Dynamics of Investment and Firm Performance: Comparative evidence from manufacturing industries.*

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Abstract

In this paper we present an empirical assessment of the statistical properties of realized investment in the French and Italian manufacturing industries. In a first step we focus on the distributional properties of investment and its lumpy nature. We confirm previous studies in showing that investment is lumpy at the firm level and compare different rules to define investment spikes. Moreover, we present a new methodology that adresses the size bias present in the literature and use such measures to evaluate the dynamic link between spike events and a set of firm level performance variables. We consider first the determinants of the probability to observe an investment spike and second the effect of such events on firm performance. In this respect, our results validate some previous findings, in particular the short term negative relation between investment spikes and productivity growth. However, by focusing on longer dynamics we find a positive effect which confirms the "learning curve" hypothesis. The disruptive

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negative effect found in previous studies can be partly explained by the difficulty to set up new plants: as put forward by Winter and Szulanski (2001), we show that replication is costly and finding similar levels of performance after such event takes time.

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1 Introduction

In this paper, we provide evidence on the link between firm investment and corporate performance. We consider the dynamics of the investment decision at the firm level in France and Italy, and center our study on the investment *spike*. We then relate such event to the firm's financial conditions as well as productive performance in order to answer the question: what are the characteristics of firms when they are investing, and what are the effects of such distorting event on their performance?

For long, the impossibility to access observed investment data has hindered empirical research on the issue. It is indeed relatively recently that scholars have started to document the lumpy nature of the investment behavior of firms. Among the first attempts is the contribution by Doms and Dunne (1998) with data on U.S. plants and firms. Inspired by this seminal paper a growing body of literature has expanded reporting similar results for other countries and industries [1]. All these studies try to answer the question of "how lumpy is investment". Comparing their data to simulated models data, Carlsson and Laséen (2005) conclude that non-convex cost models (such as "S,s" or irreversibility models) offer the best fit to explain investment decisions, rejecting the ones which infer a smooth pattern of capital accumulation. Following "S,s models" of capital accumulation, it seems that investment is triggered when the actual capital stock deviates too much from the desired level. After identifying investment events by a peak in the firm's investment rate (the ratio of investment to the existing capital), the authors find that capital growth is much lower in between spikes (Doms and Dunne, 1998). On this matter, Cooper et al. (1999), Bigsten et al. (2005) and Whited (2006) analyze how the probability to observe a spike evolves with the time since the last spike.

If investment episodes occur with lumps they might as well have disrupting effects on the firm's operation: shut down and dismiss old machines, install new ones, etc. We can thus expect that the investment event goes together with a non negligible loss - whose magnitude as well depends on how abrupt was the change - in terms of the know-how and established routines. The disrupting effect of investment on firm performance might be even greater when the investment episode involves replication, that is when a new plant is built to expand the firm's production capacity (Winter and Szulanski, 2001). Our paper thus intends to expand

[1] Among the papers using a comparable methodology to Doms and Dunne (1998), the reader might refer to Duhautois and Jamet (2001) for France, Nilsen and Schiantarelli (2003) and Nilsen et al. (2009) for Norway and Carlsson and Laséen (2005) for Sweden.

the knowledge on the costs and gains from investment on firm performance, with a focus on the timing of investment episodes and the evolution of firm variables in the years that precede and follow them. At the time of their study, Doms and Dunne (1998) stated that little was known about the conditions and effects of investment spikes. In this respect, several authors have started to investigate the relationship between capital adjustment episodes and other firm variables, such as productivity[2] and productivity growth (Power, 1998; Bessen, 1999; Huggett and Ospina, 2001; Nilsen et al., 2009 and Shima, 2010), employment growth (Asphjell et al., 2010), sales growth (Licandro et al., 2004) or other factors of production (Sakellaris, 2004; Nilsen et al., 2009). In particular, investment should affect productivity in the long run, as new capital embodies the latest technology (Jensen et al., 2001). "Learning by doing" models anticipate that it should take some time for workers to learn how to use the new technology, therefore labour productivity should follow a *U shape* curve, initially dropping and then gradually rising to a higher level than the *ex ante* one. Most of the empirical literature on the subject (Power, 1998; Huggett and Ospina, 2001; Sakellaris, 2004; Shima, 2010) reports that the effect on productivity growth is indeed negative in the short run. If the initial cost has been revealed by these studies, none of them report a positive relation between investment lumps and productivity growth, even in the long run. Power (1998) infers policy implications from her findings: "I find little evidence of a robust, economically meaningful correlation between high productivity and high recent investment. This cautions against the efficacy of fiscal policy that is based on the premise that investment causes high productivity" (p. 311).

Considering investment - and its timing - in the assessment of firm's performance could also be important in explaining why selection effects seem quite flat. Indeed, the relationship between firm performance (as measured by its profitability rate or productivity growth) and firm growth was found to be unsignificant on French and Italian data (Bottazzi et al., 2010). The specific role of investment in the mediation between firm performance, firm financial variables[3] and firm growth is still ambiguous.

In this paper we study the dynamics of the relation between realized investment and firm performance in the French and Italian manufacturing sectors. After documenting the lumpy

[2]Either leabour productivity or total factor productivity is considered. The former was used by Power (1998), Bessen (1999), and Nilsen et al. (2009), as we do here, while the latter by Huggett and Ospina (2001), Shima (2010) .

[3]Extensive works have been conducted on the relation between firm investment and financial constraints, leading to major disagreements, most notably between Fazzari et al. (1988) and Kaplan and Zingales (1997). But this issue is outside of the scope of the present paper.

nature of this variable, we consider and compare different measures of investment spikes in order to account for large capital purchases (Section 3). In Section 4, we proceed in two steps: first we analyze the determinants of the probability to observe a spike, and second we study the effects of such events on firm performance. Section 5 concludes.

2 Data Description

This paper draws upon two similar datasets, Micro.3 and EAE,[4] reporting firm level data for Italy and France, respectively. The Micro.3 database has been developed through a collaboration between the Italian Statistical Office (ISTAT) and members of the Laboratory of Economics and Management of Scuola Superiore Sant'Anna, Pisa. The EAE databank is collected by the statistical department of the French Ministry of Industry (SESSI) and provided by the French Statistical Office (INSEE). It contains longitudinal data on a virtually exhaustive panel of French manufacturing French firms located on the national territory with 20 employees or more over 1989-2007. Micro.3 is an open panel combining information from census and corporate annual reports about all the firms with 20 employees or more operating in any sector of activity on the national territory over 1989-2006. In both databases, firms are classified according to their sector of principal activity. Our study focuses on the manufacturing industry i.e. from group 171 to group 366 in the ISIC rev 3.1. classification. For consistency with our previous works with these data and because we are interested in understanding the drivers of firms' investment decisions, we exclude from the analysis firms that have undergone radical restructuring such as M&A.

