vintage capital or simply the wear-and-tear caused by loss of physical efficiency.

Table 5.8: Marginal coefficients: probit regression for transport discards

Variable	M1	M2	M3	M4	M5	M6
YG	-0.253 (0.266)	-0.136 (0.276)	-0.109 (0.279)	-0.118 (0.279)	-0.066 (0.28)	-0.094 (0.252)
WG	0.347 (0.632)	0.001 (0.658)	-0.059 (0.657)	-0.066 (0.661)	-0.016 (0.657)	-0.056 (0.637)
AGE		0.073 *** (0.014)	0.075 *** (0.014)	0.074 *** (0.014)	0.074 *** (0.014)	0.064 *** (0.012)
INNOV		0.014 (0.089)				
PDTIN			0.093 (0.093)			
PCSIN			-0.065 (0.077)	-0.036 (0.073)		-0.043 (0.071)
TURN				0.052 (0.155)		0.072 (0.144)
RDX					5.983 (7.089)	
RDN					-1.661 (1.353)	
HTEK						0.056 (0.069)
Pseudo R ²	0.06	0.17	0.17	0.17	0.18	0.11
Long likelihood	-135.6	-120.2	-119.7	-120.1	-119.4	-129.1
Chi ²	18.8	49.5 ***	50.7 ***	49.8 ***	51.1 ***	31.8 ***

Notes: As in Table 5. 6

In the last model, Model 6, we have replaced the industry dummies by high-tech dummies to see the difference between technology-intensive industries and others. The high-tech dummy has obtained a positive and significant coefficient for computers, suggesting that the probability that a computer will be scrapped is more if the firm belongs to a technology-intensive industry group. The fact that the firm belongs to a high-tech industry has a very large effect on computer discard, suggesting that on average the probability to discard computer is higher by 12 per cent in high-tech industries compared to low-tech industries. We found no such effect for machinery and transport equipment.

In our specification we have represented the innovation variables by dummies. As we noted before, the marginal effects are less useful when the explanatory variables are dummy variables. Therefore, in order to evaluate the effect of a firm being innovative or high-tech (two dummy variables we have used), on discard decisions, we have evaluated the discard probabilities using the sample estimates at various ages (ranging from minimum to maximum age for these two groups of firms). The effect of each dummy variable is evaluated at the mean of output and wage rate growth rates, using the coefficients of the probit model. Following Greene (2002), we calculate these probabilities as a function of age as;

$$\begin{aligned}
 INNOV = 0 : \Pr(D_i = 1) & \\
 &= \Phi \left[\rho_0 + \rho_y \overline{YG} + \rho_w \overline{WG} + \rho_a AGE + \rho_h \right] \\
 INNOV = 1 : \Pr(D_i = 1) & \\
 &= \Phi \left[\rho_0 + \rho_y \overline{YG} + \rho_w \overline{WG} + \rho_a AGE + \rho_n + \rho_h \right] \tag{5.9}
 \end{aligned}$$

where the bar over the variables YG and WG respectively represent the average output growth and average wage rate growth. Also the coefficients ρ_n and ρ_h are respectively the estimated probit coefficients for innovation and high-tech dummies. The function $\Phi(\cdot)$ represents the standard normal distribution. The same approach is used to differentiate between process-innovative and non-innovative firms and between high-tech and low-tech firms for all the three asset types. Figures 5.3a, 5.3b and 5.3c show these functions plotted over the range of age observed in each sample for the three asset types, machinery, computers and transport equipment. The marginal effects of each dummy

variable, as presented in Tables 5.6 to 5.8, are the difference between the two functions at mean age.

