Lumpy Investments, Factor Adjustments and Productivity[†]

Øivind A. Nilsen[*]
(Norwegian School of Economics and Business Administration, IZA, and Statistics Norway)

Arvid Raknerud
(Statistics Norway)

Marina Rybalka
(Statistics Norway)

Terje Skjerpen
(Statistics Norway)

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[*] Corresponding author: Address; Norwegian School of Economics and Business Administration, Helleveien 30, NO-5045 Bergen, Norway. Phone; +47 55 959 281, Fax; +47 55 959 543, E-mail: oivind.nilsen@nhh.no.

Abstract

This paper describes firms' output and factor demands before, during and after episodes of lumpy investment. By using a rich employer–employee panel data set for two manufacturing industries and one service industry, we focus on simultaneous variations in output, capital, materials and man hours, as well as the skill composition and hourly cost of labour. Investment spikes are followed by roughly proportional changes in sales, labour and materials, and significant increases in capital intensity. Capital adjustments are found to be smoother in the service industry than in the two manufacturing industries. This result may be related to differences in labour intensity between the industries. The changes in productivity that are associated with the investment spikes are small, which indicates that productivity improvements are not related to instantaneous technological change through investment spikes.

Keywords: Lumpy investments, Adjustment costs, Productivity, Panel data

JEL classification: C13, C33, D21, D24

1. Introduction

Several studies have pointed out that firms adjust input factors (e.g., capital and labour) in a lumpy fashion, which generates investment spikes, and with little or no investment activity between the spikes.[1] Such a pattern suggests that the smooth adjustment of capital and labour is precluded by fixed costs, (partial) irreversibilities or indivisibilities. The motivation for investment in new capital may be to increase either capacity or productivity, since new capital embodies the latest technology. The latter effect is a driving force behind productivity growth at the industry level.[2] However, Power (1998), Huggett and Opsina (2001) and Sakellaris (2004) find that the immediate impact of large investments on productivity is small, or even negative. This may reflect adjustment costs due to the disruption of production.

The focus of our analysis is on the dynamics of, and interrelationships between, input and output variables in the periods before and after an investment spike. Specifically, we investigate how new technology is adapted by the firm and how it affects the firm's productivity (relative to the industry average). Moreover, we investigate whether new capital affects the skill composition of the labour force. Following Sakellaris (2004), Letterie, Pfann and Polder (2004) and others, we adopt an explorative econometric approach. Using a non-structural approach has several advantages. First, a structural model that embeds theories of non-convexities in the adjustments of several input factors is difficult to implement because it involves dynamic optimization with multiple decision variables.[3] Second, even if we were

[1] For capital adjustment, see Doms and Dunne (1998), Caballero and Engel (1999), Cooper, Haltiwanger and Power (1999) and Abel and Eberly (2002) for the US. See Nilsen and Schiantarelli (2003) for Norway, and see Letterie and Pfann (2005) for the Netherlands. For labour adjustment, see the seminal contribution by Hamermesh (1989), and the more recent ones of Rota (1995), Abowd and Kramarz (2003) and Nilsen, Salvanes and Schiantarelli (2003).

[2] See, for instance, Jensen, McGuckin and Stiroh (2001).

[3] Most of the empirical literature investigates the adjustment of capital and labour separately. However, as pointed out by several authors, lumpiness in one factor may be caused by non-convexities in the adjustment of that factor or by lumpiness in other input factors. For interrelationship in input factors, see for instance Nadiri and Rosen (1969), and more recently Abel and Eberly (1998), and Letterie, Pfann and Polder (2004).

able to obtain estimable equations from such a model, it is not clear that this would be the best way of determining the relevant relationships between output, inputs and productivity. The model would necessarily build on restrictive, simplifying assumptions to which the resulting inferences would be sensitive. Our analysis is instead based on a reduced form random effects model, in which the endogenous variables are sales, materials, capital, hourly wage costs, total man hours and the share of total man hours worked by high-skilled workers. All variables are treated as being simultaneously determined. Efficient estimators are obtained by using the method of maximum likelihood.

This paper is based on a new and unique matched employer–employee data set from Norway, covering the period 1995–2003. While the existing literature has focused mainly on the manufacturing sector, a novelty of our study is that we describe the link between investment spikes, factor adjustments and productivity for services as well as manufacturing. Another advantage of our data set is that it includes *all* joint stock (i.e., limited dependent) companies in the industries under study. Our sample is more representative than those used in most other studies, as it represents roughly 70 per cent of all man hours in these industries and includes both large and small firms. However, since indivisibilities and fixed costs play a more important role for small firms than for large firms, some challenges also arise, which need to be addressed.

In the literature, a lumpy investment is defined as one that causes the investment-to-capital ratio to exceed a certain threshold, typically 20 per cent; see Cooper, Haltiwanger and Power (1999). However, investment-to-capital ratios that exceed 20 per cent are quite common in our sample. Moreover, since the volatility of these ratios decreases with the capital stock (before the investment), spikes are much more common for small firms than for large firms. To address this problem, we propose a modified threshold, which takes this particular form of heteroscedasticity into account.

Our results confirm that investments are lumpy, which indicates that firms concentrate their investments in short periods of time. This is consistent with non-convexities in the adjustment cost function for capital. These non-convexities may be due to fixed adjustment costs or indivisibilities.[4] Evidence suggests that adjustments of capital are smoother in the service industry than in the two manufacturing industries. In all the industries, an investment spike leads to approximately proportional changes in sales, man hours and materials after two to three years, while capital intensity increases significantly. We also find that the changes in productivity associated with investment spikes are small. This suggests that productivity improvements may have more to do with learning-by-doing than with instantaneous technological change through investment spikes.

The paper proceeds as follows. In Section 2, we describe the data, define the variables and report some descriptive statistics. In Section 3, we describe the empirical specification used. In Section 4, we discuss the empirical results. Section 5 concludes the paper.

2. Data description

2.1 The data sources

We have constructed panels of annual firm-level data for Norwegian firms in three industries, covering the period 1995–2003. The three industries are the Manufacture of machinery and equipment (NACE 29), the Manufacture of electrical and optical equipment (NACE 30–33) and Retail trade and repairs of personal and household goods (NACE 52). The first industry is a traditional manufacturing industry, the second is a high-tech industry and the last one is a service industry. Henceforth, we refer to the three industries as *Machinery*, *Electrical equipment* and *Retail trade*, respectively. The two manufacturing industries accounted for

[4] See Hamermesh and Pfann (1996) for a critical review of adjustment-cost functions.

about 17 per cent of man hours worked in the manufacturing sector in the period 1995–2003. Relative to total man hours in Norway, the share of Retail trade was about 6 per cent, while the sum of the shares of the two manufacturing industries was 3 per cent. The empirical analysis is carried out at the firm level, at which accounting information is available, and is undertaken for each industry separately. Focusing on narrowly defined industries has the advantage of reducing the heterogeneity in the sample that is due to systematic differences in technology, factor prices and demand conditions between the different types of industrial activities. We account for industry-wide effects in our empirical model by using period-specific intercepts.

Five different sources of Norwegian micro data are used. Two of them are firm-level data sets. One is based on the accounts statistics of joint stock companies, and the other comprises structural statistics for different industrial activities.[5] The three remaining data sets contain individual-level data. These are the Register of Employers and Employees (REE), the Pay Statements Register (PSR), and the National Education Database (NED). These individual-level data were integrated into a common data base and then aggregated to the firm level. After aggregation, we had unbalanced panel data sets for the following: 1,743 firms in Machinery, with approximately 900 observations per year; 1,177 firms in Electrical equipment, with approximately 600 observations per year; and 22,806 firms in Retail trade, with approximately 11,500 observations per year. The model used in the paper contains one lag and one lead. Only firms with at least three years of contiguous data and no missing variables were included. As shown in Table 1, the final samples used for estimation are considerably smaller than the original samples. Nevertheless, these samples represent

[5] The term 'structural statistics' is a general term for different industrial activities statistics, such as manufacturing statistics, building and construction statistics, wholesale and retail trade statistics, and so on. They all have the same structure and all include information about production, input factors and investments. A more detailed description of this and other data sources is in Data Appendix A.

approximately 75, 67 and 68 per cent of total man hours in Machinery, Electrical equipment, and Retail trade, respectively.[6]

(Table 1 'Number of firms in the final sample' about here)

2.2 Variable construction

Both the accounts statistics and the structural statistics distinguish between several groups of physical assets. To obtain consistent definitions of asset categories for the two sources over the sample period, all assets have been divided into two types: equipments, denoted by *e*, which includes machinery, vehicles, tools, furniture, and transport equipments; and buildings and land, denoted by *b*. The expected lifetimes of the physical assets in group *e* (of about 3–10 years) are considerably lower than those of the assets in group *b* (about 40–60 years). Total capital, K_{it}, is an aggregate of equipment capital, K_{it}^{e}, and building capital, K_{it}^{b}, for firm *i* in period *t*. When aggregating the two capital types, we use a Törnqvist volume index with time-varying weights that are common across firms in the same industry (see OECD, 2001). Thus, we follow the practice applied by most official statistical agencies, e.g., the Bureau of Labor Statistics. The Törnqvist index can be interpreted as a constant-returns-to-scale Cobb–Douglas aggregation function in which the elasticity of each type of capital is estimated from their shares of the total (annualized) cost of capital.[7] An important property of the Törnqvist volume index of capital is that it can be equivalently formulated in terms of the rental cost of

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[6] The corresponding numbers based on sales are 71, 65 and 66 per cent.