The variables we are focusing on are observed investment and investment rates. We define investment rates as current year investment over past year tangible assets (I_t/K_{t-1}). This corresponds to the ratio between the flow variable (investment) and the stock variable (capital), so that I_t/K_{t-1} can also be interpreted as the growth rate of capital. In each period, the stock of capital is updated with the value of new investment, linking the investment time series to the accumulation of capital over time. However, about 80% of the observations on the value of assets are missing in the French databank before 1996[5]. Therefore, when the investment rate

[4]Both databanks have been made available to the authors under the mandatory condition of censorship of any individual information. The data for Italy were accessed at the ISTAT facilities in Rome. More detailed information concerning the development of the database Micro.3 are in Grazzi et al. (2009).

[5]Indeed, this variable was retrieved only for firms above 100 employees until 1996.

is needed, the analysis is reduced to the 1996-2007 period. In order to undertake intertemporal comparison, we deflate the data on current value variables with output deflators at the two digit level.

Previous studies on investment have used either the plant (Doms and Dunne, 1998; Power, 1998; Nilsen and Schiantarelli, 2003) or the firm (Duhautois and Jamet, 2001; Carlsson and Laséen, 2005) as level of analysis. Our data is defined at the firm level, still, we include as additional information firms' number of plants ($Plant_t$) because we are interested in the *replication event* (Winter and Szulanski, 2001). We define such event as an increase in the firm's number of plants between time $t-1$ and t.

In the second part of the analysis we also use performance-related variables, namely the number of employees (N_t), growth rate of employment (g_t^N), defined as the logarithmic difference in the number of employees in two consecutive years, labour productivity (Π_t), computed as the firm's ration of value added to its number of employees, growth of labour productivity (g_t^{Π}), total sales (TS_t) and its growth rate (g_t^{TS}), and return on sales (ROS_t) as a proxy for profitability. ROS_t is defined as gross operative margin[6] over total sales. Such a definition of profitability that considers the ratio between a measure of profits and total revenues is a standard and widely used proxy for firm's profitability. In particular, given that we have access to a wide range of variables, we deliberately decided to pick a basic measure of profits, such as gross margins, that is not heavily influenced by accounting interferences.

We run our econometric analysis for the entire sample but also by sector. Indeed, capital intensity and turnover as well as financing conditions can be partly driven by sector-specific characteristics. We thus group firms using the Pavitt taxonomy (Pavitt, 1984) and its correspondance with ISIC sectors (at the 3-digit level) presented by Dosi et al. (2008)[7]. We choose a higher level of aggregation than the one in the dataset because the low number of observations in some ISIC groups (even at the 2-digit level) doesn't allow to perform econometric exercises at this level of disaggregation. Thus the ISIC sectors are matched with the four Pavitt groups, namely the "supplier dominated"[8], the "scale intensive"[9], "the specialized suppliers"[10] and

[6]Gross Operative Margin is valued added minus wages, salaries, and social insurances paid by the firm.

[7]The matching table we have used is found in the appendix of their paper, and is not reproduced here.

[8]In this first group, technology is acquired through the purchase of new intermediate inputs, and comprises the textile, clothing and metal products sectors.

[9]In this second group we find the sectors in which economies of scale make it important to acquire a large production capacity, such as chemicals, agricultural products or motor vehicles.

[10]This third group comprises for example the machine-tools and electrical equipment sectors.

the "science-based"[11] groups.

Although the Pavitt taxonomy is a typology based on sectoral innovation processes it appears relevant for the categorization of firms according to their investment patterns. Indeed, investment opportunities, the scale of production, the technology intensity and the need to buy technology from a supplier or the ability to produce it internally all connect to the investment decision.

3 Evidence of investment lumpiness and spike measures

In this section we present the analysis of firm investment patterns in the French and Italian manufacturing industries. The aim is to find the appropriate way to analyze within-firm heterogeneity in investment rates, first to show evidence of the appearance of lumps in investment behavior, and second to select the *investment spikes* events. We present here the different methodologies suggested in the literature as well as introduce our own.

Figure 1 shows that if most firms have very low investment rates, the tail of the distribution reveals that some undergo large investment episodes. This is apparent by the fat tail of the distributions of investment rates in a cross-section of firms. Thus the distributional analysis of the investment rate reveals substantial differences *between firms*. There is, however, at least one more dimension in which the lumpy nature of investment gets revealed and this has to do, *within any one firm*, with how firms decide to allocate investment over a certain period of time. Do firms change their capital endowment smoothly over time or, on the contrary, do we observe spikes in such patterns?

In order to provide evidence on investment lumpiness, we rank, for each firm, the investment carried out in each year from the highest to the lowest[12]. We present in Figure 2 the ranks of investment shares, the share of investment in year t being defined as investment in year t over total investment in the period : I_t/I_{tot}. The figure shows the means and medians of each rank over the sample (the first bar represents the mean investment share of *rank 1*). Therefore the highest investment share on average accounts for more than 20% of total investment, while investment shares are significantly lower in other years, revealing the *lumpy*

[11]This last group includes sectors in which science and research and development play a key role, as for pharmaceuticals, electronics and computer producers.

[12]Of course this requires to work on the balanced panel. To allow for intertemporal comparison we remind that investments in different years are deflated with the corresponding price index at the 2 digit level of industry disaggregation.

Figure 1: Distribution of investment rates in 1999, 2002 and 2006 for France (left) and Italy (right). Vertical axis in log scale.

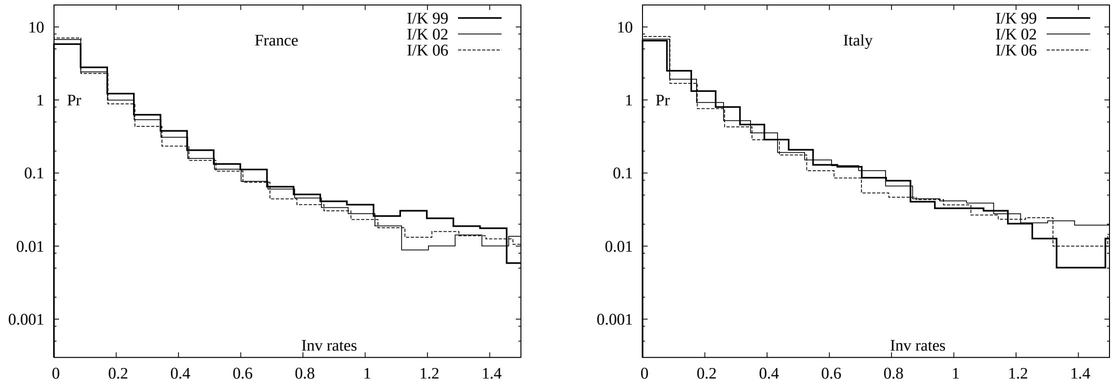
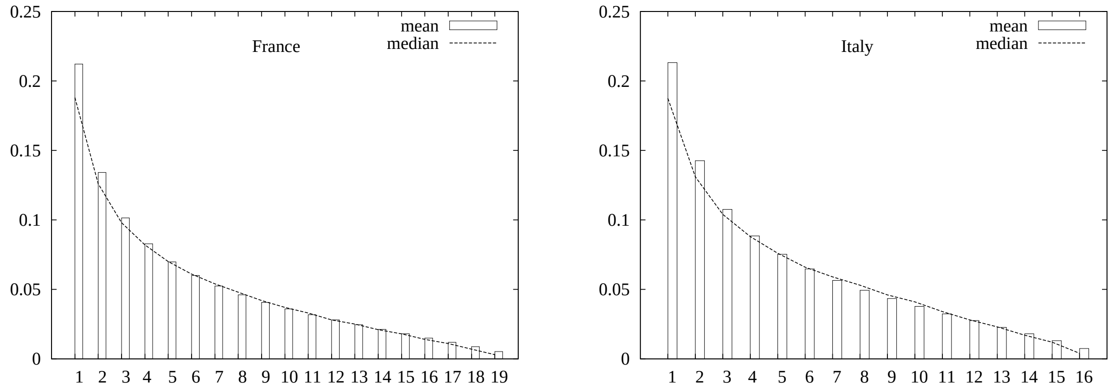


