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Evidence from Spanish Firms

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Innovation, investment and productivity: evidence from Spanish firms

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Abstract

In this paper we analyze the role of replacement and innovation activity in shaping investment behavior and labor productivity in a panel of Spanish manufacturing firms from 1990 to 2001. Investment is concentrated about large investment episodes, or investment spikes, whose nature varies by observable firm characteristics. We find evidence of replacement activity as a determinant of investment spikes for those firms that are not involved in process innovation nor plant expansion. Then we explore how large investment episodes transmit into the evolution of labor productivity under different innovative strategies. We find that expansionary and innovative firms increase their productivity after an investment spike. However, long learning curves seems 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

An important insight of the vintage literature is that new equipments embody improved technology. Another insight refers to the replacement of existing capital with a new vintage. However, there is limited empirical evidence of the link between investment, or the age of capital, and productivity.[1] This finding is consistent with a source of explanations stressing that higher productivity is not the primary motivation for investment. Nevertheless, further exploration of the impact of different forms of investment on productivity is needed to interpret the finding of little relationship between investment and productivity growth.

This paper explores the occurrence and implications of different types of investment. Expansionary investment needs not to be associated with replacement activity but it could have positive effects on labor productivity at the firm level if new machines are more productive than the old ones. However, replacement investment should imply the substitution for new equipment more productive than the old equipment was when the latter was new. Of course investment might just modify part of the production process along what could be characterized as partial replacement episodes. In such a case, the degree of partial replacement should be related to the frequency of innovation activity. We argue that a distinction between *expansion* investment and *replacement* investment is useful to more clearly identify the nature of the observed episodic behavior of firm's investment.[2] Further, we check whether any bigger productivity effects are associated in each case with lumpy investment, or investment spikes. Under embodied technical change, investment spikes should rise productivity. Clearly though, replacement does not necessarily mean the adoption of better technologies and long learning curves might be associated with new technologies.

The identification of investment heterogeneity is problematic. Some industries are characterized by infrequent replacement and expansion. Others may be characterized by rapid technological progress which requires frequent reinvestment. Available data do not provide any straightforward metric to distinguish new and replacement investment. We rely on observed expansionary behavior and on observed innovative activity to shed light on the empirical issue of expansion, replacement and productivity growth. Our empirical analysis is based on firm-level longitudinal data from which we have information on equipment investment and innovation activity. 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 containing information on product and process innovations carried out by firms as well as some details on R&D activities, labor types and other relevant features

[1] Plant-level fixed effects and plant age seems important determinants of the pattern of productivity across plants instead (Power (1998)). Also, vintage and survival effects seems to play offsetting roles in determining a cohort's relative position in the productivity distribution (Jensen et al. (2001)).

[2] Section 3 below examines in detail the various concepts related to investment heterogeneity and episodic investment behavior we consider.

qualifying the nature of investment. We consider this information particularly useful for our purposes since we take the view that innovative activities are a key ingredient associated to the *partial replacement* episodes suggested above. 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 by isolating and measuring the impact of productivity changes for replacement episodes and expansion episodes is explored.

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 investment age. The relation between replacement investment and labor productivity is described using a fixed-effect panel estimation, where the log of labor productivity is regressed on investment ages, controlling for other variables including time dummies. 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 of the role of process innovation for replacement and embodiment.

The paper is organized as follows. In Section 2 we describe our database, the steps we follow in filtering the sample and the corresponding balanced and unbalanced panel extracts. In Section 3 we review the main concepts and the definition of variables, 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 on more than 3400 large and small firms in the Spanish manufacturing sector between 1990 and 2001. The data we use collectively account for over 35% of capital investment in the Spanish manufacturing sector. The ESEE samples “small” firms (i.e., firms with less than 200 employees) with at least 10 employees, but the whole population of firms declaring 200 or more employees is in the sample. In this paper, large firms are defined as those with 200 or more employees on average over the entire sample period. Any other firm is defined as a small firm. The survey includes newborn, continuing and exiting firms. In particular, exits from the survey reflect death and attrition. Excluding those observations for which either reported value added is negative and employment data or investment data are missing there are 20627 observations on 3424 firms left.[3]

[3]The representativeness of the survey for Spanish manufacturing is discussed in Fariñas and Jaumandreu (1999).

After this basic filtering of the original sample two extracts of the ESEE are used in this paper. First, an unbalanced panel with 17916 observations on 2128 firms (653 large and 1475 small) 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 65% of firms without missing relevant information are observed four consecutive years according to this criterium. Second, a balanced panel containing 401 small and 190 large firms continuously observed for the entire sample period, which represents roughly 40% of the total number of observations from the unbalanced panel.

The process of technology diffusion through creative destruction may be the result of intrafirm replacement activity or interfirm exit and entry. In this paper, we focus on the intrafirm creative destruction process. In this sense, the balanced panel is a natural selection criteria for evaluating the role of replacement activity leading technological progress. In particular, we should expect that most 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, a hazard function, it would be better to exclude exiting firms restricting the estimation to the balanced panel. However, some exiting firms did replacement activity before exiting, because the perspectives were not so bad at the time of replacing. Excluding these firms would bias up the effect of replacement investment on firms productivity. Because selection causes the less productive firms to exit, it can be expected that mean levels of productivity across plants increase with respect to capital age. 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. When needed, we show the result for both the balanced and the unbalanced panel.

Table 1 reports the number of observations in the data set by industry. By comparing columns we see that the distribution of continuing firms in the data set across two-digit SIC (NACE) industries is roughly comparable to the distribution for the unbalanced panel of the survey.

3 Theoretical framework and definitions

Vintage capital models provide a suitable theoretical framework to analyze the relationship between firm's investment decisions and the process of technological adoption from an empirical perspective. One of the key insights of this theoretical approach refers to the replacement of existing capital with a new vintage of machines. The empirical evidence suggests that these replacement activities are infrequent and occur about periods of high investment. Further, there are a large number of periods of investment inaction. Doms and Dunne (1998) conclude that investment decisions of manufacturing plants in the US are concentrated about large investment episodes, the so called investment spikes. Cooper et al. (1999), for manufacturing plants in the US, and Nilsen and Schiantarelli (2000), using Norwegian micro data, find evidence on replacement behavior in the sense that an investment spike is more likely for older capital. The main message of these papers is that adjustment of capital at the plant level is lumpy.

Under embodied technical change, investment spikes should rise productivity possibly through a process of learning and diffusion of the new technology. However, as emphasized by Power (1998) there is a very limited evidence on the link between investment, or the age of capital, and productivity. She focuses on lumpy investment episodes and examines the relationship between investment and labor productivity at the plant-level. This approach is also related to Sakellaris (2001) who uses manufacturing data to describe the patterns of employment and capital adjustment and the response of total factor productivity during those adjustment episodes. As these authors, our approach in this paper is descriptive and non-parametric and we focus on episodes that involve lumpy adjustment in capital. Differently from them we stress on the idea that different innovative strategies should have different effects on productivity. Therefore, we are mostly concerned with the relationship between innovation activity and investment activity and its effect on labor productivity.

In this section we first describe the main features of investment behavior in Spanish manufacturing firms during the period 1990-2001. This description is intended to justify the definitions used in this paper as well as our main hypothesis in line with the theoretical framework that has been presented. In particular, as far as technical progress is embodied in new machines, the analysis of the empirical evidence on the relationship between firm's innovation activity and investment activity is motivated. A brief description of the innovation activity developed by manufacturing plants is provided at the end of this section.

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. Equipment investment represents more than two thirds of total investment in manufacturing. More precisely, average equipment investment represents 70% of total investment 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. It should be stressed that a correct measurement of real equipment assets should add the real value of all operative machines. Unfortunately, no information is available in the ESEE, and in any other survey, allowing to directly compute such a measurement. In order to measure real equipment assets, we use the perpetual inventory method. In the first period the firm is observed, the stock of capital is initialized by the book value of equipment. Then we use the perpetual inventory method to compute the whole series of real equipment assets for each firm. The perpetual inventory method assumes that equipment values decrease with age at a constant rate, which is consistent with a constant rate of embodied technical change.

The top panel of Figure 1 depicts the distribution of equipment investment rates (over capital) across the 17916 observations in the unbalanced panel. One robust finding from related studies is that most firms have investment rates distributions that are skewed to the left, but which have a long, wide right-hand tail. The frequency of little or no investment activity is particularly remarkable in our data. Roughly 17% of observations correspond to zero investment rates and 24% are below 0.02. On the other hand, more than 50% of observations for equipment investment corresponds to investment rates that are below 10%. Finally, nearly 20% of equipment investment is accounted for by 12% of observations. In particular, more than 12% of firm-year observations entail investment rates above 30%.[4]

These general descriptive measures suggest that equipment investment is an infrequent activity that occurs in bursts. The bottom panel of Figure 1 contributes to confirm this picture. The figure plots the average investment rate at the date of the firm's highest rate of investment, a "spike", as well as for the two previous and subsequent years. Thus, the spike is found over the period 1992-99 (the remaining interval apart from the two years leaded and lagged). For our data set, equipment investment appears particularly concentrated about large investment episodes. Likewise, when attention is restricted to the five-year window centered at the date of maximum investment in levels, on average, over 50% of equipment investment in the period 1992-99 corresponds to the maximum investment episode, another 27% is equally split before and after that episode, and the rest in an interval of two years (Figure 2, top). For small plants this finding is just slightly more pronounced at the maximum investment episode (Figure 2, bottom, solid line), but there are no distinct spiked pattern in the two previous and subsequent years. Finally, equipment investment intensity (real equipment investment over the real value of sales) is quite evenly distributed across sectors. Therefore, average equipment investment behavior seems representative of investment patterns in our sample.

