Innovation, machine replacement and productivity

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Abstract

This paper explores the role of replacement and innovation in shaping investment and productivity during episodes of lumpy adjustment in capital. To this purpose we use a rich firm-level panel of Spanish manufacturing data that combines information on equipment investment and firm's strategies. Investment concentrates about episodes of high investment, or investment spikes, but its nature depends upon observable heterogeneity. We find evidence of replacement activity for firms not involved in process innovation nor plant expansion. Then, we explore how large investment episodes transmit into the evolution of productivity under different innovative strategies. We find that productivity increases after an investment spike in innovative firms. However, long learning curves seem to be associated with innovative investments.

Key words: investment spikes, machine replacement, technological innovation, labor productivity, learning effects.

JEL codes: E22, C33, L60

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1 Introduction

The vintage capital literature provides two main insights for understanding the patterns of equipment investment. Firstly, it predicts that the replacement of existing by new equipment represents an important component of equipment investment. This implies that observed investment at the plant level should be lumpy and positively related to the age of existing capital. Secondly, it assumes that new equipment embody improved technology in what is called investment-specific technological change or *embodied technical progress* since Solow's (1960) seminal vintage capital model. This implies in turn that the growth rate of productivity should be related to investment at least at the micro level.

The first insight of the vintage capital literature is well documented. Doms and Dunne (1998) find strong evidence on the lumpy nature of investment decisions at the plant level for the US manufacturing sector. They observe that investment is episodic, with a large frequency of periods of almost inaction, and concentrates about periods of high investment, the so-called investment spikes. Cooper et al. (1999), using similar data for the US, find that investment spikes are more likely to occur for older capital. Nilsen and Schiantarelli (2003) using Norwegian data present additional econometric evidence on these issues and explore their aggregate implications. However, even if there is strong evidence on the embodied nature of technical progress, there is limited empirical evidence at the micro level on a positive link between investment spikes and productivity.[1]

[1] Quality improvements in durable and equipment goods were documented by Gordon (1990), among others. Power (1998) finds very limited evidence on the link at the plant-level between investment spike ages and labor productivity for the US manufacturing sector. Using similar data, Sakellaris (2004) finds some positive, but small response of total factor productivity during those adjustment episodes.

This paper explores the occurrence and implications of *observed heterogeneity* for the relation between episodes of high investment and both the age of capital and productivity. As Cooper et al. (1999) pointed out, hazard functions relating subsequent investment spikes may be upward sloped at the plant level due to *unobserved heterogeneity* even if the aggregate hazard is downward sloped or flat. Therefore, further exploration of investment heterogeneity is needed to interpret the link between investment, or the age of capital, and productivity. To this purpose we use a unique firm-level panel data set combining information on equipment investment and firm's strategies. The sample comes from the survey *Encuesta sobre Estrategias Empresariales (ESEE)* and contains annual information on Spanish manufacturing firms observed during the period 1990-2001. The ESEE has the advantage of collecting data on product and process innovation carried out by firms, as well as standard information on equipment investment, value added and worked hours. This information is particularly useful for our objectives, since innovative strategies of firms are a key determinant of the nature of the investment activities they undertake. Therefore, part of the contribution of this paper comes precisely from the use of this additional information, notably on process innovation, in combination with the notion of lumpy investment, or investment spikes. The interaction of these two key factors is explored, by isolating and measuring the impact of replacement investment and expansion episodes on productivity changes.

Expansionary investment needs not to be associated with the age of existing capital,

Vintage and survival effects seem to play offsetting roles in determining a cohort's relative position in the productivity distribution –see Jensen et al. (2001).

but it may have positive effects on productivity at the firm level if new machines are more productive than existing ones. Replacement investment may imply the substitution of old by new more productive equipment, with an associated improvement in productivity. Consequently, expansionary and replacement investment may have a similar effect on productivity even if they may have completely different effects on the profile of the hazard function relating two consecutive investment spikes. Of course, replacement investment may be partial by modifying a small part of the production process, making it difficult to observe upward slopping hazard functions at the micro level. However, the identification of this type of investment heterogeneity is in general problematic, since available data do not provide any straightforward metric to distinguish expansionary from replacement investment.

In this paper we rely on observed innovative strategies by firms as well as expansionary behavior by multiplant firms to identify investment heterogeneity. Multiplant firms are an interesting control group, since they allow for a reliable identification of expansionary behavior, i.e., those firms increasing the number of plants. Aside from expansionary behavior, the innovative behavior of firms is the central issue. Noninnovative firms are expected to face a small trend in productivity, at least compared to those firms declaring to be frequently engaged in innovative activities. The frequency in the introduction of process innovations may be positively correlated with market performance and be considered an indicator of the degree of partial replacement. Innovative firms are in general successful firms expanding their market share, and consequently investing for other motives than pure replacement. We argue that firms expanding the number of plants as well as frequently innovative firms with unchanged number of plants, may have similar investment strategies and consequently behave closely in terms of observed replacement, sales expansion and productivity growth after an investment spike. On the other side, noninnovative firms may mainly invest for replacement motives, but face both a flat evolution of sales and small productivity effects of investment spikes.

Our empirical approach is descriptive and non-parametric rather than structural. The replacement behavior of firms is described by empirical hazard functions measuring the probability of observing an investment spike as a function of the time elapsed since the occurrence of a previous investment spike. The relation between replacement investment and labor productivity is described by using panel estimation with fixed effects, where the log of labor productivity is regressed on spike ages, controlling for other variables including time dummies and the log of capital per worked hour. The objective is threefold. Firstly, to provide evidence on the replacement behavior of firms. Secondly, to provide evidence on the embodied nature of technical progress and learning. And finally, to provide some basic facts on the role of process innovation for replacement and embodiment.

The paper is organized as follows. The database is described in Section 2. In Section 3 we review the main concepts and variable definitions, together with the main features of investment behavior in Spanish manufacturing firms that serves as motivation for the empirical strategy adopted in this paper. Section 4 presents the empirical models and econometric techniques. Section 5 reports our main findings and Section 6 concludes.

2 The Data

The data set is a pooled cross-sectional time-series official survey, Encuesta sobre Estrategias Empresariales (ESEE), containing annual firm-level information for the Spanish manufacturing sector from 1990 to 2001. It samples firms with at least 20 employees, and the whole population of firms declaring 200 or more employees is in the sample. The survey includes newborn, continuing and exiting firms. After excluding those observations for which either reported value added is negative or there are missing employment or investment data, the selected sample contains 20,627 observations on 3,424 firms. It accounts for over 35% of capital investment in the Spanish manufacturing sector.[2]

Two extracts of the ESEE are used in this paper. First, an *unbalanced panel* with 17,916 observations on 2,128 firms observed at least four consecutive years during the entire sample period. Indeed, when a firm presents more than a sequence we have retained the longer consecutive cut, and if several sequences of the same length the latest one. About 62% of firms and 87% of observations without missing relevant information are observed four consecutive years according to this criterium. Second, a *balanced panel* containing 591 firms continuously observed for the entire sample period, which represents roughly 28% of firms and 40% of observations on the unbalanced panel.

The balanced panel is a natural selection criterion for evaluating replacement activities at the firm level. This is the criterion used by Cooper et al. (1999). In particular, we

[2] In this paper, *large firms* are those with 200 or more employees on average over the entire sample period. Any other firm is defined as *small*. The representativeness of the survey for Spanish manufacturing is discussed in Fariñas and Jaumandreu (1999) and Campa (2004). Also, a general description of investment data in the survey is documented in Licandro et al. (2004).

should expect that firms exiting the manufacturing sector during the sample period were in bad shape by the time previous to exit and optimally decided to postpone replacement. In fact, the market has replaced them through exit. Therefore, in order to estimate the probability of replacement as a function of capital age within the firm, it would be better to exclude exiting firms restricting the estimation to the balanced panel. However, some exiting firms did replacement activities before exiting, because the perspectives were not so bad at the time of replacing. Excluding those firms would bias upwards the effect of replacement investment on firms productivity. Consequently, the balanced panel would suffer from selection bias at the time of estimating the role of replacement on productivity and the unbalanced panel should be used instead. In this paper, most of the results refer to the unbalanced panel since we are mainly interested in estimating the effects of (replacement) investment in productivity. The balanced panel has been used as a robustness check, and we mention it when needed. A discussion on how to account for selection bias is postponed to Section 4.2. In any case, the distribution of firms in the balanced panel extract across two-digit SIC (NACE) industries is roughly comparable to the distribution for the unbalanced panel extract of the survey.

3 Preliminary evidence and definitions

3.1 Investment patterns

As far as we are interested in embodied technical progress and firm's replacement activities, the measure of investment we refer to restricts to equipment investment. It represents

70% of total investment in manufacturing among small firms and up to 86% for large firms.