Figure 2: Investment shares by rank in France (left; from 1989 to 2007); and in Italy (right; from 1991 to 2006). Investment shares on the vertical axis; ranks on the horizontal one.



Note: The highest investment episode is defined as *rank 1* and the others are consequently *rank 2..19* (16 in the Italian sample, as this one is available for 1991-2006.).

characteristic of the investment variable.

Our explorative analysis has so far confirmed the lumpy nature of investment. The volume of investment at the firm level is concentrated in a few episodes accounting for a large share of firms' total investment over the observed period. There does not appear too much room left for assuming a smoothing of investment.

Power (1998) has underlined that the difficulty lies in the right measurement and definition of an investment episode, or investment spike : "Since an "investment spike" is a theoretical rather than a numeric or algebraic concept, and lacks an unambiguous real-world analogue, there is some risk of measurement error, whichever definition of investment spike is employed.

In order to alleviate this risk, a variety of definitions of an investment spike is used to test robustness" (p 303). In what follows we therefore consider several measures of investment spikes and confront them against a series of criteria presented by Nilsen et al. (2009) (p.109):

1. "The investment must be large, both relative to the investment history of the individual firm and relative to the (cross-sectional) dispersion of investment ratios within the industry;

2. the investment must constitute a rare event,

3. the spikes must account for a disproportionate share of total industry investments."

4. The spike measure has to be unbiased (the probability to have a spike does not depend on firm size)[13] .

We present below five methodologies that allow to identify investment spikes, namely the *Absolute rule*, the *Relative rule*, the *Linear rule*, the *Exponential rule* and finally the *Kernel rule*. The first three are taken from the literature, respectively from Cooper et al. (1999), Power (1998) and Nilsen et al. (2009). The latter two are our own computations.

As a starting point, we consider as investment spikes investment rates (I_t/K_{t-1}) above a fixed threshold. In line with Cooper et al. (1999), we use a 20% rule. This threshold is set so as to eliminate "routine maintenance expenditures". The authors acknowledge it is arbitrary but test their results with several threshold values and conclude that they are robust to alternative values of the threshold. The spike dummy $S_{i,t}$ (corresponding to the observation of firm i at date t) is identified according to the following rule:

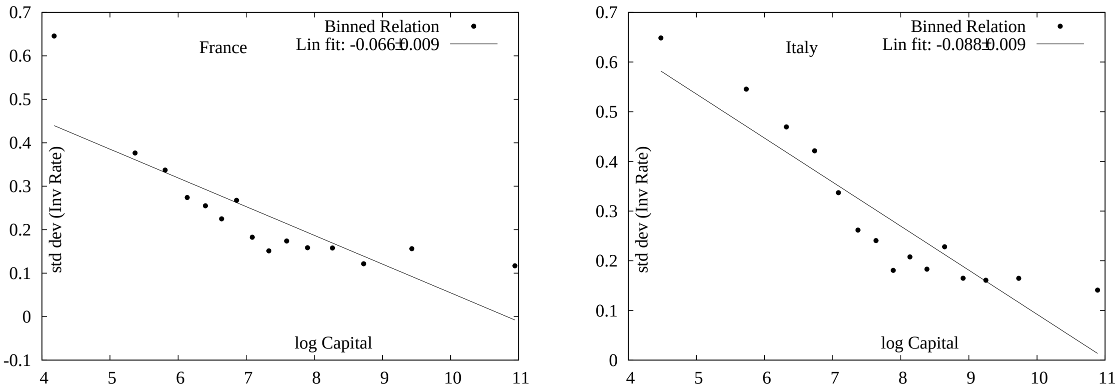
$$S_{i,t} = \begin{cases} 1 \text{ if } I_t/K_{i,t-1} > 0.20 \\ 0 \text{ otherwise} \end{cases}$$

In what follows we will refer to this spike measure as the *Absolute rule*.

As mentioned by Nilsen et al. (2009), this aboslute threshold presents a size bias. Indeed, smaller firms have relatively more volatile and higher average investment rates. This can be

[13]This fourth criterion is not literally present in their paper but the idea motivates their implementation of investment spikes

Figure 3: Log of the standard deviation of investment rates as a function of (log of) capital. Year 2001.



more precisely assessed by Figure 3: there is a negative relation between the investment rate and the level of capital (in logs), in violation with Gibrat's law[14].

In order to correct for such size bias, several things can be done. The first, as introduced by Power (1998) is to consider spikes as large investment events *relative* to each firm's typical investment behavior. She thus defines as a spike all investment events that are larger than a multiple α[15] of the firm's median investment rate over the period τ:

$$I_{i,t}/K_{i,t-1} > \alpha \operatorname*{median}_{\tau}(I_{i,\tau}/K_{i,\tau-1})$$

However, this rule presents the problem that half the spikes defined this way correspond to investment rates below 0.20. In fact, for firms that have a very low median investment rate, spikes would not correspond to an active investment behavior. Thus we adapt the rule of Power (1998) by setting a limit threshold on the minimum value of the investment rate.

The spike dummy $S_{i,t}$ is identified according to the following rule:

$$S_{i,t} = \begin{cases} 1 \, \text{if} \, I_t/K_{i,t-1} > \max[\alpha \operatorname*{median}_{\tau}(I_{i,\tau}/K_{i,\tau-1}), 0.20] \\ 0 \, \text{otherwise} \end{cases}$$

In what follows we will refer to this spike measure as the *Relative rule*.

[14]The Gibrat law (Gibrat, 1931) states that the size of a firm is independent of its growth rate of capital, also called "law of proportionate growth". Considering investment rates as growth rates we would therefore expect that they are also independent of firm size.

[15]The author compares different values of α and decides to use a value of 1,75. In order to be consistent, we therefore use such value for all the spike measures compared here.

