Zeroes and Lumps in Investment: Empirical Evidence on Irreversibilities and Non-Convexities

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Boston College Working Papers in Economics, 1996

ZEROES AND LUMPS IN INVESTMENT:

Empirical Evidence on Irreversibilities and Non-Convexities

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This revision: November 2000

JEL Classification: D21, E22.

Key Words: Investment, Irreversibility, Non-Convexity.

Abstract

The objective of this paper is to investigate if and how capital adjustment departs from the smooth pattern implied by standard model based on convex adjustment costs. Using Norwegian micro data, we start by documenting various aspects of the distribution of investment rates. We then present two pieces of econometric evidence on these issues. First, we estimate a discrete hazard model to determine the probability of having an episode of high investment, conditional on the length of the interval from the last high investment episode and we discuss what the empirical results suggest about the shape of the adjustment cost function. Second, we move beyond this

* We would like to thank G. Bertola, R. Caballero, R. Cooper, J. Eberly, P. Gottschalk, G. Imbens, T. J. Klette, K. Lang, P. Sakellaris, L. Serven, F. Windmeijer and seminar participants at the University of Bergen, Statistics Norway, the World Bank, the London School of Economics, and Boston University for useful comments and conversations. flivind Anti Nilsen gratefully acknowledges the financial support of "Norges Banks Fond for flkonomisk Forskning .

discretization of the investment problem and estimate a switching regression model that allows for the response of the investment rate to fundamentals to differ across regimes. In both cases we investigate the aggregate implications of our results.

1. Introduction

The standard investment model is based on the assumption that there are convex costs attached to adjusting capital. Following the seminal contribution by Eisner and Strotz (1963), typically the adjustment cost function is assumed to be zero and flat at zero investment and to be symmetric around zero. In these circumstances, if investment projects are divisible, there are no technological reasons why one should observe frequent episodes of zero investment. Moreover, the firm has an incentive to smooth investment over time in order to avoid paying increasing marginal adjustment costs. When investment is constrained to be non-negative (because there are infinite disinvestment costs), or when the marginal cost of adjustment is positive even for small changes in investment (i.e. when the adjustment cost function is not continuously differentiable at zero) investment will be intermittent, with zero investment periods alternating with periods of positive investment.[1] Moreover, when there are increasing returns in the adjustment cost technology (for instance, because of fixed costs), the range of inaction will increase and, in certain cases, investment activity may also be lumpy with large adjustments concentrated in a few episodes. The intermittent and lumpy nature of investment contributes to a non-smooth adjustment path for the capital stock. The non-smoothness may also be enhanced by the inherent indivisibility of investment projects, so that investment can only be changed in discrete increments.[2]

Even though the theoretical papers that analyze the consequences of various departures from the standard model of reversible investment with symmetric convex adjustment costs are rich and numerous, the empirical evidence on these issues is still limited and several issues remain unsettled. Focusing on micro level studies, Doms and Dunne (1998) provide evidence for the US that a large portion of investment at the plant level is concentrated in a few episodes. Moreover, the proportion

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[1] The partial or total irreversibility due to the nature of disinvestment costs is caused by the fact that capital goods are, at least, partly firm specific, and by the presence of lemon problems in second hand markets for capital. The basic implications of irreversibility (non-negativity of investment) were originally analyzed by Arrow (1968) and later by Lucas and Prescott (1971), Nickell (1974) and (1978), and, more recently, by Bertola and Caballero (1994), Dixit and Pindyck (1994), Abel and Eberly (1994). For a review of the macro implications of and evidence on irreversibility see Serven (1996).

[2] The presence of non-convexities in adjustment costs was noted by Rotschild (1971) and it characterizes the contribution by Caballero and Engel (1999), Cooper, Haltiwanger and Power (1999), Abel and Eberly (1994), and Caballero and Leahy (1996). See Caballero (1997) for a critical review.

of firms experiencing an investment spike is a given year is closely related to aggregate investment. Cooper, Haltiwanger and Power (1999), on the basis of micro based estimates of the hazard function, provide evidence that bursts of investment lasts for more than one period, but then the probability of a plant experiencing a large investment episode increases in the time elapsed since the last such episode. This last piece of evidence is supportive of non-convexities in the adjustment cost technology. Barnett and Sakellaris (1998) shows empirically that the relationship between the investment rate and average Q is nonlinear, using firm level data from Compustat. The Abel-Eberly (1994) model predicts that there is a range of values of Q for which investment would not be sensitive to changes in Q, while it would respond outside this range. The non-linearities found in the Compustat data are not consistent with this simple model. However, Eberly (1997), an Abel and Eberly (1999) argue that the empirical evidence is consistent with a model with irreversibilities and fixed costs, if one allows for capital goods heterogeneity. Caballero, Engel and Haltiwanger (1995) in the context of (S-s) types of models, relate investment to the gap between desired and actual capital stock and show empirically, using the LRD plant level data, that the elasticity of investment to a shock is greater when the gap is large or positive and smaller when it is small or negative. Additional evidence in favor of a non-linear response to the gap, with a region of inaction and a linear response outside that region, is presented in Goolsbee and Gross (1997) for the US airline industry.[3]

Although many pieces of the evidence we have reviewed are consistent with the presence of irreversibilities and non-convexities in the process of capital adjustment, the issue of their nature and importance is far from settled. In particular there is no agreement on the importance of these issues for understanding the evolution of aggregate investment. The objective of this paper is to use a very rich panel of Norwegian plants and firms to establish a few stylized facts about the pattern of capital adjustment, to discuss the implications of the empirical evidence for the shape of the adjustment cost function, and to draw the aggregate implications of our findings. We will investigate both the intermittent nature of investment and on the lumpiness of capital adjustment. This is important in

[3] All the contributions mentioned so far rely on micro data. Bertola and Caballero (1994) concentrate instead on the implications for aggregate investment of a model with a non-negativity constraint for investment (see also Bertola and Caballero (1990)). They argue that a combination of non-linear investment policies and idiosyncratic shocks yields a satisfactory fit of the model to aggregate data, although the residuals are non-trivial and serially correlated. Caballero and

order to assess the empirical importance of the two forms of departures from the standard model of investment, (partial or total) irreversibility due to disinvestment costs and non-convexities, due to fixed adjustment costs, that have received more attention in the recent literature.

Aggregation across plants and capital goods may give a misleading impression about the importance of zeroes and lumps in investment. For this reason we will conduct the analysis separately for investment in plant and equipment, on the one hand, and buildings, on the other. Moreover, since the data set specifies the nature of the plant (single plant, main, or secondary unit in multi-plant firms) and since the information can be aggregated at the firm level, we will analyze how the degree of intermittence and lumpiness changes as the unit of observation changes. We will indeed show that the nature of the capital adjustment process varies substantially depending upon the functional nature of the plant and upon the level of aggregation. We also show how episodes of zero investment and lumpiness vary when firms (plants) are classified according to size.

More precise conclusions concerning the nature of adjustment costs require an econometric treatment. Our approach is two pronged. First, as in Cooper, Haltiwanger and Power (1999), we estimate the hazard function describing the probability of episodes of high investment, conditional on the length of the interval from the last episode of high investment. In addition to controlling for business cycle conditions, we also control for observed and unobserved (plant) heterogeneity. The main issue here is whether or not the hazard is upward-sloping. Finally, using the estimates of the hazard model obtained at the micro level, we address the crucial question whether taking into account of non-convexities helps in understanding aggregate investment behavior, and more specifically the fluctuations in the aggregated proportion of plants experiencing an investment spike.

Second, we abandon the discretization of the problem adopted in the hazard approach and analyze the response of the investment rate to fundamentals in the context of a switching regression model of investment.[4] As Abel and Eberly (1994) suggest, the response of investment

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Engel (1999) allow for increasing returns in the adjustment costs technology and find that their non-linear model can explain aggregate sectoral data better than a linear model.

[4] Hu and Schiantarelli (1998) use this methodology to investigate financing constraint. See also Letterie and Pfann (2000) for an interesting application to the issue of investment and adjustment costs, using Dutch firm level data.

to marginal expected returns (q for short) depends on the value of the latter, and there may be no response over a certain range. In our empirical application we allow for two investment regimes and permit the coefficients of various proxies for q to differ according to q being high or low . We use the estimates of the parameters of the model to calculate the probability of each regime and discuss how they vary over the business cycle. Final we discuss whether a two-regime model allows one to provide a better explanation of aggregate investment than a standard model.

The paper is organized as follows. In Section 2, we briefly describe the data and discuss the salient aspects of the distribution of investment rates for equipment and buildings at the plant and firm level. In Section 3 we first present estimates of the hazard function for investment spikes, and then of a switching regression model. In both cases we discuss the aggregate implications of the two models. Section 4 concludes the paper.

2. The Data and the Distribution of Investment at the Plant and Firm Level

The empirical work in this paper is based on a large unbalanced panel of 1866 Norwegian production plants in the manufacturing sector for which annual information is available for at least four consecutive years over the period 1978-1991. The plant level data is collected by Statistics Norway (The Central Bureau of Statistics of Norway) and has been matched with firm level balance sheet data contained in Statistics of Accounts for all firms with more than 50 employees. The plants in our sample belong to 1252 firms and account on average for 41 percent of total investment in manufacturing. Their total investment is highly correlated with total investment in manufacturing. The correlation coefficient is 0.86 and it is highly significant.

Throughout the paper, investment is defined as purchases minus sales of fixed capital. Expenditures related to repairs of existing capital goods are not included in the definition of purchases. This distinction is a unique and very useful characteristic of the data set we are using. In most of the paper, we distinguish between plant and equipment (equipment from now on), on the one hand, and industrial buildings on the other.[5] Equipment includes machinery, office furniture, fittings and fixtures, and other transport equipment, excluding cars and trucks and represents 64 percent of total investment.[6]

In order to assess the nature of the non-smoothness of investment patterns, we focus on the salient features of the distribution of investment rates. In Figure 1, we present the distribution of investment rates for equipment and buildings for the unbalanced sample of production plants. Equipment investment represents approximately two thirds of total investment. Table 1 contains the numerical information on the frequencies for equipment, buildings, and their sum, together with the share of total real investment accounted for by investment rates within each interval.

Both distributions of investment rates are highly peaked and skewed, with fat and long right-hand tails.[7] Interestingly, episodes in which the plant refrains from engaging in any investment activity occur frequently for investment in equipment and even more so in buildings. Zero investment observations represent 21 percent of total observations for equipment and 61 percent for buildings. If we sum the expenditure on equipment and buildings, zero investment episodes represent 20 percent of the total number of observations. This illustrates the general point that aggregating across types of capital goods leads to an underestimate of the intermittent character of each type of investment. Negative investment rates occur quite rarely for both equipment and buildings (only 2 percent of the observations in both cases involve negative investment expenditures). The frequency of zero investment episodes and the infrequency of negative investment rates are consistent with investment being largely irreversible. Periods of inactivity can also be explained by the presence of fixed components of adjustment costs or with the existence of indivisiblities.