Firm's current equipment investment is deflated by the equipment investment price index in manufacturing. Investment ratios are used to relate the size of observed investment to the size of the firm. In order to compute investment ratios, an appropriate measurement of real equipment assets is needed. Unfortunately, no reliable information is available in the ESEE, as in any other survey, allowing to directly measure real equipment assets. For this reason, we use the perpetual inventory method, initializing the stock of capital in the first period the firm is observed by the book value of equipment. An important concern is the consistency of using the perpetual inventory method with vintage capital theory. An appropriate measurement of real equipment assets should add the real value of all operative vintages. Under embodied technical progress, the value of existing equipment depreciates at a rate proportional to the lifetime of capital, providing some rational to the use of the inventory method. However, it is important to notice that in this framework the asset value of equipment may not be an appropriate measure of the current contribution of equipment to output.[3]

In line with Doms and Dunne (1998), we find that investment is an infrequent activity and concentrates about large investment episodes. Figure 1 displays the distribution of equipment investment rates (investment over capital) across observations in the unbalanced panel. As it can be seen, about 18% of observations correspond to zero investment

[3]Let us assume, for instance, the productivity of any machine, irrespective of its age, is unity and its lifetime is constant. Then, the value of a machine is negatively related to its age, since its remaining life decreases as far as it ages. A firm is a distribution of machines by age. Consequently, the firm's value of equipment assets is negatively related to the average age of capital. However, the average productivity of capital is unity, irrespective of the distribution of machines by age.

rates, which are episodes of complete inaction. Additionally, around 56% of the observations corresponds to episodes of very low action, with investment rates below 10%. Figure 2 shows, for the balanced panel, the distribution of equipment investment in a five year period around the maximum investment episode, called "spike" in the figure, observed during 1992-99. Investment appears particularly concentrated around the largest investment episode. Nearly 50% of equipment investment corresponds to the spike. This finding is even more pronounced for small firms, as can be observed in the bottom panel.

3.2 Investment spikes and spike ages

Following Cooper et al. (1999) and Power (1998), episodes of high investment are measured using alternative definitions of an investment spike. Let I_t be firm's real equipment investment in period t and I_m be firm's median equipment investment over the sample period. Finally, let i_t, the rate of equipment investment in period t, be equal to the ratio of real equipment investment in t to real equipment assets at the end of period t. Two basic definitions of an *investment spike (IS)* are considered:

- A *relative investment spike (RIS)* occurs in year t if $I_t > \alpha I_m$.
- An *absolute investment spike (AIS)* occurs in year t if $i_t > \beta$.

The *RIS* definition identifies infrequent investment episodes that may not be particularly large in an absolute sense. In particular, a firm may have a zero I_m, implying that any positive investment may be an *IS*. The *AIS* definition captures large, but potentially frequent investment episodes. Firms with an average investment ratio larger than the sample mean, but very smooth across periods may have as many *IS* as observations. Therefore, these criteria may involve lumpy adjustments of a different nature.

A further complication arises if a single investment episode is spread over more than one year. These multi-year events are defined as follows:

- A *multi-year* (either relative or absolute) *investment spike (MIS)* occurs over periods $t, \ldots, t+i$ if *IS* are observed to occur from t to $t+i$.

Adjacent years of relatively intense investment activity may correspond to a form of measurement error induced by the calendar year nature of the data. In order to deal with this problem, Sakellaris (2004) excludes the possibility of consecutive investment spikes. In this paper, we take an alternative way by introducing the definition of a combined investment spike.

- A *combined investment spike (CIS)* is a *RIS* that requires additionally the *AIS* criterium holds for multi-year spikes.

Therefore, the *CIS* definition excludes those unusual investment episodes that are spread over consecutive calendar years but are small relative to the size of the firm. All other *RIS* that do not belong to the class of multi-year investment spikes are retained. In this sense, this is an appropriate definition consistent with the observation of low or nil investment activity followed by sporadic bursts of investment, the emphasis being put then on the infrequent nature of lumpy adjustment. Additionally, we propose an alternative way of combining *RIS* and *AIS* definitions:

- An *intersection investment spike (IIS)* requires the *AIS* criterium holds for all and every *RIS*.

The IIS captures a particular selection of *RIS* and *AIS*: those *RIS* that are large relative to the size of the firm and those *AIS* that are infrequent. We explore below the implications of these alternative definitions for the characterization of the role of the age of capital in investment behavior.

Our choice of scaling parameters follows closely Cooper et al. (1999) and Power (1998) by taking $\alpha = 1.75$ and $\beta = 0.20$. Table 1 reports the frequency of investment spikes and the fraction of total (sample) investment accounted for the alternative definitions of the theoretical construct of an investment spike. The first column corresponds to the *RIS* definition in Power (1998), the second column to the *AIS* definition in Cooper et al. (1999) and the last two columns to the *IIS* and *CIS* definitions introduced in this paper. The table also includes information on the distribution of firms by the number of observed *IS*. These numbers may give an idea of the frequency of short durations.

Table 1 firstly shows that the frequency of *IS* is almost invariant to the use of either the unbalanced or the balanced panel. Secondly, the share of investment represented by the *IS* is slightly larger in the balanced panel. Finally, our definition of a *CIS* is clearly more selective than the separate definitions of *RIS* and *AIS*, suggesting that a large fraction of *RIS* are *MIS*. The *IIS* definition is even more selective, suggesting that relative and absolute spikes do not generally coincide. Remember that for the *IIS* definition, we consider the simultaneous occurrence of the corresponding relative and absolute investment spikes.

With these definitions of an investment spike we define spike ages:

- A *Spike Age (SA)* is the time elapsed since the occurrence of an investment spike.

For expositional convenience, we will also use negative spike ages for the difference between the current year and that of the next investment spike.

3.3 Heterogeneity: Different types of investment strategies

Understanding the impact of different types of investment behavior on the link between investment behavior and productivity would be enlightening for economists and policy makers. But numerous measurement and conceptual problems make it difficult and problematic. Our objective is to identify some variables that might be helpful in characterizing the occurrence and implications of alternative investment strategies. To accomplish this objective, we rely on observed expansionary behavior and innovative activity to learn something on the nature of investment spikes and their effects on firm's productivity.

Expansion, replacement and obsolescence

We aim at distinguishing situations where an investment spike occurs because the firm has decided to increase size permanently, from a situation where the firm has decided to replace old by new machinery or equipment. We call these two situations *expansion* and *replacement*, respectively. Unfortunately, there is no direct observation of these two phenomena in the ESEE.

A partial evaluation of expansionary behavior is made by using information on creation and destruction of plants in multiplant firms. The following definition is implemented:

- An *expanding (contracting) firm (EF)* is a multiplant firm declaring to be increasing (decreasing) the number of plants during the sample period.

In such a situation, it should be expected that the primary motivation for investment is to increase (decrease) output capacity permanently and not to reduce the average age of capital. It is for this reason that creation and destruction of plants are treated alike, even if we also examine these two features separately below. Of course, firms can adjust their production capacity without altering the number of plants. In Section 4, we analyze further expansionary behavior by investigating the effects of different investment strategies on sales.

An *EF* is a clear, basic criterium that enables us to leave apart a number of firms that invest with an objective other than replacing the existing stock of equipment. Table 2 reports the distribution of firms according to the number of establishments they run, as well as the reported changes in that number. These figures correspond to both production and nonproduction establishments. The main results are robust to taking these data separately. Note that around 70% of of observations correspond to single plant firms. About 7% of observations are involved in either expansionary or contractionary episodes as defined above regardless of whether the balanced or unbalanced is considered. It is worth mentioning that establishments' creation and destruction is a four-annual variable until 1998 and is just collected annually since then. Thus, we observe changes in the number of plants a firm runs in 1994, 1998 and from 1999 onwards.

It should be stressed also that the simultaneous occurrence during the sample period of plant creation and plant destruction is excluded from the definition of an *EF*. Investment and scrapping do not necessarily coincide, and firms can profit from high demand periods to create new plants and from low demand periods to destroy the old ones. In this case, what seems to be an expansion or a contraction is in practice a replacement.

There are two hypothesis we would like to test concerning *EF*. Firstly, the empirical hazard of expanding firms may not be upward sloping. This may also be the case of contracting firms. Secondly, productivity may be positively affected by an *IS* in an expanding firm, but not necessarily in a shrinking multiplant firm.

A general (non implementable) definition of a replacement episode follows:

- A *replacement episode (RE)* might correspond closely to purchases of equipment to maintain output capacity lost through output decay, input decay, obsolescence, or any combination of these three elements.[4]

Output and input decay are both associated to physical depreciation. The purpose

[4]Output decay: as a machine ages it may yield less output, a form of deterioration. Another, input decay: an older machine may absorb more inputs or require more maintenance while keeping or nearly the original level of output. Scrapping: complete withdrawal of a machine from a firm's capital stock. When it cannot earn a positive quasi-rent. Thus, it reflects obsolescence, deterioration, and a limited ability to reduce the labor input on old equipment (cf. Solow et al. (1966)).

of investment in the obsolescence case may be to reduce production costs (process innovation) or to produce new goods (product innovation). In fact, firms may modify part of the production process by introducing new machinery, without replacing those machines associated to the remaining parts of the production process. We will call this type of investment behavior a *partial replacement* strategy.[5] Firms frequently involved in innovative activities should replace equipment repeatedly, being engaged in partial replacement activities. Alternatively, firms never engaged in innovative activities should replace equipment due to physical depreciation, but not obsolescence. This should have important implications for the evolution of productivity after an investment spike: no major gains of productivity should be expected from firms never engaged in innovative activities. Next we examine these concepts.