Consequently, investment is episodic and tends to be concentrated about large investment episodes which are infrequent but quantitatively important. This evidence justify the focus of this paper on episodes that involve lumpy adjustment in equipment. We will be more precise below in characterizing these investment episodes.

3.2 Investment spike and investment age

Following Cooper et al. (1999) and Power (1998) we use a definition of an investment spike to measure episodes of high equipment investment.[5] Let I_t be firm's real equipment

[4]Only a slightly smoother distribution of investment rates can be found for total investment. This is not surprising given the weight of equipment investment in total investment, and similarly occurs with the rest of the patterns reported below. See Licandro et al. (2002) for a more general description of investment behavior by those firms in our data set.

[5]See Power (1998) and the references therein for alternative definitions. Of course any parameterization is ad hoc. In what follows we will indicate the sensitivity of the results to the chosen values when corresponds.

investment in period t. Let 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 as follows:

- 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 unusual investment episodes that may not be particularly large in an absolute sense. The AIS definition captures large, potentially frequent or smooth investment activity. 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 an IS (either a RIS or an AIS) is found to occur from t to $t+j$, where $j = 1, \ldots, i$.

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 (2001) excludes the possibility of consecutive investment spikes. In this paper, we follow a different but related strategy by introducing the definition of a combined investment spike.

- A *combined investment spike (CIS)* requires the AIS criterium holds for multi-year relative investment 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 relative investment spikes 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 the RIS and the 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 will 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 for the CIS and the IIS, $\alpha = 1.75$ and $\beta = 0.20$, follows much of the literature. It is primarily determined by the frequency of investment spikes and the fraction of total sample investment accounted for by spikes. Table 2 reports these two ratios under alternative definitions of the theoretical construct of an investment spike. First, we report the implications for our data set of considering a RIS with $\alpha = 2.50$ and $\alpha = 1.75$, as assumed by Cooper et al. (1995, *CHP95* henceforth) and Power (1994 and 1998, *Power* henceforth), respectively. Second, we report the implications of considering an AIS with $\beta = 0.20$, as assumed by Cooper et al. (1999, *CHP99* henceforth) . Third, we explore an alternative definition of a *combined* investment spike proposed by Power (1998, *Pow98* henceforth), for which such a spike occurs at t if at least one of the RIS ($\alpha = 1.75$) or AIS ($\beta = 0.20$) definitions holds. None of these three definitions excludes smooth but potentially large investment episodes or sporadic bursts of investment that are small relative to the firm's size.

Table 2 shows that, for a given spike definition, the underlined characteristics are almost invariant to the use of either the unbalanced or the balanced panel. Our definition of a *CIS* is clearly more selective than the corresponding separate definitions, but a lot less selective that the *IIS* definition. Remember that for the *IIS* definition, we consider the simultaneous occurrence of the corresponding relative and absolute investment spikes. By comparing the columns *CHP95*, *Power*, *CHP99* and *Pow98*, we see that the latter definition incorporates a larger number observations as investment spikes. This suggests that relative and absolute spikes do not generally coincide. In particular, under Power's definition of a combined investment spike roughly 33% of observations in our data set are investment spikes. Clearly, an upper bound for investment observations that could be considered as spikes. This is further confirmed by comparing with the frequency of spikes obtained with the *IIS* definition.

With these definitions of an investment spike we define investment age, or the age of an investment spike:

Investment Age (IA): The investment age is the time elapsed since the occurrence of the last investment spike.

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

3.3 Different types of investment

Understanding the impact of different types of investment on the link between investment behavior and productivity could 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 on observed 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 her size permanently, from a situation where the firm has decided to replace old by new machinery or equipment. We can call these two situations *expansion* and *replacement*, respectively. But there is no direct observation of these phenomena. Instead, a preliminary evaluation of expansionary behavior is performed by using information on creation and destruction of plants inside the firm. The following definition is implemented:

Expansion episode (EE): A firm is said to be involved in an expansion (contraction) episode, if it declares to increase (decrease) 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 investment age. It is for this reason that at this point we are treating creation and destruction of plants alike. We will also examine these features separately below. Of course, firms can adjust their production capacity without altering the number of plants. In Section 4 below we will examine further expansionary behavior by investigating the effects of different investment strategies on sales.

An *EE* is a clear, basic criterium that enables us to leave apart firms that invest with an objective other than replacing the existing stock of equipment. Table 3 reports the distribution of firms according to the number of establishments they run as well as the reported changes in the number of establishments. These figures correspond to both production and nonproduction establishments. The results are robust to take them separately. Note that around 70% of observations correspond to single plant firms. The more striking feature is that only a small fraction of observations seems to be involved in expansionary or contractionary episodes regardless we consider the balanced or the unbalanced panel. One of the reasons underlying this circumstance is 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. Finally, it should be stressed that the simultaneous occurrence during the sample period of plant creation and plant destruction (possibly differed) is excluded from the definition of an *EE*. 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 contraction is in practice a replacement. In this respect, the following definition is considered:

Replacement episode (RE): A replacement episode 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.[6]

In the later situation the purpose of investment could be to substitute a physically depreciated machine, to reduce production costs (process innovation) or to produce new goods (product innovation). Clearly though, firms could 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.[7] Firms frequently involved in innovative activities should replace equipments repeatedly, being engaged in partial replacement episodes. 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

Even though expansionary and replacement investment could be both episodic it should be expected that replacement investment generates increasing hazards: machines deteriorate with age at the time they move away from the technological frontier, increasing the probability of being replaced. However, expansionary decisions do not necessarily depend on the age of capital. The nature of innovative activities undertaken by firms should be informative on the nature of investment activities. In particular, if a firm engages in process innovation, it should be expected that new equipment comes to replace older 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 non innovative firms should be guided by physical depreciation. Secondly, the frequency of process innovation is a proxy for partial replacement. Firms involved in frequent process innovation are more likely to replace a small part of their equipments every year.

Process innovation (PI): A significant modification in the production process associated to the introduction of new equipment.[8]

[6]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, reflects obsolescence, deterioration, and a limited ability to reduce the labor input on old equipment (cf. Solow et al. (1966)).

[7]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 and firms use to renovate the stocks of PCs uniformly over time.

[8]This question comes in the survey after the one referred to product innovations, and it distinguishes three alternative situations: the introduction of new equipments, new methods of organization or both. In this paper, a firm is said to be engaged in process innovation if she is in the first or the third situation.

From our definition of innovative activities, we exclude product innovations and those process innovations that only involve modifications in the methods of organization, 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.

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. Table 4 explores the determinants of innovative activity. Clearly, investment intensity appears to be a relevant explanatory variable for the probability of innovate and much more for process innovation. Further, Tables 5 and 6 display Logit regressions for the probability of innovation on investment spikes and spike ages, respectively, including year dummy variables. In all of the cases regressions restrict to firms that have only one investment spike. Clearly, the correlation between spikes and innovation is substantially higher for process innovation. The estimates can be compared to those corresponding to taking into account the spike age. These latter results are robust to include more leads or lags. Only the coefficients for the spike and the years before and after are statistically significant for process innovation. None for product innovation.

According to this evidence, the occurrence of an investment spike is highly correlated with the undertaken of process innovation. Consequently, we take the view that the frequency of innovative activities is a key ingredient associated to *partial replacement* episodes. The argument is as follows. It can be expected that purchases of equipment in those firms more frequently involved in innovative activities imply a replacement of a lower fraction of the capital stock. Put it differently, replacement should be more partial in those firms declaring process innovations more frequently.

4 Empirical models: hazards, sales and productivity

The approach adopted in this paper is descriptive and non-parametric. The replacement behavior of firms is described by empirical hazard functions measuring the probability of observing an investment spike as a function of the age of the previous spike. The relation between replacement investment and labor productivity is described using a fixed-effect panel estimation, where the log of labor productivity is regressed on spike ages, controlling for other variables including time dummies. Expansionary behavior of firms is examined as well by regressing the log of sales on spike ages. Moreover, firms in the sample are partitioned in three groups: *i)* expansionary firms are those that face an expansionary episode, *ii)* innovative firms are those that not facing an expansionary episode are involved in process innovation, *iii)* non-innovative firms are those that not facing an expansionary episode are not being involved in process innovation. A more formal distinction between innovative and non-innovative firms is proposed in the next section.

Firstly, 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. 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*'s. Table 2 contains information on these subsamples. In particular, under the CIS definition, more than 90% of observations from the balanced panel are in the corresponding subsample.

A formal definition of the hazard function follows:

Hazard function: The empirical hazard is, at every age a of an *IS*, the ratio of the number of observations for which the following *IS* is observed divided by the size of the risk set. The size of the risk set is the number of observations for which the spike age is equal to a.

Given that the occurrence of a first *IS* is required to estimate a hazard function, every observation at the left of the first *IS* is dropped. In order to test the robustness of our estimations to this arbitrary sample selection criteria, we have also estimated the hazard function for negative spike ages. The *negative* empirical *hazard* is the fraction of observations for which a previous *IS* is observed at every negative age a of the following *IS* divided by the size of the risk set.

