We investigate the timing of large investment episodes at the micro level. On examination of a large sample of Dutch firms we find considerable lumpiness in the accumulation of fixed capital. We therefore define investment spikes and estimate the probability of these spikes, conditional on time since the last spike. We also control for unobserved heterogeneity. Our first result is that the probability of a spike is very high the year following an investment spike. We also find some evidence the hazard rate does increase as time since the previous spike passes by. Therefore, our results indicate the presence of convex adjustment costs or time to build lags. In addition, a tentative conclusion is that fixed adjustment costs are relevant.

Key words: lumpy investments, duration models

JEL Code(s): D21, D92

1 INTRODUCTION

The dynamics of business investment in fixed capital are crucial to understand economic activity in various areas. Investment expenditures affect the long run growth and employment prospects of industrialized economies. Furthermore, new machines purchased by firms embody the newest technologies available and hence affect firms’ innovativeness and ability to compete in the...
market place (Chirinko (1993)). Therefore, the process of capital adjustment is an important issue on the political agenda and in economic research. However, the empirical literature on (aggregate) business investment behaviour is full of disappointments (Caballero et al. (1995)). For instance, it has been proven very difficult to obtain reasonable and intuitively appealing estimates of parameters in structural models explaining firm behaviour. In such models, it is common to assume the firm incurs adjustment costs that are inherent in the act of changing the stock of capital. If the firm installs new equipment, production may be disrupted for some time. However, it has been found in empirical studies that adjustment costs are unrealistically high implying firms need very long periods to adjust to the long run optimal stock of capital. It has been reported that even after 20 years firms have moved to only 75% of the way to the steady state level of capital in response to an unexpected economic shock (Summers (1981), Chirinko (1993)).

One reason for the rarely successful attempts to improve our understanding of fixed capital investment may be the often assumed linear quadratic (convex) shape of the adjustment cost function. The shape of the adjustment cost function affects the dynamic behaviour of factor demand (see Abel and Eberly (1994), Hamermesh and Pfann (1996)). Investment becomes a lumpy process where firms concentrate investment in short periods of time if a fixed component in the adjustment costs is important. Irreversibility implies that investment becomes intermittent: i.e. in some periods investment is equal to zero and in others positive. In contrast, firms tend to spread investment outlays over many time periods if there is a substantial convexity to the adjustment cost function.

The above implies that one avenue to improve our understanding of investment behaviour is to develop and estimate models that incorporate alternatives to the traditional assumption of convex adjustment costs. Linear quadratic adjustment costs imply a linear relationship between investment and its fundamentals. Evidence in favour of departures from the traditional assumption of linear quadratic adjustment costs is provided by Barnett and Sakellaris (1998), NS (i.e. Nilsen and Schiantarelli (2003)), Letterie and Pfann (2006) and Letterie et al. (2004) who show that the response of investment to fundamentals is non-linear. Evidence supporting the presence of a fixed component to the adjustment cost function is presented by for instance Doms and Dunne (1998) who show that firms tend to concentrate large investment outlays in a very short time period. CHP (i.e. Cooper et al. (1999)) also report evidence supporting the presence of fixed adjustment costs. They solve the dynamic optimization process of a firm under different assumptions of the adjustment cost function and of the stochastic process of profitability shocks. They link these solutions to the shape of the hazard function. For instance CHP show that if adjustment costs contain a fixed component and shocks are serially correlated the probability of observing an investment spike increases as time since the previous spike increases. In this instance the hazard is said
to be increasing. If adjustment costs are convex and if shocks are again serially correlated the hazard should be decreasing. Hence, an estimate of the hazard function provides useful indirect information concerning the shape of the adjustment cost function. CHP report for US firms a largely increasing hazard rate function. Their results imply that fixed adjustment costs play an important role in determining the optimal investment decision. However, GI (i.e. Gelos and Isgut (2001)) report a decreasing hazard rate function for Colombian and Mexican firms. Their findings suggest that for firms in these Latin American countries investment decisions are subject to partial irreversibility and a convex adjustment cost. NS find evidence of an increasing hazard rate function for Norwegian firms, suggesting the relevance of a fixed component to the adjustment cost function. Our first objective in this paper is to investigate the role of non-convexity in the adjustment cost function by estimating the shape of the hazard function as suggested by CHP using data on establishments in the Netherlands.