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[5] See the Data Appendix for details on sample selection, variable definitions and construction. The definition of equipment and building investment we use here matches the availability of capital stock data. We have obtained the replacement value of the capital stock using the perpetual inventory method, starting from a benchmark calculated using the fire insurance value available from the Manufacturing Statistics.

[6] Firms are instructed to record investment in equipment at the time of delivery. Investment in buildings is meant to be recorded when the contract is signed for existing buildings, while construction work in the year when it occurs. For multi-year projects, some firms may actually report investment purchases in equipment and buildings at the completion of the project, although it is impossible to assess how widespread the practice is. This would be the figure one actually wants to analyze the non-smoothness of investment orders, instead of expenditure.

[7] Skeweness and Kurtosis tests overwhelmingly reject normality.

Table 1 contains other interesting information concerning the nature of the distribution of investment rates. Investment rates in excess of 20 percent occur only 12 percent of the time for equipment, but they account for more than a third of total real investment expenditure. For buildings, investment rates exceed 20 percent only 5 percent of the times, but these episodes account for more than 50 percent of total investment. The importance of episodes characterized by large investment expenditures, could be potentially suggestive of the relevance of non-convexities in the adjustment cost technology, and will be investigated further below. However, there is another aspect of the distribution that is worth nothing, i.e. that small investment rates are fairly frequent and quantitatively important. Positive investment rates of less than 10 percent represents 50 percent of the observations for equipment and 29 percent for buildings and they account approximately for around a third of total investment in both cases. Further calculations reveal that 31 percent of the observations for equipment are greater than zero but smaller than 0.06, which is the figure we have used for the depreciation rate, and can therefore be characterized as replacement investment. They account for 21 percent of total equipment investment expenditure. One way to rationalize this fact is argue that replacement investment is characterized by very small (virtually zero) adjustment costs and that a fixed components becomes important only for expansion investment. In this case observing small investment rates should not be surprising. Another possible explanation for the frequency and quantitative importance of small investment rates, even in the presence of fixed adjustment costs, could be the fact that time to build and a distribution of delivery dates characterizes many investment projects spanning more than one calendar year. Finally, one may observe episodes of small investment, if there is a convex component of adjustment costs, even in the presence of fixed components.

In Table 2 we investigate further the occurrence of zero investment episodes, distinguishing by type of plant (single plant, main production unit, and secondary production unit in a multi-plant firm) and aggregating up to the firm level. The figures in the table illustrate the general point that the frequency of zero investment depends upon the functional nature of the production unit and upon the level of aggregation (plant versus firm). The intermittent character of investment is particularly pronounced for secondary production units (41 percent and 75 percent of zero observations for equipment and building respectively), which are responsible for between a fifth and a quarter of total investment spending. It is less pronounced for single plants and for the main production unit of multi-plant firms (which account for approximately a quarter and a half respectively of total investment expenditure) and their figures are very similar to the ones obtained aggregating the data up to the firm level. At the firm level, the frequency of zero investment is 6 percent for equipment and 49 percent for buildings. The figure for buildings remains, therefore quite large, while there is reduction of the frequency of zero investment for equipment. This illustrates the fact that aggregating plants into firms masks the importance of zero investment episodes.

Finally, in Table 2 we report the investment rates and the frequency of zero investment for production plants (classified according to their nature) and firms partitioned according to whether the number of employees is less than or greater than a hundred. Independently from the nature of the plant, in all cases smaller units are characterized by more intermittent investment. The same difference exists between small and large firms. Moreover, the differences in the frequency of zero investment are substantial. For equipment investment, for instance, the frequency of zero investment for small main units in multi-plant firms is (roughly) three times larger than for large main units (10 percent versus 3 percent).[8] For small firms it is two times larger than for large firms (9 percent versus 5 percent).

There are several explanations consistent with these results. First, larger plants may be considered as agglomerations of plants of smaller size. In this case non differentiability at zero investment, non convexities and indivisibilities may appear less important because of aggregation within the plant over production lines or production processes. Another possibility is that the fixed component of adjustment cost is relatively more important for small plants.

[8] The difference in the frequency of zero investment episodes according to size is statistically significant and it is robust to controlling for industrial sectors. For instance, if we estimate two separate logit models of the probability of observing zero investment for equipment and buildings as a function of dummies that capture the functional nature of the plant and its size, industry and year dummies, the t ratio on the difference of the coefficients of the size dummies (defined according to whether a unit has more or less than 100 employees) equals 21.35 for equipment and 25.94 for buildings. Detailed results are not reported here for reasons of space, but are contained in a previous version of this paper.

Finally, size is a proxy for access to capital markets. [9] The size of a plant, and even more so the size of a firm, is likely to be correlated, albeit imperfectly, with the existence of asymmetric information problems. In these circumstances internal and external sources of finance are less perfect substitutes for each other and we may observe periods of no investment when internal resources are not available and it is prohibitively expensive to gain access to external funds. However, the latter explanation is put in doubt by the following experiment. If financial constraints are an important reason for zero investments, we expect to find the frequency of zero investments, conditional on plant type and size, to be higher for plants belonging to smaller firms. However, if one calculates these frequencies for multi-plant firms they are quite similar. For instance, they equal 10 percent for small main-plants belonging to small firms, and 9 percent for small main-plants being part of a large firm. We have also split the sample according to criteria correlated with the probability of facing financial constraints (such as age, dividend payout ratio, leverage, whether quoted or not, type of ownership). However, there are no significant differences in the frequencies of zero-investments for those firms most likely to face financial constraints and those who are not, neither for the total sample, or for the separate sub-sample of small or large firms.

Since lumpiness of investment may contain information about the importance of non-convexities in the adjustment cost technology or of indivisibilities, we want to investigate further the importance of episodes characterized by large investment expenditures. In order to assess the degree of lumpiness in more details, we have concentrated on the sub-sample consisting only of those plants with observations in all of the fourteen years.[10]

Following Doms and Dunne (1998), we have ranked the investment rates for each plant (firm) from the lowest (rank 1) to the highest (rank 14). In Table 3 we report the mean investment rate for each rank as well as the shares of total investment it represents. Starting with equipment

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9 On financial constraints see, for instance, Fazzari, Hubbard and Petersen (1988) and the following literature reviewed in Bernanke, Gertler and Gilchrist (1996), Hubbard (1998) and Schiantarelli (1996).

10 The balanced plant level panel contains a total of 362 production units with 5068 total observations. We will also provide results at the balanced firm level sample containing 144 firms and 2016 total observations. Both panels are biased towards larger, healthier, and more successful plants or firms. It is interesting to note that for the balanced plant level panel the frequency of zero observation is smaller than those for the unbalanced panel (18 versus 21 for equipment and 55 versus 61 percent for buildings), but still indicate that episodes of zero investment are an important phenomenon.

investment at the plant level the mean investment rate for observations with rank 14 is 0.61. This is six times higher than the average investment rate and two and a half time the second highest investment rate. In terms of shares, 26 percent of total equipment investment is represented by the investment episodes with rank 14, while 53 percent of total investment in equipment occurs in the three highest ranked episodes. For buildings the average investment rate for observations with the highest rank is 0.41 which is more than ten times greater than the average investment rate and three times greater than the second highest investment rate. Finally, approximately 45 percent of total investment in buildings occurs in the highest ranked episode and 80 percent in the three highest ranked episodes. In Table 3 we also rank investment episodes for firms and for plant of different size. The figures suggest that episodes of large investment are also very important for firms, although the degree of lumpiness is somewhat reduced, confirming that aggregating plants into firms generates a smoother capital adjustment process. Moreover, just as there is evidence that periods of investment inactivity are more frequent for small plants (and firms), there is also evidence that investment is lumpier for smaller units.[11] This result can be easily explained if there is a fixed component of adjustment costs that does not depend upon size, or by the presence of indivisibilities.

How much do large investment episodes contribute to explaining aggregate investment? In order to answer this question we have calculated the aggregate investment rate in equipment as the ratio between total equipment investment and the total capital stock for our balanced sample. We have then regressed it against the frequency of firms experiencing the highest investment spike in each year of the sample. The regression results suggest that the spike frequency variable is positively and significantly (t = 3.09) associated with the aggregate investment rate with a correlation coefficient of 0.67. Also for buildings the frequency of firms experiencing the highest investment spike in a given year is positively (correlation coefficient = 0.86) and significantly (t = 5.78) associated with the aggregate investment rate.

The importance of episodes characterized by large investment expenditures is consistent with several scenarios. For instance investment may simply be a linear function of fundamentals, as

[11] The classification is based on the initial number of employees (fewer or more than a hundred).

implied by a standard model with quadratic adjustment costs, but the distribution of fundamentals is characterized by infrequent large realizations. In other terms, it is necessary to define lumpiness relative to a standard of comparison. However, it is interesting to note that the mean sale to capital ratio associated with the highest ranked investment rate for equipment is only 1.23 times its overall mean value (1.20 times for buildings). This comparison is informative because movements in the sales to capital ratio are likely to be positively correlated with movements in the fundamental determinants of investment. There is, therefore, prima facie evidence that the investment rate appears to respond in a non-linear fashion to changes in fundamentals. Such a response is consistent, prima facie, with the existence of what Dixit and Pindyck (1994) denote as stock fixed costs, i.e. lump-sum costs associated with taking an investment action, such as fixed costs of deciding on and placing an order. With stock fixed costs, a finite instantaneous rate of investment, in the context of a continuous time model, is not optimal and the capital stock can be shown to jump in discrete steps at isolated instants. [12] A non-linear response is generated by the model by Abel and Eberly (1994). They combine flow fixed costs (costs that occur at a given rate at each instant over the interval during which an action is taken) with an asymmetric linear component and a convex component. An important kind of non-linearity comes from the fact that their model implies a range of inaction, such that investment responds to fundamentals only outside this range. Moreover the investment rate is finite also outside the inaction range. Whether the derivative of investment with respect to fundamentals is then (a positive) constant, increasing or decreasing, depends upon the precise nature of the convex component of costs (for instance, the derivative is constant with quadratic adjustment costs). Ultimately, one has to rely on more structured econometric work in order to discriminate between the various interpretations of the investment patterns outlined above.

3. Econometric Evidence on Investment and Adjustment Costs.

[12] See Dixit and Pindyck (1994), p. 383 and following ones. See also Caballero and Leahy (1996) for the implications of stock fixed costs for the break-down of the relationship between investment and marginal q. See Doms and Dunne (1998) for simulation results that support an explanation based on the existence of trigger points different from zero.