Secondly, we examine whether investment spikes have statistically significant effects on sales. To this purpose, we run the following regression:

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

where s_{it} are the i'th firm's sales and D_{it}^d is a dummy capturing the effect of the investment spike, observed at time $t-d$, on the logarithm of firm's sales at t. Consequently, the dummy D_{it}^d takes value one if there is a spike at time $t-d$, zero otherwise. The regression includes time dummies λ_t to control for the cycle and rules out any firm-specific fixed effects, η_i. Finally, X_{it} includes other explanatory variables related to the firm's market share and firm's expectations on market evolution. The estimated parameters γ^d for $d = \{-k, ..., -1, 0, 1, ..., l\}$ give the profile of the growth rate of sales around the *IS*, which corresponds to $d = 0$, after controlling for fixed-effects, time dummies and other relevant characteristics.

We perform a similar regression analysis for labor productivity, defined as the ratio of value added to worked hours, y_{it}. In this case, we estimate an equation like (1), where s_{it} is substituted by labor productivity and X_{it} includes capital per production hour instead of the aforementioned variables.

The sales and labor productivity regressions are run for two different definitions of the corresponding samples. Firstly, we implement model (1) for those firms with one and only one investment spike. We will refer to this implementation as model (1a). This provides an immediate interpretation of the estimated values of γ^d ($d = -k$ to l) but clearly for a restricted data set. Secondly, we implement model (1) in the augmented sample of those firms having *at least* one investment spike: model (1b). In such a case the estimated values of γ^d ($d = 0$ to l) reflect the average response of the endogenous variable to all and every spike event at investment ages from zero onwards. Notice that in this case, and in order to treat all spike events symmetrically, we do not include dummy variables at the time before the year of the investment spike. Rather, we incorporate the investment rate as a regressor in order to capture the average level of the response.

In addition, as a robustness test for the results, we follow Sakellaris (2001) in implementing the model:

$$\log y_{it} = \lambda_t + \sum_{d=-k}^{d=l} \gamma^d D_{it}^d + \gamma_0\, O_{it} + \beta\, X_{it} + \eta_i + \varepsilon_{it}, \tag{2}$$

where the dummy variable O_{it} equals one if any other investment spike happened before year $t - k$ or after year $t + l$, which is the window centered about every spike event a firm with at least one spike event experiences. 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.

In applying this characterization to investment data, we compare the estimated coefficients corresponding to the three subgroups with the averages obtained for the panel. Notice that the three cuts of the data set are independent. Therefore, the estimation results are robust to considering a joint regression alternative. In addition, firms expanding the number of establishments may exhibit different patterns from firms involved in downsizing. We explore in detail this circumstance when reporting the corresponding estimation results below.

5 Results

As noted previously, investment age is constructed, and the empirical models estimated, using the definition of a combined investment spike, CIS, on the unbalanced panel data set. Nevertheless, interesting qualifications result from the consideration of alternative definitions of investment spikes as well as from the analysis of the balanced panel. In particular, as a robustness test, part of the results below are presented for two alternative definitions of investment age: specifically, those corresponding to the IIS and the RIS definitions of an investment spike.

5.1 The nature of investment spikes

We begin our characterization of the timing relationship between investment spikes by examining the Kaplan-Meier nonparametric hazards. Figure 3 plots the empirical hazard function under alternative definitions of an investment spike for the unbalanced panel extract. The hazard is upward sloping under both the CIS and the RIS with $\alpha = 1.75$ (labelled *Power*) definitions whereas it is not under the AIS with $\beta = 0.2$ and the RIS with $\alpha = 2.50$ (*CHP99* and *CHP95*, respectively). Let us summarize the main findings from these empirical hazards. Firstly, it turns out that for the longer durations the Kaplan-Meier hazard may be increasing under the RIS definition depending upon the value of the scaling parameter α. This does not hold, however, under the AIS definition for which the empirical hazard is found to be decreasing for several alternative values above and below the CHP99 threshold. Secondly, both the AIS and RIS definitions imply decreasing empirical hazards for the shorter durations, the sharpest decline occurring after investment age one. This reflects the multi-year spike phenomenon documented in the existing literature on investment spikes. Finally, the CIS definition substantially reduces the probability associated with having a spike at age one, without particularly altering the shape of the empirical hazard after that age. Something similar occurs when the IIS definition is implemented but for the hazard becoming overall flatter, as it will become apparent from the discussion about Figure 7 below.

The parametric estimations of the hazards controlling fixed effects confirm the empirical approximation to the probability of an investment spike at different investment ages.[9] Also, the results are robust to the use of the negative hazard functions. Duration coefficients are statistically significant for all of the models but the duration effects are stronger for the RIS and CIS definitions and always monotonically increasing under our definition of a combined investment spike. We test for a positive joint cyclical effect which is not rejected. Overall, we interpret these results as supporting the use of the CIS definition. Results presented below provide further support for this interpretation. Therefore, except where otherwise indicated the CIS definition is the one that it is retained.

Next, we distinguish among investment types. Figure 4 plots the empirical hazard for those firms not involved in expansionary episodes (Non Exp.) against both that for firms involved either in creation (Crea.) of plants or destruction (Dest.) of plants during the sample period. Comparisons should be taken with caution since the number of firms in each subgroup is quite different. However, it seems that the hazard is upward sloping when the non expansionary subsample is considered. On the other hand, creation and destruction do not seem to make a difference in terms of the hazard for the nature of investment spikes. This may reflect that investment in firms involved in expansionary episodes is not guided by replacement behavior. The corresponding parametric estimates confirm that indeed the higher duration coefficients are found for non-expansionary firms in both the balanced panel and the unbalanced panel. In all of the cases the coefficients represented are statistically significant. Again, the small number of observations in either

[9] In all of the cases the corresponding hazards with fixed effects have been estimated (conditional logistic regressions). The parametric estimates basically confirm the qualitative results obtained with the empirical hazards and are consistent with the replacement hypothesis: duration coefficients are statistically significant and, in general, monotonically increasing. For ease of exposition, in this paper we omit these estimates which are available upon request.

of the expansionary subgroups suggests caution in evaluating the parametric estimates.

Finally, we analyze the role of process innovation in characterizing the nature of investment spikes. For this purpose we consider innovative and non-innovative firms among those not involved in expansionary episodes in the unbalanced panel extract. Figure 5 plots the empirical hazard for different categories of innovative activity. We find that the more often process innovation is declared the flatter is the empirical hazard. 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 of innovation affects the hazard by splitting the group of non expansionary firms into two subgroups: innovative and non innovative firms. Namely, we start from a cutoff frequency of innovation of 17% (roughly 2 over 12 years of declared process innovation for a firm in the balanced panel) to a cutoff frequency of 25% (1 over the 4 consecutive years a firm is required to be recorded to belong to the unbalanced panel extract we use) to assign firms to these subgroups. In all of these cases the hazard for the group *non innovative* is above that for *innovative* firms across all the durations. As a compromise value we select a frequency of process innovation greater than 20% to label a firm as innovative. Table 7 reports the frequency with which an investment spike is found for innovative and non-innovative firms according to this criterium among those non-expansionary, as well as for firms that seem to be involved in expansionary episodes. This frequency is higher in the non-expansionary sub-group under both categories of innovative activity.

Consequently, to better qualify the differences in the role of capital vintages we examine the empirical hazards for firms involved in expansionary episodes as well as under innovative and non innovative behavior among those non-expansionary. Figure 6 plots the corresponding empirical hazard functions for the three subgroups. As Fig. 6 shows, replacement activity seems particularly associated to (non-expansionary) non-innovative firms. On the other hand, an increase in the frequency of innovation reduces the slope of the hazard. This may reflect that partial replacement episodes are associated to innovative firms indeed. Finally, as a test of robustness, we look at the corresponding empirical hazards according to the RIS and IIS definitions. In Figure 7, we represent the hazards for expansionary and non-expansionary firms as well as for innovative and non-innovative firms among those non-expansionary under these two alternative definitions of an investment spike. These results provide further support for the aforementioned interpretations. In particular, empirical hazards are informative on replacement behavior, expansionary firms investment spikes are of a different nature and innovative firms are characterized by partial replacement episodes.

5.2 Expansion and replacement

In light of the previous results we now turn to a statistical measure for the different types of investment. As it has been stated above, this measure analyzes the effects of an investment spike on sales. First, we evaluate whether the preliminary distinction in terms of the creation (destruction) of establishments' variable provides a clear cut of the sample through the behavior of sales. Then, we look whether there are any differences according to the innovative behavior of firms.

Tables 8 and 9 report our estimates for the impact of investment spikes on sales according to equation (1) and for firms with only one combined investment spike (model 1a). Similar results are obtained when we consider the augmented sample that incorporates all firms with at least one CIS. Notice that sales regressions with random effects are run controlling for expected market evolution (*mkev*, expanding – *E*– or stable – *S*) and market share (*mksh*, increasing – *I* – or constant – *C*).

The second column of Table 8 report the estimated values of γ^d for the whole sample. These coefficients do not significantly differ from those estimated for either the expansionary or non-expansionary subgroups, which are therefore omitted. However, the impact of investment age dummies on sales is significantly different inside these subgroups. Clearly, sales are larger on average after the IS for those firms involved in the creation of plants among those in the expansionary group at all duration leads. On the other hand, the impact of the IS is significantly below the whole sample average at all duration leads in the destruction subgroup. These results are robust when the balanced panel is considered instead, the low precision of the estimates that results from the small number of observations in this case suggests caution though. We argued that creation and destruction do not seem to make a difference in terms of the hazard and thus are not guided by replacement behavior. Here we see that our estimates meaningfully relate large investment episodes with a expanding volume of sales after investment age zero when we observe creation of plants inside a firm. This does not hold, however, for firms engaged in downsizing.