There is a risk that estimates of the duration parameters are affected by unobserved heterogeneity. Disregarding this may lead to negative duration dependence, when in fact positive duration dependence exists. CHP, GI and NS follow the approach by Heckman and Singer (1984) to account for unobserved heterogeneity and assume that the distribution of the heterogeneity term can be approximated by a finite number of mass points with appropriate probabilities. In addition to this we also use the approach developed by Meyer (1990) to account for heterogeneity and consider the assumption that the stochastic term capturing heterogeneity is gamma distributed. This is the second purpose of our study.

We employ a dataset made available by Statistics Netherlands and investigate investment behaviour of firms in the Netherlands. Like many of the recent empirical studies mentioned above ours is focused on investigating micro level investment decisions. The purpose of starting analysing firms at the micro level is that various studies have shown that building models for aggregate investment should be based on a proper understanding of investment at a very low level of aggregation (see Caballero et al. (1995), CHP). Though policy makers may be more interested in understanding the fundamentals of aggregate investment, we believe that first one should be able to comprehend the dynamics of micro level factor demand decisions. To this end we first motivate our use of hazard rate models in the context of investment decisions in section 2. Next, we present the data in section 3. In section 4 we discuss our empirical results. Finally, section 5 concludes.

2 DURATION MODELS AND INVESTMENT DECISIONS

It is common to assume that a firm incurs a cost when the capital stock is changed. Apart from the cost to purchase the capital assets, these adjustment
costs can be a consequence of a disrupted production process when new capital is installed. Alternatively personnel may have to be retrained to be able handling equipment embodying new technologies. Traditionally it has been assumed that such costs have a convex mathematical shape. Under this assumption a firm should smooth its investment expenditures over time in order to keep the intertemporal adjustment cost low. However, Doms and Dunne (1998) first documented that US firms tend to concentrate investment outlays in a rather small period of time. In a small number of consecutive years the investment is very high whereas in the years surrounding this investment lump it is much lower. This result has been confirmed for other countries as well (for Norway see NS; for the Netherlands see Letterie and Pfann (2006)). These empirical observations are refuting the convex adjustment cost assumption. Rather it is consistent with a non convex shape. For instance, it seems firms incur a fixed adjustment cost which is independent of the size of the investment expenditure which leads to the spikes observed in the investment data (see Abel and Eberly (1994), Letterie and Pfann (2006)).

Various studies have investigated what happens to the dynamics of investment decisions under alternative assumptions to the traditional conjecture of convex adjustment costs. For example, CHP develop a model of machine replacement. It accounts for indivisibility of investment, a fixed component to the adjustment cost function and an adjustment cost component proportional to output that is lost when resources are diverted away from production, the cost of disruption. They solve the dynamic optimisation problem in terms of a hazard function. CHP show that if exogenous shocks are serially correlated and if a number of additional assumptions hold that the probability of investment (machine replacement) increases as the time since the last replacement increases. To put it differently, the hazard function is increasing in time. The intuition is that due to the fixed cost component, which is independent of the investment size, the firm has an incentive to concentrate its investment in a very narrow time window in order to avoid incurring the fixed cost each time with very small capital expenditures. Hence, after the investment outlay the firm does not adjust the capital stock for a number of periods. Meanwhile the existing stock of capital depreciates and new equipment is likely to be more productive compared with the capital currently employed by the firm due to technological innovation. As a consequence, as time passes by since the previous retooling effort of the company the incentive to replace the wearing off machines increases.

However, under the prevalent assumption of convex costs of adjustment, investment should be serially correlated if shocks are also serially correlated. The intuition is that due to convex adjustment costs a firm has an incentive to adjust only partly to a large shock. A smooth investment pattern yields the

1 See Hamermesh and Pfann (1996) for an overview of the literature concerning various assumptions on the adjustment cost function.
lowest discounted value of the current and future adjustment costs. Hence if a company makes a large capital adjustment in a certain year, this is probably a partial response to a large demand or technological shock for instance. In the next period a large adjustment is likely as well, because the firm still needs to bridge the gap between its current and desired stock of capital. Furthermore, if shocks are serially correlated the large investment episodes are likely to continue for some time, but in the end they will fade away. Hence if adjustment costs are convex and shocks are serially correlated the hazard should be decreasing.\footnote{GI demonstrate that an alternative explanation for the observation of a downwards sloping hazard function is the presence of irreversibility combined with a convex adjustment cost or a time-to-build effect.}

If shocks are uncorrelated and adjustment costs are irrelevant, the probability of undertaking a spike is, holding all else constant, constant over time. In this case the optimization problem of the firm is static and the company will adjust its stock of capital to the desired level instantaneously. An investment spike will occur for instance if a large demand shock hits the company. If these shocks are uncorrelated then the likelihood of a spike is stable through time implying that the hazard rate should be flat (see also CHP and NS).