Innovation and partial replacement

The nature of innovative activities undertaken by firms may be informative on the nature of investment strategies. In particular, if a firm engages in process innovation, it may be expected that new equipment comes to replace old equipment. We use the frequency of process innovation to two different purposes. First, firms never engaged in process innovation would not be affected by obsolescence. Replacement activities in noninnovative firms may be guided mainly by physical depreciation. Consequently, *IS* may not have

[5] In some extreme cases, partial replacement policies could take the form of a smooth replacement rule, which does not necessarily generate investment spikes. Adjustment costs of investment are relatively low for flexible technologies and allow firms to have smooth investment strategies, as we observe for most computer networks based on PCs. In this case, the adjustment cost of replacing an old by a new PC is low, making it optimal to renovate the stocks of PCs almost uniformly over time.

significant effects on productivity. Secondly, the frequency of process innovation is a key ingredient associated to both *firm expansion* and *partial replacement*. The argument is as follows. On one side, firms frequently engaged in process innovation are expected to be successful, which may imply that with high probability they would increase their market shares and sales. On the other side, it can be expected that purchases of equipment in those firms more frequently involved in innovative activities imply a replacement of a small fraction of the capital stock. Replacement may be more partial in those firms declaring process innovations more frequently. Finally, firms frequently engaged in process innovation are expected to have productivity gains after an *IS*.

Let us introduce the following operative definition:

- A *process innovation (PI)* is a significant modification in the production process associated to the introduction of new equipment.[6]

From our definition of innovative activities, we exclude product innovations and those process innovations that only involve modifications in the methods of organization, which are both reported in the ESEE. The definition of process innovation adopted in this paper is going to be necessarily associated to some form of investment activity, which needs not to be the case for product innovation or process innovation restricted to new methods of organization.

[6]This question comes in the survey after the one referred to product innovation, and it distinguishes three alternative situations: the introduction of new equipment, new methods of organization or both. In this paper, a firm is said to be engaged in process innovation if she answers yes to the corresponding question and declares to have been in the first or the third situations.

In any case, process innovation appears to be a rather stable activity and does not seem as episodic (infrequent) as investment. Empirical hazards are typically flat. Tables 3 and 4 display Logit regressions for the probability of a firm being engaged in process innovation as a function of a contemporaneous *IS* or *SA* (spike age) in the range $t-2$ to $t+2$, respectively, including year dummy variables. The reported results are those of the logistic model implemented over firms that have only one *IS*. Clearly, the correlation between spikes and innovations is substantially higher for process innovation. More important, coefficients for the spike and the years before and after are statistically significant for process innovation only, none for product innovation. These results are robust to include more leads or lags, and to consider the whole sample with at least one *IS*.

4 Empirical models: hazards, sales and productivity

The approach adopted in this paper is descriptive. The replacement behavior of firms is described by the mean of hazard functions measuring the probability of observing an investment spike *(IS)* as a function of the age of the previous spike. The relation between replacement investment and productivity is described by using a fixed-effect panel estimation, where the log of labor productivity is regressed on spike ages, controlling for other variables including time dummies. Moreover, firms in the sample are partitioned in three groups: *i)* expanding firms *(EF)*, *ii)* innovative firms, i.e., those frequently involved in process innovation, and *iii)* noninnovative firms. A more formal distinction between innovative and noninnovative firms is proposed in the next section. In addition, we estimate the relation between spike ages and sales, to better understand the (non)expansionary behavior of (non)innovative firms.

4.1 Hazard functions

We are interested in estimating the probability of observing an investment spike as a function of the age of the previous spike, the so-called hazard function. The main issue here is whether the hazard is upward sloping or not. In order to do this estimation, we do need the occurrence of at least one *IS*. In this paper, we restrict the analysis to subsamples of both the balanced and the unbalanced panels for which firms have at least one *IS*, and thus subject to selection bias.

In order to estimate empirical hazard functions, or Kaplan-Meier nonparametric hazards, data are reorganized in the following way. A unit of observation is a sequence of observations belonging to the same firm, starting the year after the observation of an *IS* and ending either when a subsequent *IS* is observed or at the last observation corresponding to this firm (this is a case of truncation). Consequently, a firm is decomposed at most in as many units of observations as *IS* are measured. A unit of observation is associated to an *IS*. The position of each observation in a unit corresponds to the spike age *(SA)*. A formal definition of the empirical hazard follows:

- An *empirical hazard function* is, at every age a of an *IS*, the ratio of the number of units of observation for which an *IS* is observed at age a divided by the size of the risk set. The size of the risk set is the number of units of observation that have reached age $a-1$ without facing an IS at this age.

The empirical hazard may not capture well the shape of the hazard function due to the presence of unobserved heterogeneity. Following Nilsen and Schiantarelli (2003) we have also parameterized the hazard as a logistic function with fixed effects and duration dependence dummies (see below). But the parametric estimates of the hazard model do not lead to substantially different conclusions. For ease of exposition we omit these estimates which are available upon request.

4.2 Sales and productivity

We examine whether investment spikes have statistically significant effects on sales and productivity. To this purpose, we run the following type of regression:

$$\log y_{it} = \lambda_t + \sum_{d=-k}^{d=l} \gamma^d D_{it}^d + \beta X_{it} + \eta_i + \varepsilon_{it}, \tag{1}$$

where y_{it} represents i'th firm's sales or labor productivity. Sales are directly observed and labor productivity is computed as the ratio of value added to worked hours. The regression includes year dummies λ_t to control for the cycle and any growth trend. It also rules out firm-specific effects η_i, which are assumed to be fixed. X_{it} includes other explanatory variables as industry and size dummies in all regressions, firm's market share and firm's expectations on market evolution in sales regressions, and capital per worked hour and capacity utilization in productivity regressions. Notice that controlling for capital per worked hour in the productivity regressions may allow us to interpret the remaining factors as total factor productivity.

The spike age dummy D_{it}^d takes value one if there is a spike at time $t - d$, zero otherwise. It captures the effect on sales or productivity of an investment spike aged d. The estimated parameters γ^d give the profile of sales and productivity around an *IS*, which corresponds to $d = 0$, after controlling for firm specific-effects, time dummies and other relevant characteristics.

We implement model (1) using two different samples. Firstly, we include firms with one and only one investment spike. This provides an immediate interpretation of the estimated values of γ^d for a restricted data set. Secondly, we implement model (1) in the augmented sample of those firms having *at least* one investment spike. In such a case, the sum of the age dummies is restricted to positive spike ages, $k = 0$, and appears as many times as the number of observed *IS*. Parameters γ^d are then assumed to be invariant to the different *IS* and reflect the average response of the endogenous variable to every spike event. In addition, we include the investment rate as a regressor to capture the average level of the response.

Finally, as a robustness test, we follow Sakellaris (2004) in adding to the empirical model (1) an additional dummy variable O_{it}, which equals one if any other investment spike happened before year $t - k$ or after year $t + l$. In this alternative model a firm is decomposed in as many units of observations as *IS* are measured. This specification captures the average response about every spike event while controlling for the response of the endogenous variable to any other investment spike outside the window $t-k$ to $t+l$.

The spike age dummies and most variables in X_{it} may be endogenous. The implementation of model (1) introduces sample selection bias, as well as the criteria in Section 2 to build the balanced and unbalanced panels. In the following, we assume

$$E\left(\eta_i \mid D_{it}^d, X_{it}\right) \neq 0$$

$$E\left(\varepsilon_{it} \mid D_{it}^d, X_{it}\right) = 0.$$

Under these assumptions, the fixed-effects account for endogeneity operating through η_i and for sample selection bias.[7]

5 Results

5.1 The nature of investment spikes

We begin our characterization of the timing relationship between consecutive investment spikes by estimating Kaplan-Meier nonparametric hazards. The use of alternative definitions of an *IS* and the organization of the sample by the extent of innovative activity allow us to qualify conveniently some of the most interesting results.