[7] The aggregate capital stock is calculated as $K_{it} = \left(K_{it}^{b}\right)^{v_t}\left(K_{it}^{e}\right)^{1-v_t}$, where $v_t = \sum_i R_{it}^{b} / \sum_i (R_{it}^{b} + R_{it}^{e})$ and, for $j \in \{e,b\}$, $R_{it}^{j} = (r+\delta_j)K_{it}^{j}$. Thus, R_{it}^{j} is the annualized cost of capital. The median depreciation rates, δ_j, are about 0.2 for equipment and 0.05 for buildings. These are obtained from the accounts statistics: see Raknerud, Rønningen and Skjerpen (2003). The real rate of return, r, which we calculated from the average real return on 10-year government bonds for the period 1996–2002, is 4.2 per cent.

capital.[8] Thus, it is straightforward to aggregate capital owned by the firm and capital obtained through operational leasing.[9] Since operational leasing contributes substantially to firms' capital inputs (see Data Appendix B for details), both owned and leased capital are included in K_{it}^{j}, for $j \in \{e, b\}$. Table 2 presents an overview of the data sources used to construct our capital measures together with the definitions and sources of the other variables used in our study.

(Table 2 'Overview of variables and data sources' about here)

Investments in the two types of capital are denoted by I_{it}^{e} and I_{it}^{b}. We define an investment as any purchase of a fixed capital good that is capitalized, i.e., taken into the firm's balance sheet, and depreciated over its expected lifetime.[10] Note that this definition of an investment implies that sales of fixed capital goods are not subtracted. Our justification of this is that gross purchases, rather than purchases net of sales, is the most adequate measure of embodied technological change. In line with accounting rules, we consider repairs as operating costs, unless they improve the quality of the asset (in which case, the value of the asset increases relative to its *ex ante* expected value). In this case, the additional value is considered an investment (see McGrattan and Schmitz, 1999 for a discussion). Financial leasing is also considered to be investment: Under financial leasing, most of the risks and rewards are transferred to the firm that leases, and capitalizes, the asset (see Hawkins, 1986).

The main focus of the paper is to estimate the effects of investment spikes, S_{it}, on some key variables. In accordance with the literature, we define investment spikes only for

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[8] That is, $\ln K_{it} = v_t \ln R_{it}^{b} + (1 - v_t) \ln R_{it}^{e} + \text{constant}$. Cf. the previous footnote.

[9] With an operational leasing agreement, the firm that leases an asset does not capitalize it in its balance sheet but pays leasing costs, such as rents on buildings.

[10] See Raknerud, Rønningen and Skjerpen (2003) for details of this definition.

equipments. One justification for this is that equipments account for the largest share of total capital expenditure. Another argument is that equipment capital reflects the type of investment that is often assumed to embody technological progress.[11]

Traditionally, the concept of a spike has been applied in two main ways. If the ratio of equipment-investment to equipment capital, $I_{it}^{e}\big/K_{i,t-1}^{e}$ (hereafter, the *investment ratio*), exceeds 0.2, there is an absolute spike (see Cooper, Haltiwanger and Power, 1999). Alternatively, if $I_{it}^{e}\big/K_{i,t-1}^{e}$ exceeds the median investment ratio by a factor of ρ, which is typically set between 1.5 and 3 (see Power, 1998), there is a relative spike, which is expressed by:

$$I_{it}^{e} / K_{i,t-1}^{e} > \rho \ \text{median}_{s}\left(I_{is}^{e} / K_{i,s-1}^{e}\right),$$

where the median is calculated for each firm, *i*, based on all the observations for that firm.

An investment spike is meant to represent a sudden and unusual burst in the firm's investment activity. *A priori*, an investment spike should fulfil the following three criteria. First, the investment must be large, both relative to the investment history of the individual firm and relative to the (cross-sectional) dispersion of investment ratios within the industry. Second, the investment must constitute a rare event. Third, the spikes must account for a disproportionate share of total industry investments. However, if we apply either the concept of a relative spike, or the concept of an absolute spike, the identified investment spikes in our data set are neither unusual, nor do they account for a disproportionate share of total investment. Hence, we propose the following modified definition of an investment spike, S_{it}:

[11] This is not to deny that spikes in building capital may be interesting for some purposes, e.g., in productivity analysis. For example, in Retail trade, the capacities and location of shops and inventories may affect both sales and variable factor costs (e.g., transportation costs) and thus productivity.

$$S_{it} = \begin{cases} 1 & \text{if } I_{it}^{e} / K_{i,t-1}^{e} > \max\left[\alpha\sigma\left(K_{i,t-1}^{e}\right), 0.20\right] \\ 0 & \text{else} \end{cases} ,$$

where

$$\sigma\left(K_{i,t-1}^{e}\right) \equiv E\left(\left|\left(I_{it}^{e} / K_{i,t-1}^{e}\right) - \xi\right|\right)$$

is the expected absolute deviation from the mean investment ratio, $\xi \equiv E\left(I_{it}^{e} / K_{i,t-1}^{e}\right)$, considered as a function of $K_{i,t-1}^{e}$. The first argument in the max operator takes into account that fluctuations in investment ratios increase as the denominator decreases; i.e., $\sigma\left(K_{i,t-1}^{e}\right)$ is decreasing in $K_{i,t-1}^{e}$.[12] For a fixed value of α, there is a threshold value, ${K_{i,t-1}^{e}}^{*}$, such that for $K_{i,t-1}^{e} > {K_{i,t-1}^{e}}^{*}$, the second argument of the function, $\max\left[\alpha\sigma\left({K_{i,t-1}^{e}}^{*}\right), 0.20\right]$, is binding. Thus, for firms with sufficiently large equipment capital stocks, the criterion coincides with that of a 20 per cent investment ratio.

A comparison of our combined rule, $I_{it}^{e} / K_{i,t-1}^{e} > \max\left[\alpha\sigma\left({K_{i,t-1}^{e}}^{*}\right), 0.20\right]$, applied to our data, and Power's relative rule applied to US data, for different values of α and ρ, is presented in Table 3. Our rule generates surprisingly similar results to those obtained by Power (1998). However, the absolute spike criterion, which corresponds to $\alpha = 0$, does not

[12] We model $\sigma\left(K_{i,t-1}^{e}\right)$ as a generalized Box–Cox transformation of equipment capital, i.e., $\sigma\left(K_{i,t-1}^{e}\right) = \gamma_0 + \gamma_1\left(\left(K_{i,t-1}^{e} + \eta\right)^{\lambda} - 1\right) / \lambda$. When estimating this regression function for each industry, we use the method of non-linear least squares with $\left| I_{it}^{e} / K_{i,t-1}^{e} - \hat{\xi} \right|$ as the left-hand side variable, where $\hat{\xi}$ is the global empirical mean of the investment ratio. We find a clear pattern: the estimate of γ_1 is negative and highly significant in all industries. Thus, there is a strong negative relationship between the absolute deviation of the investment ratio of the firm and its capital stock (at the beginning of the year). That is, the fluctuations in the investment ratios of small firms are much larger than those of large firms. Furthermore, we find that the estimates of λ and η are close to zero, which implies a log-linear model in $K_{i,t-1}^{e}$.

produce credible results. When $\alpha = 1.75$, our combined rule for identifying investment spikes classifies about 10 per cent of the observations as spikes; these observations account for one-third of all investments. The 20 per cent threshold was binding for 4–6 per cent of the investment observations. Our results are robust to variations in α within the range of 1.75 to 3.25 (cf. Table 3).