The above discussion indicates that the shape of the hazard function is related to the shape of the firm’s adjustment cost function. Therefore estimating a duration model for investment decisions provides an indirect method to infer the form of the adjustment cost function.

3 THE DATA

The data in this paper stems from two groups of datasets held by Statistics Netherlands, linked together using unique identifiers. Production statistics are collected on an annual basis for all firms with more than 10 employees, reporting levels of sales, labour force, value of profits and other variables. Also available for each year are the investment statistics, containing information on levels of expenditure on all types of fixed assets by firms with more than 20 employees.

We use the data on both production and investment for firms in the manufacturing sector over the period 1978–1995, therefore including all firms with more than 20 employees. We require full information for the firm over the period 1978–1982 for both investment expenditure and the level of sales growth in order to be able to construct an approximation to the initial capital stock, subsequently calculating the replacement value of capital stock using the perpetual inventory method (see also the appendix). Although this requirement is stringent we retain over 40,000 observations containing information on the investment-to-capital ratio for firms over the period 1983–1995. However, it
probably leads to some selection bias. In fact we expect that larger and more successful establishments will be present in our data due to this.

In this paper we concentrate on investment in equipment which is defined as expenditure on machinery and assorted equipment, excluding that on computers, transport (both internal and external to the firm), and on buildings and land. It represents 65% of total investment expenditure in the sample period. This is the same percentage of total investment as found by NS for Norwegian firms. Much of the subsequent analysis is based upon the premise that investment is a lumpy process, and that the investment smoothing behaviour predicted by models with convex, symmetric adjustment cost is rarely observed. The average investment rate in the sample is 0.115, which compared to the median of 0.053 indicates that the distribution is skewed to the right. This provides some preliminary evidence that investment is lumpy as predicted by models incorporating fixed adjustment costs since large investment rates tend to affect the mean more than the median.\(^3\)

The definition of a point above which capital stock adjustment is deemed to be 'large', a spike, is necessarily subjective. Two definitions have dominated the literature; an absolute investment spike and a relative investment spike. In the first definition all investment adjustments above a particular threshold are defined spikes, where the most common cut-off applied is 20% of existing capital stock (cf. CHP, GI and NS). According to this definition 13% of the investment rates in our data are considered to be a spike. Power (1998) argued that this definition does not capture sporadic episodes of investment that are not large in absolute terms but only relative to the typical adjustment undertaken by the firm. She suggested the definition of a spike relative to the firm-specific median investment rate over the sample period, where a ‘spike’ is considered to have occurred if the investment rate is some multiple of the median, where she adopted 1.75. Power preferred the use of the median rather than the arithmetic mean because of the skewed distribution of investment rates. NS employ a similar definition but use as a multiple of the median the value 2.5. We take this value as well. Furthermore, they require the investment rate to be higher than the rate of depreciation. We follow this suggestion and assume that the rate of depreciation equals 5%. According to this definition 14% of our investment data are spikes.

In the terminology of duration models we have data with multiple events per unit of observation, i.e. a firm’s investment level can spike more than once during the sample period. It is clearly improbable that a firm has built up the capital stock observed during the sample period without generating

\(^3\) At least 10% of our data have a zero investment rate, 25% of the investment rates are smaller than 0.017, 75% are smaller than 0.122 and 90% are smaller than 0.241. Some of the investment rates are very large. From our further analyses we have excluded firms for which an investment rate exceeds 2.
large investment episodes before. However, we have no information on the number of periods between the firm's first spike observed in the sample and the previous spike. Therefore we cannot calculate the duration between spikes until the firm investment level has spiked for the first time. More than half of the observations in the dataset occur prior to the first spike, leading to a reduction in the dataset. In case of the absolute (relative) spike definition 11362 (13239) data points remain. Furthermore we must treat each spike as an independent event, because to treat the nth 1st spike differently from the nth would be inconsistent given that we have no knowledge of the number of spikes occurring prior to the first spike observed. In fact the actual value of n is unknown.