Likewise, turning to the non-expansionary subgroup, the response of sales to an investment spike for firms involved in innovative activities is substantially above the average response of the whole sample. Table 9 reports these results. Also, selected market dummies display interesting results. First, market evolution is non significant for expansionary firms while market share is. Second, the role of expectations of market share seems more important for non-innovative firms. Overall, we interpret these estimates as supporting the view that what we call partial replacement episodes correspond more closely to an investment pattern associated to expanding activity.

Figure 8 summarizes the estimated values corresponding to the impact on sales of investment age for those firms with a single investment spike. Sales rise after an investment spike in innovative firms nearly as much as it does for firms increasing the number of establishments. However, sales exhibit no pattern in non-innovative firms. We conclude that innovative firms substantially improve their sales as a result of large investment episodes.

Once we have what we think is a clearer picture of the nature of investment spikes, or investment ages, we next turn to the analysis of the link among innovation, investment and productivity. To this purpose we concentrate on lumpy investment activity under different innovative strategies.

5.3 Innovation, investment and productivity

Up to this point we have characterized some patterns of investment behavior of Spanish manufacturing firms. We concentrate on large investment episodes and we fundamentally ask under what circumstances the probability of having an investment spike is more clearly increasing in the time since the prior spike. We found evidence of lumpy investment activity particularly associated to non-expansionary episodes for those firms which do not seem much involved in process innovation. We interpret these results as supporting differential investment patterns due to investment heterogeneity. The question is then whether we can find also differential effects of large investment episodes in productivity. Further, we would like to know whether we can disentangle how these effects combine in the aggregate across time. This will allow us to understand the type of composition effects that may obscure the relationship between investment and productivity as well as the offsetting roles of any vintage and survival effects.

To this purpose and in light of the findings reported above we explore the three subgroups we have been analyzing: expansionary, innovative and non-innovative firms. Again, we explore creation and destruction separately among firms involved in expansionary episodes. We run panel regressions over these subgroups as in equation (1) but with average labor productivity as the endogenous variable and controlling for the cycle and fixed effects. Also, we include as an explanatory variable the log capital per production hour as it is standard when measuring productivity effects. First, we restrict to firms with only *one* spike, (1a). Then, we extend the productivity regressions to the augmented sample with *at least one* spike, (1b). Finally, we implement the alternative regression (2) that estimates the effects of investment age centered on any spike year around a window $[-2, +6]$ and controlling for the effect of all other spikes. The results are robust to alternative choices of the window.

Table 10 reports our estimates for the impact of an investment spike on productivity according to (1a). The estimated values suggest that labor productivity during the spike episode is higher on impact for expansionary firms. We do not find significant differences at the IS between the two other subgroups and with the average obtained for this extract of the panel. Rather, significant differences show up in subsequent years. This can be shown first by taking the estimated values of γ^d (d = -2 to 6) as differences from γ^0 (bottom of Table 10). With fixed effects relative magnitudes are meaningful *per se*. According to this strategy, we do not find significantly different effects at investment ages after zero from the spike year to age three. However, labor productivity seems to stay flatter during the IS for innovative firms. In all of the cases labor productivity drops temporarily after the IS and some positive effects can be found only after investment age three. Clearly, after age four, the overall effect comes from the response in innovative firms which is significantly above the average whereas the response for expansionary and non-innovative firms is below. In particular, expansionary firms have the higher productivity response on the spike year which dampens in the short-medium run afterwards. Notice that the standard error of the γ^d coefficients indicates a lower precision of the estimates obtained for the expansionary subgroup.

As we did before, it is also meaningful to compare dynamic patterns among subgroups. Figure 9 summarizes the response of productivity after an IS in the 91-01 sample with only one CIS for the non-expansionary subgroup. Clearly, the response in productivity to an investment spike is significantly different for innovative and non-innovative firms. In particular, the response for both subgroups is increasing but that for innovative firms exhibits sizeable lags which could be associated to diffusion and long learning curves. On the other hand, expansionary firms have the higher productivity response on the spike year which dampens in the short-medium run afterwards. The intuition is that if replacement consists of the same machines then one should expect unimportant lags on productivity effects.

We provide further support to this interpretation by considering the sample that incorporates all firms that have at least one spike. In this case, the estimated values capture the average effect over all IS a firm experiences at all and every investment age, model (1b). Remember that in this case we include the investment rate as an independent regressor rather than estimating the effect of investment ages before zero. Figure 10 summarizes these estimates. The estimated values re-inforce the interpretation given above. We do find that the effect of investment spikes on productivity is increasing with investment age for the innovative group. We do not find this effect in the non-innovative group. We consider this result as evidence of embodied technical progress: gains in productivity are associated to investment spikes for innovative firms. Something intermediate seems to occur for firms in the expansionary subgroup (omitted). These firms' response is similar to that of non-innovative firms before age three but a somewhat increasing response is found after this investment age, although it is smaller than in the innovative group. Therefore, long learning curves and diffusion seems to be associated with expansionary and innovative investments.

As a robustness test we consider model (2) where we compute the evolution of the variable of interest, labor productivity here, about the IS taking into account the average level of the variable outside the window of that IS. With this specification similar results are obtained, even more in favor of differential responses among subgroups along the lines suggested above (Figure 11). On the one hand, labor productivity about the investment spike event turns out to be lumpy, with a substantial drop between 2% and 4% one year after the spike for innovative and non innovative firms. On the other hand, it is only for innovative firms that labor productivity slowly starts to recover after investment age two. We interpret this observation as an evidence in favor of smooth diffusion curves. Finally, with RIS, only one spike and whole sample, the results seem closer to similar responses among subgroups whereas under IIS, the results seem closer to different responses, particularly for the estimated values across the whole sample with at least one investment spike (Figure 12).

We conclude that productivity gains seem associated to large investment episodes. Further, this effect is substantial on impact for those firms we have characterized are particularly involved in expansionary activity. However, heterogeneous investment patterns tend to overlap in the aggregate as far as investment spikes arise contemporaneously. When we look to the productivity effects of recent investment we might expect no strong relationship since the innovative component takes time to show up. When we look to investment age effects we might expect no strong relationship since the non-innovative component is dampening as time goes by. Of course, the global effect depends crucially on the relative contribution of these two components. Further, the dynamics of replacement seems to be relatively more governed by echoes. Keeping track of the contribution of expansionary and replacement episodes as well as the engagement in innovative activity by the manufacturing sector could be a useful device for policy making.

6 Concluding remarks

In this paper we have analyzed the role of replacement and innovation activity in shaping investment behavior and labor productivity in a panel of Spanish manufacturing firms from 1990 to 2001. The paper looked fundamentally to large investment episodes, since there is evidence that investment is episodic and concentrates about investment spikes. Throughout these episodes we described the replacement behavior of firms. Our goal has been to provide some basic facts of the role of process innovation for replacement and embodiment.

Firstly, it turns out that the statistical analysis we develop gives rise to implications on hazards rates of a very different nature for different cuts of the data set. These cuts correspond to *i)* either the firm is facing an expansionary episode (i.e., involved in a *pure* expansion (contraction) in the number of establishments) or not, and *ii)* either the firm is involved in process innovation or not, among those not facing an expansionary episode. Secondly, we find that an investment spike has statistically significant different effects on sales for the aforementioned different cuts of the data set. Sales rise after an investment spike in innovative firms but exhibit no pattern in non-innovative firms. Thus, we would expect that innovative firms improve their market shares after an investment spike. We interpret these findings as evidence that replacement activity is more clearly observed in non-innovative firms and that innovative firms are for the most part characterized by partial replacement episodes.

The question is then whether our distinction between expansionary behavior and innovative activity contributes to a more precise assessment of the link between labor productivity and recent investment or 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, expansionary firms have the higher productivity response contemporaneously to the investment spike, and subsequent effects are dampened along farther duration leads. However, productivity does not particularly 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 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 affect expenditure on replacement investment as much as expenditure on expansion investment.

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Table 1: Frequency of observations in data set by industry

		UNBALANCED PANEL			BALANCED PANEL		
	INDUSTRY	Total	Small	Large	Total	Small	Large
1	Ferrous and non ferrous metals	456	187	269	208	90	118
2	Non-metallic minerals	1234	769	465	540	348	192
3	Chemical products	1233	546	687	524	317	207
4	Metal products	1871	1473	398	732	553	179
5	Industrial and agriculture machinery	1018	709	309	416	270	146
6	Office and data processing machine	169	92	77	60	36	24
7	Electrical and electronic goods	1645	944	701	593	370	223
8	Vehicles, cars and motors	846	285	561	341	72	269
9	Other transport equipment	350	188	162	143	81	62
10	Meat and preserved meat	481	343	138	192	144	48
11	Food and tobacco	1835	1309	526	647	515	132
12	Beverages	392	181	211	132	60	72
13	Textiles and clothing	1958	1445	513	856	606	250
14	Leather and shoes	583	540	43	204	204	*
15	Timber and furniture	1054	977	77	327	279	48
16	Paper and printing products	1316	977	339	592	452	140
17	Rubber and Plastic products	1087	799	288	444	307	137
18	Other manufacturing products	388	309	79	141	108	33
	Observations	17916	12073	5843	7092	4812	2280
	Firms	2128	1475	653	591	401	190

Table 2: Comparison of investment spike definitions.