(Table 3 'Comparing different rules for identifying investment spikes' about here)

Turning to the other variables (cf. Table 2), the logarithm of sales, *s*, is defined as the logarithm of operating revenues. The variable m is the logarithm of materials, which are operating expenses minus payroll expenses, depreciation, write-downs and operational leasing. The logarithm of man hours, *mh*, is the logarithm of the sum of all individual man hours worked by employees in the given firm according to the contract. The logarithm of hourly labour costs, *w*, is the logarithm of all recorded labour costs in the firm, including wages, bonuses and commissions, payroll taxes, and so on, minus the logarithm of man hours, *mh*. For each industry, we distinguish between two educational groups, high-skilled and low-skilled. High-skilled workers are those who have post-secondary education, i.e., persons who have studied for at least 13 years. (For a description of the educational levels, see Table A1.) The man hours worked by high-skilled persons were aggregated to the firm level and divided by the total number of man hours worked in the given firm; this defines *ssk*. That is, *ssk* is the share of man hours worked by high-skilled workers.

2.3 Descriptive statistics

Panel (a) of Figure 1 reports investment ratios for equipment capital at the industry level. In each of the three industries, the firms invested more intensively at the beginning of the period than at the end. This pattern could be influenced by the ending of the recession around 1993–

1994, when firms had low capital stocks following years of low investment activety. When capital stocks increased at the firm level, investment ratios fell. Nevertheless, average investment ratios remained high throughout the period. Panel (b) of Figure 1 shows the shares of investment observations classified as investment spikes according to our criterion, with $\alpha = 1.75$. We see the same declining pattern as for the investment ratios in panel (a): 8–13 per cent of the observations are classified as investment spikes in 1996, compared with 5–7 per cent doing so in 2002.[13]

(Figure 1 'Investment ratios and relative frequencies of spikes' about here)

To assess the degree of lumpiness of investments, panels (a) and (b) in Figure 2 present the distributions of investment ratios classified as spikes and non-spikes, respectively, based on our combined rule with $\alpha = 1.75$. In addition, panel (c) shows the distributions of all the investment ratios, $I_{it} / K_{i,t-1}$, in our data. These distributions are similar for the three industries. In general, investment spikes are large. Less than 10 per cent of the spikes correspond to investment ratios smaller than 0.5. The distributions are also skewed to the right, with a median value of about 0.8. The distributions of all the investment ratios (see panel (c)) are asymmetric and have a tail similar to that of the exponential distribution. Investments of zero occur quite often: about 22 per cent of the investment observations in each of the two manufacturing industries and 26 per cent of those in Retail trade are zeros.

(Figure 2 'Distribution of investment ratios' about here)

The panels of Figure 3 show the means of some key variables in the different industries. Note that the two manufacturing industries consist, on average, of larger firms (in

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[13] Up to 33, 29 and 24 per cent of the firms in Machinery, Electrical equipment and Retail trade, respectively, experienced at least one spike during the period 1996–2002.

terms of man hours) than does Retail trade.[14] The average hourly wage in manufacturing is higher than that in Retail trade, while the growth rates of average hourly wage are similar between the three industries (see panels (a) and (b)). Electrical equipment can be characterised as a high-tech industry, in which human capital is important. This is confirmed by panel (c) of Figure 3, which shows that the share of man hours worked by high-skilled workers in Electrical equipment is more than twice as high as the shares in the two other industries. The share of man hours worked by high-skilled workers increased slowly between 1996 and 2002 in Electrical equipment, but was quite stable over time in the other two industries.

(Figure 3 'The means of variables in different industries over time' about here).

Labour productivity, measured as sales per man hour, exhibited an upward trend during 1996–2002 (see panel (d)). Labour productivity is much higher in Retail trade than in the two manufacturing industries. This reflects greater materials intensity in Retail trade (see panel (e)) and does not mean that the efficiency of the workers is highest in Retail trade. It is not appropriate to compare labour productivity across industries with different materials intensities. Note also that the two manufacturing industries are more equipment capital intensive than is Retail trade (see panel (f)). However, the growth rates of average capital intensity in the three industries are similar.

3. Methodology

We are interested in studying how the performance of firms, measured by a vector of response variables, X_{it}, evolves over time, before, during and after the occurrence of an investment

[14] Similar differences are found when we measure firm size with regard to capital.

spike. We first define a vector of covariates, Z_{it}, which identifies the position of the firm in a 'window' of observations around the spike. Let T_i^{start} and T_i^{end} denote the first and last years in which firm *i* is included in the sample. We define Z_{it} as follows:

$$Z_{it} = \begin{bmatrix} Z_{1i} \\ Z_{2,it} \\ Z_{3,it} \\ Z_{4,it} \end{bmatrix} = \begin{bmatrix} max_{T_i^{start} \le s \le T_i^{end}} S_{is} \\ S_{it} \\ (1 - S_{it}) S_{i,t-1} \\ (1 - S_{it})(1 - S_{i,t-1}) max_{s \le t-2} S_{is} \end{bmatrix}$$

The first component of Z_{it}, Z_{1i}, is an indicator of whether the firm experiences at least one investment spike during the period $\left[T_i^{start}, T_i^{end}\right]$. The second component, $Z_{2,it}$, is an indicator of a spike in year *t*, while the third component, $Z_{3,it}$, is an indicator of a spike in year $t-1$ but not in year *t*. Finally, $Z_{4,it}$ is an indicator of whether there was an investment spike during the period $\left[T_i^{start}, t-2\right]$ but not in year t or year $t-1$. This last covariate is used to identify possible shifts in the average level of X_{it} after the spike, relative to its normal level before the spike. Note that if there is a multi-year spike, i.e., if $Z_{2,it} \equiv S_{it} = 1$ for a consecutive sequence of years, $Z_{3,it} = 0$ until *one year* after the *last* year in this sequence, while $Z_{4,it} = 0$ until *two years* after the *last* year in this sequence.

The response variables in the vector X_{it} are as follows:

$$X_{it} = \left(s_{it}, m_{it}, w_{it}, ssk_{it}, k_{it}, mh_{it}\right)'.$$

We investigate the co-movements of the elements of X_{it} as functions of the covariates, Z_{it}. For this purpose, we specify the following simple random effects model:

$$X_{it} = u_i + \mu_t + \beta_1 Z_{1i} + \sum_{k=2}^{4} \beta_k Z_{k,it} + e_{it}, \; t = T_i^{start}, T_i^{start} + 1, ..., T_i^{end},$$

where u_i is a 6×1 vector of random effects, with a mean of zero and an unrestricted covariance matrix, μ_t is a vector of fixed time-specific intercepts common to all firms in the industry, $\beta_1, .., \beta_4$ are four 6×1 vectors of regression parameters that describe the relationships between X_{it} and Z_{1i}, $Z_{2,it}$, $Z_{3,it}$ and $Z_{4,it}$, and e_{it} is a vector of idiosyncratic error terms with an unrestricted covariance matrix.

For the group of firms that experience no spikes, the pattern of X_{it} over time has a simple two-way structure, fluctuating randomly around $u_i + \mu_t$, where the common movement is given by μ_t. By contrast, firms that experience spikes, i.e., firms with $Z_{1i} = 1$, may differ systematically from other firms, both before, during and after the spike. By assumption, the random effect, u_i, is independent of the dummy variables $Z_{1i}, Z_{2,it}, Z_{3,it}$ and $Z_{4,it}$. Note that β_1 is the (common) vector of fixed effects for firms with at least one spike, relative to firms that experienced no spikes during the observation period (i.e., the reference category). Because the spikes should account for a disproportionately large share of aggregate investment, one would expect that large firms are overrepresented among firms with spikes. That is, the components of β_1 corresponding to s, m, k and mh should be positive. If a spike occurs in year *t*, this is accompanied by a shift in X_{it} equal to β_2, relative to the years before the spike. In the year just after a spike, there is a shift equal to β_3. The impact of a spike in a subsequent year is β_4. Thus, β_4 can be interpreted as the ‘long-run’ effect on X_{it} of the spike, relative to the normal level of X_{it} before the spike.

Although our model is similar to that of Sakellaris (2004), there are differences. First, our approach allows investment spikes to have persistent effects. This is because β_4 is not constrained to zero. By contrast, Sakellaris (2004) forces the effects of lumpy investments (in year t) to vanish by year $t+2$. Furthermore, we estimate the equations simultaneously within a Seemingly Unrelated Regression Equations (SURE) system; i.e., we do not estimate an equation for each of the components of X_{it} separately. This makes estimation more efficient by exploiting the fact that firms' gross error terms, $u_i + e_{it}$, are correlated over time because of the firm-specific random variable, u_i (cf. Avery (1977) and Baltagi (1980), who address this issue within a feasible GLS framework in the context of a balanced panel). The model is estimated separately for each of the three industries by using the method of maximum likelihood.[15]

4. Empirical results

Table 4 reports the estimated values of the parameter vectors, β_k, for Machinery, Electrical equipment and Retail trade for the model described in the previous section. We use the notation $\beta_{k,j}$, in which the second subscript denotes an element in the vector *X*; e.g., $\beta_{k,s}$ denotes the sales component, $\beta_{k,m}$ denotes the materials component, and so on (see Table 4, column 1). Furthermore, $\hat{\beta}_k$ denotes the maximum likelihood estimate of β_k. For the components of X_{it} that are measured on the log scale, the corresponding β_k components can be interpreted as relative changes.