4 ESTIMATION OF DURATION MODELS

The purpose of this section is to provide evidence on the shape of adjustment costs by considering the hazard function at the micro level. Let us first develop some notation. We denote by $T_{ij}$ the time at which a firm indexed i has an investment spike during the jth spell of zero investment. In other words it is the time at which firm i has its jth investment spike. The variable t represents calendar time, $t - (T_{ij} - 1 + 1)$ the interval from the last spike. Note that a zero interval refers to the case of two spikes in adjacent periods. The variable $z_{it}$ is a set of additional variables. With these definitions the hazard rate can be written as

$$P_{ijt} = P R \left[ T_{ij} = t | T_{ij} \geq t, t - (T_{ij} - 1 + 1), z_{it} \right]$$

(1)

We present various estimates of this function. First, in section 4.1 we present results based on the non-parametric Kaplan–Meier estimator. In section 4.2 we follow CHP who use the semi parametric specification developed by Meyer (1990) and allow for two different strategies to control for unobserved heterogeneity. Controlling for this is important since downward sloping empirical hazard rates may reflect unobserved heterogeneity. In section 4.3 we discuss the method of Heckman and Singer (1984) used by CHP in the context of investment spikes and assume that the unknown distribution of heterogeneity can be approximated by a finite number of mass points and corresponding probabilities. Next in section 4.4 we adopt the approach used by Meyer (1990) and Dolton and van der Klaauw (1995) who assume heterogeneity can be captured by a gamma distribution.

4.1 The Kaplan–Meier Estimator

Although empirical estimates of the hazard function are inconsistent under heterogeneity in either dimension of the panel, over time or the cross-section,
### Table 1 – Kaplan–Meier Hazard Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Absolute spikes</th>
<th>Relative spikes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duration 0</td>
<td>0.27* (0.01)</td>
<td>0.21* (0.01)</td>
</tr>
<tr>
<td>Duration 1</td>
<td>0.18* (0.01)</td>
<td>0.16* (0.01)</td>
</tr>
<tr>
<td>Duration 2</td>
<td>0.14* (0.01)</td>
<td>0.14* (0.01)</td>
</tr>
<tr>
<td>Duration 3</td>
<td>0.13* (0.01)</td>
<td>0.13* (0.01)</td>
</tr>
<tr>
<td>Duration 4</td>
<td>0.12* (0.01)</td>
<td>0.12* (0.01)</td>
</tr>
<tr>
<td>Duration 5</td>
<td>0.10* (0.02)</td>
<td>0.12* (0.01)</td>
</tr>
<tr>
<td>Duration 6</td>
<td>0.09* (0.02)</td>
<td>0.10* (0.02)</td>
</tr>
<tr>
<td>Duration 7</td>
<td>0.09* (0.02)</td>
<td>0.12* (0.02)</td>
</tr>
<tr>
<td>Duration 8 and higher</td>
<td>0.06* (0.02)</td>
<td>0.06* (0.02)</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses. Duration $i$ means $i + 1$ years since the last spike. A * indicates significance of at least 5%.

The Kaplan–Meier estimator serves as an informative point of departure for understanding the duration dependence of investment spikes. It is computed as the fraction of spikes in the sample by the number of establishments at risk for every zero spike period length. It measures the empirical probability of observing a spike conditional on the event that the firm has not experienced a spike over a period of a certain length.

As Table 1 shows, the Kaplan–Meier hazard is essentially downward sloping for both spike definitions from a high of over 21% in the period immediately after, stabilising subsequently at a level of 9–18% for duration up to 7 years. This means for instance that the probability of observing a spike is highest after a spike has occurred. For duration 8 and higher the hazard is 6%. This result is comparable to that reached for Mexico and Colombia by GI. A decreasing hazard points at the relevance of convex adjustment costs, but this result should be taken with caution since unobserved heterogeneity is not accounted for yet.