In this section we will present two pieces of econometric evidence on the importance of fixed costs and irreversibilities (total or partial) in accounting for the non-smoothness of the investment patterns observed in the micro data. First, as in Cooper, Haltiwanger and Power (1999), we estimate the hazard function describing the probability of episodes of high investment, conditional on the length of the interval from the last episode of high investment, and other controls. We also discuss the macroeconomic implications of our results and their relevance in understanding the fluctuations in the aggregate proportion of firms that experience episodes characterized by large investment expenditures. Second, we abandon the discretization of the problem adopted in the hazard approach and analyze the response of the investment rate to fundamentals in the context of an endogenous switching regression model of investment that captures the essence of the model in Abel and Eberly (1994). Finally, we compare the predicted aggregate investment pattern from a one-regime OLS model and the switching regression model.

3a. The Shape of the Hazard and Fixed Adjustment Costs

The Cooper, Haltiwanger and Power (1999) model of machine replacement allows for indivisibilities, a fixed component of adjustment costs, independent of size, and a component proportional to output that represents the opportunity cost associated with the diversion of resources away from production. The model is developed under the assumption of perfect capital markets. Under the hypothesis of serially correlated exogenous shocks to firms profitability and some additional assumptions, they show that, given the state of the economy, the probability of machine replacement increases as the time since last replacement increases.[13] In other words, the hazard is increasing. With serially correlated shocks and convex adjustment costs, investment should also be

[13] This result holds under some restrictions on the size of the fixed costs and the curvature of the utility function (utility must not be too concave). The different degree of lumpiness between small and large units may provide further information on the nature of adjustment costs. In many contributions the fixed component is assumed to increase with the size of the capital stock, sometimes proportionately as in Caballero and Leahy (1996). This is meant to reflect forgone profits due to the loss of production that is likely to be associated with installation of capital. If this were the only source of non-convexity, it would be difficult to use the shape of the cost function to rationalize our finding that investment is lumpier for smaller plants. However, this results can be easily explained if there is also a fixed component of adjustment costs that does not depend upon size, as in Cooper, Haltiwanger, and Power (1999), or by the presence of indivisibilities.

serially correlated and, therefore, the hazard decreasing. With serially uncorrelated shocks and no adjustment costs, the hazard should be flat.

In modeling the hazard we assume that time is discrete and we denote with T_{ij} the time at which firm i has an investment spike during the j-th spell of zero investment. The hazard rate can the be written as:

$$p_{ijt} = \Pr\left[T_{ij} = t \;\middle|\; T_{ij} \geq t, t-(T_{ij-1}+1), x_{it}\right] \tag{1}$$

where t represents calendar time, $t-(T_{ij-1}+1)$ the interval from the last spike (a zero interval represents the case of two adjacent spikes), and $\boldsymbol{x}_{it}$ a set of additional conditioning variables. We parameterize the hazard as a logistic function and we model the duration dependency in a very flexible way by introducing a set of duration dummies, D_{sit}, equal to one if the interval from the last spike is s=0,1,2, etc.. More precisely:

$$P_{ijt} = \frac{1}{1+\exp\left(-\sum_{s=0}^{S}\gamma_s D_{sit} - \beta' x_{it}\right)} \tag{2}$$

where S denotes the longest spell duration. Notice that given the parameterization in (2) we can drop subscript j, since the D_{sit}, and $\boldsymbol{x}_{it}$ variables summarize all the differences in the hazard across spells (i.e. $P_{ijt} = P_{it}$). Define now dichotomous indicator variable, y_{it}, that equals one if firm i has an investment spike in period t and zero otherwise. Notice that P_{it} denotes the conditional probability that y_{it} equals one. Then it is easy to show that the log-likelihood function can be written as:[14]

$$\log L = \sum_{i=1}^{N}\sum_{t=\underline{t}_i}^{\bar{t}_i}\left[y_{it}\log(P_{it}/(1-P_{it})) + \log(1-P_{it})\right] \tag{3}$$

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14 See Allison (1982), for instance.

where $\underline{t}_i$ and $\bar{t}_i$ denote respectively the first and last year for which firm s i observations can be used for estimation. In other terms, we have observed firm s i first spike at time $\underline{t}_i - 1$. The form of the log-likelihood implies that if firm specific effects are absent and if we treat the initial conditions as fixed constants, the parameters can be estimated using the standard maximization routines for binary logit models. In a first specification, we have included in the vector $\boldsymbol{x}_{it}$, year dummies, sector dummies, initial size dummies (according to whether the firm has more or less than 100 employees), dummies that capture whether a plant belongs to a multi-plant firm or not, and dummies that capture the nature of the plant (main or secondary) in multi-plant firms. Finally, we have included the age of the plant at the beginning of the first spike, and a set of dummies to capture the year in which the first spike occurs. The inclusion of this ample menu of variables is meant to reduce the risk that the estimates of the duration dependence parameters, $\_{s}$, may be contaminated by unobserved heterogeneity, resulting in negative duration dependence, when in fact there is positive duration dependence (the conditional probability of an investment spike increases the longer the interval from last spike).

However, since this risk cannot be eliminated we have also estimated the model allowing for firm specific constants (in addition to year and duration dummies and age at the first spike). As it is well known, the parameter estimates are consistent only when the number of time series observations is large enough to allow for a large number of switches between spike and non-spike episodes (the incidental parameters problem). Whether or not these conditions are satisfied for our sample will be discussed below.

Because of the problems associated with the fixed effect logit estimator, we have also applied the approach proposed by Heckman and Singer (1984), in which a random firm specific effect is included in the hazard. Rather than parametrizing its distribution, they then assume that it is discrete, with a small number of mass points. Continuing to treat the initial conditions as fixed, the log likelihood function can be written as:

$$\log L = \sum_{i=1}^{N} \log \sum_{v=1}^{M} pr_v \prod_{t=\underline{t}_i}^{\bar{t}_i} P_{itv}^{y_{it}} (1 - P_{itv}^{(1-y_{it})}) \tag{4}$$

where $P_{itv} = \left[1 + \exp\left(-\sum_{s=0}^{S} \gamma_s D_{sit} - \beta' x_{it} - c_v\right)\right]^{-1}$, with c_v denoting the random effect ($v = 1, ..., M$), and pr_v the associated probability.[15] In order to estimate the model we must define what is meant by an investment spike. We will use two definitions of spikes: 1) an absolute spike, when the investment rate exceeds 20 percent; 2) a relative spike when the investment rate exceeds 2.5 the median investment rate for each plant and it is greater than the depreciation rate (set at 6 percent for equipment and 2 percent for buildings).[16] The model is estimated separately for equipment and buildings for the unbalanced panel of production plants.

In Table 4a we report the results for equipment, starting from the OLS estimates of a model in which y_{it} is regressed only on the set of duration dummies (duration 0 denotes consecutive spikes, duration 1 a one year interval between spikes, etc.). This yields the standard Kaplan-Meier non-parametric estimate of the hazard for the entire panel. The Kaplan-Meier estimator suggests that the hazard is the highest for both equipment and building and for all the spike definitions in the period immediately following a spike and then declines sharply in the following period. After that there are fluctuations around a pretty flat trend for the absolute spike definition, and a slight upward trend after four years have passed since the last spike for the relative spike definition. However, the probability of a spike remains substantially lower, even for the longest duration, than the value attained in a period immediately adjacent to a spike. Note, finally, that Kaplan-Meier estimate of the hazard is consistent only if there is no (temporal or firm specific) heterogeneity in the sample.

The second set of results reported in Table 4a are the estimates obtained from the logit model that controls for time, sector, and other firm specific characteristics. Only the coefficients for the duration dummies are reported for brevity sake. Duration 0, meaning that two spikes occur in

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[15] See Dustman and Windmeijer (1997) for an application of the Heckman and Singer (1984) approach to the case of a logistic hazard. We are grateful to Frank Windmeijer for making his computer program available to us.

[16] With this formulation we avoid classifying as a spike, for those firms that have a zero or very small median value of the investment rate, episodes in which investment is less than depreciation.

adjacent periods, is used as the reference case in estimation so that now the duration i dummies (i = 1,.., 9 plus) represent deviations from this case. For all definitions of spikes also in this case the hazard is the highest in the period immediately following a spike and it falls sharply after that. It then remains relatively flat, using the absolute spike definition, while the hazard eventually rises after an initial fall, using the relative spike definition. The interesting difference relative to the Kaplan-Meier estimates is that the coefficients of duration 8 or higher is not significantly different from zero with the relative spike definition. This implies that the probability of having a spike at the longest durations is not significantly different from the value it had in the year immediately following a spike. In Table 5 we report the conditional probability of a relative spike for the worst recession year, 1983, and for the year of greatest expansion, 1986.[17] As implied by the duration dummies coefficients, the conditional transition probability first falls, then it gradually flattens out and finally starts rising after four years from the last spike. The swings are quite large in years of expansion. For instance, the probability of an investment spike in 1986 is 39.7 percent in the year immediately following a spike. It then falls to 22.1 percent at duration 1 and it reaches a minimum value of 18.6 percent at duration 3. It then increases up to 39.9 percent at duration 9 or higher. The pattern is the same in recessions years, but less pronounced (transition probabilities fluctuate between 11.7 and 5.3 percent). Summarizing, the conditional transition probability for the relative spike definition displays an overall U shape (or a J shape, after the drop from duration 0 to duration 1), that is more pronounced during booms and less pronounced during contractions.

The third set of results in Table 4a are obtained from the estimation of the logit models with fixed effects. These have been obtained by estimating the unconditional likelihood function allowing for firm specific constants, in addition to the duration and year dummies.[18] When we allow for firm specific fixed effects, we still find evidence that the probability of observing another investment spike is high immediately after an episode of large investment expenditure. However, contrary to the

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[17] We have also assumed that the plant is the main plant of a multi-plant firm in the metal and engineering sector, with median size and age.

[18] The use of the standard conditional logit model (Chamberlain (1980, 1983) is not appropriate in this case, due to the presence among the regressors of variables that represent the timing of the realization of an investment spikes in the past (see Card and Sullivan (1988)).

previous results, now the hazard increases rather quickly for both spike definitions, the increase is monotonic in all cases but one, and it very significant. Moreover, generally the conditional probability of an investment spike rises quickly beyond the value attained in the period immediately after a spike.

However, we must treat these latter results with caution because of the incidental parameters problem. In our unbalanced panel the number of observations ranges between two and thirteen. 64 percent of the observations belong to firms with eight or more years of observations, and 38 percent to firms with eleven or more years of observations. It is not clear a priori whether or not this time span and the variation in y_{it} that occurs during it is enough to render the small sample bias problem unimportant. However, a set of Monte Carlo experiments we have conducted suggests that the fixed effect logit leads to a substantial overestimate of the slope of the hazard, to the point that even if the true hazard is flat, the estimated hazard would appear significantly upward sloping.[19]

Note that in order to be included in the sample used to estimate the fixed effects model a firm must have had at least two spikes (an initial one to start the dating of the duration dummies and another one during the estimation period). We present in Table 4a also the results obtained by applying the standard logit estimator (without fixed effects) to this smaller sample. Now for both spike definitions, the hazard displays an overall U shape, with the conditional probability of a spike rising, respectively, after five or three years since the last spike. Moreover, at the longer durations, the conditional probability of a spike rises significantly above its value in the year immediately following a spike. One caveat about these results is that they may be affected by sample selection problems. By including in the sample firms that have experienced at least two spikes, we have indeed selected a group for which lumpiness may indeed be more important.