For the unbalanced panel extract, Figure 3 plots the empirical hazard under the alternative definitions of an *IS*, for $\alpha = 1.75$ and $\beta = 0.2$ as discussed in Section 3.2. There are two important observations. Firstly, the probability of having an *IS* at age one is very high for all definitions, except for *CIS*. It reflects the well known accountability problem that a single *IS* may be registered over two consecutive calendar years. Indeed, the *CIS* definition has been introduced to lessen that problem. Secondly, the hazard is upward

[7] See Verbeek and Nijman (1992) and Vella (1998).

sloping under both *CIS* and *RIS* definitions, but it is not under *AIS* and *IIS* definitions. Under the *AIS* definition, there is an important number of firms with at least as many *IS* as half of the number of observations. Instead, under the *RIS* definition the number of firms in this situation is nil. Consequently, the *AIS* definition tends to concentrate *IS* on a small number of firms with many *IS*, i.e., those firms with a large investment rate on average. Since durations are short for firms with many *IS*, and there are many firms of this type under the *AIS* definition, the hazard tends to be decreasing, as observed in Figure 3. The parametric estimation of the hazards, using conditional logistic regressions with fixed effects, confirms these two observations.[8] Overall, we interpret these observations as supporting the use of the *CIS* definition. Therefore, except where otherwise indicated the *CIS* definition is the one retained below. As a robustness test, we report the results corresponding to two alternative definitions of an investment spike, those corresponding to the intersection *(I)IS* and the relative *(R)IS*.

Next, we distinguish firms according to the frequency of innovative activities. For this purpose, we select those that are nonexpanding firms (i.e., not *EF*) in the unbalanced panel extract. As an illustration, Figure 4 plots the empirical hazard for different categories, depending on the number of periods the firm declares to introduce process innovation. It can be observed that the more often process innovation is declared the flatter the empirical hazard is. In particular, it turns out that 1 or 2 years of process innovation make enough difference. Therefore, we examine in further detail how the frequency

[8]For ease of exposition, we omit these estimates which are available upon request. Duration coefficients are statistically significant for all of the models, but the duration effects are stronger for *RIS* and *CIS* definitions and always monotonically increasing under our definition of a *CIS*.

of innovation affects the hazard by splitting the group of nonexpanding firms into two subgroups: innovative and noninnovative firms. Let us introduce the following operative definition:

- An *innovative firm* is a nonexpanding firm (i.e., not an *EF*) that declares to introduce process innovation at least 20% of the time.

For a firm in the balanced panel, it means that it declares to introduce process innovation at least 3 different years over 12. A nonexpanding, noninnovative firm is called *noninnovative*.[9]

To better qualify the role of replacement activities in driving firm's investment behavior, we have estimated empirical hazards for expanding, innovative and noninnovative firms. Comparisons must be taken with caution since the number of firms in each subgroup is quite different. As Figure 5 shows, the empirical hazard for noninnovative firms is upward sloped, implying that replacement activities seem particularly associated with firms that declare a low frequency of process innovation. The empirical hazard is flat for both innovative and expanding firms.[10] This may reflect that expanding firms are investing for other motives than replacement, and innovative firms are either expanding

[9] The frequency of *CIS* is higher in the nonexpanding sub-group under both categories of innovative activity. It is only slightly higher for noninnovative firms among these two groups, and their figures are very similar in both panels. These figures suggest that episodes of large investment are equally important in all firms, although the degree of lumpiness is somewhat reduced in *EF* regardless of whether they are continuously observed or not. Therefore, differences in replacement activity do not come from differences in the frequency of *IS*.

[10] The empirical hazards show no important differences between expanding and contracting firms, reflecting that investment in both types of firms is not guided by replacement behavior. On the other hand, the corresponding parametric estimates confirm that indeed the duration coefficients are higher for nonexpanding firms in both the balanced and the unbalanced panel. Again, the small number of observations in the *EF* subgroup suggests caution.

or undertaking partial replacement or both. As a robustness test, Figure 6 shows the corresponding empirical hazards for *RIS* and *IIS* definitions. These figure provides further support for the aforementioned interpretations that innovative firms may be expanding or engaged in partial replacement, but replacement activities seem particularly associated to noninnovative firms.

5.2 Expansion and replacement

In this section, we present model (1) regressions for sales using four different groups: expanding, contracting, innovative and noninnovative firms. The objective is to better understand the nature of investment in innovative and noninnovative firms, by comparison with expanding and contracting firms (the *EF* group). Notice that these four cuts of the sample are independent. Therefore, the estimation results are robust to alternatively considering the joint regression with group dummies.

In order to asses the degree of significantly different expansionary behavior we first present estimates in Tables 5 and 6. They correspond to firms with only one *CIS* for both the unbalanced and the balanced panel. Figure 7, instead, comprises the point estimates for the unbalanced panel only in order to asses the duration dependence in more detail. Similar results were obtained for the augmented sample incorporating all firms with at least one *CIS*. Sales regressions were run controlling for fixed-effects, and both expected market evolution, *mkev*, and market share, *mksh*. Both variables take three possible values: expanding (E; I for increasing), stable (S; C for constant) or declining.

Firstly, as it can be seen in Figure 7 for the unbalanced panel, sales are increasing after an *IS* for expanding firms, but it is flat for contracting firms. These results are robust when the balanced panel is considered, though the low precision of the estimates, which results from the small number of observations, suggests caution. In the previous section, we argue that creation and destruction of plants do not seem to make a difference in terms of the hazards. Here, however, we see that our estimates meaningfully relate large investment episodes with an increasing volume of sales for expanding firms only. This does not hold for multiplant shrinking firms.

Secondly, from the same figure we may say that the behavior of sales around an *IS* is quite similar for expanding and innovative firms. Something similar occurs when we compare noninnovative and contracting firms. This may be taken as evidence on an expansionary behavior of innovative firms. Noninnovative firms, instead, seem to invest mainly to replace old equipment.

5.3 Innovation, investment and productivity

In the previous sections, we show evidence on lumpy investment activity particularly associated to firms declaring not being much involved in process innovation. We also show that these firms are not expanding sales, from which we conclude that their investment activity is mainly addressed to replace old by new machines. It is important to notice, that noninnovative firms do not perceive these new equipment as an innovation in the production process. We also show evidence on a flat hazard for firms frequently involved in process innovation, as well as a clear expansionary pattern. Innovative firms may be involved in an expanding strategy or in partial replacement. We interpret these results as supporting differential investment patterns due to observed heterogeneity. The question is then whether we can find also differential effects of large investment episodes in productivity for these different groups.

To this purpose, we study the effect of an *IS* on productivity for expanding, innovative and noninnovative firms. We run panel regressions over these three groups as in equation (1), with average labor productivity as the endogenous variable, controlling for time dummies and fixed effects. Moreover, we include as controls the log of capital per worked hours and capacity utilzation, as it is standard when measuring productivity effects. This allow us to interpret the results as the effect of an *IS* on total factor productivity. In order to do so, we first restrict the sample to firms with only one *CIS*. Then, we extend productivity regressions to the augmented sample with at least one *CIS*. Finally, we implement the alternative regression proposed by Sakellaris (2004), that estimates the effects of spike ages centered on a time window of $[-2, +6]$ years, but controlling for the effect of all other spikes.

Table 7 reports our estimates for the restricted sample of firms with one and only one *IS*. In all of the cases, we do not find significantly different effects up to age three, but a positive effect can be found for innovative firms after spike age four. As we did before, it is also meaningful to compare dynamic patterns among groups. Figure 8 summarizes the response of productivity to an *IS* in the sample with only one *CIS*. Clearly, the response in productivity to an investment spike is different for innovative and noninnovative firms. In particular, the response for both groups is increasing, but that for innovative firms exhibits a larger slope and sizeable lags. We interpret this result as evidence on *embodied technical progress*: even if noninnovative firms may be profiting from some form of disembodied technical progress, gains in productivity associated to investment spikes are larger for firms declaring that investment in new equipment is contemporaneous to the introduction of process innovation. The observation that gains in productivity for innovative firms come with some delay, may be due to diffusion and long learning curves.

We provide further support to this interpretation by considering the sample including all firms with at least one spike. In this case, the estimated coefficients capture the average effect of spike ages for all *IS*s experienced by a firm. Rather than introducing dummies for negative spike ages, we include the investment rate as an independent regressor here in order to capture the average level of the response. Figure 9 summarizes these estimates, which reinforce the interpretation given above. We do find that the effect of investment spikes on productivity is increasing with spike age for the innovative group. We do not find this effect for the noninnovative group, though coefficients are increasing up to spike age three. As an additional robustness test, we follow the strategy proposed by Sakellaris (2004). Results for the innovative and noninnovative groups are in Figure 10. Similar results are obtained, even more in favor of differential responses among groups along the lines suggested above. Finally, Figure 11 include the point estimates using *RIS* and *IIS* definitions. These figures give an additional support to the previous interpretation.[11] Another interpretation is that if investment spikes arise contemporaneously, investment patterns at the micro level will tend to overlap. The productivity gains of recent investment may be low since the innovative investments require diffusion. The variation in productivity with respect to investment age may be low since noninnovative investments will dampen as time goes by. Consequently, the aggregate effect will depend on the dynamics of innovation and replacement investment.