#### 4.2 Semi Parametric Duration Models

In this section we adopt the approach suggested by CHP to estimate the hazard from the distribution of durations between spikes in the context of investment decisions. It is based on a semi-parametric specification developed by Meyer (1990) to estimate the effect of duration and covariates on the conditional probability of investment spikes. This model extends the approach of Prentice and Gloeckler (1978) in estimating the effect of time on the failure rate non-parametrically, thereby allowing more flexibility in the form of the duration dependence. A particular strength of the Meyer approach is that it specifically addresses the interval censored nature of our data. Since the data
is constructed from annual reports investment is grouped into discrete intervals, years, despite the fact that the underlying expenditure is a continuous distribution. Following the CHP model, the hazard for any firm, \( i \), at time \( t \), i.e. the probability that the investment level of firm \( i \) spikes at time \( t \), given that it has not spiked before time \( t \) is defined as

\[
\lim_{\Delta \to 0} \frac{\Pr(t + \Delta > T_i \geq t | T_i \geq t)}{\Delta} = h_i(t)
\]  

(2)

\( T_i \) is the length of the spell for establishment \( i \). The hazard is parameterized by the proportional hazard form:

\[
h_i(t) = h_0(t) \exp(z_i(t)' \beta)
\]

(3)

where \( h_0(t) \) is the unknown baseline hazard at time \( t \), \( z_i(t) \) is a vector of time-varying explanatory variables. It captures some control variables like year and sector dummies and information on initial size (i.e. number of employees). \( \beta \) is a vector of parameters associated with these covariates. Therefore the probability that a spell lasts until time \( t+1 \) given that it has lasted until time \( t \) is given by

\[
P[T_i \geq t + 1 | T_i \geq t] = \exp \left[ - \exp \left( z_i(t)' \beta + \gamma(t) \right) \right]
\]

(4)

The expression \( \gamma(t) = \ln \left[ \int_t^{t+1} h_o(u) \, du \right] \), denotes the duration parameter of the model. The likelihood function is given by

\[
L^1(\gamma, \beta) = \prod_{i=1}^{N} L_i(k_i, d_i) = \prod_{i=1}^{N} \left[ 1 - \exp \left( \exp \left( \gamma(k_i) + z_i(k_i)' \beta \right) \right) \right]^{\delta_i}
\]

\[
\times \prod_{t=1}^{k_i-1} \exp \left( - \exp \left( \gamma(t) + z_i(t)' \beta \right) \right)
\]

(5)

where \( C_i \) is the censoring time and \( \delta_i = 1 \) if \( T_i \leq C_i \) and 0 otherwise, and \( k_i = \min(\text{int}(T_i), C_i) \). In this formulation the first term represents the probability of exit during the discrete interval \([k_i, k_i + 1]\) given that the spell has lasted until \( k_i \), and the second term the probability that the spell lasts until \( k_i \). The log-likelihood function for \( N \) establishments can be written as

\[
l(\gamma, \beta) = \sum_{i=1}^{N} \left[ \delta_i \log \left[ 1 - \exp \left( \exp \left( \gamma(k_i) + z_i(k_i)' \beta \right) \right) \right] 
\]

\[
- \sum_{t=1}^{k_i-1} \exp \left( \gamma(t) + z_i(t)' \beta \right)
\]

(6)
### TABLE 2 – SEMI PARAMETRIC HAZARD MODEL WITH DISCRETE MASS POINTS

<table>
<thead>
<tr>
<th>Variable</th>
<th>Absolute spikes</th>
<th>Relative spikes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No mass point</td>
<td>With mass points</td>
</tr>
<tr>
<td>Duration 1</td>
<td>−0.42∗ (0.06)</td>
<td>−0.35∗ (0.06)</td>
</tr>
<tr>
<td>Duration 2</td>
<td>−0.56∗ (0.07)</td>
<td>−0.41∗ (0.08)</td>
</tr>
<tr>
<td>Duration 3</td>
<td>−0.62∗ (0.09)</td>
<td>−0.39∗ (0.11)</td>
</tr>
<tr>
<td>Duration 4</td>
<td>−0.55∗ (0.11)</td>
<td>−0.22 (0.15)</td>
</tr>
<tr>
<td>Duration 5</td>
<td>−0.83∗ (0.15)</td>
<td>−0.37 (0.21)</td>
</tr>
<tr>
<td>Duration 6</td>
<td>−0.75∗ (0.19)</td>
<td>−0.15 (0.27)</td>
</tr>
<tr>
<td>Duration 7</td>
<td>−0.72∗ (0.24)</td>
<td>0.04 (0.36)</td>
</tr>
<tr>
<td>Duration 8 and higher</td>
<td>−0.96∗ (0.28)</td>
<td>0.22 (0.54)</td>
</tr>
<tr>
<td>$v_2$</td>
<td>13.32 (276.03)</td>
<td>1.76∗ (0.34)</td>
</tr>
<tr>
<td>$p_1$</td>
<td>0.16∗ (0.07)</td>
<td>0.81 (0.85)</td>
</tr>
<tr>
<td>$p_2$</td>
<td>0.84∗ (0.04)</td>
<td>0.19 (0.12)</td>
</tr>
<tr>
<td>LL</td>
<td>−5085.87</td>
<td>−5077.58</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses. Duration $i$ means $i+1$ years since the last spike. We aggregate industries into broad sectors: food (F), textiles and clothing (T&C), paper and lumber (P&L), plastics (Pl), primary metals (Me), machinery (Ma), transport (Tr) and other (Oth). Sector, year and size dummies are included in the estimations but not reported here to save space. A ∗ indicates significance of at least 5%.