The second way we could correct the size bias starts from the same premises as Nilsen et al. (2009). In order to correct for the excessive volatility of investment of smaller firms, they search for a rule that conditions the threshold value on the size of the firm. Thus instead of imposing a homogeneous threshold to all firms, it will be negatively related to each firm's size. To do so they assume that $E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}]$ is a log-linear function in $K_{i,t-1}$[16]

$$E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}] = \hat{\gamma}_0 + \hat{\gamma}_1 \ln K_{i,t-1} \tag{1}$$

They then identify spikes with the following rule:

$$S_{i,t} = \begin{cases} 1 \text{ if } I_t/K_{i,t-1} > \max[\alpha E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}], 0.20] \\ 0 \text{ otherwise} \end{cases}$$

Similarly to the relative rule, Nilsen et al. (2009) need to define the spike as a maximum between the expected value and a threshold (0.20). This threshold is needed because the expected value from the linear regression may become negative. As shown in Figure 4, it is also because the linear fit is quite below the observed investment rates for large values of capital[17]. In what follows we will refer to this spike measure as the *Linear rule*.

Here instead we suggest a variation on the rule described above. Indeed, Figure 4 suggests that the relation between the investment rate and the log of capital is much better approximated by a non linear function such as the exponential function or a Kernel regression. We thus create such *Exponential* and *Kernel* rules and test them against the measures of investment spikes already defined in the literature.

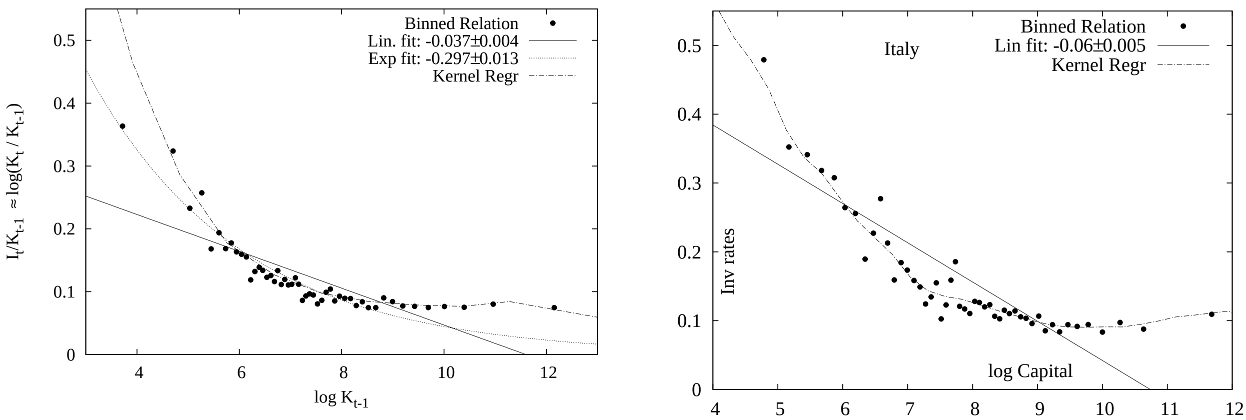
In order to compute the exponential rule for the definition of spikes, we estimate the parameters of the exponential function [18] linking the observed investment rates and the log of capital. We then use the estimated parameters $\hat{\beta}_0$ and $\hat{\beta}_1$ to get the expected investment rate as conditioned on the firm's size:

[16] $\hat{\gamma}_0$ and $\hat{\gamma}_1$ are the estimated parameters of the linear relation between observed investment rates and the log of capital: $I_{i,t}/K_{i,t-1} = \gamma_0 + \gamma_1 \ln K_{i,t-1} + e_{i,t}$. The parameters are year and sector specific (at the Pavitt group level).

[17] The exponential rule presented below presents a similar shortcoming.

[18] The parameters are year and sector specific (at the pavitt group level).

Figure 4: Linear and kernel fit of the relation between size and investment rates for France (left) and Italy (right) in 2003



Note: The observations are binned into 50 groups and the mean of each bin is represented on the plot - they are shown as "Binned Relation" on the plot.

$$E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}] = exp^{\hat{\beta_0}+\hat{\beta_1}\ln K_{i,t-1}} \tag{2}$$

The spike dummy $S_{i,t}$ is then identified the same way as for the linear rule.

$$S_{i,t} = \begin{cases} 1\,\text{if}\, I_t/K_{i,t-1} > \max[\alpha E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}], 0.20] \\ 0\,\text{otherwise} \end{cases}$$

In what follows we will refer to this spike measure as the *Exponential rule.*

Although, as revealed by Table 2, the exponential rule is already satisfactory in removing the size bias, there is no theoretical background justifying that the non-linear function f that links firm size (as proxied by the log of its capital) and investment rates should be of exponential shape. Therefore we use a kernel regression as an alternative fit. Indeed, such nonparametric regression sets no premises on the shape of the relationship. The kernel density estimation is determined on a number n of equidispaced points[19].

$$E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}] = \hat{f}(\ln K_{i,t-1}) \tag{3}$$

[19] In our computations, we set $n = 15$. We estimate the kernel density function f:$I_t/K_{i,t-1} = f(\ln K_{i,t-1}) + e_{i,t}$. As for the previous estimations, the parameters are computed for each Pavitt sector and each year.

Table 1: Descriptive statistics of spikes, according to different rules

	Absolute rule	Relative rule	Linear rule	Exponential rule	Kernel rule
France					
Mean investment rate (all sample : 0.14)	0.47	0.54	0.60	0.57	0.53
% of spikes in nb of obs.	18.28	13.18	11.58	12.22	13.45
% of total investment accounted by spikes	28.36	20.69	27.07	27.51	34.67
Italy					
Mean investment rate (all sample : 0.12)	0.53	0.58	0.59	0.59	0.53
% of spikes in nb of obs.	15.07	11.89	12.39	10.74	13.14
% of total investment accounted by spikes	36.56	31.20	35.70	32.90	41.50

The spike dummy is identified according to the following rule:

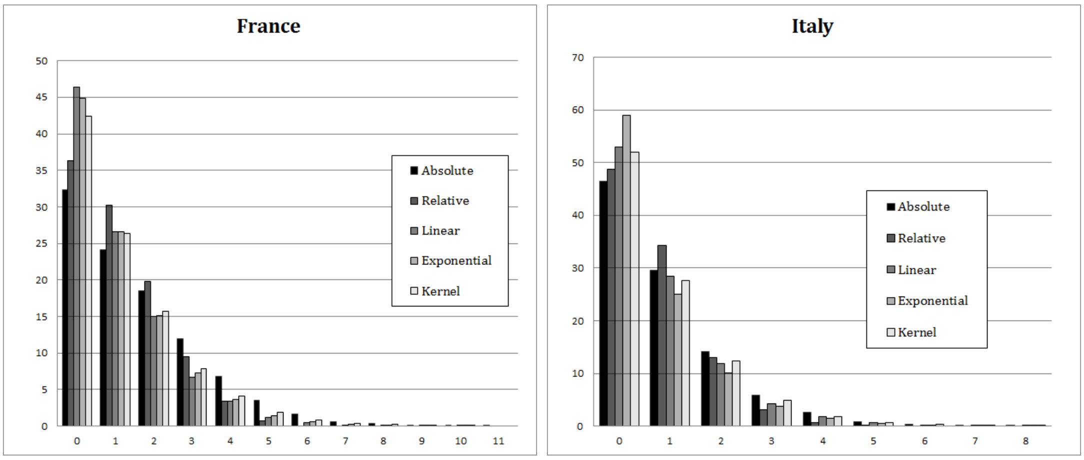
$$S_{i,t} = \begin{cases} 1 \text{ if } I_t/K_{i,t-1} > \alpha E[(I_{i,t}/K_{i,t-1})|K_{i,t-1}] \\ 0 \text{ otherwise} \end{cases}$$

It is important to note that contrary to the relative, linear and exponential rules, there is no need of a minimum threshold value to define the kernel spike dummy. Indeed, since the kernel fit is closest to the true distribution of the observations, the estimation is not as biased as the linear and exponential rules for large values of capital (see Figure 4). In what follows we will therefore refer to this spike measure as the *Kernel rule*.