BALANCED PANEL						
	Relative		Absolute	Combined		
	$\alpha = 2.50$	$\alpha = 1.75$	$\beta = 0.20^*$	$\alpha = 1.75 \cup \beta = 0.20$	$\alpha = 1.75 \cap \beta = 0.20$	
	CHP95	Power	*CHP99*	*Pow98*	*IIS*	*CIS*
No Spike	5855	5242	5547	4779	6010	5714
Spike	1237	1850	1545	2313	1082	1378
(%)	(17.4%)	(26.1%)	(21.8%)	(32.6%)	(15.3%)	(19.4%)
Inv't(%)	(30.4%)	(43.8%)	(36.1%)	(48.1%)	(31.9%)	(35.6%)
n. of firms						
with 1	121	78	109	40	150	127
2	107	98	120	74	148	154
3	102	128	89	105	112	154
4 or more	133	259	175	357	70	112
UNBALANCED PANEL						
No Spike	14879	13417	13910	12055	15272	14430
Spike	3037	4499	4006	5861	2644	3486
(%)	(16.9%)	(25.1%)	(22.4%)	(32.7%)	(14.8%)	(19.5%)
Inv't(%)	(27.7%)	(40.2%)	(35.6%)	(46.8%)	(29.0%)	(33.6%)
n. of firms						
with 1	618	545	507	406	656	697
2	417	535	408	491	450	564
3	219	358	244	390	211	316
4 or more	212	403	384	674	107	168

$^*\beta = 0.20$ also used in *CHP95* and in *Pow98* for RIS $\cup$ AIS.

Table 3: Creation and destruction of plants

BALANCED PANEL										
Plants	% Obs.	Obs. with change in plants							Firms' dist. 1st year	Total
		$\leq$-3	-2	-1	0	1	2	$\geq$3		
1	69.6	28	16	83	4409				401	4937
2	12.4	12	0	19	694	83			75	883
3	5.1	7	1	12	271	16	16		35	358
4	2.6	5	2	8	136	6	3	6	17	183
5	2.0	1	3	8	99	9	5	7	12	144
6	1.5	6	4	5	68	7	1	7	7	105
7	1.0	2	0	4	48	2	2	6	6	70
8	1.2	4	1	4	58	1	3	7	7	85
>8	4.6	13	5	9	220	5	11	33	31	327
Total		78	32	152	6003	129	41	66	591	7092
UNBALANCED PANEL										
1	67.7	74	45	196	10378				1436	12129
2	12.4	40	13	45	1677	189			261	2225
3	5.0	18	4	31	645	45	37		114	894
4	3.3	19	5	22	411	24	16	19	70	586
5	2.1	6	10	15	253	22	12	22	42	382
6	1.4	9	7	11	167	10	8	19	23	254
7	1.4	9	4	7	166	8	6	17	32	249
8	0.9	7	1	7	110	2	4	16	22	169
>8	5.7	52	17	27	650	23	24	107	128	1028
Total		234	106	361	14457	323	107	200	2128	17916

Table 4: Innovation and investment. Logit estimation (fixed-effects) by type of innovation

	Product Innovation		Process Innovation	
	Coefficient	std. err.	Coefficient	std. err.
Inn_1	0.538	0.05	0.552	0.05
r&dsal	0.104	0.02	0.045	0.02
wor&d	-0.002	0.01	0.015	0.01
invsal	1.742	0.49	5.882	0.51
pty	0.231	0.11	0.276	0.10
d91	0.469	0.14	0.578	0.12
d92	0.393	0.14	0.303	0.12
d93	0.363	0.13	0.410	0.12
d94	0.395	0.13	0.461	0.11
d95	0.194	0.13	0.279	0.11
d96	0.358	0.13	0.226	0.11
d97	0.479	0.13	0.344	0.11
d98	0.462	0.12	0.470	0.11
d99	0.499	0.12	0.159	0.11
d00	0.529	0.12	0.253	0.11
Obs.	8754		10984	
LR χ^2_{15}	186.46		382.84	

Table 5: Innovation and investment spikes. Logit estimation (fixed-effects). Unb. Panel

	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 6: Innovation and investment age. Logit estimation (fixed-effects). Unb. Panel.

	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 7: CIS in Expansionary, Innovative and Non-Innovative firms.

	Unbalanced Panel		Balanced Panel	
	Non Spikes	Spikes	Non Spikes	Spikes
Expansionary	3142	611 (16.3%)	1273	251 (16.5%)
Innovative	5763	1361 (19.1%)	2223	513 (18.7%)
Non-Innov.	5525	1514 (21.5%)	2218	614 (21.7%)

Table 8: Random-effects regressions of the impact of investment spikes on sales: whole sample (Total) and those firms involved in expansionary episodes of either creation or destruction.

	Unbalanced Panel			Balanced Panel		
	Total	Creation	Destruction	Total	Creation	Destruction
Spike_{-3}	0.349(0.02)	0.347(0.07)	0.281(0.06)	0.427(0.04)	0.442(0.17)	0.305(0.07)
Spike_{-2}	0.431(0.02)	0.419(0.07)	0.324(0.06)	0.495(0.04)	0.442(0.17)	0.399(0.08)
Spike_{-1}	0.535(0.02)	0.584(0.07)	0.433(0.06)	0.553(0.04)	0.524(0.17)	0.422(0.08)
Spike	0.654(0.02)	0.823(0.07)	0.555(0.06)	0.637(0.04)	0.717(0.16)	0.515(0.07)
Spike_{+1}	0.718(0.02)	0.886(0.08)	0.560(0.06)	0.676(0.04)	0.634(0.19)	0.504(0.08)
Spike_{+2}	0.742(0.03)	0.929(0.09)	0.564(0.07)	0.720(0.04)	0.668(0.19)	0.530(0.07)
Spike_{+3}	0.770(0.03)	1.071(0.10)	0.610(0.07)	0.786(0.05)	0.801(0.22)	0.601(0.09)
Spike_{+4}	0.820(0.03)	1.117(0.11)	0.591(0.08)	0.816(0.06)	0.921(0.21)	0.559(0.09)
Spike_{+5}	0.851(0.04)	1.160(0.13)	0.501(0.09)	0.866(0.06)	1.088(0.28)	0.615(0.11)
Spike_{+6}	0.891(0.04)	1.204(0.15)	0.518(0.10)	0.933(0.07)	0.979(0.33)	0.720(0.12)
mkev_E	0.054(0.02)	0.070(0.06)	0.017(0.04)	0.027(0.03)	0.216(0.13)	-0.045(0.05)
mkev_S	0.034(0.02)	0.063(0.05)	0.002(0.04)	0.033(0.03)	0.200(0.12)	-0.078(0.04)
mksh_I	0.112(0.02)	0.137(0.05)	0.095(0.04)	0.134(0.03)	0.206(0.12)	0.087(0.05)
mksh_C	0.078(0.01)	0.083(0.05)	0.050(0.03)	0.079(0.03)	0.151(0.12)	0.062(0.04)
cons.	18.01(0.08)	19.22(0.21)	19.31(0.22)	18.76(0.15)	19.56(0.23)	19.91(0.28)
σ_u	1.861	1.558	1.906	1.586	0.447	1.234
σ_e	0.295	0.323	0.285	0.305	0.363	0.216
ρ	0.975	0.959	0.978	0.964	0.603	0.970
Obs.	5165	522	699	1524	180	252
Groups	697	66	83	127	15	21

Year dummy variables are not shown.
Standard errors are in parentheses.

Table 9: Random-effects regressions of the impact of investment spikes on sales for the Innovative and Non Innovative subgroups.

	Unbalanced Panel		Balanced Panel	
	Non Innov.	Innov.	Non Innov.	Innov.
Spike_{-3}	0.287(0.04)	0.422(0.03)	0.409(0.07)	0.432(0.05)
Spike_{-2}	0.358(0.04)	0.528(0.03)	0.484(0.07)	0.492(0.03)
Spike_{-1}	0.434(0.04)	0.640(0.03)	0.485(0.07)	0.610(0.03)
Spike	0.520(0.04)	0.761(0.03)	0.494(0.07)	0.758(0.03)
Spike_{+1}	0.574(0.04)	0.857(0.03)	0.556(0.08)	0.801(0.03)
Spike_{+2}	0.605(0.04)	0.883(0.04)	0.627(0.08)	0.837(0.03)
Spike_{+3}	0.613(0.05)	0.899(0.04)	0.629(0.09)	0.922(0.03)
Spike_{+4}	0.616(0.05)	1.029(0.05)	0.659(0.10)	0.942(0.03)
Spike_{+5}	0.698(0.06)	1.088(0.05)	0.674(0.11)	1.014(0.03)
Spike_{+6}	0.757(0.07)	1.106(0.06)	0.688(0.12)	1.154(0.03)
y93	-0.114(0.03)	-0.099(0.03)	-0.098(0.07)	-0.006(0.05)
y94	-0.029(0.03)	-0.065(0.03)	-0.085(0.07)	0.086(0.05)
mkev_E	0.044(0.03)	0.062(0.03)	-0.034(0.07)	-0.023(0.05)
mkev_S	0.036(0.03)	0.028(0.02)	-0.008(0.06)	0.023(0.04)
mksh_I	0.163(0.03)	0.048(0.02)	0.276(0.06)	0.002(0.04)
mksh_C	0.100(0.02)	0.041(0.02)	0.146(0.05)	-0.033(0.04)
Cons.	17.186(0.11)	18.187(0.11)	17.49(0.21)	19.31(0.21)
σ_u	1.686	1.664	1.263	1.358
σ_e	0.305	0.260	0.330	0.250
ρ	0.968	0.976	0.936	0.967
Obs.	1955	1989	528	564
Groups	276	272	44	47

Year dummy variables are shown if significant.
Standard errors are in parentheses.