The last set of results presented in Table 4a has been obtained by applying the random effect with mass points approach by Heckman and Singer (1984a,b) to the larger sample. After some

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[19] In the first experiment we have assumed that the estimates we have obtained from the fixed effects logit constitute the true model. Two hundred replications suggest that the coefficients of the duration dummies are overestimated and that the bias increases at longer durations. If in each replication the firm specific constants are not re-estimated, the bias virtually disappears. This means that it is indeed the estimation of the large number of incidental parameters that causes the problem. In the final experiment we have assumed that the hazard is flat and we have used the other parameters estimated by the logit fixed effects as the true ones. The researcher would have concluded that the hazard was, on average, significantly upward sloping. Details of the experiments are reported in

experimentation we have allowed for three mass points for the absolute spike definition and two mass points for the relative spike definition. Again, we treat the initial conditions as fixed. For the absolute spike definition the slope the hazard is greater in this case compared to the one obtained applying the standard logit to the same sample. However this differences does not lead to substantially different conclusions. For the relative spike definition, the estimate of the coefficients of the duration dummies are identical to the results obtained using the standard logit model up to the third figure after the decimal point. Results do not change if we allow for a larger number of mass points (up to four). In general, it appears that the firm level characteristics we have included as regressors do a good job in controlling for heterogeneity. Moreover, defining the spike in relation to each individual firm s overall experience, further reduces the importance of unobserved heterogeneity.

As a final experiment, we have investigated whether the slope of the hazard differs between small and large firms. However, the χ^2 test on the joint significance of the duration dummies interacted with a dummy that equals one if the plant is small suggests that the difference is not significant even at the 10 percent level, independently form the spike definition used. The lumpier nature of investment for small firms may be associated with a greater excess sensitivity of small firms to the availability of internal sources of finance. In order to test for the role played by financial factors, we have added as an explanatory variable in the hazard model firm level cash flow (divided by the capital stock) and cash flow interacted with a dummy that equals one if the firm (not the plant) is small.[20] Note that it is appropriate to examine the role played by the availability of internal resources at the firm, not at the plant level. Although we do not report the results in full details, it is important to note that the cash flow coefficient is positive and significant (for instance, it is equal to 0.76 with a t ratio equal to 3.04 using the absolute spike definition), but there is no significant difference between plants belonging to small or large firms.[21] This evidence suggests that the

the appendix of the 1998 version of this paper.

[20] Cash flow is defined as pre-tax profits before year end adjustments, plus depreciation, minus taxes, minus profits on disposal of fixed assets (net of losses). This exercise is in the spirit of Fazzari, Hubbard, and Petersen (1988).

[21] The conclusions reached before concerning the shape of the hazard still hold. If we also add the plant level current and lagged sales to capital ratio to the set of explanatory variables, the former has a positive effect on the probability of observing an investment spike. At the same time the conclusions concerning the role of cash flow are not altered.

different degree of lumpiness in investment between small and large firms is not likely to be related to the existence of financial constraints.

If we discount the fixed effect results and the logit results for the smaller sample, we must conclude that the evidence that the hazard for equipment investment is eventually upward sloping is mixed. The econometric results from the standard logit model suggest that, at least for the relative spike definition, there is evidence that the hazard has an overall U shape and it is actually J shaped after the initial fall from duration 0 to duration 1. This can be interpreted as evidence in favor of the presence of a fixed component of adjustment costs that eventually becomes dominant. The high value of the hazard in the period immediately following a spike continues to be consistent with the fact that several investment projects may give rise to expenditures that are spread over many months, belonging to different years. It is also consistent with a model of investment in which there are convex components to adjustment costs. The presence of convex costs may also explain why the hazard continues to decrease mildly before turning upward.[22] These results should be compared with those in Cooper, Haltiwanger and Power (1999), where they allow for unobserved heterogeneity using the mass point approach, but with a different specification of the hazard (see Meyer (1990)). They conclude that the hazard increases steadily and substantially immediately after the initial drop from duration 0 to duration 1 for a large fraction of plants. In our case, for the relative spike definition, the hazard is instead J shaped from duration 1 onward. In both cases, the fact that the hazard slopes upward implies that fixed costs are important. The fact that it takes longer in our case, suggest that the issue of convex components in adjustment costs should be further investigated.

The results for buildings strengthen the case of the importance of fixed components in adjustment costs (see Table 4b). Even if one discounts, the fixed effects results (indicating a strongly upward sloping hazard after the period adjacent to a spike) for the incidental parameters problem, the standard logit results for both the absolute and relative spikes definition do suggest a U shaped hazard. The mass point results coincide with those for the standard logit model, confirming that not much is gained from allowing a discrete distribution for the constant term.

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[22] The evidence in Abel and Eberly (1999), Eberly (1997), and Goolsbee and Gross (1997) is consistent with the presence of convex components of adjustment costs, when the firm adjusts.

A different issue of great importance is the whether the hazard rate is pro- or counter-cyclical. In all the models, the estimate of the year dummies coefficients suggest that the probability of an investment spike increases significantly in booms and decreases in recessions. For instance, the correlation coefficient between the rate of growth in manufacturing GDP and the year dummies coefficients in the standard logit model for equipment, with the high spike definition, is 0.67 (t = 2.9). Moreover, the results reported in Table 5 on the conditional transition probabilities for 1983 and 1986 show that the probability of an episode characterized by large investment expenditures is substantially higher in booms, compared to recessions. This is true at all durations. We know, from a theoretical point of view, that there are two contrasting forces at work here. On the one hand, firms would want to replace machines at times when the opportunity cost of lost output is small. On the other hand, they would also want to introduce new machines when returns are high. Empirically, the latter factor dominates.

How important are non-convexities in understanding aggregate investment fluctuations? More specifically, is there a gain in taking into account of the interaction between macro shocks and the distribution across firms of the length of the interval since the last investment spike? For the logit model based on the absolute spike definition, there is not going to be much gain beyond that generated by the fact that the hazard is definitely higher in the period immediately adjacent a spike. This is because, after duration zero, the hazard is relatively flat. Changes in the cross sectional distribution may play a bigger role in the logit model based on the relative spike definition, since in that case we have found empirical support for a U shaped hazard. We, therefore, focus on the macro implications of this model.

In the context of the Cooper, Haltiwanger and Power (1999) model of discrete investment, the behavior of aggregate investment is represented by the aggregate proportion of plants experiencing an investment spike (that can be thought, at each point in time, as the product of the hazard times the frequency of firms with a given duration, summed over all possible durations). One way to address this question is to conduct a dynamic simulation of the estimated model at the level of each firm, and to construct three simulated measures of the aggregate frequency of spikes.[23] The

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[23] The simulation works as follows. For each firm we have used the estimated year and duration parameters obtained

first one allows for both year and duration effects; the second one only for year effects; the third one only for duration effects. The ability of these three measures to track the actual aggregate proportion of firms experiencing a spike will then be compared.

In Figure 2 we report the results obtained for the standard logit hazard model for equipment of Table 4a, using the relative spike definition, and one drawing per firm. In the Figure, f1 represents the estimated frequency based on the full model, allowing for the consequences of both common macro shocks and changes in the distribution of interval lengths. f2 represents the frequency obtained when the duration parameters are set to zero, and, for this reason, can be seen as being generated by a model that allows for common macro shocks, but assumes a flat hazard. f3 is the frequency obtained when the coefficients of the year dummies are set to zero and all the action comes from changes in distribution of delivery dates. We also plot the actual frequency based on the sample of 6609 observation used in estimation of the conditional logit model.

Several features of the results are worth noting. First, f2 provides quite a good fit for the aggregate proportion of firms experiencing an investment spike and adequately captures the main turning points in the series. This means that common macro shocks play the major role in explaining fluctuations in the observed aggregate frequency of investment spikes. However, allowing for changes in the cross sectional distribution of dates since last adjustment improves somewhat the ability of the model to track the aggregate proportion data. For instance the correlation coefficient between the simulated and actual aggregate proportion increases from 0.853 to 0.959. In conclusion, while there are interesting cyclical movements in the cross sectional distribution, they are small compared to the fluctuations generated by common macro shocks. Our conclusion concerning the dominant role of aggregate shocks are consistent with those reached by Cooper, Haltiwanger and

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from the standard logit model, to calculate the estimated hazard rate for the first year the firm appears in the sample used for estimation. For this first observations we use the information that the spike occurred in the previous period. We then have drawn a random number from a uniform distribution between zero and one. If this number falls short of (exceeds) the estimated hazard rate, then we define the observation as an investment spike (non-spike). We then repeat the process for the following years, using the simulated length of the interval from the last spike to calculate the hazard. We have experimented taking either one set of drawings per firm or up to fifty drawings. In both cases, we then calculate for each year the aggregate frequency of investment spikes. The results suggest that using one or more drawing for each firm makes no difference to the overall conclusions.

Power (1999), although they emphasize that changes in the cross-sectional distribution may be important at particular times. [24]

3b. A Switching Regression Model of Investment

The main limitation of the hazard approach used in the previous sub-section is that investment decisions have been modeled as a discrete process (either an investment spike occurs or it does not). This abstract from the fact that firms not only decide whether they should invest, but outside the inaction range, decides also how much to invest. Moreover it introduces a degree of arbitrariness in deciding what constitutes an investment spike. In this section we will develop a switching regression model, in which the response of investment to fundamentals differ according to the regime firms are in.[25]

The theoretical model by Abel and Eberly (1994) suggests that, in the presence of fixed costs and partial irreversibilities, the firm may find itself in one of three regimes. More specifically, there exists a range of value of the shadow value of capital, q, for which the firm will follow a policy of zero investment. Above this range the firm will have positive investment, while negative investment will occur below it. In both cases investment will be an increasing function of it shadow value (the relationship may differ for positive or negative investment). As we have already explained in Section 2, there are very few observation with negative investment for equipment investment, rendering virtually impossible to estimate a three-regime model. For this reason we will estimate a two-regime model (a "high" and "low" q regime). In the high q regime we expect the firms to respond more to changes in fundamentals. In the low q regime we do not impose that investment does not respond at all, but we would expect a weaker response to changes in fundamental. We do not impose a zero response because there may be some small investment, particularly of a replacement nature, that may have fairly costless to adjust. The econometrician does not observe in which regime the plant is in, but can estimate the probability

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[24] Thomas (1999) and Khan and Thomas (2000), in the context of an equilibrium business cycle model with non-convex adjustment costs, argue that the contribution of distributional changes to the aggregate business cycle is small, once one takes into account of equilibrium price movements.