(Table 4 'Estimates of the parameter vectors β_k' about here)

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[15] The computer algorithm is written in GAUSS.

Figures 4, 5 and 6 illustrate the results of Table 4 by showing the development of a representative firm's response values before, during and after the occurrence of an investment spike. The vertical axis measures the average difference between firms without spikes and firms with spikes over a sequence of four periods. On the horizontal axis, $< t-1]$ represents all years before the spike, t represents the year in which the spike occurred, $t+1$ is the year following the spike, and $[t+2>$ corresponds to two or more years after the spike. The graphs show the average levels of X_{it} in these four periods; i.e., β_1, $\beta_1+\beta_2$, $\beta_1+\beta_3$ and $\beta_1+\beta_4$, respectively.

(Figure 4 'Firms' responses to investment spikes – Machinery' about here)

(Figure 5 'Firms' responses to investment spikes – Electrical equipment' about here)

(Figure 6 'Firms' responses to investment spikes – Retail trade' about here)

According to $\hat{\beta}_1$, in all three industries, firms that experience one or more spikes have, on average, significantly higher levels of (log) sales, (log) materials, (log) man hours and (log) stock of capital than do firms without spikes. This could be because our definition of a spike implies that the spike threshold declines with the level of the equipment capital stock.[16]

The immediate effect of an investment spike is revealed by the estimates of β_2. The estimated coefficient of capital, $\beta_{2,k}$, implies that, for Machinery, the estimated relative growth in capital from t – 1 to t is 0.53. For Electrical equipment and Retail trade, the corresponding estimates are 0.40 and 0.33, respectively. Recall from Table 3 that spikes

[16] Nilsen and Schiantarelli (2003) found significant differences in the investment patterns of small and large firms and plants, with more frequent episodes of inactivity and lumpier investment for smaller units.

account for 35 per cent of all investment recorded in the sample. Lumpy investment implies that firms concentrate their investments in short periods of time. This is consistent with the existence of non-convex adjustment costs for capital caused by either fixed adjustment costs or indivisibilities. The estimated components of β_2 corresponding to *s, m, k* and *mh* are lower for Retail trade than for the two manufacturing industries. This indicates that non-convexities in adjustment costs are less important in Retail trade. The effect of an investment spike in the year after the spike is represented by β_3. In Machinery, the estimated change in the capital stock between *t* and *t* + 1 is negative; i.e., $\hat{\beta}_{3,k} < \hat{\beta}_{2,k}$, although the decrease is moderate. In the other industries, the effect of the spike is virtually the same in *t* and *t* + 1. This result is consistent with the findings of Sakellaris (2004); i.e., that lumpy capital adjustments are followed by smooth adjustments. The estimates of $\beta_{3,k}$ are slightly lower then the estimates of $\beta_{2,k}$ in all the three industries: $\hat{\beta}_{3,k}$ is smaller in Retail trade (0.29) than in Machinery and Electrical equipment (0.46 and 0.38, respectively).

The estimates of $\beta_{4,k}$ imply that the relative changes in the capital stock from year $t-1$ (just before the spike) to $[t+2>$ (two or more years after the spike) are positive and highly significant for all three industries. This means that the capital stock remains at the new higher level after the investment spike. Moreover, the estimated effects are similar in the three industries, although the estimate in Retail trade (0.24) is below those in the two manufacturing industries (0.30 and 0.34). The development of the log of capital intensity (capital per man hour) is depicted in Figures 4–6 (in the upper panels). The growth rates of capital intensity from *t* – 1 to $[t+2>$ are 0.18, 0.17 and 0.15 in Machinery, Electrical equipment and Retail trade, respectively. Thus, investment spikes are accompanied by similar ‘long-run’ increases in capital intensity in all three industries.

Turning to sales, we find that the increase in log sales from period $t - 1$ to t is 0.17, 0.22 and 0.08 in Machinery, Electrical equipment and Retail trade, respectively. The estimates of $\beta_{4,s}$ in Table 4 show that, two or more years after the spike, the relative increase in sales is about 10 per cent in Machinery and Retail trade, and about 20 per cent in Electrical equipment. Thus, the capital stock grows at a higher rate than do sales.

The growth patterns for materials and man hours are similar to that of sales. That is, the changes in sales, man hours and materials are almost proportional, although the growth rate of about 20 per cent two years after the spike for Electrical equipment exceeds that for the other industries (about 10 per cent). Adjusting labour seems as costless as adjusting materials and easier than adjusting the capital stock. The observed pattern of factor adjustments is not consistent with the traditional assumptions of homothetic production technology and (strictly) convex adjustment costs, with technological change driven by Hicks-neutral innovations. Our findings indicate instead that firms face non-convex capital-adjustment costs.

In Figures 4–6 (lower panels), we present our results for labour productivity, skill composition and wages. Note that the skill composition, measured as the share of man hours worked by high-skilled employees, is fairly constant.[17] This may be because investments classified as spikes stem from technological shocks only to a limited degree. It has been found that such technological changes, particularly computerization, affect the organization of work and the composition of the work force.[18] That there is no evidence in our study that investment spikes are associated with changes in the composition of the workforce at the micro level may indicate that technological change accompanies steady investment over time

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[17] The findings of Sakellaris (2004) are similar.

[18] See, for instance, Autor, Levy and Murnane (2003), and Berman, Bound and Machin (1998). See also Machin (2003) for a review of the literature on changes in skill composition as a response to technological change.

rather than investment spikes. The lack of change in the composition of the work force is also reflected in average wages being unaffected by investment spikes in all three industries.

General technological upgrading and increased productivity is accounted for by the fixed time-specific effects. Thus, our estimates measure the effects of investment spikes around these time trends and do not contradict the finding of increased productivity over time illustrated in Figure 4. We find evidence that labour productivity changes during an investment spike. Power (1998) finds that productivity growth decreases as the number of years since the last investment spike increases.[19] However, as she points out "the quantitative magnitudes are small, and most of the growth rate coefficients are not statistically significant" (p. 307). Huggett and Ospina (2001) find that a fall in productivity growth is associated with large equipment investments.

In summary, our findings of small and insignificant changes in productivity associated with investment spikes are consistent with several international studies based on the estimation of econometric models using firm- or plant-level data. These studies also find evidence of unchanged skill compositions and wages. This indicates that productivity improvements are related more to learning-by-doing than to instantaneous technological changes through investment spikes. A similar conclusion is reached by Bessen (2000), who finds that productivity at new plants improves as a result of learning-by-doing, which, unlike an investment spike, takes place smoothly.

Finally, we investigate whether our results attach too much weight to small firms, given that firms are not weighted by their relative contributions to total industry output when estimating the empirical model. They may do if small and large firms respond differently to investment spikes. In that case, it would also be difficult to compare our results with those of

[19] See Sakellaris (2004) for related findings using US manufacturing data.

the existing literature, which deals almost exclusively with large firms. To examine this question empirically, we re-estimated our model by excluding firms with less than 50,000 man hours (about 25 full-time employees). While this substantially reduced our sample of firms, the estimates of the parameter vectors, β_2, β_3 and β_4 not statistically different from those obtained using the full sample. We conclude that our results are not artefacts of certain 'small business' anomalies. On the contrary, small and large firms seem to respond similarly to investment spikes.

5. Conclusions

In this paper, we used a new and rich matched employer–employee data set from Norway for two manufacturing industries and one service industry to describe changes in the demand for capital and labour, changes in labour productivity and changes in the skill composition of the labour before, during, and after an investment spike. Traditional definitions of an investment spike capture neither sudden nor unusual bursts in investment activity when applied to a representative sample of firms. Hence, we proposed a modified definition of an investment spike, which is more suitable for samples comprising small and large firms. Under the modified definition, the threshold value for an investment spike increases with the volatility of the investment ratio as a function of the capital stock (immediately before the investment). The threshold is *negatively* related to the size of the firm.

By applying our definition of an investment spike, we obtained a number of important findings. First, spikes account for a large share of aggregate industry investment. Second, investment spikes are accompanied by almost proportional increases in sales, materials and man hours. Third, two or more years after the spike, there is substantial capital deepening, but labour productivity is relatively unaffected. Fourth, the growth patterns of materials and man hours are similar and much smoother than are those for capital. In addition, the observed patterns of factor adjustment are not consistent with the assumptions of homothetic production technology and (strictly) convex adjustment costs; rather, they indicate the presence of non-convexities in capital-adjustment costs.