6 Concluding remarks

In this paper, we analyze the role of replacement and innovation activities in shaping investment behavior and labor productivity in a panel of Spanish manufacturing firms from 1990 to 2001. There is an ample evidence at the micro level on the episodic nature of investment, which concentrates about investment spikes. The empirical literature also concludes that, after controlling for unobserved heterogeneity, the probability of observing an investment spike is increasing with the age of capital. In this paper, we rely on expansionary and innovative behavior of firms, a particular form of observed heterogeneity, to estimate hazard functions and look to the patterns of productivity around large investment episodes. Our goal has been to provide some basic facts on the role of process innovation for replacement and embodiment.

Firstly, we find that hazard functions are of a very different nature depending on the observed characteristics we consider. Replacement activities are more likely for non-

[11] In all of the regressions summarized by Figures 9 to 11 we find estimates that are significant, and significantly different among groups from spike age 3 onwards. These results, which are in line with those reported in Table 7, are available upon request.

innovative firms, while innovative firms are probably engaged in some form of partial replacement. Secondly, we find that investment spikes have statistically significant different effects on sales for the aforementioned different subsamples of the data set. Sales rise after an investment spike in innovative firms, but do not exhibit such a pattern in noninnovative firms. Thirdly, innovative firms behave as expansionary firms: both expand sales after an investment spike and both exhibit flat hazard functions; but noninovative firms only share with contractionary firms a slow growth pattern of sales after an investment spike. As may be expected, contractionary firms do not exhibit an increasing hazard.

The question is then whether our distinction between expansionary behavior and innovation activities contributes to assess the link between productivity and investment age. We find evidence that innovative firms increase their productivity after an investment spike but slowly, exhibiting smooth diffusion curves. On the other hand, productivity does not improve in non-innovative firms after an investment spike.

These findings suggest that the cyclical variation in total investment spending will be incorrectly anticipated if the dynamics of innovation and replacement investment are ignored. Also, our empirical findings are potentially relevant to policy making. Changes in tax laws and the rate of interest are likely to have very different aggregate effects depending on the age of capital and the innovative behavior of firms.

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Table 1: Comparison of investment spike definitions

BALANCED PANEL	Relative	Absolute	Combined	
	$\alpha = 1.75$	$\beta = 0.20^*$	$\alpha = 1.75$ and $\beta = 0.20$	
	RIS	*AIS*	*IIS*	*CIS*
No Spike	5242	5547	6010	5714
Spike	1850	1545	1082	1378
(%)	(26.1%)	(21.8%)	(15.3%)	(19.4%)
Inv't(%)	(43.8%)	(36.1%)	(31.9%)	(35.6%)
n. of firms				
with 1	78	109	150	127
2	98	120	148	154
3	128	89	112	154
4	122	65	51	80
5	118	41	18	31
6	19	40	1	1
6 or more		29		
UNBALANCED PANEL				
No Spike	13417	13910	15272	14430
Spike	4499	4006	2644	3486
(%)	(25.1%)	(22.4%)	(14.8%)	(19.5%)
Inv't(%)	(40.2%)	(35.6%)	(29.0%)	(33.6%)
n. of firms				
with 1	545	507	656	697
2	535	408	450	564
3	358	244	211	316
4	224	179	81	128
5	160	94	25	39
6	19	59	1	1
6 or more		53		

Table 2: Creation and Destruction of Plants

n. of plants	Firms' dist. 1st year freq. (%)	n. of firms with change in n. of plants ≤-3	-2	-1	0*	1	2	≥3	Firms' dist. last year freq. (%)	Total Obs.
BALANCED PANEL										
1	401 (67.85)				344	37	11	9	406 (68.70)	4937
2	75 (12.69)			38	28	2	0	7	77 (13.03)	883
3	35 (5.92)		12	4	9	2	3	5	33 (5.58)	358
4	17 (2.88)	1	3	6	3	1	2	1	14 (2.37)	183
5	12 (2.03)	3	2	1	1	0	1	4	14 (2.37)	144
6	7 (1.18)	1	2	4	0	0	0	0	12 (2.03)	105
7	6 (1.02)	3	3	0	0	0	0	0	3 (0.51)	70
8	7 (1.18)	3	3	0	1	0	0	0	8 (1.35)	85
>8	31 (5.25)	21	1	1	4	2	1	1	24 (4.06)	327
Total	591 (100)	32	26	54	390	44	18	27	591 (100)	7092
UNBALANCED PANEL										
1	1436 (67.48)				1285	95	21	35	1460 (68.61)	12129
2	261 (12.27)			111	114	15	7	14	262 (12.31)	2225
3	114 (5.36)		25	18	39	11	7	14	101 (4.75)	894
4	70 (3.29)	10	14	11	19	5	5	6	63 (2.96)	586
5	42 (1.97)	13	4	6	10	0	2	7	52 (2.44)	382
6	23 (1.08)	8	3	5	3	2	0	2	33 (1.55)	254
7	32 (1.50)	15	6	2	3	1	3	2	21 (0.99)	249
8	22 (1.03)	9	8	0	2	0	1	2	14 (0.66)	169
>8	128 (6.02)	71	7	8	17	5	2	18	122 (5.73)	1028
Total	2128 (100)	126	67	161	1492	134	48	100	2128 (100)	17916

*gives the number of firms with no change (0) in n. of plants

Table 3: Innovation and Investment Spikes. Logit Estimation (Fixed Effects, Unb. Panel) of the probability of an innovation of either product or process

	Product Innovation		Process Innovation	
	Coefficient	Std. Err.	Coefficient	Std. Err.
Spike	0.172	0.12	0.736	0.11
y91	0.820	0.22	1.211	0.21
y92	0.648	0.22	1.055	0.21
y93	0.714	0.21	1.318	0.21
y94	0.698	0.22	1.034	0.21
y95	0.417	0.22	0.885	0.21
y96	0.675	0.22	1.027	0.21
y97	0.903	0.22	0.986	0.21
y98	0.711	0.22	0.910	0.21
y99	0.787	0.23	0.610	0.21
y00	0.801	0.23	0.725	0.22
y01	0.279	0.25	0.459	0.23
Obs.	2997		3544	
n. of firms	376		447	
LR χ^2_{12}	32.30		102.24	
Prob $> \chi^2$	0.001		0	

Table 4: Innovation and Spike Ages. Logit Estimation (Fixed Effects, Unb. Panel) of the probability of an innovation of either product or process

	Product Innovation		Process Innovation	
	Coefficient	Std. Err.	Coefficient	Std. Err.
Spike_{-2}	-0.075	0.16	-0.187	0.15
Spike_{-1}	0.033	0.15	0.288	0.14
Spike	0.190	0.13	0.836	0.12
Spike_{+1}	0.188	0.14	0.415	0.13
Spike_{+2}	-0.070	0.16	0.100	0.15
y91	0.781	0.22	1.148	0.21
y92	0.632	0.22	1.005	0.21
y93	0.705	0.22	1.297	0.21
y94	0.694	0.22	1.024	0.21
y95	0.407	0.23	0.864	0.21
y96	0.668	0.22	1.012	0.21
y97	0.891	0.22	0.952	0.21
y98	0.698	0.22	0.859	0.21
y99	0.765	0.23	0.540	0.22
y00	0.776	0.23	0.623	0.22
y01	0.257	0.25	0.393	0.23
Obs.	2997		3544	
n. of firms	376		447	
LR χ^2_{15}	35.06		118.43	
Prob $> \chi^2$	0.004		0	

Table 5: Sales – Fixed-effects regressions of the impact of investment spikes on sales for the Expanding and Contracting subgroups (*EF* group)

	Unbalanced Panel		Balanced Panel	
	Expanding	Contracting	Expanding	Contracting
Spike_{-3}	0.344(0.07)	0.282(0.06)	0.516(0.14)	0.305(0.07)
Spike_{-2}	0.415(0.07)	0.326(0.06)	0.560(0.14)	0.397(0.08)
Spike_{-1}	0.578(0.07)	0.435(0.06)	0.701(0.14)	0.420(0.07)
Spike	0.819(0.07)	0.558(0.06)	0.867(0.13)	0.512(0.07)
Spike_{+1}	0.881(0.08)	0.563(0.06)	0.853(0.16)	0.500(0.08)
Spike_{+2}	0.923(0.08)	0.567(0.07)	0.896(0.16)	0.526(0.07)
Spike_{+3}	1.064(0.10)	0.612(0.07)	1.054(0.18)	0.596(0.09)
Spike_{+4}	1.109(0.11)	0.594(0.08)	1.152(0.18)	0.555(0.09)
Spike_{+5}	1.148(0.13)	0.504(0.09)	1.383(0.24)	0.611(0.11)
Spike_{+6}	1.189(0.14)	0.520(0.10)	1.354(0.28)	0.716(0.12)
mkev_E	0.135(0.05)	0.094(0.04)	0.161(0.10)	0.084(0.05)
mkev_S	0.085(0.05)	0.051(0.03)	0.113(0.10)	0.062(0.04)
mksh_I	0.074(0.06)	0.016(0.04)	0.250(0.11)	-0.047(0.05)
mksh_C	0.065(0.05)	0.003(0.04)	0.220(0.10)	-0.079(0.04)
y93	-0.214(0.07)	-0.159(0.05)	-0.295(0.14)	-0.135(0.07)
cons.	19.27(0.08)	19.43(0.06)	19.43(0.15)	19.91(0.07)
Obs.	522	699	180	252
n. of firms	66	83	15	21
R^2	0.967	0.977	0.897	0.978
Prob $> F$	0.000	0.000	0.000	0.000

Heteroskedasticity-corrected standard errors are in parentheses.
Year dummy variables are shown when significant in at least one regression.
Industry dummy variables are not shown.
$F-$test for joint significance.