We can now compare the performance of our five spike measures based on the four criteria defined by Nilsen et al. (2009) and presented at the beginning of this section. In order to do so, we use a few descriptive statistics, as shown in Tables 1 and 2, and we refer to the distribution of firms according to their number of spikes (Figure 5).

1. *The investment episode must be large relative to the investment history of the individual firm.* The results presented in Table 1 show that for all spike measures in the data, the mean investment rate conditional on the observation being a spike exceeds 0.40; while the mean value for the entire sample is 0.14 for France and 0.12 for Italy.

Figure 5: Distribution of firms per number of spikes, according to different rules (**Left**:France; **Right**: Italy). Frequencies on the vertical axis.



2. *The investment must constitute a rare event.* Figure 5 confirms this statement for all spike measures. It shows the number of spikes per firm by measure of spike. Across all measures we find that the number of spikes per firm is quite heterogeneous, with almost half of the firms having no spike in the period we are considering. The large majority of firms experiment either zero, one or two spikes, whatever measure is considered. On the contrary a few firms undergo a spike almost at each period.

3. *The spikes must account for a disproportionate share of total industry investments.* If the first two criteria were equally met by all spike measures, this third one allows to shed light on a certain heterogeneity across methodologies. As shown in Table 1, the gap between the share of observations and share of total investment accounted by spikes differs greatly. On that issue, the absolute and relative rules perform poorly compared to the linear, exponential and kernel ones. Indeed for the last three measures few observations account for a large share of investment. In particular, with the kernel rule, the spikes, representing about 13% of observations, account for more than 34% of total investment in France and for more than 41% in Italy.

4. *The spike measure has to be unbiased (the probability to have a spike does not depend on firm size).* Again this criteria allows us to select out the absolute and relative rules for having a size bias (small firms are overrepresented, as shown in Table 2). At the opposite, the kernel rule, for Italy, slightly overrepresents large firms. Still, the kernel

Table 2: Share of observations across size classes, comparing rules

Size class	**All sample**	Absolute	Relative	Linear	Exponential	Kernel
France						
Small	**17.51**	32.33	31.52	25.15	21.09	18.35
Medium	**67.78**	60.81	61.85	64.11	68.66	67.64
Large	**14.71**	6.86	6.63	10.73	10.25	14.01
Italy						
Small	**8.56**	13.5	13.77	11.05	10.48	6.20
Medium	**65.53**	69.2	68.90	68.24	68.00	65.00
Large	**25.09**	17.2	17.33	20.71	21.00	28.00

Note: Here we compare the share of observations in each size class for the French sample and for the observations considered as a spike according to each rule. "Small" stands for $lnK < 6$, "Medium" for $6 \geq lnK < 9$ and "Large" for $lnK \geq 9$.

rule performs best in replicating the true distribution of the sample for both countries.

The picture of investment patterns would not be complete without investigating the links between this micro-behavior and the business cycle. In Figure 6 we plot the frequency of highest and lowest ranks occurring in every year, and compare them with the evolution of the GDP growth rate in France and in Italy. Figure 6 shows that the growth rate of GDP is positively correlated with the frequency of investment spikes, and negatively correlated with the frequency of lowest values, in both countries.

Firms thus synchronize their investment decisions and react to aggregate shocks : they invest more frequently in the high part of the cycle than in the low part. This confirms similar observations by Gourio and Kashyap (2007) and by Doyle and Whited (2001).

4 Investment and firm performance

Our empirical investigation of the interrelation between investment spikes and firm performance will proceed in two steps. First we will identify the determinants of investment spikes, and compare our results across countries. In a second step we will turn to the effects of investment events on firm performance, as measured by firm size, firm growth, profitability, and productivity.

Figure 6: GDP growth rate and frequency of firm spikes in France (**Left**) and in Italy (**Right**)
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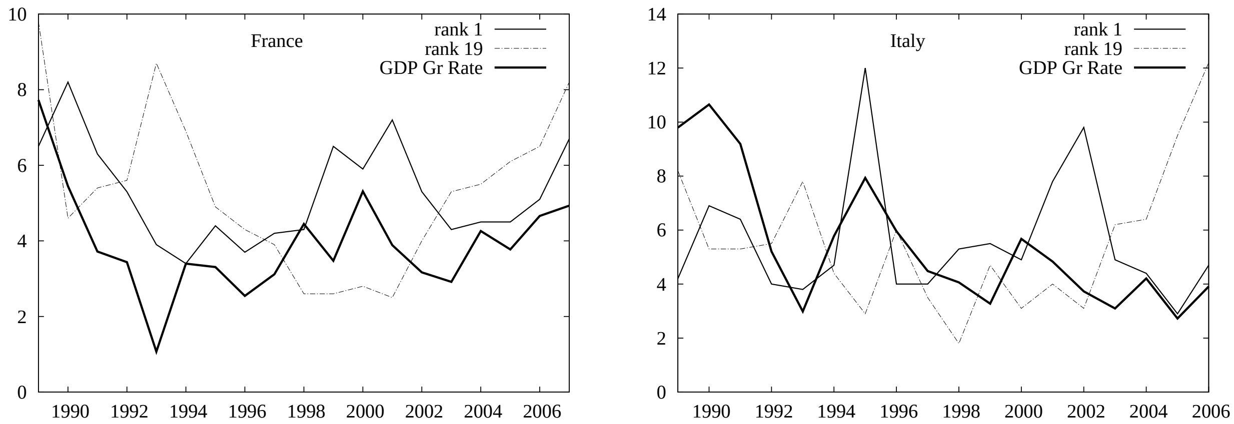

Note: As a reminder, *rank 1* is the highest investment episode by firm, *rank 19/16* is the lowest.

If previous studies on the subject have considered *jointly* the relation between firm performance variables before and after an investment spike (Sakellaris, 2004; Licandro et al., 2004; Nilsen et al., 2009), we run both analyses in separate models. The first step considers the effect of firm characteristics on the probability to observe a spike, and in a second step we study the effect of such spike, once it has been observed, on firm characteristics.