[25] See also Letterie and Pfann (2000) for related work.

of each regime occurring. More precisely, the estimated model is:

$$
\begin{aligned}
\frac{I_{it}}{K_{it-1}} &= g(q_{it}) + u_{1it} \qquad if \qquad \gamma q_{it} - c - \varepsilon_{it} > 0 \\
\frac{I_{it}}{K_{it-1}} &= h(q_{it}) + u_{2it} \qquad if \qquad \gamma q_{it} - c - \varepsilon_{it} \leq 0
\end{aligned}
\tag{5}
$$

q_{it} denotes various proxies for the shadow value of capital. $g(q_{it})$ and $h(q_{it})$ are either linear or quadratic functions. We expect $g(q_{it})$ to be greater than $h(q_{it})$. Moreover $\begin{pmatrix} u_1 \\ u_2 \\ \varepsilon \end{pmatrix} \sim N(0, \Sigma)$, and

$$
\Sigma = \begin{pmatrix} \sigma_{11}^2 & \sigma_{12} & \sigma_{1\varepsilon} \\ \sigma_{21} & \sigma_{22}^2 & \sigma_{2\varepsilon} \\ \sigma_{\varepsilon 1} & \sigma_{\varepsilon 2} & 1 \end{pmatrix}.
$$

Most of the results presented below are, we assume that obtained under the additional simplifying assumption that the error terms in the investment function are not correlated with those in the switching function ($\sigma_{1\varepsilon} = \sigma_{2\varepsilon} = 0$). However we also present a set of results in which convergence has been obtained for the more general model. The likelihood function for each observations, under the $\sigma_{1\varepsilon} = \sigma_{2\varepsilon} = 0$ assumption is:

$$
\begin{aligned}
l_{it} &= \frac{1}{\sigma_{11}} \phi\left(\frac{1}{\sigma_{11}}\left(\frac{I_{it}}{K_{it-1}} - g(q_{it})\right)\right) \Phi(\gamma q_{it} - c) \\
&+ \frac{1}{\sigma_{22}} \phi\left(\frac{1}{\sigma_{22}}\left(\frac{I_{it}}{K_{it-1}} - h(q_{it})\right)\right) \left(1 - \Phi(\gamma q_{it} - c)\right)
\end{aligned}
\tag{6}
$$

where $\phi(\;)$ and $\Phi(\;)$ are the normal density and the cumulative distribution functions. When $\sigma_{1\varepsilon}$ and $\sigma_{2\varepsilon}$ are allowed to differ from zero, the likelihood of each observation becomes:

$$l_{it} = \frac{1}{\sigma_{11}}\phi\left(\frac{1}{\sigma_{11}}\left(\frac{I_{it}}{K_{it-1}} - g(q_{it})\right)\right)\Phi\left(\frac{\gamma q_{it} - c - \frac{\rho_1}{\sigma_{11}}\left(\frac{I_{it}}{K_{it-1}} - g(q_{it})\right)}{\left(1-\rho_1^2\right)^{1/2}}\right)$$

$$+\frac{1}{\sigma_{22}}\phi\left(\frac{1}{\sigma_{22}}\left(\frac{I_{it}}{K_{it-1}} - h(q_{it})\right)\right)\left(1-\Phi\left(\frac{\gamma q_{it} - c - \frac{\rho_2}{\sigma_{22}}\left(\frac{I_{it}}{K_{it-1}} - h(q_{it})\right)}{\left(1-\rho_2^2\right)^{1/2}}\right)\right) \tag{7}$$

where $\rho_1 = \frac{\sigma_{1\varepsilon}}{\sigma_{11}}$ and $\rho_2 = \frac{\sigma_{2\varepsilon}}{\sigma_{22}}$. The likelihood function for the entire sample is:

$$L = \sum_{i=1}^{N}\sum_{t=1}^{T_i} \log(l_{it}) \tag{8}$$

Due to the computational complexity of the model, we concentrate on equipment investment, which is by far the most important component (constituting two thirds of total investment). Although it would be desirable, it is practically impossible to control for plant specific-time invariant effects in the investment equations and in the switching function. However, we will include in all three of them, industry dummies, time dummies, a dummy to distinguish single plants from multi-plants, a dummy to distinguish main from secondary plants and a dummy to distinguish small from large plants (on the basis of initial employment being smaller or greater than one hundred employees). All three equations include also time dummies that capture, among other things, changes in the real price of investment goods.

In modeling the shadow value of capital, q_{it} , we have assumed that firms have information only up to time *t*-1, in order to minimizes endogeneity problems. Note that most firms are not quoted on the stock market in Norway, so that one cannot use the market value of the firm in constructing a proxy for marginal *q*. Moreover, we are using plant level data containing a sizeable fraction of establishments belonging to multi-plant firms, for whom it is not clear anyway how firm level stock market valuations should be used. Given these considerations we have experimented with four different proxies for q_{it} . We start with either once lagged values of the operating profit rate, π/K (see the results reported in columns (1) and (3) of Table 6), or of the sales to capital ratio, S/K (columns (2) and (4)). The former is legitimate approximation to the shadow value of capital under the assumption of perfect competition, constant returns to scale and firms using only once lagged information on the profit rate to forecast future profitability. The latter can be shown to be proportional to the marginal q under the assumption of a Cobb-Douglas production function, imperfect competition, and the information set including only one lag on the sales to capital ratio. We then expand the information set available to firms and assume that they use two lags of both the profit and sales to capital ration to forecast their future value in a bivariate VAR context and compute the present discounted value of either the profit rate, qπ (column (5)) or the of the sales to capital ratio, qS (columns (6) and (7)).[26] Finally we allow the investment response in each regime to be non-linear by adding a quadratic term to the specification.

The most important conclusion that can be drawn from the results reported in Table 6 is that, independently from the proxy for q_{it} used in estimation, investment reacts differently to fundamentals in the two regimes. More specifically, when fundamentals are high the response is larger than when fundamentals are low. For instance, when the lagged profit rate is used as a proxy (see column (1)), and the correlation coefficients are set to zero, the coefficients of q_{it} are respectively .082 and .026. In all cases the coefficients are statistically different, using a likelihood ratio test, at the one percent significance level.[27] This result is quite important, because it is in line with the basic predictions of the Abel and Eberly (1994, 1999) model, even without having to introduce additional considerations about the heterogeneity of investment goods. The availability

[26] See Abel and Blanchard (1986) and Gilchrist and Himmelberg (1995) and (1998) for a discussion. The last two papers apply the approach to firm level data, while the first paper contains an application to aggregate data.

[27] See Goldfeld and Quandt (1976) on why using the χ^2 distribution and standard degrees of freedom yields a test that favors non rejection of the null, even if the likelihood ratio test may not have a χ distribution in the switching regression case.

of plant level data for different categories of investment is a possible explanation as to why we are able to get fairly sharp results that had eluded some of the previous researchers. For instance, that in a multiple regime model, Barnett and Sakellaris (1998) find that the high q_{it} regime is characterized by lower, not higher response of investment to fundamentals.[28] In columns (3) through (7) we have added a quadratic term to the investment function, and we find evidence that, especially in the high q_{it} regime, the derivative of investment with respect to q_{it} is positive, but decreasing, i.e. the $g(q_{it})$ function is concave. It remains true that at any observed value of q_{it}, the response remains higher in the high q_{it} regime. Another important result that is consistent with the descriptive evidence is the fact that the threshold value of q_{it} at which there is a switch to the high response regime is higher for smaller firm (judging from the coefficient on the dummy for initial employment, not reported in the table).

Whereas all the results in columns (1) through (6) are obtained under the restriction that the correlation coefficient between the errors in the investment equation and the one in the switching function equals zero, in column (7) we relax this restriction for the model that assumes that fundamentals are proportional to the present discounted value of the sales to capital ratio, based on a bivariate VAR for the sale to capital ratio and the profit rate. Our basic conclusions still hold, and are actually strengthened, since now the response of investment to fundamentals increases, particularly in the high q regime. There is a problem, however with the results in column (7) in that the estimated correlation coefficient between the error term in the high q_{it} regime and the one in the switching function, ρ_1, is very close to one in absolute value (the estimate of ρ_2 equals instead .295), suggesting that in effect they are the same error term, and hence that the likelihood function should, perhaps, be modified.[29]

Finally we want to address the aggregate implications of our results. Again we are interested in the importance of the irreversibilities and non-convexities in understanding aggregate investment fluctuations. In the context of our switching regression model, we will ask the question

[28] Note that their estimation method does not allow for random shocks in the switching function.

[29] Although this issue is worth of future investigation, it is comforting that our conclusions hold across different specifications.

whether we can explain the aggregate investment rate better if we allow for a two-regime model instead of a two-regime model. We use our model to calculate expected investment for each firm in each year (the expected value of the investment rate in each regime times the probability of each regime occurring, evaluated at our parameter estimates). We then calculate the expected aggregate investment rate in each year as the sum of the expect investment rate for each firm weighted by the firm capital stock relative to the total. We repeat the same calculation for a model estimated by OLS on all the observations, and we plot the two fitted series together with actual aggregate investment in Figure 3. Both fitted series track aggregate investment fairly well. The series based on the two-regime model is only very marginally more closely associated to the actual series (the correlation coefficient between actual on fitted aggregate investment is .96 when the latter is based on the switching regression model and .95 when it is based on the OLS model). In Figure 3 we also plot the average ex post probability of being in the high q_{it} regime obtained from the switching regression model. The average ex post probability also tracks the movements in actual investment rates quite well. [30]

4. Conclusions

The descriptive evidence we have discussed implies that the occurrence of zero investment episodes at the plant level is a very important phenomenon both for equipment and buildings, and particularly for the latter. Moreover, the proportion of observations characterized by negative investment rates is very small. Aggregating across investment goods and, even more importantly, across plants masks the importance of periods of inactivity. At the plant level there is evidence that few episodes characterized by large investment account for a large fraction of total investment

The descriptive evidence at the plant level is consistent with the existence of disinvestment costs (leading to irreversibility, partial or total), non-convexities and indivisibilities.

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[30] The ex post probability takes into account of information about investment. See, for instance, Hu and Schiantarelli (1998), eq. (8), for details.

The existence of a large fraction of observations characterized by small investment rates may raise some questions. However, if we assume that adjustment costs for replacement investment are very small, and fixed components become relevant only for expansion investment, one should not be surprised to observe small positive investment rates. Moreover, the observation of frequent small investments may be the result of time to build and of the distribution of delivery lags across calendar years. Finally, it may also suggest that the adjustment cost function also includes convex components, together with the fixed components.