Table 6: Sales – Fixed-effects regressions of the impact of investment spikes on sales for the Innovative and Noninnovative subgroups

	Unbalanced Panel Noninnovative	Innovative	Balanced Panel Noninnovative	Innovative
Spike_{-3}	0.294(0.04)	0.427(0.03)	0.416(0.07)	0.433(0.05)
Spike_{-2}	0.369(0.04)	0.535(0.03)	0.493(0.07)	0.493(0.05)
Spike_{-1}	0.447(0.04)	0.649(0.03)	0.497(0.07)	0.612(0.05)
Spike	0.534(0.04)	0.770(0.03)	0.508(0.07)	0.759(0.05)
Spike_{+1}	0.589(0.04)	0.867(0.03)	0.571(0.08)	0.803(0.06)
Spike_{+2}	0.622(0.04)	0.895(0.04)	0.645(0.08)	0.839(0.06)
Spike_{+3}	0.631(0.05)	0.911(0.04)	0.650(0.09)	0.923(0.06)
Spike_{+4}	0.635(0.05)	1.042(0.04)	0.683(0.10)	0.945(0.09)
Spike_{+5}	0.718(0.06)	1.101(0.05)	0.700(0.11)	1.017(0.09)
Spike_{+6}	0.777(0.07)	1.118(0.06)	0.715(0.12)	1.157(0.09)
mkev_E	0.161(0.03)	0.048(0.02)	0.275(0.06)	0.003(0.04)
mkev_S	0.102(0.02)	0.042(0.02)	0.147(0.05)	-0.032(0.04)
mksh_I	0.042(0.03)	0.064(0.03)	-0.033(0.07)	-0.022(0.05)
mksh_C	0.031(0.03)	0.028(0.02)	-0.010(0.06)	0.023(0.04)
y93	-0.147(0.03)	-0.097(0.03)	-0.091(0.07)	-0.005(0.05)
y94	-0.111(0.03)	-0.064(0.03)	-0.074(0.03)	0.086(0.05)
cons.	17.31(0.04)	18.44(0.04)	17.48(0.07)	19.31(0.06)
Obs.	1955	1989	528	564
n. of firms	276	272	44	47
R^2 (within)	0.971	0.980	0.944	0.971
Prob $> F$	0.000	0.000	0.000	0.000

Heteroskedasticity-corrected standard errors are in parentheses.
Year dummy variables are shown when significant in at least one regression.
Industry dummy variables are not shown.
$F-$test for joint significance.

Table 7: Productivity – Fixed-effects regressions of the impact of investment spikes on productivity (Unbalanced Panel 1991-2001)

	Total	Expansionary	Innovative	Non Innov.
Constant	7.689(0.48)	5.803(1.23)	8.657(0.25)	7.902(0.32)
lnkper_1	0.214(0.06)	0.443(0.14)	0.099(0.03)	0.174(0.04)
Spike_{-2}	0.153(0.02)	0.155(0.04)	0.163(0.03)	0.162(0.04)
Spike_{-1}	0.205(0.02)	0.231(0.04)	0.229(0.03)	0.189(0.04)
Spike	0.247(0.02)	0.322(0.04)	0.257(0.03)	0.216(0.04)
Spike_{+1}	0.216(0.03)	0.280(0.05)	0.250(0.03)	0.189(0.04)
Spike_{+2}	0.246(0.03)	0.305(0.05)	0.270(0.04)	0.224(0.04)
Spike_{+3}	0.258(0.03)	0.329(0.06)	0.267(0.04)	0.246(0.05)
Spike_{+4}	0.291(0.03)	0.344(0.07)	0.348(0.04)	0.227(0.05)
Spike_{+5}	0.319(0.04)	0.350(0.08)	0.375(0.04)	0.267(0.06)
Spike_{+6}	0.336(0.04)	0.376(0.09)	0.377(0.05)	0.291(0.06)
y93	-0.118(0.02)	-0.132(0.04)	-0.074(0.03)	-0.136(0.03)
R^2	0.92	0.90	0.93	0.93
No. of obs.	4465	1071	1717	1677
Prob $> F$	0.00	0.00	0.00	0.00

Heteroskedasticity-corrected standard errors are in parentheses.
Industry (and insignificant year) dummy variables are not shown.
$F-$test for joint significance.

Figure 1: Distribution of investment rates for equipment (Unbalanced Panel)

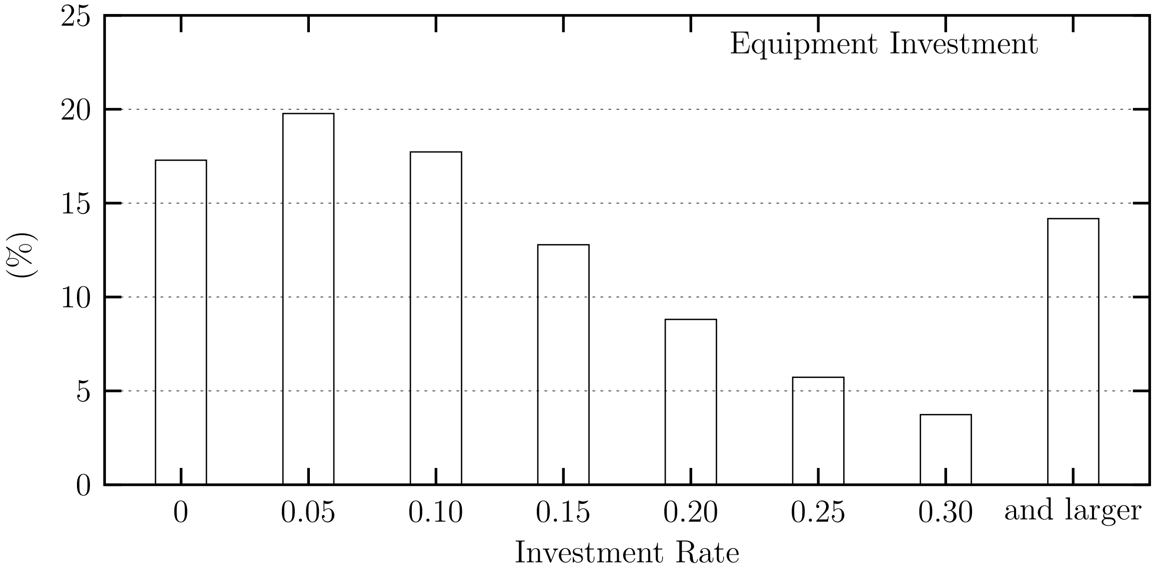
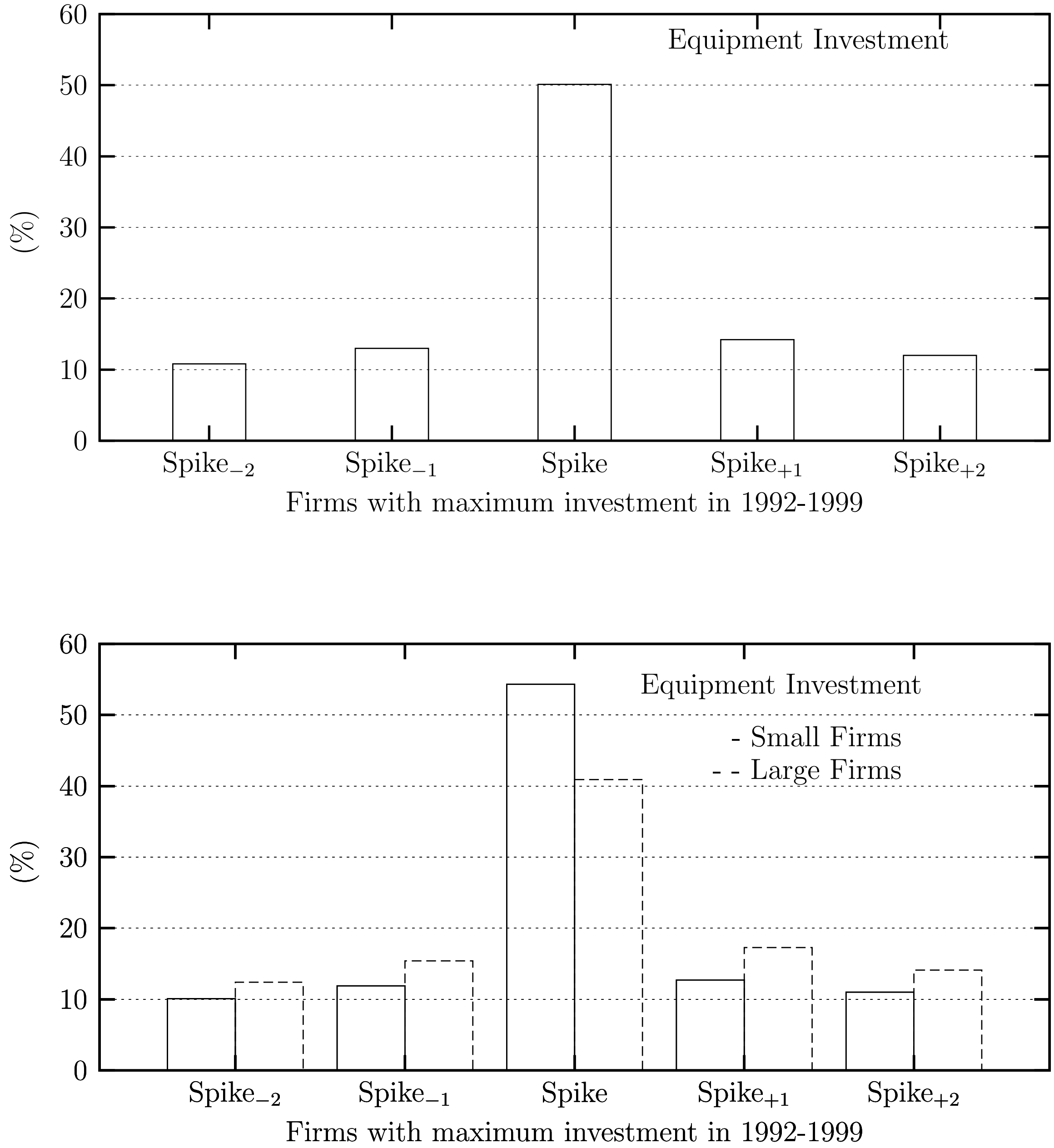