Tables 2 and 3 report the estimates obtained by maximization of (6) in the first and third column. We have depicted the same estimates in both tables to facilitate comparison with the estimates obtained for both types of controlling for heterogeneity. Note that duration 0, meaning that two investment spikes occur in adjacent periods, is used as the reference case in the estimation of our model. Hence, the coefficients of the variables duration $i$ ($i = 1, 2, \ldots, 8$ and higher) measure deviations from this case.

The results based on the absolute spike definition indicate that the hazard is highest the period immediately after the spike. This indicates that large investment expenditures are spread over several periods. This feature of the data may reflect that firms need time to build or that large investment outlays are subject to convex adjustment cost as well for instance. Besides this the hazard function is largely decreasing for duration 1 and higher which is in line with the estimates presented by CHP using the same econometric model (without controlling for unobserved heterogeneity) and the same spike definition. The empirical hazard function based on the relative spike definition also indicates that the probability of observing a spike is highest immediately after a spike. However, this hazard function shows no clear pattern for duration 1 and higher and contrasts sharply with the findings of CHP who do
### TABLE 3 – SEMI PARAMETRIC HAZARD MODEL WITH GAMMA DISTRIBUTION

<table>
<thead>
<tr>
<th>Variable</th>
<th>Absolute spikes</th>
<th>Relative spikes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No gamma</td>
<td>With gamma</td>
</tr>
<tr>
<td>Duration 1</td>
<td>0.42*     (0.06)</td>
<td>0.22*     (0.10)</td>
</tr>
<tr>
<td>Duration 2</td>
<td>0.56*     (0.07)</td>
<td>0.22       (0.15)</td>
</tr>
<tr>
<td>Duration 3</td>
<td>0.62*     (0.09)</td>
<td>0.14       (0.21)</td>
</tr>
<tr>
<td>Duration 4</td>
<td>0.55*     (0.11)</td>
<td>0.06       (0.26)</td>
</tr>
<tr>
<td>Duration 5</td>
<td>0.83*     (0.15)</td>
<td>0.08       (0.33)</td>
</tr>
<tr>
<td>Duration 6</td>
<td>0.75*     (0.19)</td>
<td>0.10       (0.38)</td>
</tr>
<tr>
<td>Duration 7</td>
<td>0.72*     (0.24)</td>
<td>0.25       (0.45)</td>
</tr>
<tr>
<td>Duration 8 and higher</td>
<td>0.96*  (0.28)</td>
<td>0.21       (0.52)</td>
</tr>
<tr>
<td>σ²</td>
<td>0.77*     (0.30)</td>
<td>–</td>
</tr>
<tr>
<td>LL</td>
<td>–5085.87</td>
<td>–5078.80</td>
</tr>
<tr>
<td>LR-Test H₀: σ² = 0</td>
<td>χ²(1) = 14.15</td>
<td>χ²(1) = 7.51</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses. Duration i means i + 1 years since the last spike. We aggregate industries into broad sectors: food (F), textiles and clothing (T&C), paper and lumber (P&L), plastics (Pl), primary metals (Me), machinery (Ma), transport (Tr) and other (Oth). Sector, year and size dummies are included in the estimations but not reported here to save space. A * indicates significance of at least 5%.

not employ the relative spike definition. Apparently the spike definition does affect the empirical findings. The estimates discussed in this section should be interpreted with considerable caution as well since they may be biased as a consequence of unobserved heterogeneity. Therefore in the next sections we present estimates of the hazard function that take into account the possibility of heterogeneity.