4.1 Determinants of the probability to have a spike

In order to choose the variables that potentially affect the investment decision at the firm level we follow previous findings on the issue using the level of investment (Smolny, 2003; Bigsten et al., 2005; Bokpin and Onumah, 2009) or investment spikes (Nilsen and Schiantarelli, 2003;Bigsten et al., 2005) as the dependent variable. We also compare our results to the ones of Sakellaris (2004) and Asphjell et al. (2010) which study the interrelation of investment with factor demand.

From these papers we draw that firm size, firm financial conditions and growth opportunities may be important in determining investment decisions. Sakellaris (2004) and Asphjell et al. (2010) find that employment and investment spikes are synchronized, although the former specifies that employment increases before an investment spike. The author interprets such result by the fact that firms adjust their more flexible factor (labour) before adjusting the fixed one (capital).

Another important feature of investment determinants is related to the dynamics of investment across periods. Investigating the shape of investment spikes hazard functions (defined as the probability of having a new spike as a function of time since the last spike), Cooper et al. (1999), Bigsten et al. (2005) and Whited (2006) present different findings. The first two analyses show a negative duration dependence (the likelihood of having a new spike decreases with the time since the last spike), but the latter one reveals increasing hazard functions. Finally, such duration effects were already uncovered by Caballero and Engel (1999) in their AR(2) model of investment.

4.1.1 Econometric method

The aim of our analysis is first to understand the conditions in which firms decide to invest. In order to do so we have to estimate the effect of firm characteristics on the probability that a firm invests (i.e an investment spike is observed).

We thus use a binary dependent variable $y_{i,t}$ that takes value 1 if there is a spike and 0 if not. The effect of the independent variables on the probability to observe a spike is determined using a random effects logistic regression[20]. For each firm i and period $t \in [1997; 2007]$:

$$y_{i,t} = \beta X_{i,t-1} + \gamma D_{i,t} + v_i + u_{i,t} \tag{4}$$

where $X_{i,t-1}$ is a vector of observed exogenous variables (firm characteristics such as corporate performance variables), $D_{i,t}$ is a vector of duration dummies (time since last spike[21]), and v_i is a firm-specific unobserved random-effect. β and γ are vectors of coefficients and $u_{i,t}$ is a serially uncorrelated logistic disturbance term. Time (year) and sectoral (2-digit) dummies are also included in the regressions. The vector of duration dummies is composed of three elements D_1, D_2 and D_3 which take value 1 if the last investment spike of firm i was observed respectively in period $t-1$, $t-2$ or $t-3$ and zero otherwise[22].

We run a series of regressions in which the dependent variable is defined with the kernel spike rule. We test several models with different firm performance variables. In order to limit endogeneity issues, we test how performance in the previous year ($t-1$) impacts the probability to have a spike today (year t). Firm performance variables include firm size, productivity in

[20]The fixed effect estimator is not much appropriate in our analysis given how dummies $D_{i,t}$ are constructed. Indeed these dummies capture the time since the last investment spike also controlling for other conditions that depend on the timing of the spike. As such taking averages of these firm level dummies is not much meaningful.

[21]See details in the appendix.

[22]This specification has also been used by Cooper et al. (1999) and Bigsten et al. (2005).

levels (log of labor productivity, Π_{t-1}) and return on sales, ROS_{t-1} in models 1, 2 and 3. As proxies for firm size we use the log of sales (TS_{t-1}), the log of the number of employees (N_{t-1}) for both countries and also the number of plants ($Plant_{t-1}$) for France[23]. Contrary to many specifications used in the literature (such as Whited, 1992 and Whited, 2006), we use profitability computed as the return on sales ratio rather than the cash flow ratio as a proxy for access to internal finance. In our sample, these two variables are extremely highly correlated (the Spearman's rho coefficient is 0.91). Models 4 to 6 also consider labor productivity growth (g^{Π}_{t-1}), sales growth (g^{TS}_{t-1}) and employment growth (g^{N}_{t-1}). Finally we use a dummy that takes value 1 if the firm had positive exports in year $t-1$ and zero otherwise. The influence of the macroeconomic environment is captured by our time and sectoral dummies. Indeed, as shown in Figure 6 and by several studies (Federer, 1993; Doms and Dunne, 1998; Chatelain et al., 2001; Gourio and Kashyap, 2007), investment decisions are largely determined by the business cycle due to changes in demand, in monetary policy and uncertainty over the cycle.

4.1.2 Results

The results are presented in Table 3.They are robust both with respect to different specifications of the econometric model and largely also across countries and sectors[24].We also comment below results at the Pavitt sectoral level in order to indicate whether results on the entire sample mirror similar patterns within sectors.

Estimates of model 1 suggest that higher sales in the past year have a positive effect on the probability of having a spike this year. The same is true for profitability: a higher profit rate in year $t-1$ increases the probability of having a spike in year t. Both results confirm that firms invest more when they are in good financial conditions.

Labor productivity exerts a different effect in the two countries: in Italy, higher productivity is related to a bigger chance of having an investment spike in the following year, whether in France the effect is negative. Results at the sectoral levels however indicate that such positive effect of labor productivity on the probability to have a spike is only signicant in the first sector (the Supplier Dominated sector). However the result on the French data is confirmed in three out of four sectors.

The results of the regressions also suggest that having had investment spikes in the previous

[23]Such information is not available for Italy.

[24]Results at the Pavitt sectoral level are discussed here but not shown.

years increases the probability of having a relevant event of investment. These patterns, which hold both for France and Italy, suggest that large investment projects are more likely to span over more than one fiscal year. Such “multi year spikes” are quite frequent in the data. Also notice that in both countries although the positive effects of spikes is always significant, its magnitude decreases over time: having had a spike three years ago is around one third as important in explaining today’s spike as compared to having had a spike in the past year. Such negative duration dependence is thus a confirmation of previous findings in other countries (Cooper et al., 1999; Bigsten et al., 2005), although our results only refer to the first years of the hazard function.

In model 2 we consider employment as proxy for firm size, rather than sales. Results confirm the previous findings and lend support to their robustness. The effect of labor productivity is again different in both countries, still positive in Italy but without any statistical significance in France. It is interesting to notice that at the sectoral level , we find a positive and significant effect of the past productivity level on the probability to have an investment spike in the supplier dominated sector, as in Italy.

For France (model 3) we use as further control for firm size the number of plants for each firm. The effect of firm size on the probability of having a spike is still positive whereas the effect of labor productivity becomes positive. This last result is also driven entirely by a positive relation in the supplier dominated sector. The relation is not significant in the other ones.

In models 4 to 6 we also include the first differences of sales, employment and productivity in the regressions. Coefficients of variables in levels do not change much, whether some interesting patterns emerge in the role of growth rates. A growth of sales in the previous year has a positive effect on the probability of realizing a large investment this year. It reflects for instance the need for the firms to expand their capacities as the sales are growing. Indeed, past sales growth can be interpreted as a proxy for growth opportunities. Moreover a positive effect of past sales growth lends support to the conjecture that internal finance is much relevant for the decision of investing at the firm level. When looking at results at the sectoral level, such finding is general to all sectors in France but limited to the scale intensive sector in Italy.