Figure 2: Investment evolution (%) about maximum investment episode (top figure – Balanced Panel) and distribution by average size (bottom figure – Balanced Panel)



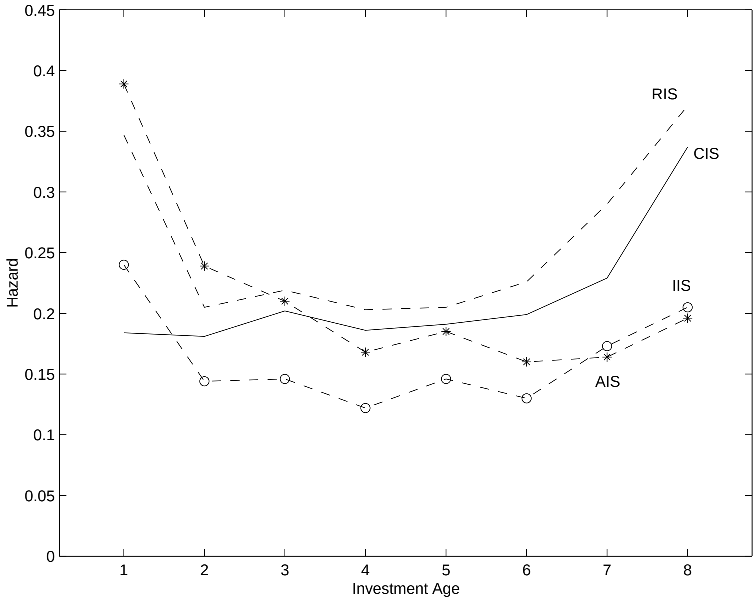


Figure 3: Empirical (Kaplan-Meier) hazard functions: comparison of *IS* definitions (Unbalanced Panel)

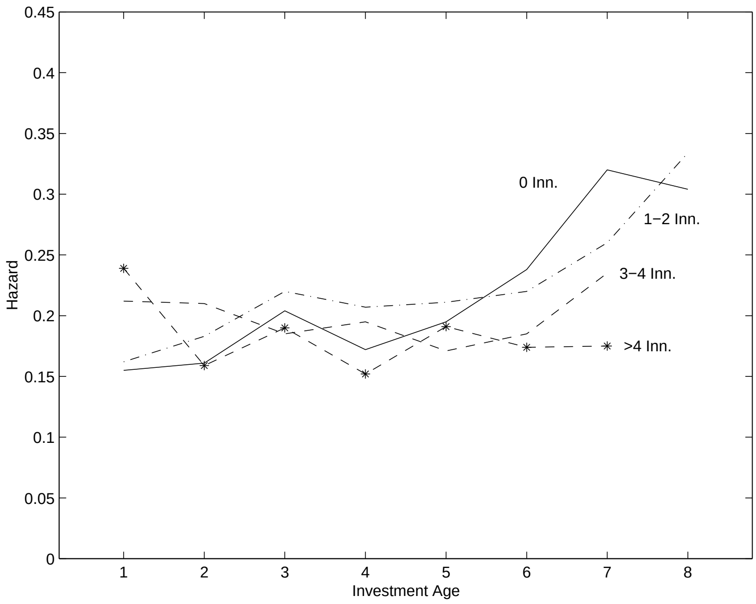


Figure 4: Empirical (Kaplan-Meier) hazard functions: CIS definition under different frequency of innovation (Unbalanced Panel)

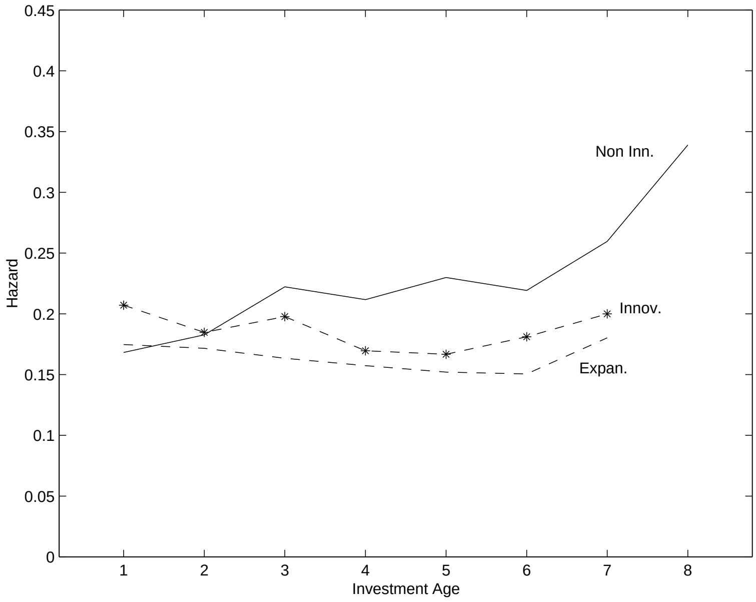


Figure 5: Empirical (Kaplan-Meier) hazard functions: CIS. Expansionary, Innovative (>20%) and Non-Innovative Firms (Unbalanced Panel)

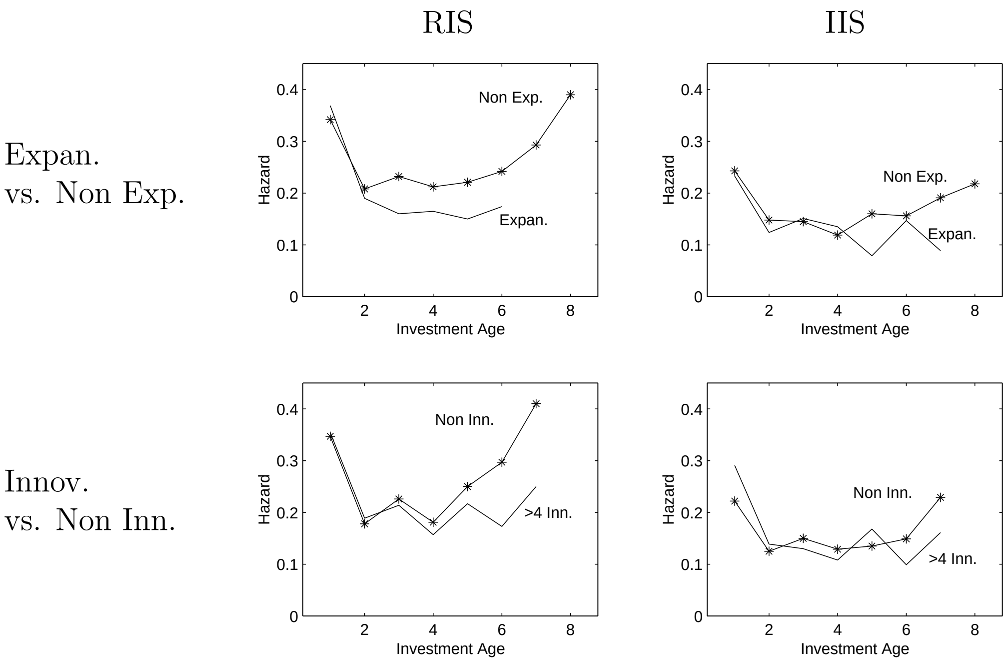


Figure 6: Empirical (Kaplan-Meier) hazard functions: comparison of expansionary and innovative behavior under RIS and IIS definitions (Unbalanced panel). Missing values correspond to non-statistically significative estimated durations.