Another result of great interest is that the frequency of zero investment (and lumpiness) varies substantially across plants and firms of different sizes. In particular, small plants or firms are characterized by a much higher incidence of zero investment expenditure. This can be explained by the existence of fixed costs that do not vary with a firm's size, and/or with the existence of indivisibilities . These differences are also consistent, in principle, with the existence of financial constraints, the severity of which is greater for smaller firms. However, the evidence suggests that the latter is not the most likely explanation.

The econometric results allow us to sharpen our assessment about the importance of irreversibilities and non-convexities. As far as the shape of the hazard for equipment investment is concerned, the results obtained from a menu of discrete time duration models suggest that for equipment investment, the hazard, after an initial fall, is either fairly flat, using the absolute spike definition or U shaped (J shaped after an initial drop), using the relative spike definition. For buildings, there is more evidence of an increasing hazard, after the initial drop, regardless of the spike definition used. The fact that, at least with one of the spike definitions for equipment and always for buildings, the hazard slopes upward at longer durations is consistent with the presence of fixed costs that eventually dominate. The high value of the hazard in the period immediately following a spike can be explained by the fact that several investment projects may give rise to expenditures that are spread over many months, belonging to different years. It is also consistent with a model of investment in which there are convex components to adjustment costs. The presence of convex costs may also rationalize why the hazard continues to decrease for a while before turning upward.

The hazard approach adopts a discretization of the data that is, in some degree, arbitrary and, in any case, is likely to lead to a loss of information. The switching regression approach allows us to take into account jointly of the discrete-continuous nature of investment choices. The estimation results suggest that equipment investment respond to fundamentals differently, depending upon the value of fundamentals themselves. In particular the response is close to zero for low values of fundamentals, but it increases sharply above a stochastic threshold. This is quite supportive of a generalized adjustment cost function that combines fixed costs, irreversibilities and convex adjustment costs, as in Abel and Eberly (1994).

What are the aggregate implications of our results? Simulation results for the hazard model for equipment investment, using the relative spike definition, suggests that business cycle shocks common to all firms play the crucial role in explaining the aggregate proportion of investment spikes. Changes over time in the cross-sectional distribution of the interval since the last high investment episode help in explaining such fluctuations, but their contribution is small, relative to the one of common macro shocks. Similarly, using the switching regression model, there is only a miniscule improvement in explaining aggregate investment, when one uses a two-regime model at the level of the firm. In conclusion, the descriptive statistics and the econometric results provide ample evidence in support of the importance of irreversibilities and non-convexities at the micro level. However, the gains generated by these departures from standard investment models in explaining aggregate investment are small at best.

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DATA APPENDIX[31]

1. Criteria for Sample Selection

Firms with more than 50 percent of the equity owned by the central or local governments have been excluded from the sample, as well as observations reported as copied from previous year . This expression means that the information was missing. In an attempt to eliminate plants whose capital stock has a negligible role in production, we deleted observations where the calculated replacement value of equipment and/or buildings was less than 200,000 NOK (1980).[32] We have also deleted plants for which production was zero (or negative) and there were no other plants within the firms with positive production. Finally, we only used plants for which four or more consecutive observations were available. There were 5,280 different plants in the initial sample. Our final sample contains 1866 production units for which there are no missing years and for which the number of consecutive observations is greater or equal to four. The total number of plant-year observations in the final sample is 22067 plant-year observations (18043 for production units only). The firm level panel contains 1252 firms for a total of 10730 observations. In the balanced plant level panel for production units we have 362 plants with a total of 5068 observations. The balanced firm level sample includes 144 firms with a total of 2016 firm-year observations.

2. Variable Definition and Construction [33]

Investment (I_t^j): Real (fixed price) investment at time t in type j of capital equals purchases minus sales (dismissals) of fixed capital. Our definition of investment in equipment includes machinery, office furniture, fittings and fixtures, and other transport equipment, excluding cars and trucks (using the codes in Manufacturing Statistics, [501]+[521]+[531]-[641]-[661]-[671]).[34] Data for buildings, in addition to those directly used for production, include also offices, and inventory storage buildings ([561]-[601]). We will call the aggregate of these three categories buildings used for production. Vehicles include cars and trucks ([511]-[651]). Other fixed assets include housing for employees, building for spare-time activities, sites and property ([541]+[551]+[571]+[581]-[681]-[691]-[711]-[721]).

Replacement value of capital stock ($PI_t^j K_t^j$): The replacement value of capital is calculated separately for equipment and buildings using the perpetual inventory formula

$$PI_t^J K_t^J = PI_{t-1}^J K_{t-1}^J \; ?\left(1-\delta^J\right)?\left(1+\Pi_t^J\right) + PI_t^J I_t^J$$

[31] See also Halvorsen et al (1991) for further details.

[32] Approximately 30,000 US$.

[33] See also Halvorsen et al. (1991).

[34] Other transport equipment includes railroads internal to the plant, funiculars, transport cranes, conveyer belts, etc.

where superscript j indicates the different types of capital. PI^j_t denotes the price of investment goods (from the Norwegian national accounts) and _ ^j_t the corresponding inflation rates between t-1 and t. The depreciation rates, _ ^{j}, are also taken from the Norwegian National Accounts (0.06 and 0.02 for equipment and buildings, respectively). In the calculation of the replacement value of capital we use the fire insurance value of the capital stock. This variable is available only for the sum of machinery, fixtures and fittings, and other means of transport, one the one hand, and for buildings used for production, on the other. For each of these types of capital we use the first reported fire insurance value ([871] and [881] for equipment and buildings, respectively) greater than or equal to 200,000 NOK in 1980 prices as a bench-mark. From these initial values we calculate the replacement value backwards and forwards, using the investment figures.[35]

Investment rate (I^j_t/K^j_{t-1}): The investment rate for equipment and buildings is calculated by normalizing real investment in year t by the real replacement value of the capital stock in the beginning of the year.

[35] If the replacement value of capital became negative, it was set equal to zero. When calculating the capital stock forward it may happen that the replacement value becomes negative because of large sales of capital goods. When calculating it backwards the replacement value becomes negative if the net purchase of fixed capital is larger than the replacement value in year $t+1$.

Table 1. Distribution of investment rates (plant level, unbalanced panel)

Investment rates	Equipment # obs.	Equipment percent	Equipment share	Buildings # obs.	Buildings percent	Buildings share	Equipment+Buildings # obs.	Equipment+Buildings percent	Equipment+Buildings share
< 0	385	2%	-0.018	329	2%	-0.093	457	3%	-0.030
$= 0$	3788	21%	0.000	11062	61%	0.000	3637	20%	0.000
$0 < \ < 0.05$	5993	33%	0.159	4265	24%	0.180	8752	49%	0.261
$0.05 \leq \ < 0.10$	3092	17%	0.215	825	5%	0.155	2649	15%	0.247
$0.10 \leq \ < 0.20$	2650	15%	0.264	659	4%	0.196	1520	8%	0.240
$0.20 \leq \ < 0.30$	955	5%	0.121	291	2%	0.128	434	2%	0.105
$0.30 \leq$	1180	7%	0.258	612	3%	0.434	594	3%	0.177
Total	18043	100%	1.000	18043	100%	1.000	18043	100%	1.000

Notes: Percent refers to the frequency of observations in each interval. Share refers to the ratio of real investment in each interval to total real investment (net of assets sales)

Table 2. Frequency of zero investment and investment shares by plant type and size

	All plants					Small			Large		
	Nbr. of	**Equipment**		**Buildings**		**Nbr. of**	**Equip.**	**Build.**	**Nbr. of**	**Equip.**	**Build.**
	obs.	**freq.**	**share**	**freq.**	**share**	**obs.**	**freq.**	**freq.**	**obs.**	**freq.**	**freq.**
All prod. plants	18043	21 %		61 %		11688	29%	70%	6355	7%	45%
Single	4489	7 %	0.200	55 %	0.221	2608	9%	62%	1881	5%	47%
Multi	13554	26 %		63 %		9080	34%	73%	4474	7%	44%
Main	6105	6 %	0.559	49 %	0.576	2961	10%	59%	3144	3%	39%
Second	7449	41 %	0.241	75 %	0.203	6119	46%	80%	1330	18%	54%
Firms	10730	6%		49%		4768	9%	60%	5962	4%	40%

Notes: Share refers to the ratio of real investment for each type of plant to total real investment (net of assets sales)

Table 3. Lumpiness of investment: mean of ranked investment rates (balanced panel)

	All Plants		All Firms		Small Plants		Large Plants	
Equipment	I/K (t)	share	I/K (t)	share	I/K (t)	share	I/K (t)	share
1	-0.010	0.00	0.002	0.02	-0.020	-0.00	-0.004	0.00
2	0.015	0.02	0.023	0.03	0.011	0.00	0.018	0.02
3	0.020	0.02	0.030	0.03	0.015	0.01	0.025	0.02
4	0.025	0.03	0.041	0.03	0.018	0.02	0.034	0.03
5	0.031	0.03	0.047	0.04	0.024	0.03	0.040	0.04
6	0.035	0.04	0.052	0.05	0.025	0.03	0.047	0.04
7	0.045	0.05	0.066	0.05	0.040	0.04	0.051	0.05
8	0.035	0.05	0.076	0.06	0.023	0.04	0.059	0.06
9	0.082	0.06	0.089	0.07	0.083	0.05	0.081	0.06
10	0.099	0.08	0.105	0.08	0.101	0.07	0.096	0.08
11	0.118	0.09	0.129	0.09	0.123	0.08	0.114	0.09
12	0.158	0.11	0.163	0.11	0.171	0.11	0.146	0.11
13	0.229	0.16	0.213	0.14	0.264	0.20	0.198	0.16
14	0.610	0.26	0.408	0.21	0.853	0.32	0.385	0.25
Overall	0.102	1.00	0.103	1.01	0.113	1.00	0.092	1.01
Freq. of zeroes	18%		3%		31%		6%	
	All Plants		All Firms		Small Plants		Large Plants	
Buildings	I/K (t)	share	I/K (t)	share	I/K (t)	share	I/K (t)	share
1	-0.103	-0.06	-0.088	-0.05	-0.077	-0.02	-0.115	-0.07
2	-0.013	-0.00	-0.016	-0.00	-0.002	-0.00	-0.017	-0.00
3	0.000	0.00	0.001	0.00	0.001	0.00	0.000	0.00
4	0.001	0.00	0.002	0.01	0.000	0.00	0.001	0.00
5	0.001	0.01	0.003	0.01	0.000	0.00	0.002	0.01
6	0.001	0.01	0.005	0.02	0.000	0.00	0.002	0.01
7	0.002	0.02	0.006	0.03	0.001	0.01	0.003	0.02
8	0.003	0.03	0.011	0.04	0.001	0.01	0.006	0.03
9	0.021	0.04	0.026	0.05	0.021	0.02	0.021	0.05
10	0.030	0.06	0.037	0.07	0.030	0.04	0.031	0.06
11	0.048	0.09	0.054	0.10	0.047	0.06	0.049	0.09
12	0.076	0.13	0.089	0.13	0.069	0.09	0.082	0.14
13	0.153	0.22	0.154	0.19	0.165	0.21	0.143	0.23
14	0.461	0.05	0.460	0.39	0.605	0.57	0.335	0.42
Overall	0.046	1.00	0.054	0.99	0.050	0.99	0.041	0.99
Freq. of zeroes	55%		36%		67%		44%	
Nobs.	5068		2016		2562		2506	