#### 4.3 The Heckman-Singer Approach to Control for Unobserved Heterogeneity

Heckman and Singer (1984) assume that the unknown distribution of heterogeneity can be approximated by a discrete distribution with a finite number of mass points. M is the number of mass points which are denoted by \( \nu_m \). These are estimated together with the corresponding probabilities: \( pr_m \). Using the same notation as in 4.2, the likelihood function can be given as

\[
L^2(\gamma, \beta, pr, \nu, M) = \prod_{i=1}^N \sum_{m=1}^M pr_m L_i(k_i, \delta_i | \nu_m)
\]

The expression \( L_i(k_i, \delta_i | \nu_m) \) corresponds to the term \( L_i(k_i, \delta_i) \) in equation (5) where terms like \( \exp \{ (\gamma (t) + z(t)') \beta \} \) should be replaced by \( \exp \{ (\gamma (t) + z(t)') \beta + \nu_m \} \). Note that \( \nu_1 \) is normalized at zero.
The estimates are presented in table 2 as well. Our experiments have shown that two mass points are sufficient to control for unobserved heterogeneity. A higher number of mass points does not increase the likelihood. In line with our estimates depicted in section 4.2, the results based on the absolute spike definition indicate that the probability of a spike is high in the period immediately after the first spike. The coefficients for duration 1, 2 and 3 are significantly negative indicating the hazard is significantly lower for these durations than for duration 0. Afterwards the hazard tends to increase. The coefficients on the higher durations are not significantly different from the hazard at duration 0. Thus this model supports the presence of fixed adjustment costs which imply an increasing hazard, though the evidence is weaker than found by CHP (in the model where they control for unobserved heterogeneity). However, the estimates of the hazard function based on the relative spike definition indicate that the coefficients for duration 1 and higher do not differ significantly from the hazard at duration 0. In other words the hazard is flat in this case. We argued before in section 2 that this finding could be supported by the absence of adjustment costs and shocks that are serially uncorrelated. Hence, the estimates based on different spike definitions are not in line with each other once more.

4.4 The Gamma Distribution to Control for Unobserved Heterogeneity

Following Meyer (1990) we assume that unobserved heterogeneity is present and that it can be captured by a multiplicative error term to the hazard. The hazard then becomes:

$$h_i(t) = \theta_i h_o(t) \exp\left( z_i(t)' \beta \right)$$

(8)

where $\theta_i$ is a random variable independent of $z_i(t)$. To test for unobserved heterogeneity we assume that $\theta$ is distributed gamma normalised to have mean one and variance $\sigma^2$. As Meyer shows, under these assumptions the closed form expression for the log-likelihood of the model is given by

$$l(\gamma, \beta, \sigma^2) = \sum_{i=1}^{N} \log \left\{ 1 + \sigma^2 \sum_{t=0}^{k_i-1} \exp\left\{ \gamma(t) + z_i(t)' \beta \right\} \right\}^{-\sigma^2}$$

$$-\delta_i \left[ 1 + \sigma^2 \sum_{t=0}^{k_i} \exp\left\{ \gamma(t) + z_i(t)' \beta \right\} \right]^{-\sigma^2}$$

(9)

The results based on maximization of (9) are given in Table 3. The likelihood ratio tests (LR-test) reported at the bottom indicate that the null hypothesis $\sigma^2=0$ is rejected. Hence, unobserved heterogeneity should be accounted for.
These estimates confirm once more that the probability of observing a spike immediately after a spike is rather high. The coefficient on duration 1 and 2 is substantially lower than the reference case duration 0 in the estimates based on both the absolute and relative investment spike. At higher durations the hazard tends to increase. For duration 3 and higher the hazard does not differ significantly from that for duration 0. In case of the absolute spikes the coefficient for duration 2 does not differ from zero as well. Therefore, these results provide some weak evidence that fixed costs are relevant for understanding the dynamics of capital.