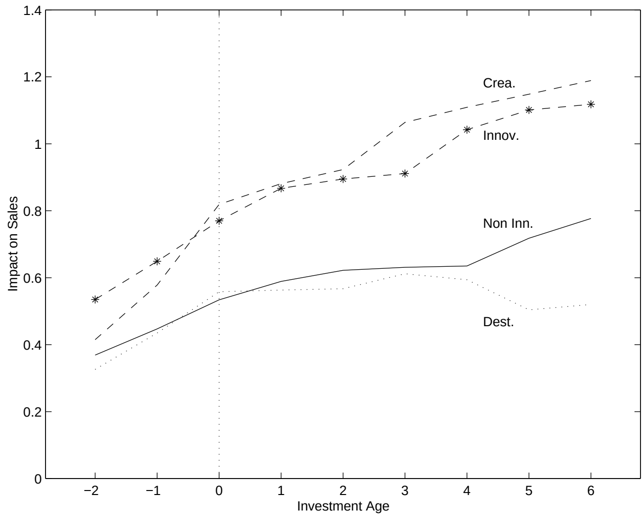


Figure 7: The impact of investment spikes on sales (Unbalanced Panel)

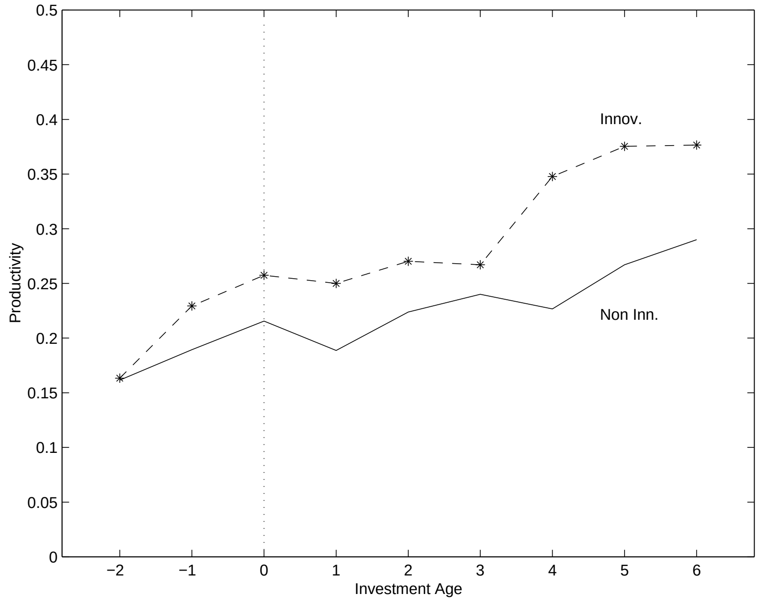


Figure 8: Productivity effects of an investment spike occurred in 1991-2001. Firms with only one spike (Unbalanced Panel)

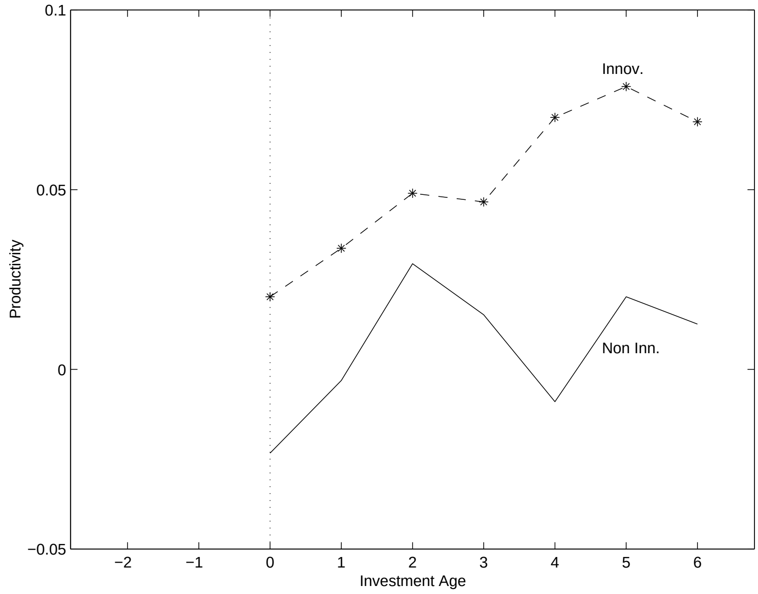


Figure 9: Productivity effects of investment spikes occurred in 1991-2001. Whole sample (Unbalanced Panel)

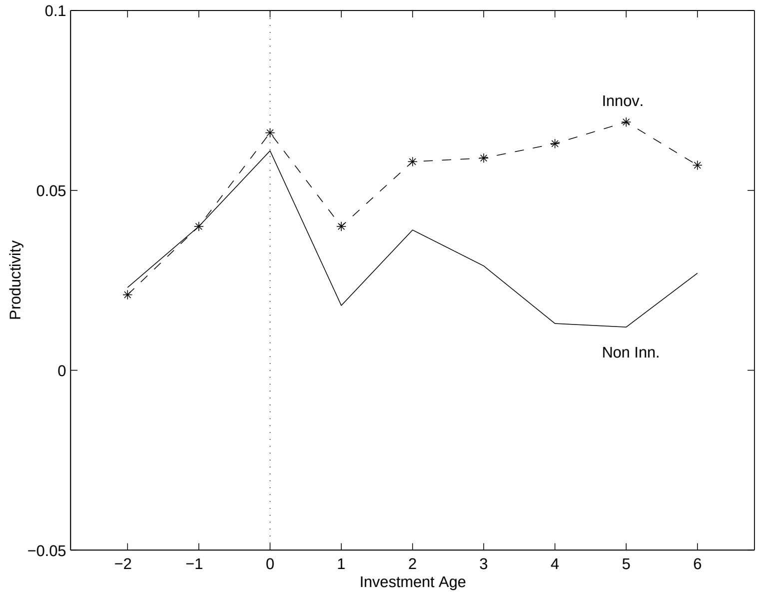


Figure 10: Productivity effects of investment spikes occurred in 1991-2001. Whole sample with [-2,+6] window ((Unbalanced Panel, model (1′): Innov. $\gamma_0 = 0.056$; Non Inn. $\gamma_0 = 0.059$; std. err. $\gamma_0 = 0.009$)

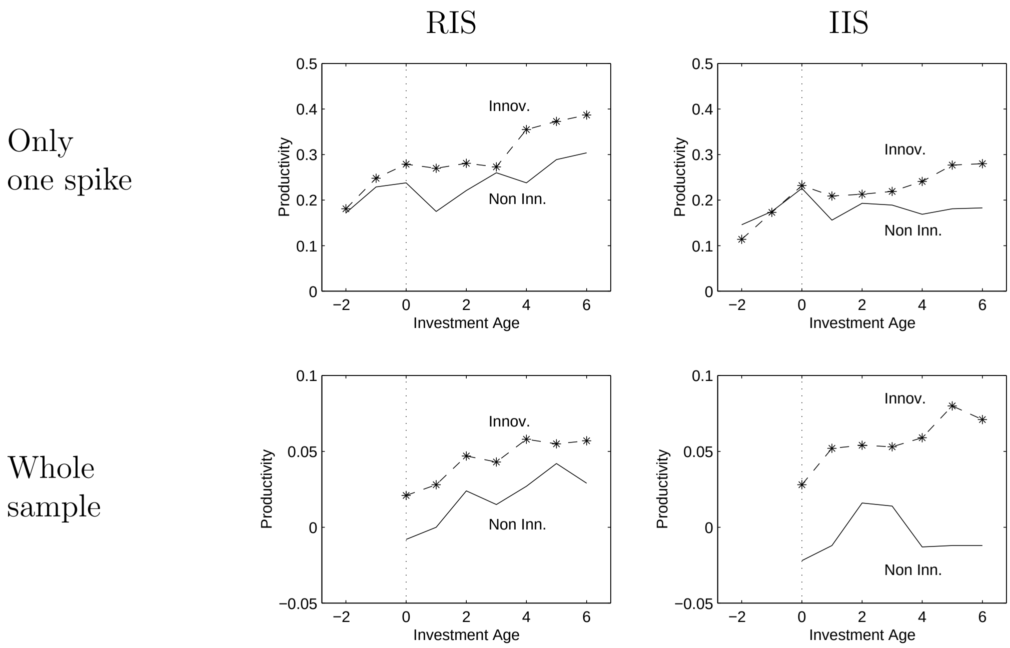


Figure 11: Productivity effects of investment spikes occurred in 1991-2001 under RIS and IIS definitions (Unbalanced Panel)