The trend in productivity, on the contrary, does not appear to influence that decision when we consider the entire sample. Still in the French science based sector we find a negative effect of past productivity growth on the probability to invest : firms that have recently gained in productivity do not need to invest.

Results on growth of employment, although only significant for France, are much interesting for the perspective they provide in terms of timing of the decision of hiring and investing : an increase in employment anticipates capital adjustment episodes, confirming the results by Sakellaris (2004). Finally, being an exporter generally doesn't affect the probability to have an investment spike. However, here the unsignificance of the export dummy for the entire sample hides diverging effects at the sectoral level in the French dataset. Indeed, the export dummy significantly and negatively impacts the probability to have a spike in the supplier dominated sector, but has a positive effect in the scale intensive sector.

Our analysis of the determinants of the probability to observe an investment spike reveals similarities across countries and sectors. After controlling for firm size, we find that growing and profitable firms have a higher profitability to invest, while productivity (in levels as well as in growth rates) has almost no impact. Finally, the hazard function seems to be decreasing in the first three years.

Table 3: Determinants of investment spikes, Kernel rule

	France						Italy			
	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)	model (1)	model (2)	model (4)	model (5)
TS_{t-1}	0.015***	-	-	0.014***	-	-	0.012***	-	0.012***	-
	(0.0009)			(0.0009)			(0.0026)		(0.003)	
N_{t-1}	-	0.011***	-	-	0.010***	-	-	0.0127***	-	0.013***
		(0.001)			(0.0010)			(0.003)		(0.002)
$Plant_{t-1}$	-	-	0.014***	-	-	0.016***	-		-	-
			(0.0022)			(0.0021)				
ROS_{t-1}	0.262***	0.238***	0.228***	0.243***	0.223***	0.204***	0.183***	0.129***	0.183***	0.130***
	(0.0110)	(0.0112)	(0.0121)	(0.0112)	(0.0114)	(0.0123)	(0.044)	(0.042)	(0.045)	(0.043)
Π_{t-1}	-0.012***	0.002	0.006***	-0.011***	0.002	0.008***	0.016*	0.033***	-0.012	0.029**
	(0.0015)	(0.0016)	(0.0021)	(0.0015)	(0.0016)	(0.0021)	(0.009)	(0.008)	(0.010)	(0.008)
g^{Π}_{t-1}	-	-	-	0.002	-0.003	-0.004	-	-	0.006	0,001
				(0.0041)	(0.0042)	(0.0042)			(0.013)	(0.013)
g^{TS}_{t-1}	-	-	-	0.017***	0.023***	0.025***	-	-	0.038**	0.042**
				(0.0046)	(0.0047)	(0.0047)			(0.017)	(0.017)
g^{N}_{t-1}	-	-	-	0.078***	0.075***	0.078***	-	-	0,019	0,016
				(0.0069)	(0.0069)	(0.0069)			(0.023)	(0.023)
$Export_{t-1}$	-	-	-	-0.002	0.001	0.004*	-	-	0,007	0.008
				(0.0021)	(0.002)	(0.0020)			(0.011)	(0.011)
D_1	0.160***	0.164***	0.164***	0.156***	0.158***	0.158***	0.131***	0.132***	0.126***	0.128***
	(0.0057)	(0.0057)	(0.0057)	(0.0056)	(0.0056)	(0.0056)	(0.013)	(0.0134)	(0.013)	(0.013)
D_2	0.062***	0.064***	0.064***	0.061***	0.063***	0.063***	0.078***	0.078***	0.077***	0.077***
	(0.0042)	(0.0043)	(0.0043)	(0.0042)	(0.0042)	(0.0042)	(0.012)	(0.0118)	(0.012)	(0.012)
D_3	0.049***	0.051***	0.051***	0.050***	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.012)	(0.0117)	(0.012)	(0.012)
Obs	122381	122381	122381	122158	122158	122158	15877	15877	15746	15746
Log likelihood	-41718.014	-41807.898	-41851.711	-41478.772	-41555.185	-41577.103	-6414.0397	-6415.27	-6357.1407	-6357.9548

4.2 Effects of investment spikes on firm performance

W now turn to the second part of our analysis which focuses on the effects of investment spikes on firm performance. Firms invest for a reason: they want to improve their performance in some way, but we may wonder whether we really observe a significant increase in firm performance in the years after an investment spike. Moreover, it is important for firms to assess the time-span between the moment at which the investment is carried out and its effect on performance. Such time-lag might as well differ across performance variables and investment project types. Indeed, an investment in capacity such as the purchase of an extra piece of machinery which technology is already used by the firm might be more easily and fastly integrated than an investment in a new technology or the setting up of a new plant. This latter type of investment may require a learning period and/or the reorganization of some production units which are both costly in the short run.

Several papers have investigated the link between investment and productivity (and productivity growth) starting from the seminal work of Power (1998) (Bessen, 1999; Huggett and Ospina, 2001; Sakellaris, 2004; Licandro et al., 2004; Nilsen et al., 2009 and Shima, 2010). More particularly, Power (1998), Huggett and Ospina (2001) find that productivity decreases after an investment, and that most of the growth rate coefficients are not even significant. Still, Bessen (1999) finds that in new plants, labour productivity increases with time, which he attributes to a learning-by-doing process. Power also finds a positive correlation between labour productivity and plant age, and concludes that "selection and learning could be important determinants of the pattern of productivity across plants" (Power, 1998, p. 311). However, she doesn't find such relation with investment age. Shima (2010) also reports a negative relation between technical efficiency and machinery age. Nilsen et al. (2009) find an increase in productivity levels during the investment (from date $t-1$ to t) but such effect disappears after the investment. However their analysis also reveals that the group of firms having at least one investment spike in the period shows significantly higher level of productivity than the group with no investment spike. Licandro et al. (2004) have also studied how productivity changes before and after a spike. Going further, they are able to isolate expansionary investment episodes from replacement ones: expansionary firms are the ones declaring to increase their number of plants in the period. We will also consider the change in the number of plants as a signal for expansion investment. However we will focus on the *event* of the setting of a new plant rather than using such information to classify the firm as expansionary for the entire period. Licandro et al. (2004) find that productivity increases during the spike, and drops after. They also find some positive effects after three years but the significance level is low.

As for the link between productivity growth and investment spikes, the interrelation between the adjustment episodes and other firm variables has to be differentiated across time. In order to properly account for such dynamics, Sakellaris (2004) has introduced a methodology that enables to analyze the relation between an *event* and firm characteristics before and after such event. Therefore he is able to account for the *relative* importance of the variables of interest (firm growth, productivity and the like) around the investment spike. This methodology has been later adapted by Nilsen et al. (2009) on Norwegian data and Asphjell et al. (2010) on Dutch data in their studies on the interrelation between investment spike episodes and the evolution of labour productivity (Nilsen et al., 2009) or employment (Asphjell et al., 2010).