5 CONCLUSION

We model investment activity using data on large investment episodes, applying a semi-parametric hazard model. Our findings tend to support the earlier work of Cooper et al. (1999) and of Nilsen and Schiantarelli (2003), but contradict findings of Gelos and Isgut (2001). In particular, we also find serial correlation of investment projects at low durations. That the probability of undertaking a major investment should be highest in the period immediately subsequent to a spike is consistent with the fact that very large investment projects will be spread over more than one year, as found by Doms and Dunne (1998), and also that smaller projects may well extend over several months, which fall in different years because of the use of calendar years. This feature of the data implies that adjustment costs are likely to contain a convex element. Our results show that the positive duration dependence identified by CHP and NS is also present in our sample of firms. We find some evidence that the hazard is upward-sloping. This means that the next years directly after an investment episode, which lasts 1 or 2 years, the probability of observing a new spike tends to be quite low. After some more years the incentive to conduct a major investment (retooling effort) increases again due to depreciation and technological innovations for instance and it becomes profitable to incur the cost of investing. Such a pattern of investment suggests that a fixed component of adjustment costs is important in our sample. However, the evidence we find is less convincing than that of CHP.

The difference between the findings of the studies mentioned above and ours may depend on the fact that data from different countries are used. However, the differences may also be due to the fact that different methodologies are employed. First, the econometric technique differs across the above mentioned studies. The estimates of CHP and ours are derived from a semi-parametric specification developed by Meyer (1990) whereas GI and NS parameterize the hazard as a logistic function. The results we present in this study and which are derived from different econometric specifications of the hazard function also yield different conclusions. Secondly, the
studies employ different definitions of the investment spike. Our own results indicate that the conclusion may depend on the spike definition employed. Therefore future research is necessary to find out whether results for empirical hazard rates depend on the methods used by the researcher. An obvious problem with the hazard function methodology is that it only provides indirect evidence on the structure of the adjustment cost function of the firm. To obtain more precise insight into the mathematical representation of the firm’s optimization problem future analysis should advance a more structural approach.

DATA APPENDIX: VARIABLE DEFINITION AND CONSTRUCTION

*Price of Investment Goods (PI)*: Implicit Price Deflator from the Dutch National Accounts. Base year is 1990.

*Producer Price Index (P)*: Sector Price Information at the two-digit level collected by Statistics Netherlands. Base year is 1990.

*Real Investment (I)*: We focus on investment in equipment. This includes machinery, office furniture, fittings and fixtures, and other transport equipment, excluding cars and trucks. The code used by Statistics Netherlands for equipment investment is: v66. The nominal investment data are deflated using PI.

*Real Production (Y)*: Code used by Statistics Netherlands v1109. The nominal variable is deflated using P.

*Real Replacement Value of Capital Stock at the end of period t* (\(K_t\)): The replacement value is computed using the perpetual inventory method. This method requires a starting value for the capital stock. Our data do not provide information on insurance or book value of the capital stock. Therefore we estimate the starting value as follows. The nominal stock of capital at the end of year \(m = 1977 + n\), where \(n\) is an integer larger than or equal to 1, is given by

\[
K_m = I_m + (1 - \delta)I_{m-1} + \cdots + (1 - \delta)^{n-1}I_{78} + (1 - \delta)^nK_{1977}
\]

where \(\delta\) is the rate of depreciation set equal to 0.05. If we assume that in year \(t\) the firm grows at a rate equal to \(g_t\) then investment in the \(n\) periods should be approximately sufficient to ensure that

\[
K_m = (1 + g_{1978}) \cdots (1 + g_m)K_{1977}.
\]

Given the values \(g_t\) it is possible to solve for the value of \(K_{1977}\) by substituting out \(K_m\) from the above two equations in this appendix. We approximate
by calculating the firm’s real production growth using \( Y \) from time \( t - 1 \) to \( t \) over the period 1978 to \( m \). Since our data start in 1978 we assume \( g_{1978} = g_{1979} \). The value of \( n \) is set equal to 5. The reason is that we need a sufficiently long period to estimate the starting value of capital, because firms tend to concentrate investment in a relatively short period of time. If \( n \) is very small the probability of underestimating the starting value of the capital would be considerable. To ensure that the initial stock of capital is positive we set \((1 + g_{1978}) \ldots (1 + g_m) = 1 \) if \((1 + g_{1978}) \ldots (1 + g_m) < 1 \).

Given the initial value the replacement value of the capital stock at the beginning of year \( t \) is calculated using the perpetual inventory formula:

\[
K_t = I_{t-1} + (1 - \delta)K_{t-1}
\]

The investment rate \((I_t/K_{t-1})\): The rate of investment for equipment is defined by the ratio of real investment in year \( t \) by the real replacement value of the capital stock at the end of year \( t - 1 \).

REFERENCES