The changes in labour productivity associated with investment spikes are small. This may be because investment spikes temporarily disrupt production. The small changes in productivity may indicate that general technological upgrading and increased productivity at the industry level are explained by trend factors, rather than by lumpy investment behaviour. We also found that the skill composition is not affected by investment spikes. This suggests that productivity improvements are related more to learning-by-doing than to instantaneous technological changes through investment spikes. This finding is consistent with results often obtained in related empirical studies.

We found interesting differences between the two manufacturing industries and the service industry. Capital adjustments are smoother in the service industry than in the two manufacturing industries. This suggests that the structure of capital-adjustment costs differs between the capital-intensive manufacturing industries and the relatively labour-intensive Retail industry. The responses of sales and input factors (other than capital) to lumpy investments indicate that non-convex adjustment costs are less important in Retail trade than in the manufacturing industries.

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Data Appendix

A. Detailed data description

As mentioned above, the empirical analysis is carried out at the firm level. In the accounts statistics, a firm is defined as "the smallest legal unit comprising all economic activities engaged in by one and the same owner" and corresponds in general to the concept of a company (Statistics Norway, 2001). A firm can consist of one or more establishments. The establishment is the geographically local unit conducting economic activity within an industry class. Another unit is the consolidated group, which consists of a parent company and one or more subsidiaries. Both the parent company and the subsidiaries are firms as defined here.

All joint-stock companies in Norway are obliged to publish company accounts every year. The accounts statistics contain information obtained from the income statements and balance sheets of joint-stock companies, in particular, the information about the book values of a firm's tangible fixed assets at the end of a year, their depreciation and write-downs. However, they do not contain data on purchases of tangible fixed assets, since data on investments do not have a specific standard in the annual report. Instead, these are provided in the notes on the annual report and are hence not included in the statistics. The accounts statistics in their present version are available from 1993. Currently, the most recent data are for 2003.

The structural statistics are organized according to the NACE standard.[20] They are based on General Trading Statements, which are given in an appendix to the tax return. The EU's structural regulations require statistics at the firm level. However, out of consideration to Norwegian users, local kind-of-activity units statistics have been compiled for

[20] The Standard Industrial Classification (SN2002) in Statistics Norway is based on the EU standard NACE Rev. 1.1.

employment, turnover, the compensation of employees and gross investments. Since the manufacturing statistics are available at the firm level only from 1996, data at the plant level aggregated to the firm level were used for earlier years. In addition to the variables that are also included in the accounts statistics, the structural statistics contain data about purchases of tangible fixed assets and operational leasing. These data were matched with the data from the accounts statistics. For the firm identification number, we use the registration number given to the firm in the Register of Enterprises, one of the Brønnøysund registers,[21] which is operative from 1995.

The Register of Employers and Employees (REE) contains information obtained from employers. All employers are obliged to send information to the REE about each individual employee's contract start and end, working hours, overtime and occupation. An exception is made only if a person works less than four hours per week in a given establishment and/or is employed for less than six days. In addition, this register contains identification numbers for the firm, the establishment and the employee. These data are available for the period 1995–2004.

The Pay Statements Register (PSR) contains annual data obtained from the Norwegian Internal Revenue Service. This register provides information on wages, bonuses and commissions, variable additional allowances and deductions, received by wage earners in each establishment. Moreover, this data set includes some demographic information, for example, regarding age. Merging these data with the REE by using personal identification numbers yields information about the occupations and earnings of wage earners in different establishments from 1995 to 2004. This can easily be aggregated to the firm level.

[21] See www.brreg.no.

The National Education Database (NED) gathers all individually based statistics on education from primary to tertiary education and has been provided by Statistics Norway since 1970. We use this data set to identify the duration of education. For this purpose, we utilize the first digit of the NUS variable. This variable is constructed on the basis of the Norwegian standard classification of education and is a six-digit number, the leading digit of which is the code of the educational level of the person. According to the Norwegian standard classification of education (NUS89),[22] there are nine educational levels in addition to the major group for "unspecified length of education". The educational levels are given in Table A1.

(Table A1 'Educational levels' about here)

B. Operational leasing

Figure B1 shows operational leasing costs as a share of total (annualized) costs of capital. In the two manufacturing industries, operational leasing costs constituted around 40 per cent of the total costs of building capital in 1996, and 60–70 per cent in 2002. In Retail trade, this share is over 90 per cent for the whole period. For equipment capital, operational leasing costs represent a substantial share of the total costs of capital. For example, in 1996, this share was around 40 per cent in both manufacturing industries and was about 30 per cent in Retail trade. Figure B1 shows why leasing should be included in the capital input measure, regardless of whether the focus is on equipment capital or aggregate, total capital. In particular, leasing considerably smooths capital adjustments. This is confirmed by the distribution of firm-level annual growth rates of capital (not shown), which is much less skewed to the right than if

[22] A new version of the Norwegian standard classification of education has been available since 2000 (NUS2000). We used the definitions of educational levels from the old version (Statistics Norway, 1989, p. 20), because the individuals incorporated in our data completed their education under the old educational system.

(operational) leasing had been excluded from the capital measure, as in, e.g., Carlsson and Laséen (2005).

(Figure B1 ‘Operational leasing’ about here)

Table 1. Number of firms in the final sample

Year	Machinery	Electrical equipment	Retail trade
1996	500	300	6,958
1997	531	336	7,618
1998	538	347	7,893
1999	544	344	8,039
2000	548	353	8,026
2001	567	367	8,122
2002	560	378	8,108
Total number	883	577	12,661

Table 2. Overview of variables and data sources

Variable	Interpretation	Data source(s)
K^j	capital stock [a,b] of type *j*, $j \in \{e,b\}$	accounts statistics, structural statistics
I^j	purchases of capital [a] of type *j*, $j \in \{e,b\}$	structural statistics
s	log of sales [a]	accounts statistics
m	log of materials [a]	accounts statistics
mh	log of man hours [c]	REE
w	log of hourly labour costs [a,c]	REE, PSR, accounts statistics
ssk	share of man hours worked by high-skilled persons [c]	REE, PSR, NED
Derived	variables:	
k	log of total capital, *K*	
lp	log of labour productivity: $s - mh$	
ki	log of capital intensity: $k - mh$	
mi	log of materials intensity: $m - mh$	
S	Investment spike indicator	

[a] The variable is deflated by the consumer price index. The units of measurement are 1000 NOK in 1995 prices.

[b] Capital stock at the end of the year

[c] Man hours according to labour contracts

Table 3. Comparing different rules for identifying investment spikes

Power's relative rule. US data			Our combined rule. Norwegian data		
ρ	**Share of # observations**	**Share of total investment**	α	**Share of # observations**	**Share of total investment**
			0	22	39
1.75	14	46	1.75	9	35
2.50	8	31	2.50	5	30
3.25	5	26	3.25	4	27

Table 4. Estimates of the parameter vectors β_k

	Parameter estimates (standard errors)			
	β_1	β_2	β_3	β_4
Machinery				
s	0.90 (0.10)	0.17 (0.02)	0.13 (0.03)	0.12 (0.03)
m	0.89 (0.11)	0.16 (0.03)	0.10 (0.03)	0.10 (0.03)
w	0.04 (0.02)	0.03 (0.01)	0.01 (0.02)	0.00 (0.02)
ssk	0.00 (0.01)	–0.01 (0.00)	–0.01 (0.01)	–0.01 (0.01)
k	0.90 (0.10)	0.53 (0.04)	0.46 (0.04)	0.30 (0.05)
mh	0.87 (0.10)	0.11 (0.02)	0.15 (0.02)	0.12 (0.02)
Electrical equipment				
s	0.67 (0.14)	0.22 (0.03)	0.24 (0.03)	0.21 (0.03)
m	0.70 (0.15)	0.23 (0.03)	0.27 (0.04)	0.23 (0.04)
w	0.04 (0.03)	0.04 (0.02)	0.02 (0.02)	0.02 (0.02)
ssk	0.02 (0.02)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)
k	0.56 (0.14)	0.40 (0.05)	0.38 (0.05)	0.34 (0.06)
mh	0.58 (0.12)	0.12 (0.02)	0.19 (0.03)	0.17 (0.03)
Retail trade				
s	0.73 (0.07)	0.08 (0.01)	0.11 (0.02)	0.10 (0.02)
m	0.74 (0.07)	0.09 (0.01)	0.10 (0.02)	0.09 (0.02)
w	0.12 (0.02)	0.02 (0.02)	0.01 (0.01)	0.01 (0.02)
ssk	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
k	0.64 (0.07)	0.33 (0.03)	0.29 (0.03)	0.24 (0.03)
mh	0.53 (0.06)	0.07 (0.02)	0.11 (0.02)	0.10 (0.02)