Table 4a. Hazard Models results for equipment

	High spikes					Relative spikes				
	Kaplan Meier	Logit	Fixed effects logit	Logit smaller sample	Mass points logit	Kaplan Meier	Logit	Fixed effects logit	Logit smaller sample	Mass points logit
duration 0	0.288					0.276				
	(33.492)					(34.017)				
duration 1	0.152	-0.767	-0.172	-0.472	-0.721	0.134	-0.841	-0.410	-0.537	-0.841
	(14.162)	(-7.703)	(-1.465)	(-4.441)	(7.164)	(13.237)	(-8.715)	(-3.738)	(-5.236)	(-8.715)
duration 2	0.123	-0.919	0.208	-0.427	-0.835	0.122	-0.828	-0.033	-0.386	-0.828
	(9.688)	(-7.515)	(1.420)	(-3.279)	(-6.759)	(10.472)	(-7.338)	(-0.256)	(-3.220)	(-7.338)
duration 3	0.106	-1.113	0.434	-0.492	-0.966	0.105	-1.059	-0.032	-0.534	-1.059
	(6.877)	(7.312)	(2.355)	(-3.036)	(-6.475)	(7.308)	(-7.482)	(-0.200)	(-3.582)	(-7.482)
duration 4	0.117	-1.034	0.944	-0.300	-0.891	0.141	-0.721	0.565	-0.150	-0.721
	(6.366)	(-5.998)	(4.361)	(-1.622)	(-5.104)	(8.139)	(-4.730)	(3.130)	(-0.921)	(-4.730)
duration 5	0.111	-1.304	1.078	-0.490	-1.137	0.146	-0.848	0.745	-0.187	-0.848
	(4.933)	(-6.193)	(4.030)	(-2.170)	(-5.343)	(6.632)	(-4.597)	(3.352)	(-0.954)	(-4.597)
duration 6	0.138	-1.047	1.995	-0.048	-0.846	0.176	-0.634	1.408	0.140	-0.634
	(5.148)	(-4.537)	(6.544)	(-0.192)	(-3.630)	(6.666)	(-3.103)	(5.528)	(0.640)	(-3.103)
duration 7	0.110	-1.350	2.387	-0.152	-1.125	0.143	-0.837	1.578	0.055	-0.837
	(3.425)	(-4.537)	(6.037)	(-0.465)	(-3.739)	(4.357)	(-3.126)	(4.721)	(0.195)	(-3.126)
duration 8	0.141	-0.788	3.604	0.742	-0.540	0.175	-0.412	2.559	0.651	-0.412
	(3.747)	(-2.514)	(8.181)	(2.093)	(-1.708)	(4.565)	(-1.425)	(6.802)	(2.079)	(-1.425)
duration 9, higher	0.063	-1.580	4.414	0.548	-1.276	0.207	0.009	4.026	1.600	0.009
	(2.004)	(-4.242)	(7.706)	(1.320)	(-3.401)	(5.239)	(0.030)	(9.077)	(4.775)	(0.030)
Const.1		--		--	-0.959					-1.246
(probability)					[0.384])					[0.554]
Const.2					-1.025					-1.247
(probability)					[0.470]					[0.446]
Const.3					-0.125					
(probability)					[0.146]					
Number of observations:	5884	5884	3905	3905	5884	6609	6609	4732	4732	6609
R^2,Pseudo R^2	0.211	0.076	--	0.007	--	--	--	--	--	--
$\chi^2_{year}(12)$		96.33	207.24	141.60	--		--	--	--	--

Notes: Duration 'I' denotes 'I' years since the last spike. *t*-ratios in brackets. Additional regressors in 'Logit', 'Logit smaller sample, and 'Mass points logit' include year dummies and firm characteristics (see pg. 20 in the main text)

Table 4b. Hazard Models results for buildings

	High spikes					Relative spikes				
	Kaplan Meier	Logit	Fixed effects logit	Logit smaller sample	Mass points logit	Kaplan Meier	Logit	Fixed effects logit	Logit smaller sample	Mass points logit
duration 0	0.185					0.442				
	(19.566)					(41.804)				
duration 1	0.060	-1.149	-0.384	-0.722	-1.149	0.174	-1.240	0.662	0.794	-1.240
	(5.355)	(-5.621)	(-1.494)	(-3.174)	(-5.621)	(11.294)	(-11.658)	(-5.513)	(-7.023)	(-11.658)
duration 2	0.046	-1.128	3.866	-0.389	-1.128	0.185	-1.090	-0.285	-0.600	-1.090
	(3.767)	(-5.121)	(1.171)	(-1.393)	(-5.121)	(9.969)	(-8.821)	(-2.037)	(-4.600)	(-8.821)
duration 3	0.031	-1.590	0.826	-0.387	-1.590	0.207	-0.867	0.087	-0.395	-0.867
	(2.215)	(-4.779)	(1.820)	(-1.038)	(-4.779)	(8.694)	(-5.825)	(0.516)	(-2.534)	(-5.825)
duration 4	0.067	-0.714	2.482	0.914	-0.714	0.261	-0.525	0.693	-0.035	-0.525
	(4.232)	(-2.392)	(5.057)	(2.490)	(-2.392)	(8.367)	(-2.949)	(3.357)	(-0.187)	(-2.949)
duration 5	0.066	-0.632	3.431	1.391	-0.632	0.189	-0.940	0.531	-0.413	-0.940
	(3.634)	(-1.811)	(5.768)	(3.161)	(-1.811)	(4.484)	(-3.629)	(1.803)	(-1.549)	(-3.629)
duration 6	0.087	-0.290	4.843	2.247	-0.290	0.301	-0.286	1.598	0.302	-0.286
	(4.315)	(-0.793)	(7.178)	(4.641)	(-0.793)	(5.792)	(-1.038)	(4.856)	(1.048)	(-1.038)
duration 7	0.058	-0.600	5.743	2.456	-0.600	0.242	-0.575	1.825	0.097	-0.575
	(2.483)	(-1.290)	(7.137)	(4.129)	(-1.290)	(3.133)	(-1.350)	(3.599)	(0.219)	(-1.350)
duration 8	0.047	-0.609	6.938	3.103	-0.609	0.238	-0.475	2.290	0.105	-0.475
	(1.777)	(-1.080)	(7.311)	(4.319)	(-1.080)	(2.454)	(-0.893)	(3.648)	(0.194)	(-0.893)
duration 9, higher	0.029	-0.490	8.746	4.292	-0.490	0.333	0.365	4.021	1.228	0.365
	(1.387)	(-0.811)	(8.082)	(5.416)	(-0.811)	(3.181)	(0.701)	(5.545)	(2.179)	(0.701)
Const.1					-1.231					-0.251
(probability)					[0.294])					[0.815]
Const.2					-1.239					-0.252
(probability)					[0.680]					[0.185]
Const.3					-1.231					
(probability)					[0.027]					
Number of observations:	3467	3467	3467	1644	3467	3978	3978	3214	3214	3978
R^2,Pseudo R^2	0.122	0.104		0.166						
$\chi^2_{year}(12)$		33.19	109.45	91.98						

Notes: See Table 4a.

Table 5. Conditional probability of an investment spike (equipment,relative spike definition)

	1983	1986
duration 0	11.6	39.7
duration 1	5.4	22.1
duration 2	5.4	22.4
duration 3	4.4	18.6
duration 4	6.0	24.2
duration 5	5.3	22.0
duration 6	6.5	25.9
duration 7	5.4	22.2
duration 8	8.0	30.4
duration 9	11.7	39.9

Notes: The probabilities are calculated for the main plant in a multi-plant firm in sector 'Metal Products and Machinery (381-382)', with 150 employees, age of 14 years in 1978, and with its first investment spike taking place in 1978.

Table 6. Switching regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Regime 1							
$(\pi/K)_{it-1}$	0.082		0.172				
	(4.347)		(4.932)				
$(\pi/K)^2_{it-1}$			-0.102				
			(-2.799)				
$(S/K)_{it-1}$		0.012		0.035			
		(4.642)		(5.219)			
$(S/K)^2_{it-1}$				-0.003			
				(-4.028)			
$(q^{\pi})_{it}$					0.946		
					(4.898)		
$(q^{\pi})^2_{it-1}$					-3.086		
					(-2.764)		
$(qS)_{it}$						0.048	0.149
						(5.219)	(22.084)
$(qS)^2_{it}$						-0.006	-0.016
						(4.028)	(-10.184)
Regime 2							
$(\pi/K)_{it-1}$	0.026		0.052				
	(10.600)		(13.438)				
$(\pi/K)^2_{it-1}$			-0.048				
			(-8.996)				
$(S/K)_{it-1}$		0.004		0.013			
		(10.577)		(14.051)			
$(S/K)^2_{it-1}$				-0.002			
				(-10.361)			
$(q^{\pi})_{it}$					0.289		
					(13.443)		
$(q^{\pi})^2_{it-1}$					-1.488		
					(-9.005)		
$(qS)_{it}$						0.017	0.019
						(14.051)	(13.687)
$(qS)^2_{it}$						-0.003	-0.005
						(-10.361)	(-10.227)
Switching							
$(\pi/K)_{it-1}$	1.433		1.401				
	(15.746)		(16.423)				
$(S/K)_{it-1}$		0.210		0.225			
		(16.433)		(17.471)			
$(q^{\pi})_{it}$					7.799		
					(16.466)		
$(qS)_{it}$						0.305	0.388
						(17.471)	(27.542)
σ_{11}	0.206	0.205	0.205	0.206	0.205	0.206	0.254
	(79.878)	(80.057)	(80.233)	(80.032)	(80.191)	(80.032)	(.)
σ_{22}	0.028	0.028	0.028	0.028	0.028	0.028	0.019
	(52.740)	(52.630)	(52.772)	(52.803)	(52.661)	(52.803)	(-236.871)
Log L	17661.2	17674.0	17703.8	17754.0	17703.9	17754.0	19540.0
Nbr of obs	14453	14453	14453	14453	14453	14453	14453