Figure 5.3: Effect of innovation on predicted discard probabilities

Figure 5.3a: Machinery

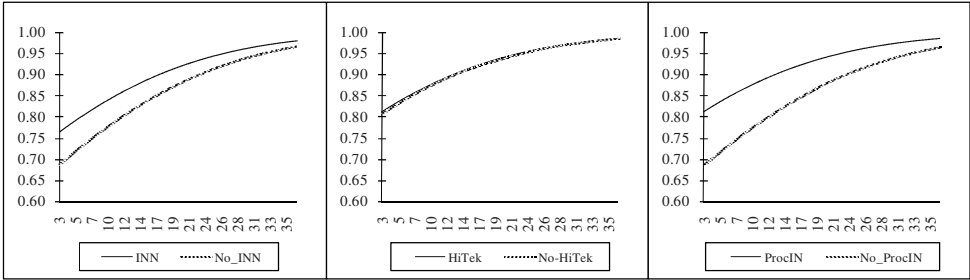


Figure 5.3b: Computers

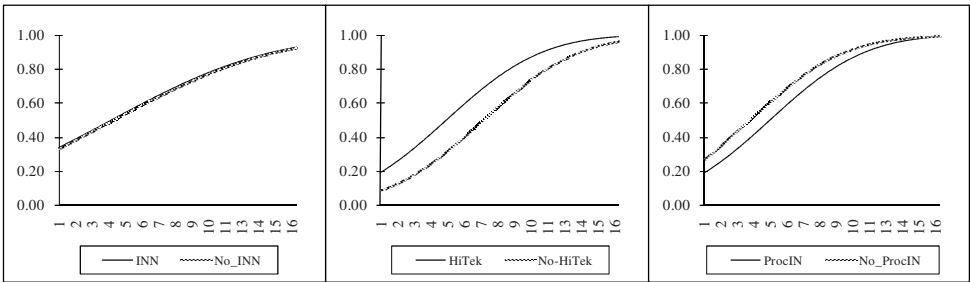
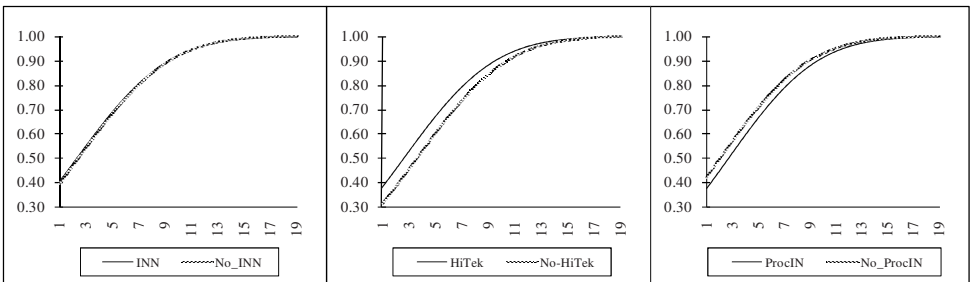


Figure 5.3c: Transport equipments



Note: The figure represents the effect of each dummy variable on discard probabilities at various ages, evaluated at the mean of output and wage rate growth rates, using the probit coefficients. The solid lines are cases where dummy= 1 and the dotted lines are cases where dummy=zero. (No_)INN=(non-)innovative firms; (No_)ProclN=(non-)Process innovative firms; (No_)Hitek=(non-)High-tech firms.

Though the estimated coefficient of innovation is not significant (see M2 in Table 5.6), it can be seen from the Figure 5.3a that, there is apparent difference between innovative and non-innovative firms in machinery discard. This difference reduces as the age of the machinery increases. In other words the probability that a machine will be discarded at a lower age is higher after the implementation of a process-innovation. This probability converges, however, as we move to firms with high asset age. From the figure and also from the estimated marginal coefficient for process-innovation, it appears that this effect observed in total innovation is driven by the process-innovation (note that the product-innovation is not significant). Those firms which introduce a process-innovation seem to have higher probability to discard their machinery.

It can be seen from Figure 5.3b that the effect of a firm being innovative or non-innovative is not significant for computers at any point in age. Nevertheless, there exists a difference between the high-tech and low-tech firms in terms of their discard probabilities. The probability that a high-tech firm with relatively low asset age will discard is larger than the probability for a low-tech firm, and this difference, as observed from M6 in Table 5.7, is statistically significant at mean. Though the difference between high-tech and non high-tech firms seems to decline as the asset reaches the sample maximum age, the difference exists through out its lifespan. For transport equipment (Figure 5.3c), there is hardly any difference between innovative and non-innovative, or high-tech and non-high-tech firms.

Thus overall from the probit results we can conclude that process-innovation is more important for machinery discards than product-innovation, along with the age of the asset. For computers, we find some evidence for a significant impact of product-innovation, along with the age of the asset. For transport equipment, however, innovation plays no role; rather it is only the age that matters. From the magnitude of the marginal effect coefficients, it is evident that the age effect is bigger in asset type computers and transport equipment, compared to that of machinery, where the effect of process-innovation dominates.