Figure 1. Investment ratios and relative frequencies of spikes

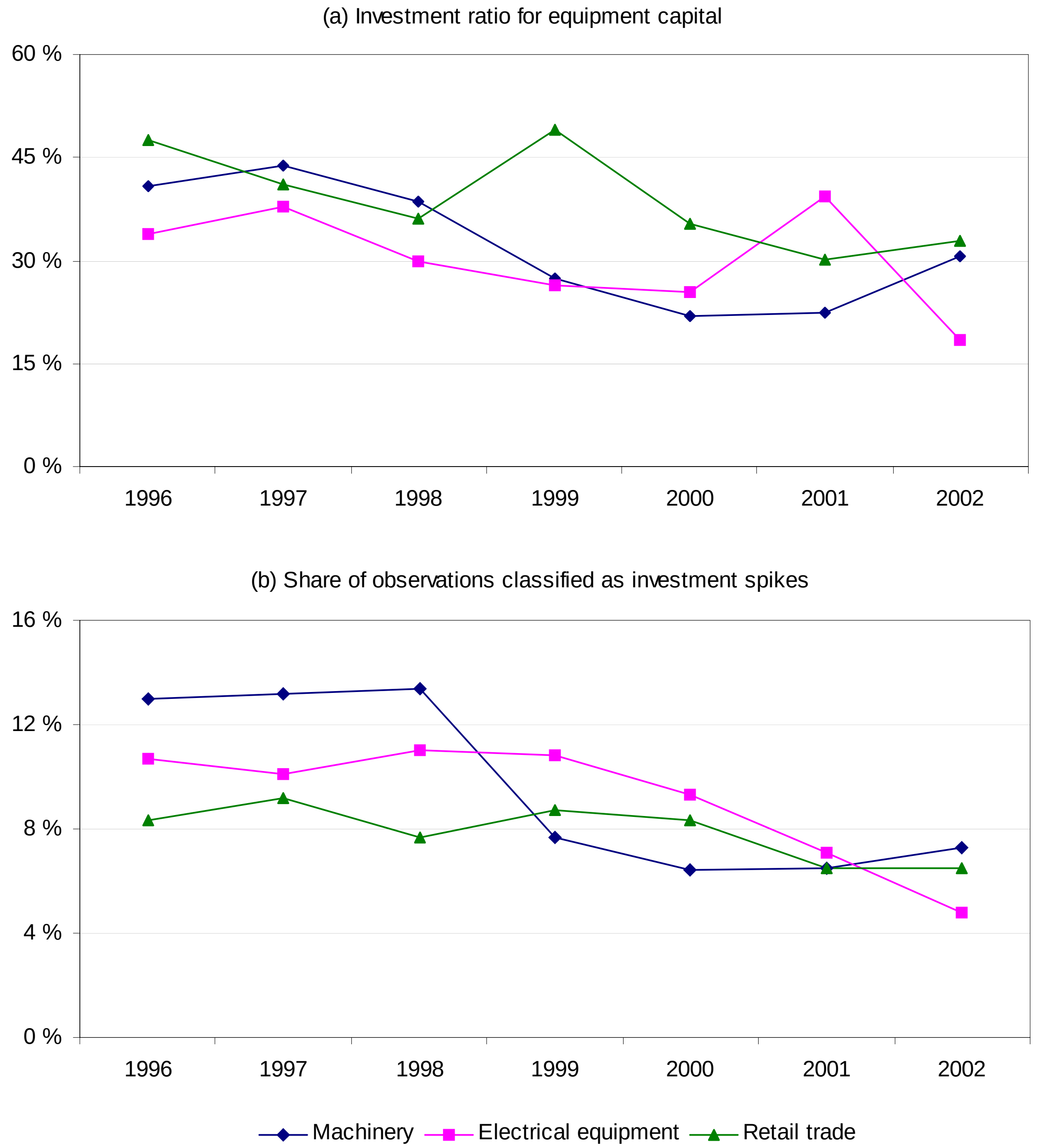


Figure 2. Distribution of investment ratios

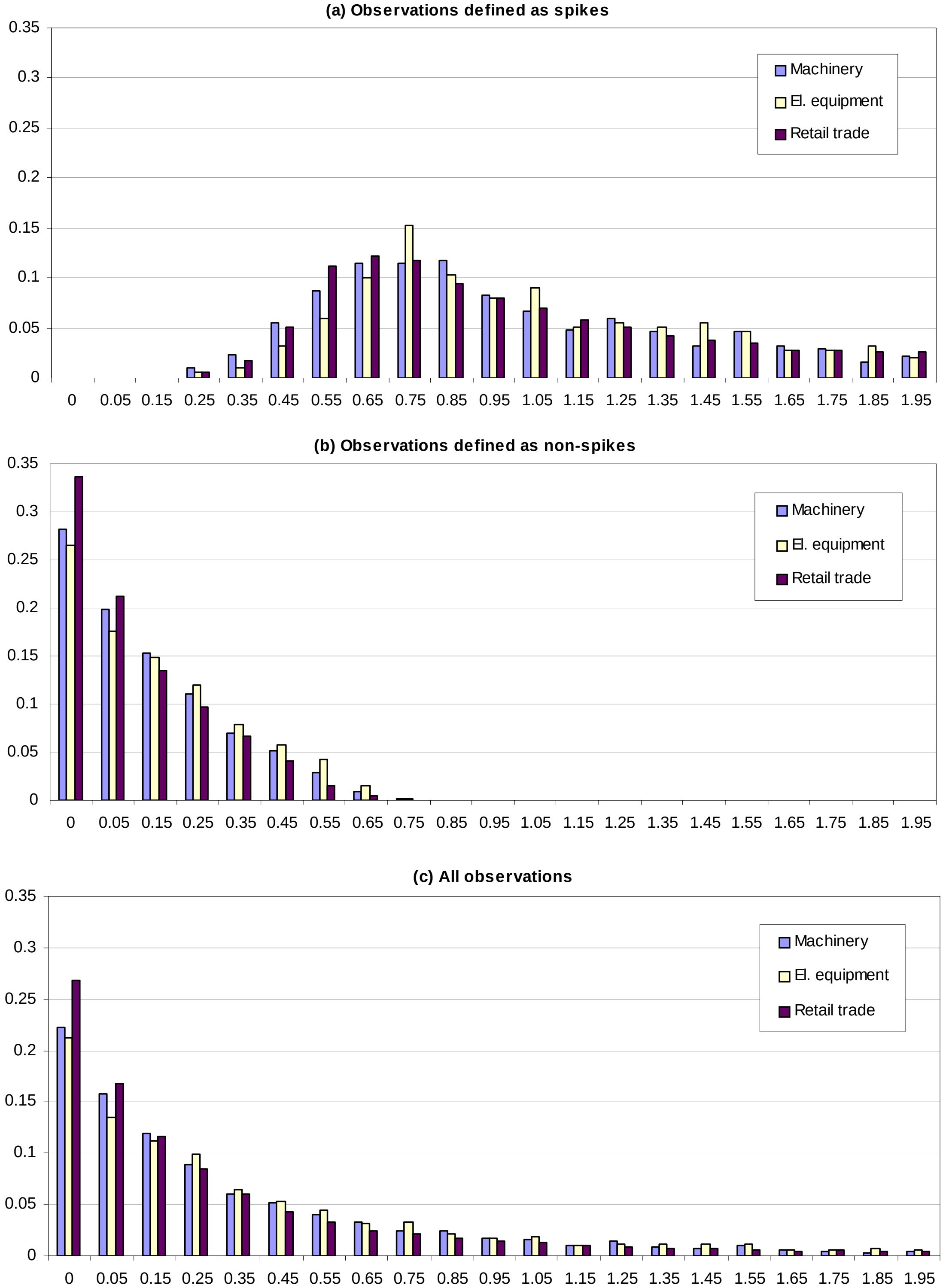


Figure 3. The means of variables in different industries over time

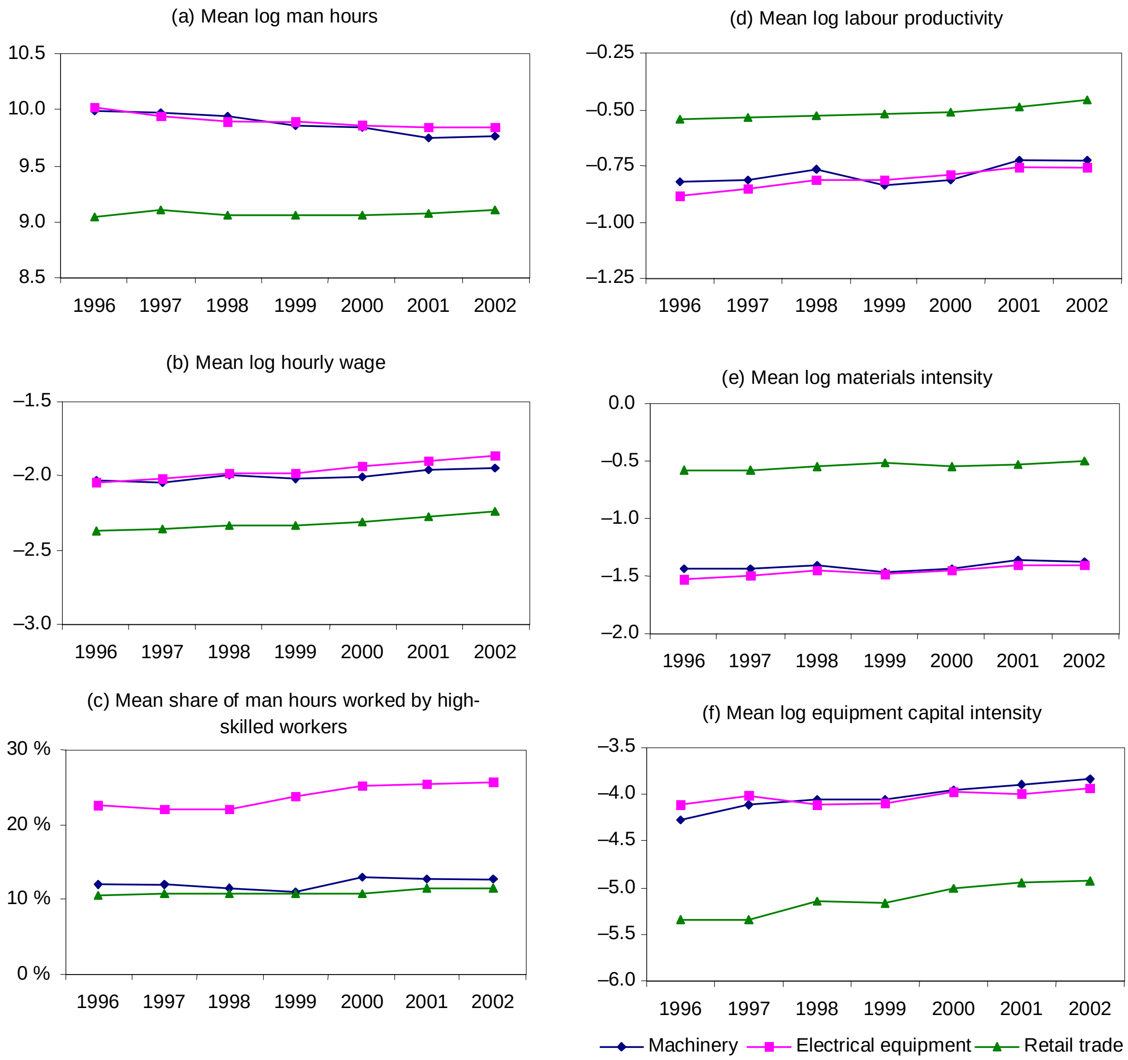