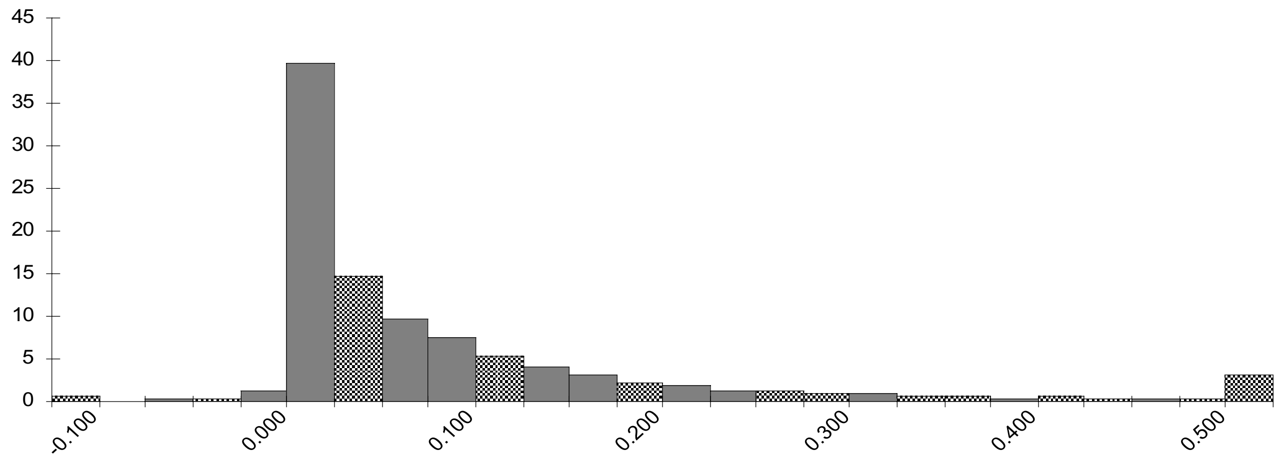

Figure 1a: Distribution of investment rates for Equipment (plant level, unbalanced panel)

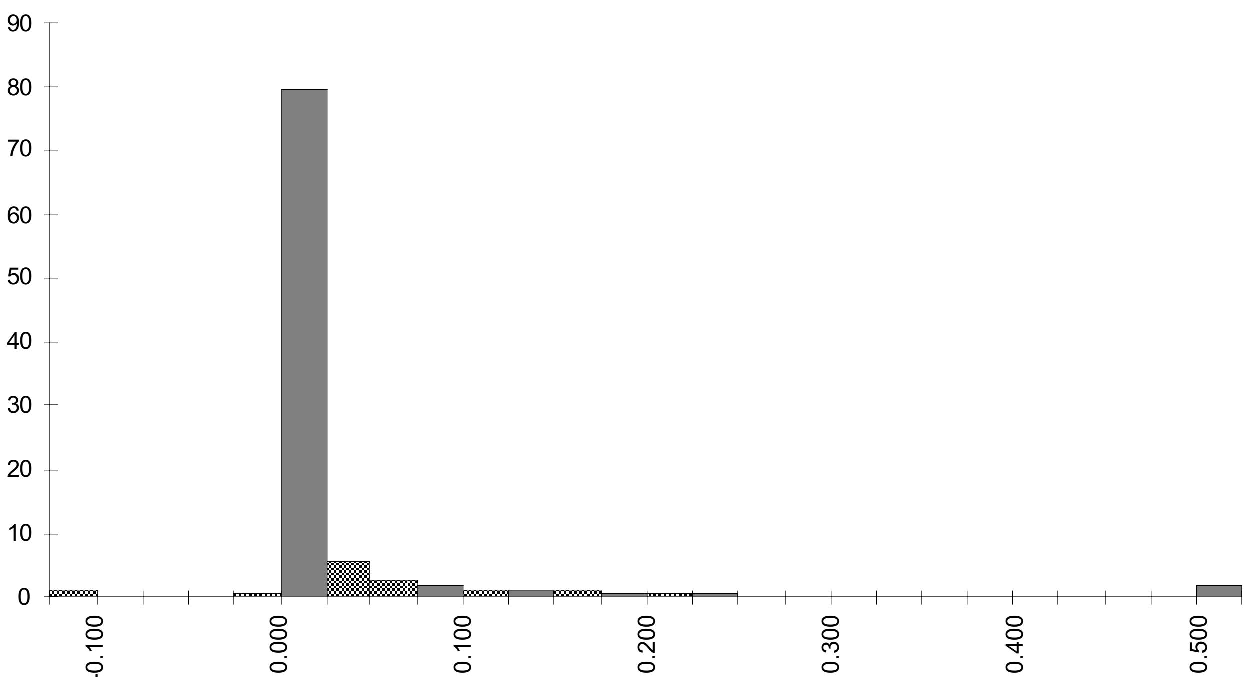

Figure 1b: Distribution of investment rates for Buildings (plant level, unbalanced panel)

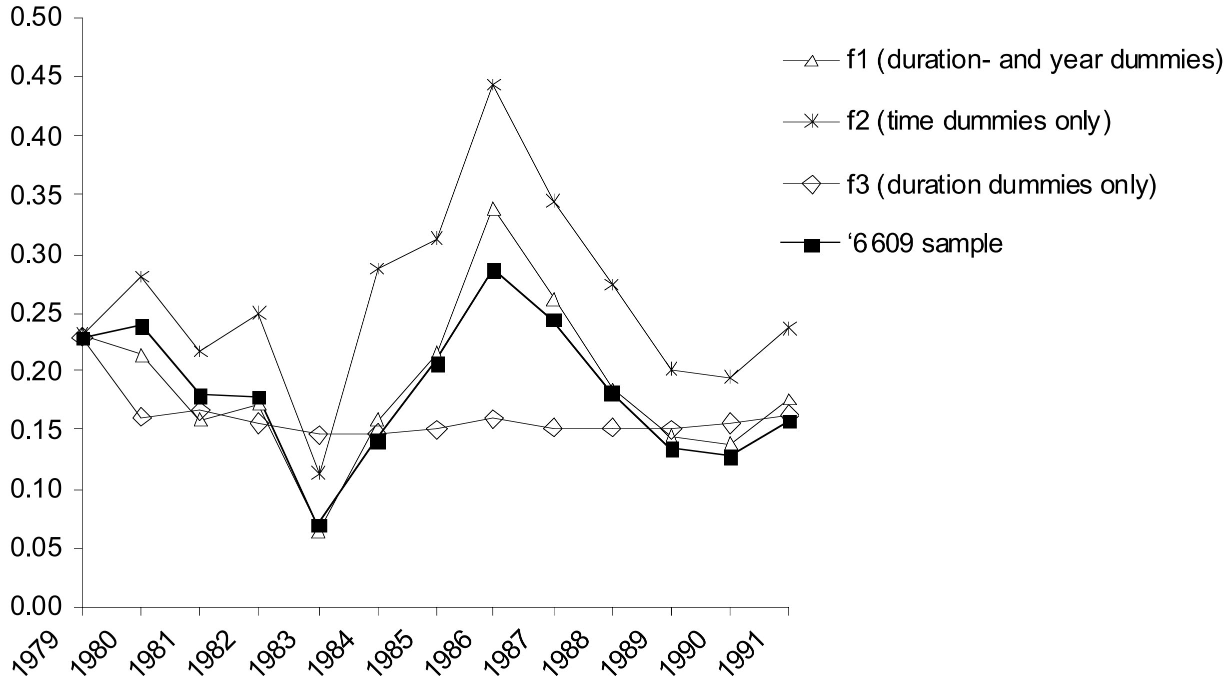

Figure 2: Simulated Relative Spike Frequencies for Equipmen (logit model)

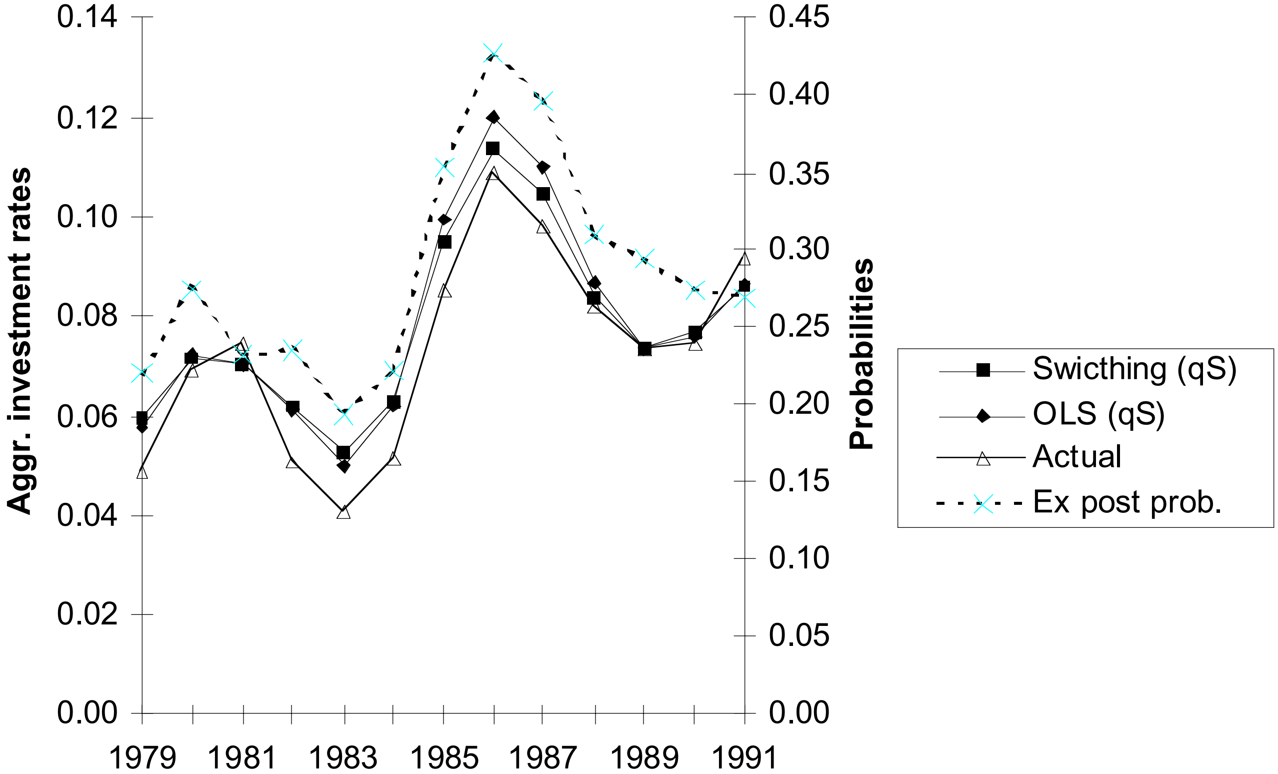

Figure 3: Aggregate investment rates for equipment