Also we observed that the role of product and process innovation differs between computers and machinery discard decisions. We presume that the process-innovation does not show any impact on computer discard due to the very definition of the computer asset. Much of the advances in computing technology must have been incorporated in the firm's production process through numerically controlled machines, which belongs to the machinery category. Therefore, the observed effect of process-

innovation on machinery may also reflect its effect on computing technology embodied in machinery. In the manufacturing sector, the use of computer or associated equipment may largely be for the administrative purposes rather than in the production process. The effect of increasing turnover caused by product-innovation may suggest that –assuming that the growing turnover is also an indicator of increasing market operation of the firm in terms of the new product- firms may need to allocate more administrative resources to this product, for instance to control its marketing. This may lead to replacement of old (and often slower) computer and associated equipments by faster ones, thus having a positive effect on computer discard. This requires further scrutiny though. In the case of machinery, the introduction of a new product by the firm may not have a significant effect on discard. The introduction of a new product by the firm may not require replacing existing machinery; rather it may require expanding capacity, which might require new machinery.

Determinants of Discard Rates: The OLS Results

In order to understand how the economic and innovation variable influence the magnitude of discard, rather than the decision to discard, we have estimated equation (5.5) using ordinary least squares. The dependent variable is the log of (1+ average discard rate over 1999-2001). The results for machinery, computers and transport equipment are presented respectively in Tables 5.9, 5.10 and 5.11. As in the case of the probit analysis, all the models except the last one are estimated with industry dummies, and in the last model the industry dummies are replaced by high-tech dummies.

Most coefficients appear to be quite stable across different specifications and our discussion will be based mostly on Model 4. The R^2 values are generally low for all assets. It may be noted that similar is often the case with earlier firm level replacement models even with time-series data (e.g. Eisner, 1972). As presumed in the neoclassical models, output growth and wage rate increase show no significant effect on discard rates in any of the three asset types. The process-innovation is found to play a positive and significant role in machinery discard (M3 and M4 in Table 5.9), which is in compliance with our probit results. However, innovation variables are not significant in the case of transport and computers. This result contrasts with our results from the probit analysis that product-innovation plays a positive role in discard decisions of computer. This may suggest that though firms' decision on computer discard is affected by the product-innovation, the magnitude of the discard is not affected by the same. Model 6 for computer discards suggests that firms belonging to high-tech industries discard much

more than low-tech firms; the high-tech dummy has obtained a significant positive coefficient.

Table 5.9: OLS estimates for machinery discard

Variable	M1	M2	M3	M4	M5	M6
Intercept	0.069 *	0.08 *	0.077 *	0.075 *	0.072 *	0.043 ***
	(0.041)	(0.045)	(0.044)	(0.045)	(0.043)	(0.01)
YG	0.009	0.009	0.01	0.008	0.007	0.005
	(0.03)	(0.03)	(0.03)	(0.03)	(0.031)	(0.031)
WG	-0.024	-0.02	-0.022	-0.022	-0.021	-0.021
	(0.053)	(0.053)	(0.053)	(0.053)	(0.052)	(0.052)
AGE		-0.001	-0.001	-0.001	-0.001 *	-0.001
		(0.001)	(0.001)	(0.001)	(0.0005)	(0.000)
INNOV		0.001				
		(0.009)				
PDTIN			-0.009			
			(0.008)			
PCSIN			0.009 *	0.006 *		0.006
			(0.006)	(0.004)		(0.006)
TURN				-0.001		0.005
				(0.017)		(0.014)
RDX					0.109	
					(0.322)	
RDN					0.09	
					(0.129)	
HTEK						0.003
						(0.006)
R ²	0.061	0.066	0.071	0.069	0.069	0.009
Adj R ²	0.018	0.018	0.020	0.017	0.018	-0.008

Notes: Dependent variable is $\ln(1+Dr)$. *** indicates significance at 1 per cent, ** at 5 per cent and * at 10 per cent. Figures in parenthesis are heteroscedasticity adjusted standard errors. All the models, except M6 are estimated with industry dummies.

The age variable has a significant positive effect on discard rates both for computer as well as transport equipment, which is in conformity with the probit results. While the magnitude of the coefficient is 0.006 in computers, it is 0.009 in transport equipment. This implies that a one year higher age may lead to a 0.6 and 0.9 per cent increase in (1+) discard rate. Surprisingly the age variable has obtained a negative coefficient in machinery, though it is significant only in M5. Though the magnitude of the coefficient is very small, this result is somewhat puzzling, as the probit results have shown a significant positive effect of age on discard decisions. This may be because of the distinct feature of

machinery as compared to computers or transport equipment. The machinery, as defined in our data, is a composite asset, and this composition of the asset matters for discard rates. Production activity comprises an array of processes, and the machine associated with each process may have different characteristics in terms of efficiency and scrapping pattern.³² It is possible that firms keep part of their very old assets leading to a higher average age, but a lower discard rate. Therefore, though they may decide to discard, the relative magnitude of discard as a per cent of the capital stock is low. This implies that age can still be a factor in the decision to discard as seen in our probit analysis, though it tends to show an insignificant impact on discard rate. Also, one should not trivialize the possibility that there can be measurement error in the discard.