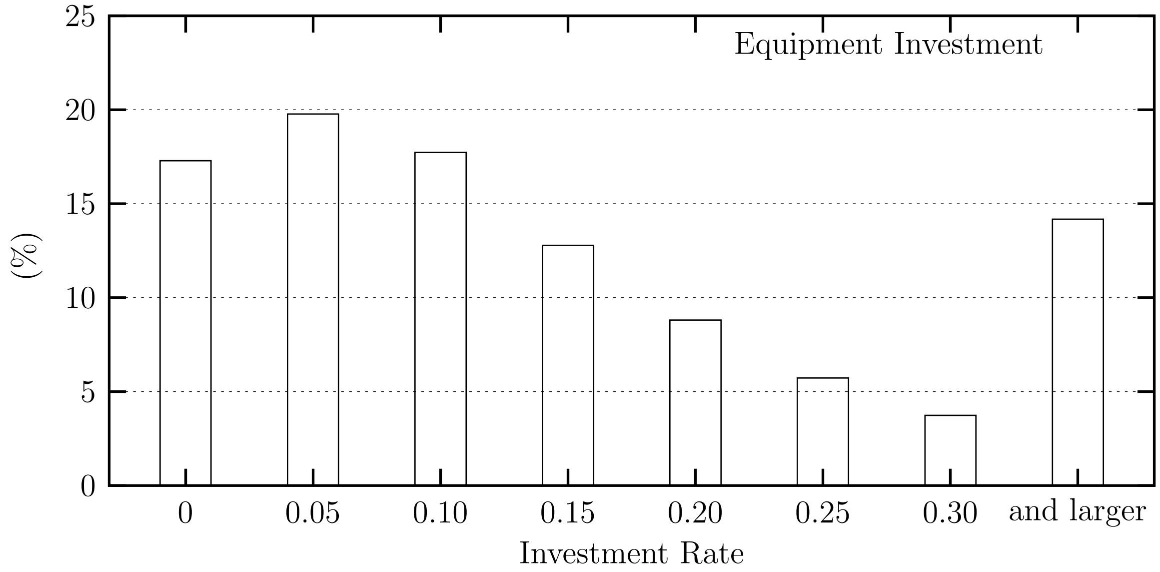
Table 10: Fixed-effects regressions of the impact of investment spikes on productivity. Unbalanced panel 1991-2001: model (1a).

	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.
Industry (and non-significative year) dummy variables are not shown.
$F-$test for joint significance.

$\gamma^d - \gamma^0$:				
with $d = -2$	-0.094	-0.167	-0.094	-0.054
-1	-0.042	-0.091	-0.028	-0.027
0	0.000	0.000	0.000	0.000
1	-0.031	-0.042	-0.007	-0.027
2	-0.001	-0.017	0.013	0.008
3	0.011	0.007	0.010	0.030
4	0.044	0.022	0.091	0.011
5	0.072	0.028	0.118	0.051
6	0.089	0.054	0.120	0.075

Figure 1: Investment rates distribution (top figure – Unbalanced Panel) and average investment rates about maximum investment episode (bottom figure – Balanced Panel).



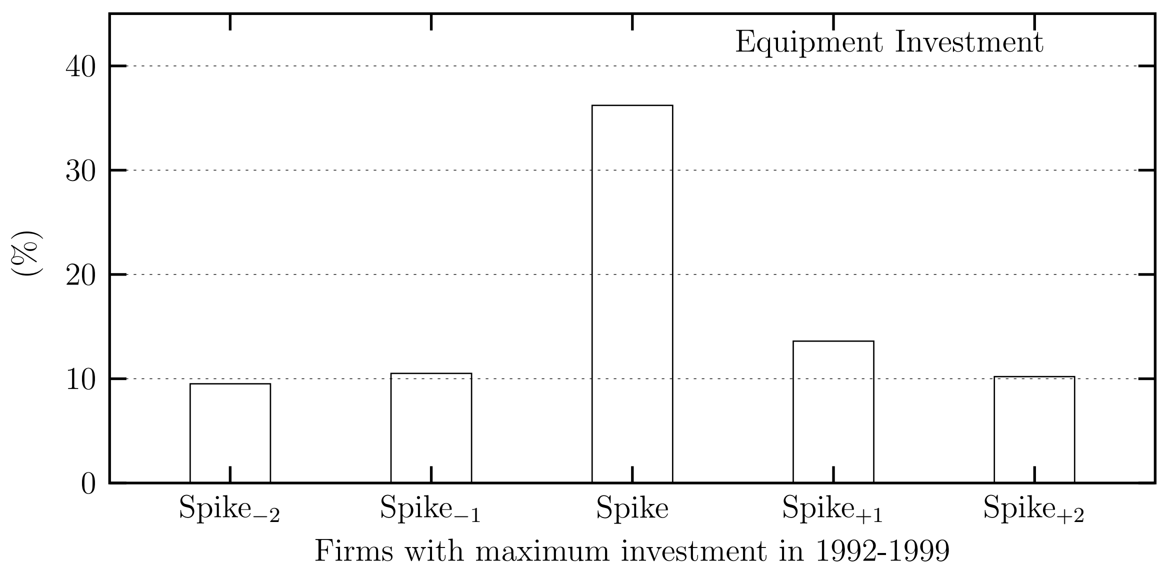
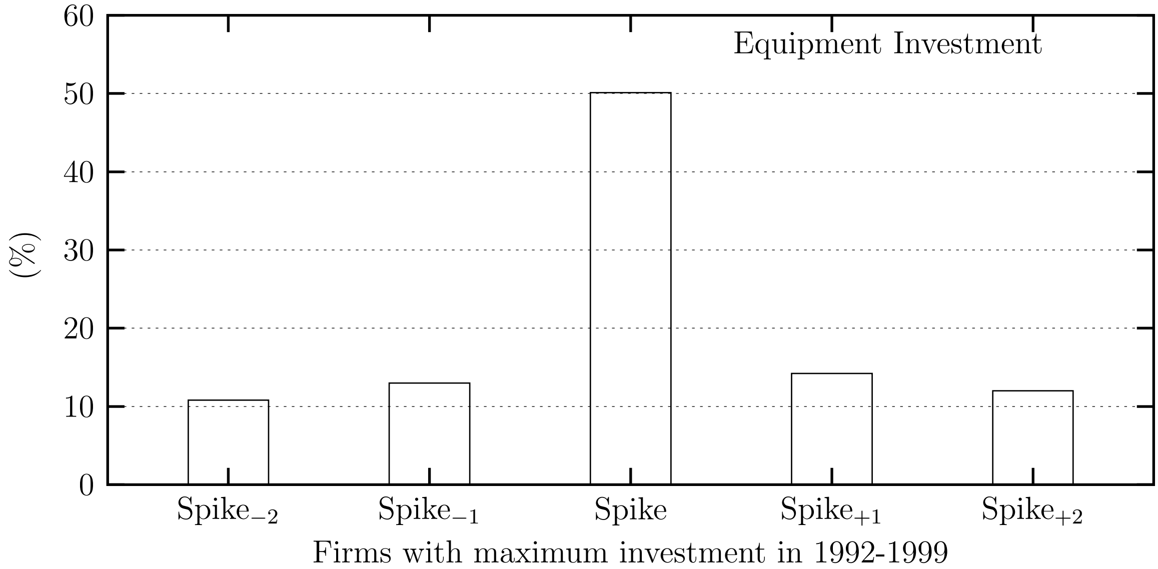
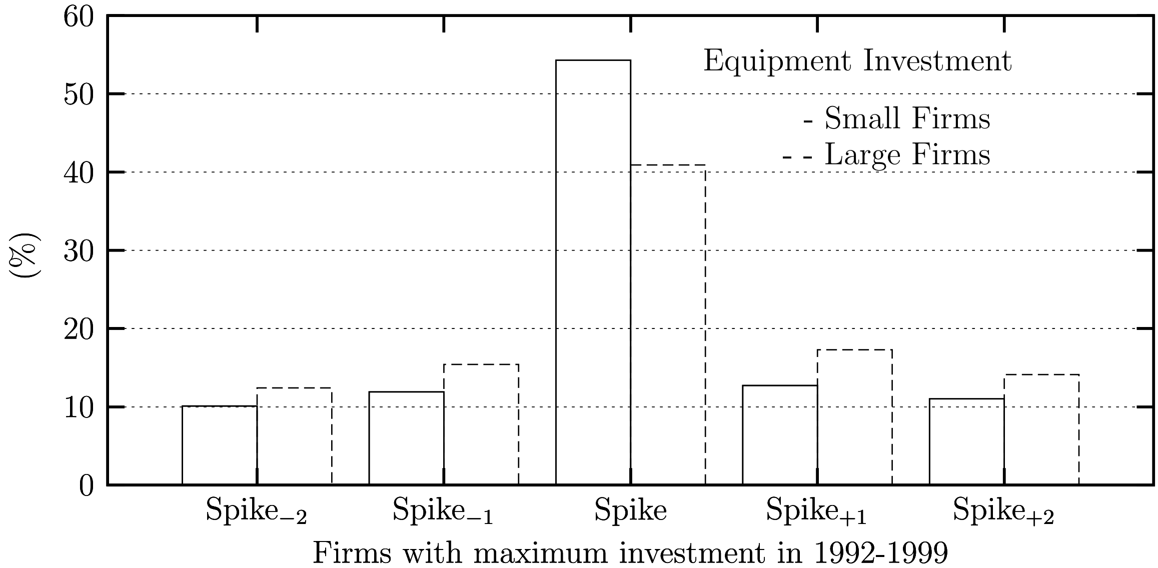