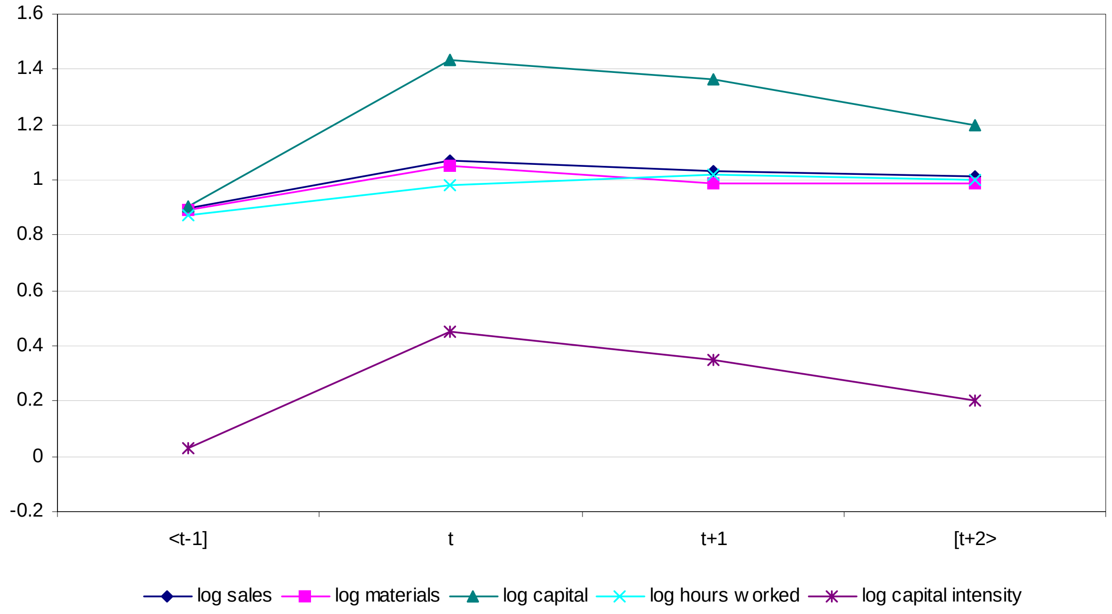


Figure 4: Machinery. Firm characteristics before, during and after an investment spike. Measured as deviations from firms without spikes



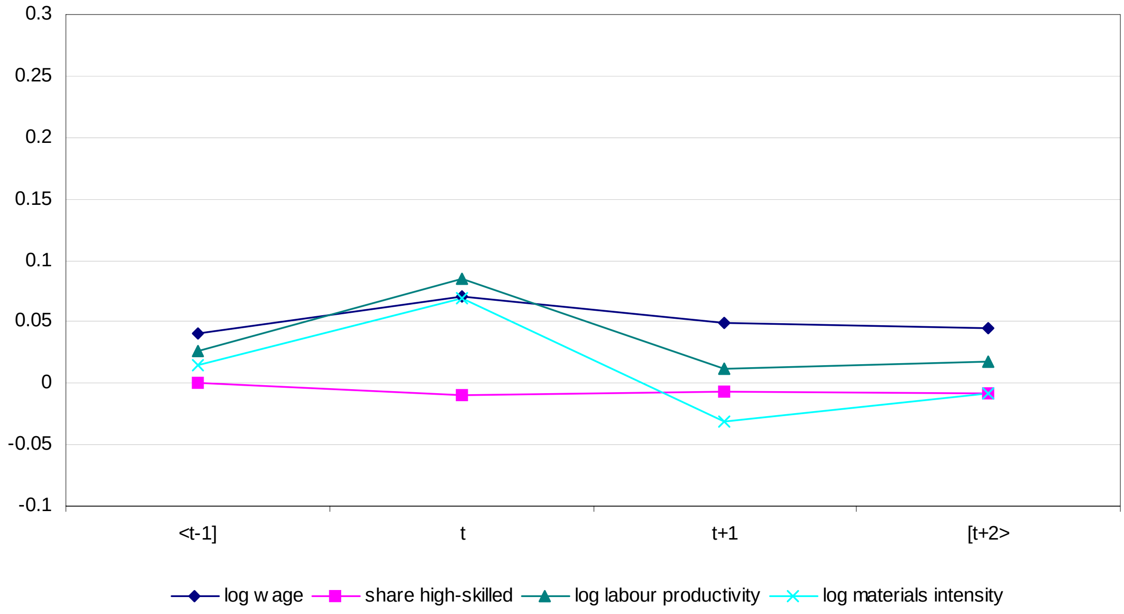
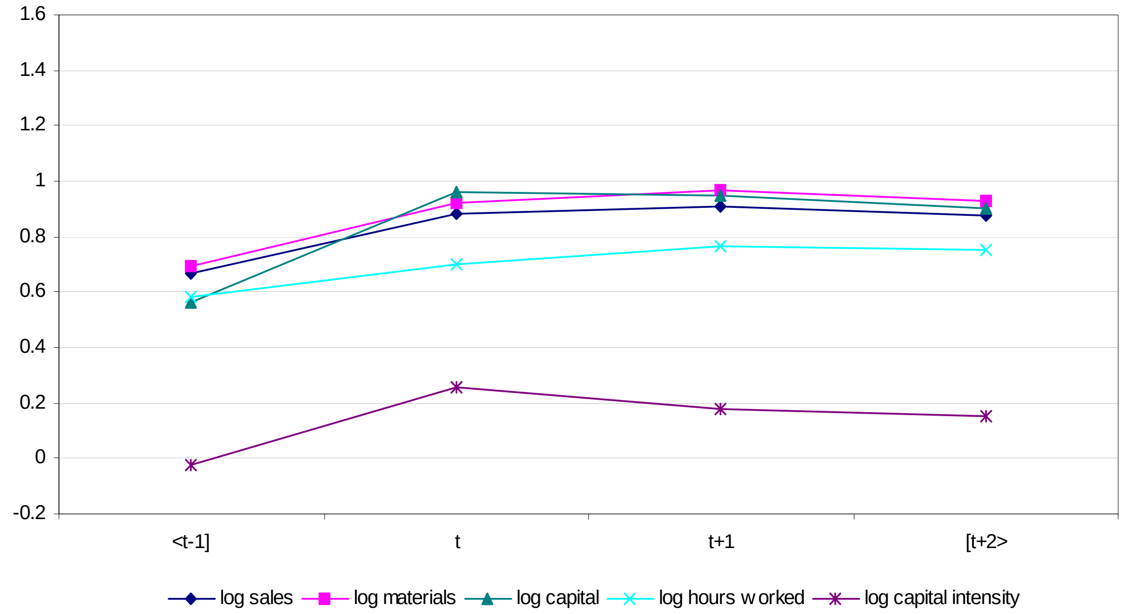