Table 5.10: OLS estimates for computer discard

Variable	M1	M2	M3	M4	M5	M6
Intercept	0.139 (0.106)	0.087 (0.106)	0.086 (0.107)	0.082 (0.107)	0.076 (0.109)	0.0002 (0.012)
YG	0.028 (0.037)	0.031 (0.037)	0.031 (0.037)	0.028 (0.038)	0.029 (0.037)	0.028 (0.049)
WG	-0.005 (0.074)	-0.032 (0.074)	-0.032 (0.074)	-0.037 (0.074)	-0.034 (0.074)	-0.042 (0.069)
AGE		0.006 *** (0.002)	0.006 *** (0.002)	0.006 *** (0.002)	0.006 *** (0.002)	0.006 *** (0.001)
INNOV		-0.003 (0.011)				
PDTIN			0.002 (0.01)			
PCSIN			-0.004 (0.01)	-0.005 (0.01)		-0.005 (0.009)
TURN				0.015 (0.022)		0.025 (0.017)
RDX					-0.097 (0.643)	
RDN					0.103 (0.177)	
HTEK						0.015 * (0.009)
R ²	0.090	0.116	0.116	0.117	0.069	0.009
Adj R ²	0.047	0.069	0.066	0.068	0.017	-0.008

Notes: As in Table 5.9

³² See chapter 2 of Pack (1987) for a detailed description of how different machinery is merged in the production process in textile industry, for example.

Table 5.11: OLS estimates for transport equipment discard

Variable	M1	M2	M3	M4	M5	M6
Intercept	0.521 *** (0.009)	0.435 *** (0.041)	0.434 *** (0.04)	0.456 *** (0.043)	0.485 *** (0.042)	0.076 *** (0.029)
YG	0.009 (0.067)	0.016 (0.064)	0.026 (0.063)	0.029 (0.064)	0.031 (0.07)	0.024 (0.065)
WG	0.247 (0.177)	0.204 (0.172)	0.177 (0.174)	0.184 (0.176)	0.204 (0.166)	0.179 (0.186)
AGE		0.009 ** (0.004)	0.01 *** (0.004)	0.009 ** (0.004)	0.009 ** (0.004)	0.008 ** (0.003)
INNOV		0.008 (0.024)				
PDTIN			0.036 (0.025)			
PCSIN			-0.029 (0.026)	-0.014 (0.022)		-0.018 (0.023)
TURN				0.003 (0.038)		0.039 (0.038)
RDX					-1.032 (0.851)	
RDN					-0.159 (0.425)	
HTEK						-0.007 (0.02)
R ²	0.130	0.159	0.169	0.161	0.166	0.037
Adj R ²	0.063	0.086	0.092	0.084	0.089	0.011

Notes: As in Table 5.9.

Thus the overall conclusion emerging from the OLS analysis is that the differences in discard rates across firms are not primarily driven by the differences in output or wage rate growth. Rather they are predominantly driven by the age of the asset for transport equipment and computers, suggesting the importance of obsolescence and wear-and-tear. While process-innovation plays a role in machinery discard, innovation tends to play no role in the discard rates of transport equipments and computers.

5.6 Concluding Remarks

This chapter has made an attempt to relate firms' decisions to discard and the amount of discards to innovation, economic and age variables. To date there is only little empirical evidence on actual discard behaviour and its determinants, particularly in terms of the effect of innovation. As a prelude to the empirical analysis we have provided a review of the determinants of discards identified in different schools of thought. Evidently, the review suggests that modelling the discard decision is a complex task, and hence one

needs to use an eclectic approach. We observe that neoclassical models assume discards as a constant proportion of capital stock, and hence assign no role for economic or innovation variables. On the other hand, vintage capital and evolutionary models stress the importance of input prices, innovation and age of the capital. Many technology studies have identified the possible importance of innovation in determining the lifetime of capital assets, as rapid change in technology will have an impact on firm's discard decisions as capital assets may become obsolete well before the end of their physical life time. Taking this into account, we have derived ideas from various theoretical models and specified our empirical model, where discard decisions (and rates) are expressed as a function of output growth, input prices, age of capital and innovation indicators. Given our data limitations, we have followed two basic empirical approaches — a probit analysis where the decision to discard or not is related to output, price, innovation and age variables, and a cross-section ordinary least square analysis where average firm-level discard rates are related to the selected variables.