Figure 2: Investment evolution (%) about maximum investment episode (top figure – Balanced Panel) and distribution by average size (bottom figure – Balanced Panel)





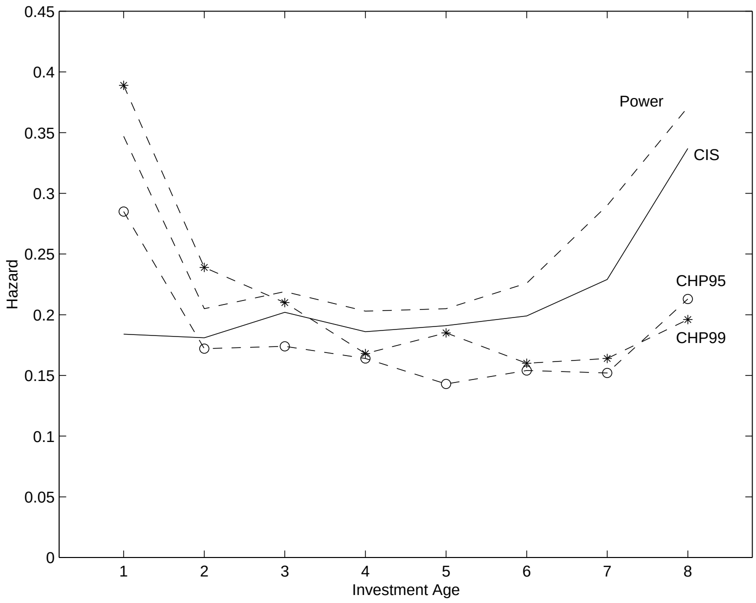


Figure 3: Empirical (Kaplan-Meier) hazard functions: comparison of IS definitions. Unbalanced Panel

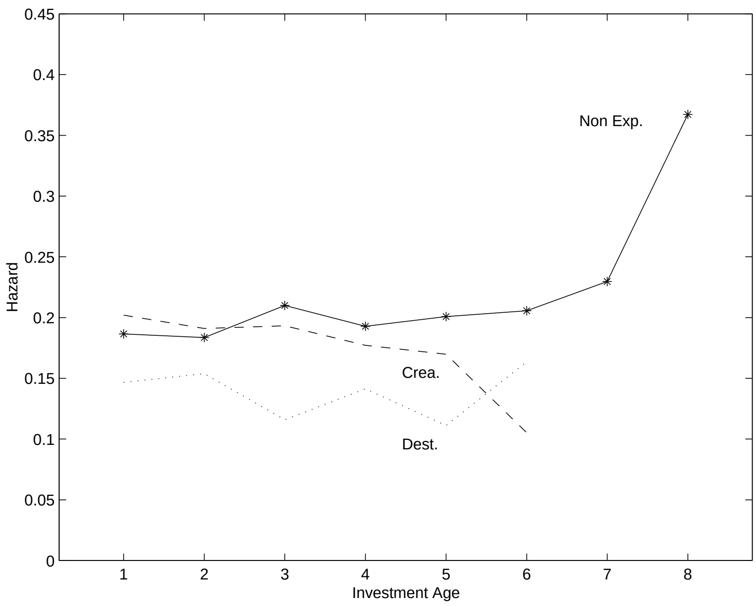


Figure 4: Empirical (Kaplan-Meier) hazard functions: different types of investment. Unbalanced Panel. Missing values correspond to non-statistically significative estimated durations.

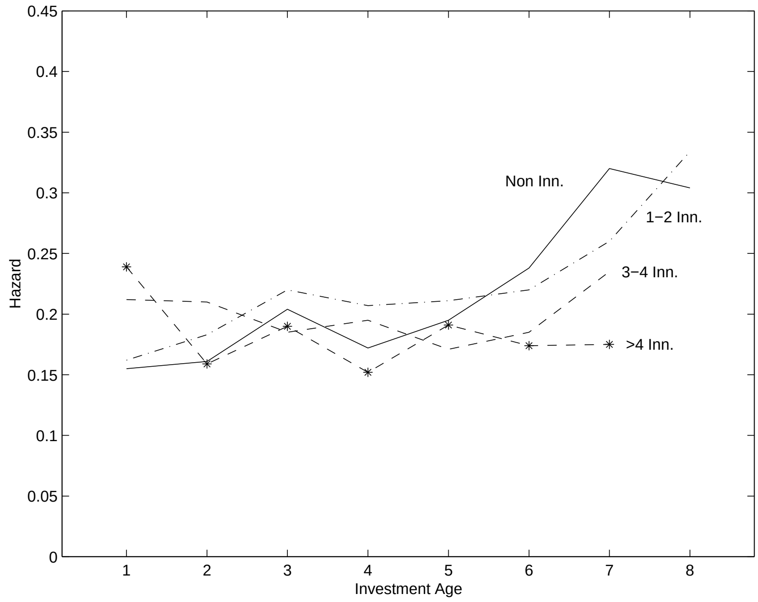


Figure 5: Empirical (Kaplan-Meier) hazard functions: CIS. Frequency of Innovations, Unbalanced Panel.

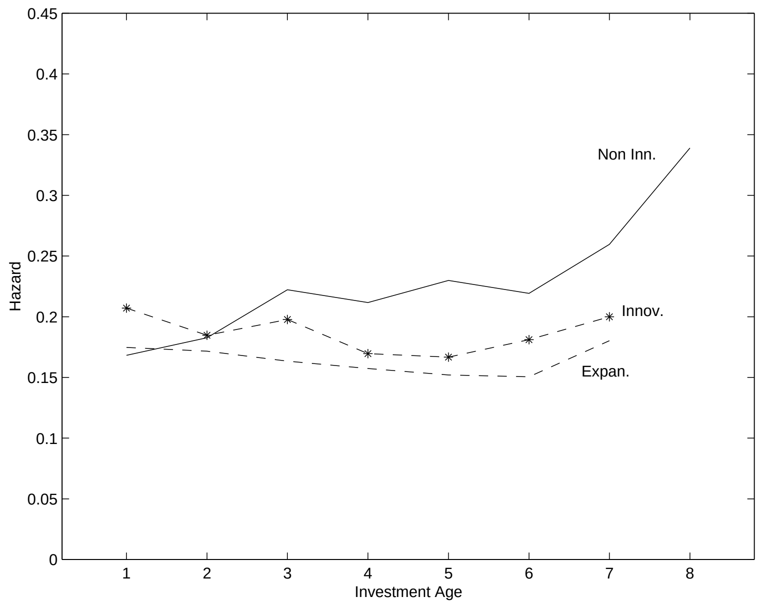


Figure 6: Empirical (Kaplan-Meier) hazard functions: CIS. Expansionary, Innovative (>20%) and Non-Innovative Firms, Unbalanced Panel.

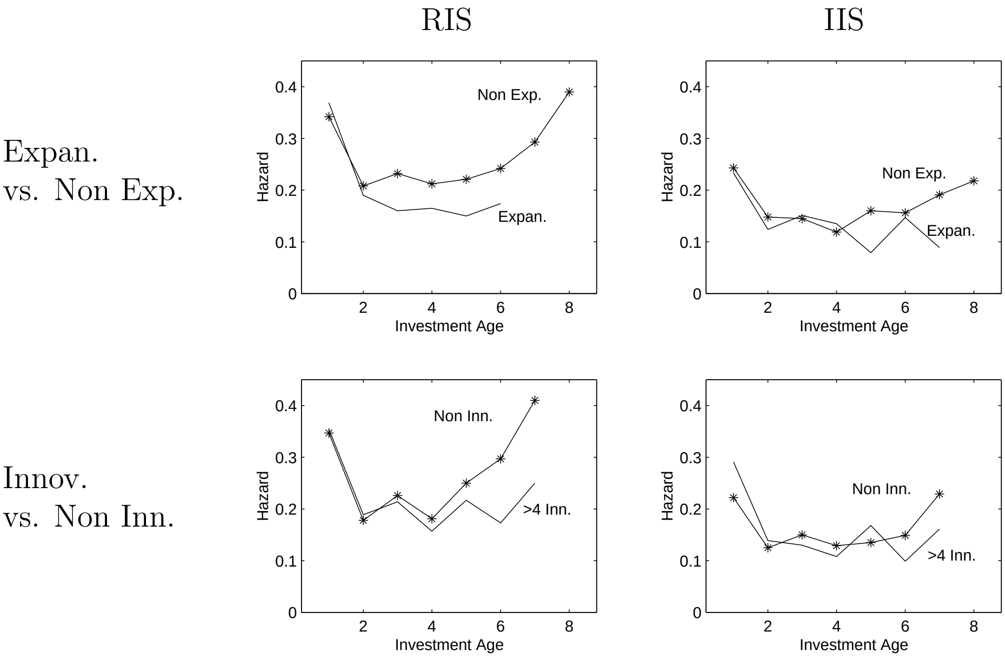


Figure 7: Empirical (Kaplan-Meier) hazard functions: comparison of expansionary and innovative behavior under RIS and IIS definitions. Unbalanced panel. Missing values correspond to non-statistically significative estimated durations.