Figure 5: Electrical equipment. Firm characteristics before, during and after an investment spike. Measured as deviations from firms without spikes



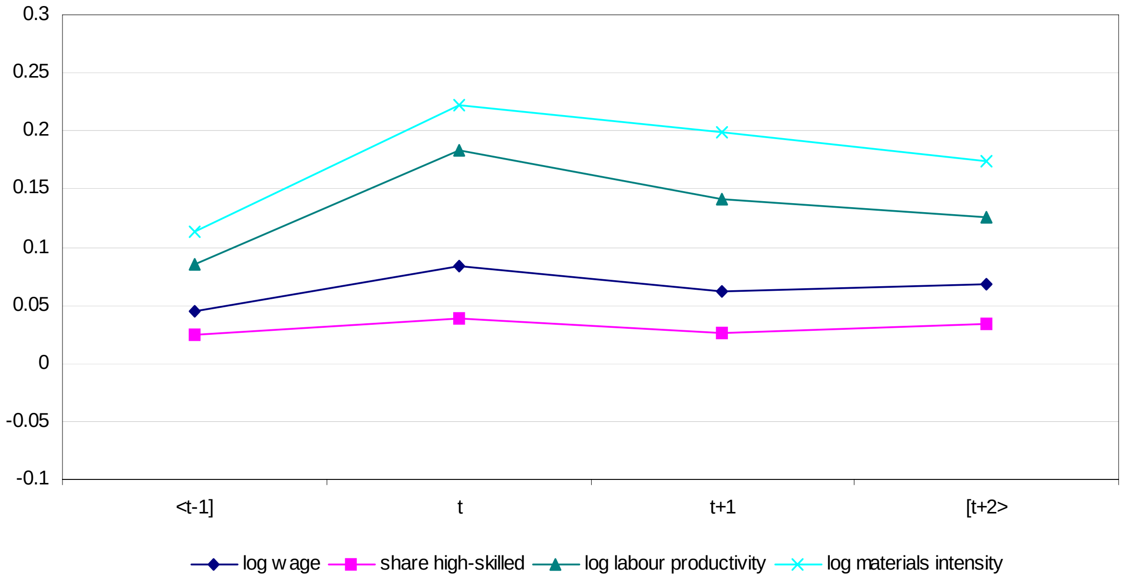
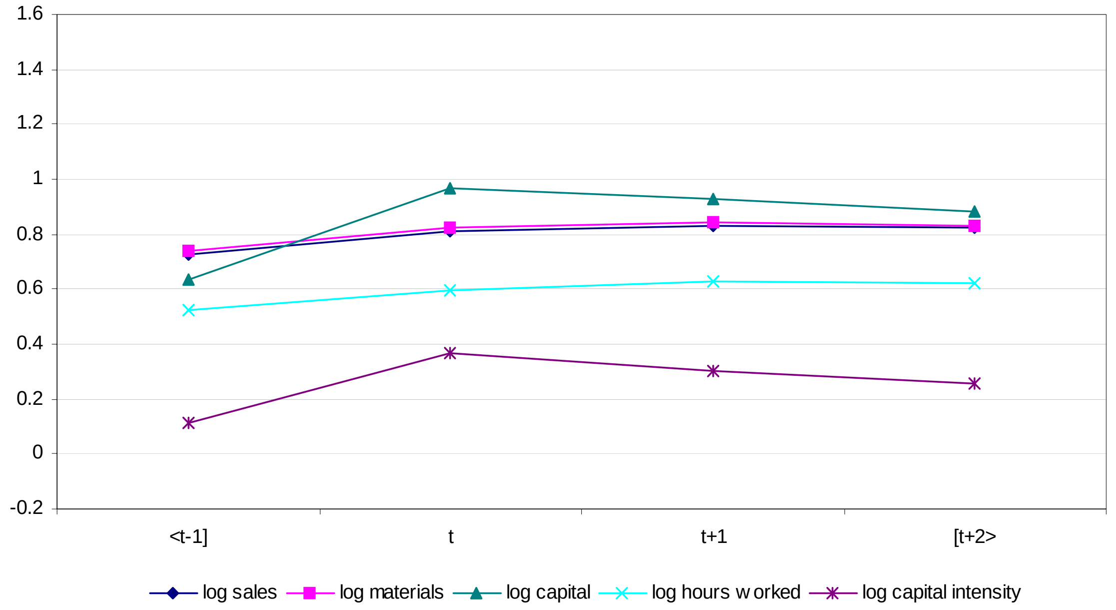


Figure 6: Retail trade. Firm characteristics before, during and after an investment spike. Measured as deviations from firms without spikes



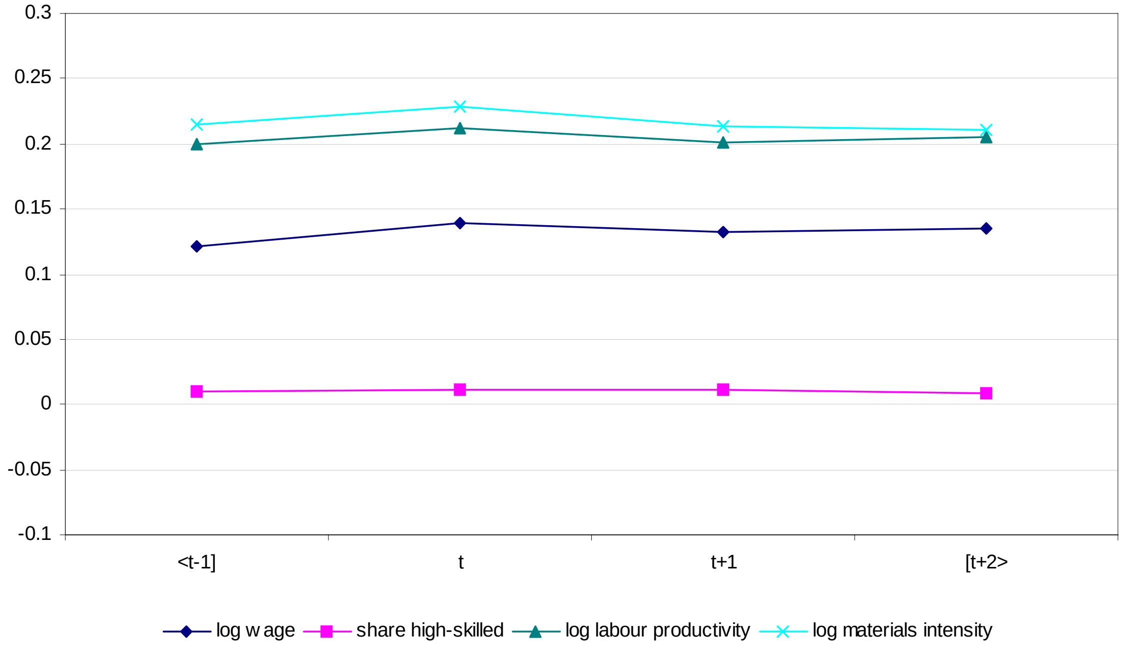


Table A1. Educational levels in the NUS89

Tripartition of levels	Level	Class level
	0	Under school age
Primary education	1	$1^{st} – 6^{th}$
Secondary education	2	$7^{th} – 9^{th}$
	3	10^{th}
	4	$11^{th} – 12^{th}$
Post-secondary education	5	$13^{th} – 14^{th}$
	6	$15^{th} – 16^{th}$
	7	$17^{th} – 18^{th}$
	8	19^{th}+
	9	Unspecified

Figure B1. The share of operational leasing costs for different types of capital