Our empirical results seem to provide supporting evidence on the relationship between innovation and discard rates. We obtain significant positive effects of process-innovation in a firm on machinery discards. If we interpret a new process introduced by the firm as an indicator of external innovation, its positive effect on machinery discard may be considered as supportive evidence for Salter's vintage capital model and evolutionary scrapping rules. If the product-innovation causes a relatively larger turnover share the firm tends to have a larger probability to discard its computer. Moreover, firms belonging to high-tech industries seem to have a higher probability to discard their computers. Discarding of transport equipment seems to have no association with innovation variables.

As in the case of previous studies (Parks, 1977; Das, 1992; Cockburn and Frank, 1992), our results suggest that the average age of the asset is a major determinant of the scrapping decision. This is also in conformity with vintage capital and evolutionary models (see Table 5.1). Age of the asset is considered to be an indicator of physical wear-and-tear. Following the recent literature, however, we consider age as an indicator of more than the engineering considerations; it can be interpreted as an indicator of embodied technological change and obsolescence alongside efficiency loss (Wolff, 1991; Bahk and Gort, 1993; Gittleman et al., 2006). However, without additional information about the technical changes in the machinery producing sector, it is quite difficult to say whether it is obsolescence or wear-and-tear that dominates in machinery discard. In addition, machinery is a composite asset, where the wear-and-tear between different

components can be quite different, which will cause to have ambiguous effect of age on discard. We could however, say that given the significant effect of age on computer discard, and given the characteristics of computer asset and the enormous technological change this asset is witnessing, it is most likely that it is the obsolescence that dominates the computer discard. Also note that we have evidence that high-tech industries have a higher discard probability for computer. Here, if we assume that computers are relatively more important for high-tech industries and therefore, in these industries discards are more sensitive to technological change in computers, the discard probability will also be higher. Thus obsolescence seems to be main driver of discard decision in computers and this seems to be sensitive to the nature of the industry. For machinery it is not clear whether obsolescence or wear-and-tear that plays the main role; one needs further asset detail to make firmer conclusion on this.

The output and wage rates growth rates are not significant for the decision to discard, which is in contradiction with vintage capital models. Output growth is expected to be an important determinant of discard decisions, as an intense use of an asset due to output expansion may cause it to wear out faster. Nevertheless, this is not visible in our results, probably due to the lack of a time element in our analysis. It is expected that firms facing high wage growth may consider moving towards new labour-saving technology, that will accelerate scrapping and replacement. However we did not obtain such a result; the wage rate is found to be insignificant. This may be due to the fact that hiring and firing rules in the Netherlands are quite rigid, so that the substitution is less cost-effective, at least in the short run.

It is important to note that there are other relevant determinants of discard such as repair and maintenance costs, external price and technology shocks, policy regulations etc. that are omitted in our analysis. However, the omission of these variables is considered to be less problematic in so far their effect will be the same across all firms. A major limitation of this study is the lack of panel data. The main aim of the study was to look at the precise relationship between innovation and discard decision, which further restricted our analysis to a cross-section as we did not had sufficient firm-level information on innovation on a time-series basis. It should, however, be noted that most empirical studies on investment behaviour use panel data, (see Hall et al., 1998 for a review). Admittedly, more research is, required to quantify the effect of innovation on discard behaviour, using more dynamic time series data, as the current exercise does not account for such issues.

Another area for improvement is in distinguishing between within and outside innovation. It is not evident from our data whether the innovation variables used in the study represents innovation taken place within the firm or outside. All that we know is that the firm has introduced a new process developed either within or outside. For instance, in computer discards, innovation outside the firms (for instance such as software updates) may be very important. Thus it is important to have a more rigorous input-output analysis that takes into account the innovation dynamics of asset-producing sectors and how this feeds into the discard behaviour of firms. It would also be useful to have more detailed asset classification, as there can be much heterogeneity among different types of capital equipments in terms of their discard behaviour.³³ Unfortunately as Statistics Netherlands has stopped their discard surveys it may not be possible in the future to continue with this analysis in a more comprehensive framework. Nevertheless, similar exercise can be replicated with data for other countries, for instance statistical agencies in Canada and Japan continue to collect data on capital discards.

³³ Importance of capital heterogeneity, particularly in investment studies at micro level have been highlighted by Boddy and Gort (1971) and Goolsbee and Gross (1997).