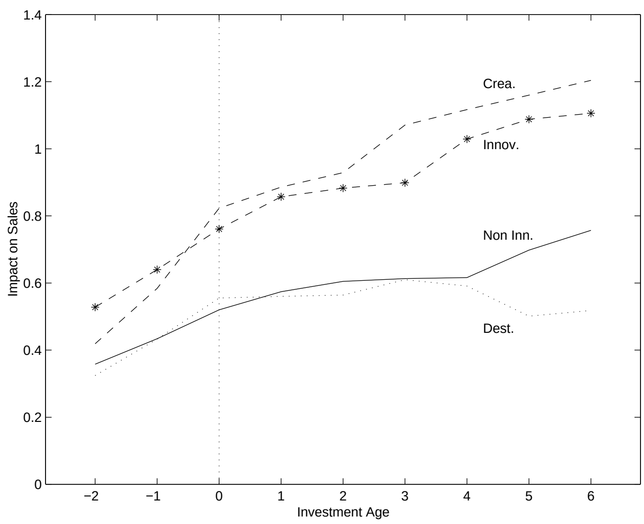


Figure 8: The impact of investment spikes on sales. Unbalanced Panel.

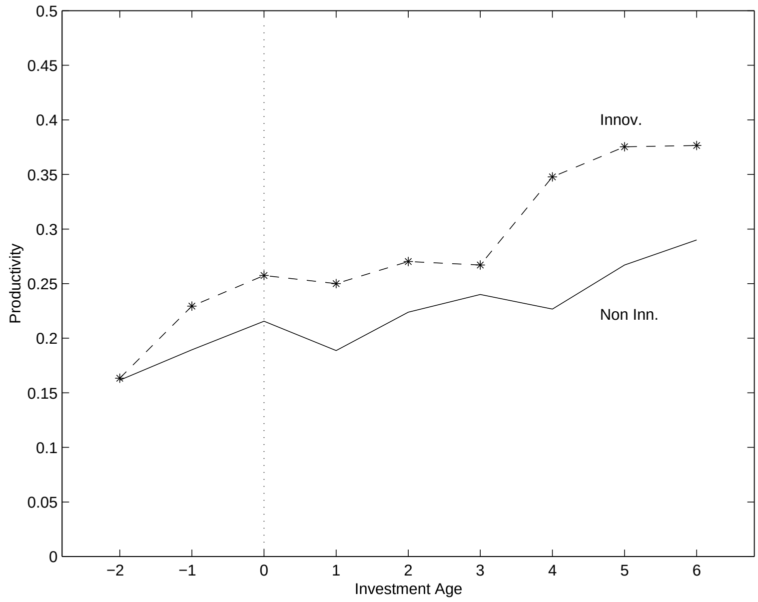


Figure 9: Productivity effects of an investment spike occurred in 1991-2001. Firms with only one spike: model (1a). Unbalanced Panel.

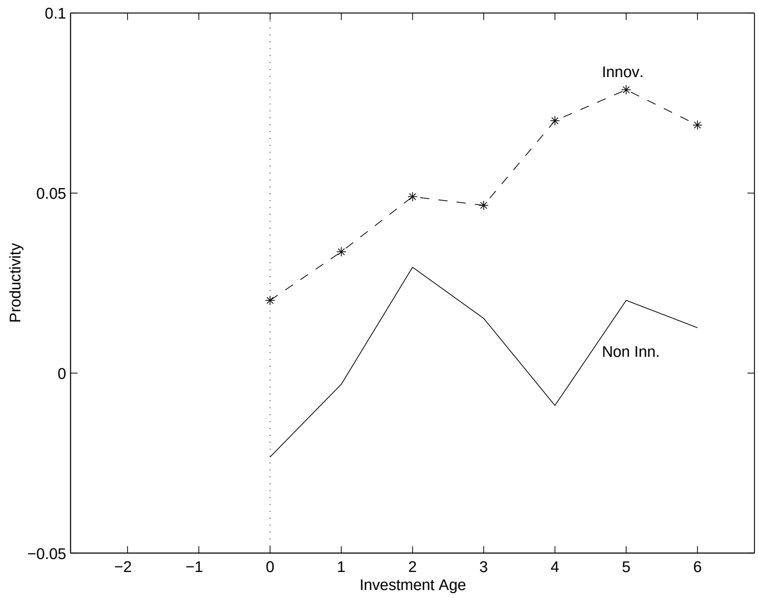


Figure 10: Productivity effects of investment spikes occurred in 1991-2001. Whole sample: model (1b). Unbalanced Panel.

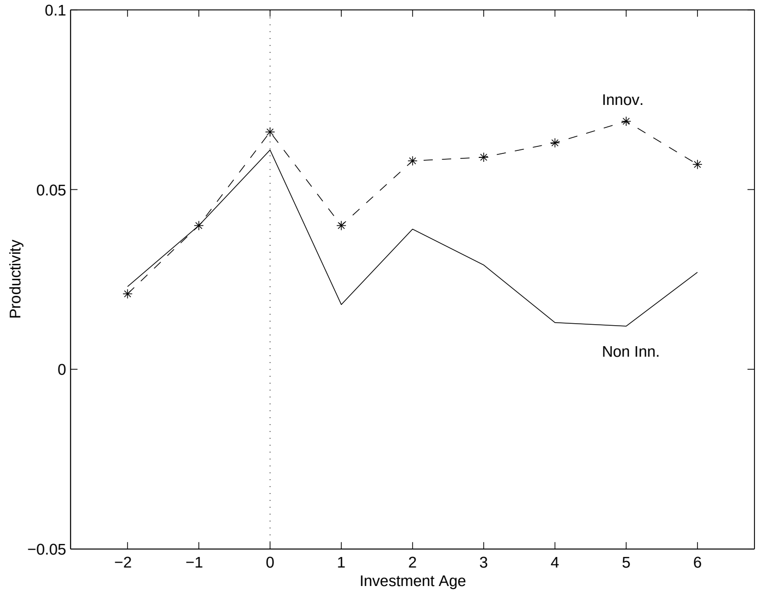


Figure 11: Productivity effects of investment spikes occurred in 1991-2001. Whole sample with [-2,+6] window, model (2). Unbalanced Panel. (Innov. $\gamma_0 = 0.056$; Non Inn. $\gamma_0 = 0.059$; std. err. $\gamma^0 = 0.009$).

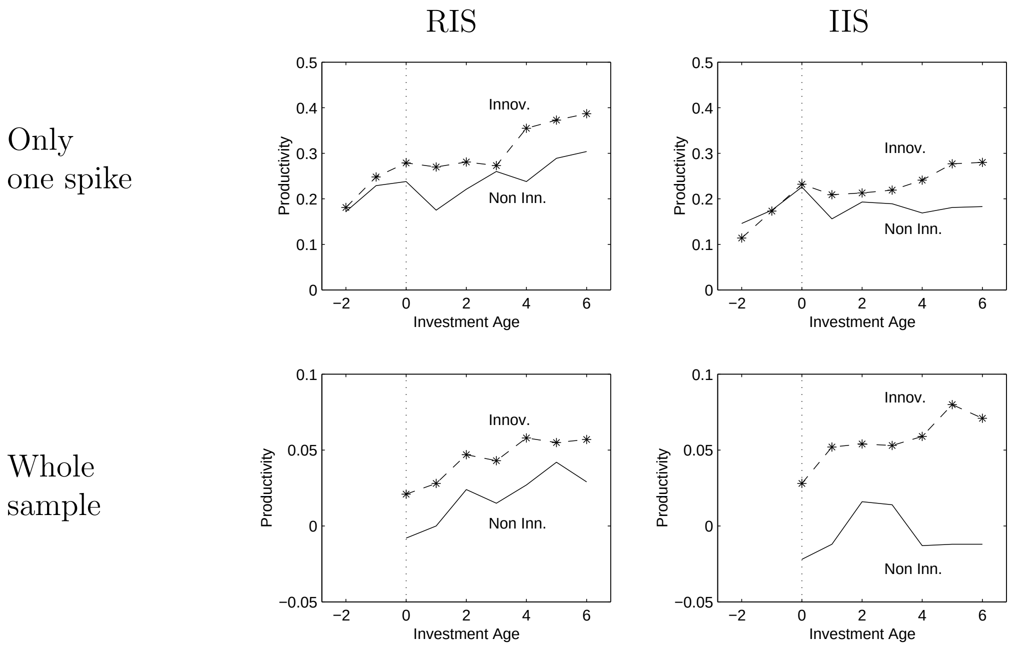


Figure 12: Productivity effects of investment spikes occurred in 1991-2001 under RIS and IIS definitions. Only one spike, top – model (1a), and whole sample, botttom – model (1b). Unbalanced panel.