Besides the effect on productivity, Licandro et al. (2004) also consider the effect on sales which is positive for expansionary firms but unsignificant for innovative firms. Finally, Sakellaris (2004) and Nilsen et al. (2009) take a broader perspective in assessing the evolution of a group of firm factors of production before and after an investment spike. This allows them to present a comprehensive story of how firms adjust their different factors of production around an investment spike. Still, we depart from these papers by separating the conditions in which firms invest from the effects of such investment events, and by focusing on performance variables rather than production factors.

4.2.1 Econometric method

We investigate the impact of investment spikes on seven performance variables : the profitability rate (ROS_t), total sales in levels[25] (TS_t) and growth rates (g_t^{TS}), the number of employees in levels (N_t) and growth rates (g_t^N) and of course labour productivity in levels (Π_t) and growth rates (g_t^{Π}). We regress each performance variable on a group of spike dummy variables using a random effects model. For each of the seven regressions, taking $X_{i,t}$ as one of our variables of interest:

$$X_{i,t} = \beta D_{i,t} + \gamma_1 D_{before,i,t} + \gamma_2 D_{least,i} + v_i + \epsilon_{i,t} \tag{5}$$

[25] As before, all variables in levels are taken in logs.

where $D_{i,t}$ is a vector of duration dummies (time since last spike, using the Kernel rule): it is composed of three elements D_0, D_1 and D_2 which take value 1 if the last investment spike of firm i was observed respectively in period t, $t-1$ or $t-2$, and zero otherwise. D_{before} is a dummy that takes value 1 if the last investment spike was observed more than 2 years before t and zero otherwise. Thus the coefficient γ_1 reveals the effect of investment spikes on firm performance in the long run. The dummy D_{least} takes value 1 in all firm-year observations of firms having at least one investment spike in the period and zero otherwise. Thus if the coefficient γ_2 is positive it reveals that firms with at least one investment episode are relatively more performant than the group of firms with no investment episode. The use of a random effects model allows to preserve this last variable. Finally, v_i is a firm-specific unobserved random-effect, β is a vector of coefficients and $\epsilon_{i,t}$ is the error term. Time (year) and sectoral (2-digit) dummies are also included in the regressions.

We also expand our model in order to isolate strictly expansionary investment events from non-expansionary ones. Using the plant data available in the French database, we construct a dummy $\delta Plant_{i,t}$ which takes value 1 if the firm has increased its number of plants between $t-1$ and t, and zero otherwise. If in the same year the firm also has an investment spike episode (meaning the dummy D_0 takes value 1), then we can identify such investment spike as an *expansionary* investment event. Moreover, it allows us to study the effect of investing to set up a new plant on firm performance. Thus we add to the existing model a set of interacted dummies $D_{i,t} * \delta Plant_{i,t}$ for $t = 0, 1, 2$ which account for such an expansionary episode in years t, $t-1$ or $t-2$:

$$X_{i,t} = \beta D_{i,t} + \lambda D_{i,t} * \delta Plant_{i,t} + \gamma_1 D_{before,i,t} + \gamma_2 D_{least,i} + v_i + \epsilon_{i,t} \tag{6}$$

where the vector of coefficients λ indicates the effect in year t of the setting of a new plant in years t, $t-1$ or $t-2$.

4.2.2 Results

The results are presented in Tables 4 to 7. In model 7 we show the effect of past investment spikes on firm performance in France and in Italy. In model 8, we analyze the combined effect of having a spike and an increase in the number of plants on French firms' performance [26].

[26] We recall that the plant data is not available in the Italian dataset.

Our analysis of the effect of investment spikes on firm performance variables show significant differences between both countries. We observe a stronger effect of investment episodes on French firms' performance than Italian ones. Moreover, controlling for investment spikes being linked to an increase in the number of plants (thus specifying the type of investment carried out) reveals to be very important in our analysis. We also performed our analysis at the Pavitt sectoral level and comment on the additional information we gain from a more disaggregated perspective.[27]

Profitability

We have shown in the first part of our analysis that firms tend to invest when their financial conditions, as proxied by the profitability rate, are relatively good. The positive and significant coefficient of the variable D_{least} (in Table 4) tells us that firms having had at least an investment episode in the period are relatively more profitable than non-investing firms in the French sample. However, in the Italian sample we cannot find any significant difference in profitability between the investing and non investing groups. Still, when we consider a more disaggregated level of analysis, we find that investing firms in the Italian supplier dominated sector are more profitable than non-investing ones, while investing firms in the specialized suppliers sector are relatively less profitable.

When we consider the dynamic effect of investment spikes on profitability, we only see an increase in profitability in the same year of the spike event in France, and no significant effect after, or at all in Italy. Thus it would seem that profitability is an important determinant of the investment decision but the expenses associated with the purchase of new capital have no effect after the spike. Taking the analysis to the sectoral level we actually find that profitability significantly changes after an investment spike in two out of four sectors, that is the supplier dominated and specialized suppliers sectors, in both countries. The coefficients are significant and positive in the short and even in the long run in both sectors in France and in the latter sector in Italy. Only in the Italian supplier dominated sector (comprising for example Textiles) we find a lasting negative effect of investment spikes on profitability.

In model 8 we control for the fact that some of the investment spikes coincide with an increase in the number of plants in the firm. Firms establishing a new plant incur a negative shock on their profitability rate. More specifically, it is a short term shock in the supplier

[27]Tables of results at the Pavitt sectoral level are not shown here.

dominated group and a middle term shock in the scale intensive one[28]. Still, net of such effect we find that having had a spike in $t-1$ or in $t-2$ significantly increases firms' profitability in the supplier dominated and special suppliers sectors.

Table 4: Effects of investment spikes, Kernel rule (1)

	Profitability		
	France		**Italy**
	model (7)	model (8)	model (7)
D_0	0.011**	0.009***	0,022
	(0.0049)	(0.0026)	(0.102)
D_0*δ Plant	-	-0.006	-
		(0.0043)	
D_1	0.007	0.008***	0.020
	(0.0049)	(0.0026)	(0.103)
D_1*δ Plant	-	-0.016***	
		(0.0055)	
D_2	-0.000	0.005*	0,0143
	(0.0049)	(0.0027)	(0.104)
D_2*δ Plant	-	-0.010	-
		(0.0059)	
D_{before}	0.003	0.001	0.015
	(0.0044)	(0.0023)	(0.102)
D_{least}	0.014**	0.018***	0,032
	(0.0062)	(0.0034)	(0.103)
Obs	132990	113565	21766
R^2	0.0039	0.0112	0,0016

Productivity and productivity growth

Turning to the effect of investment spikes on productivity (in levels), a slightly different picture emerges for both countries. For firms in Italy an investment spike in year t, $t-1$, $t-2$ or before has a positive effect on the level productivity. Further, after controlling for having had a spike in the previous years there is no residual significant difference between firms having invested in the period and firms that haven't (the dummy variable D_{least} doesn't have a significant effect on productivity). What one observes in France is rather different. Model 7 shows that there is significant difference between investing and non investing firms (the coefficient of D_{least} is significant and positive), but no positive effect of past spikes on firms' productivity. In addition, the contemporaneous relation between an investment spike and productivity is

[28] In this latter group, net of such shock there is no effect of the spike on profitability, however investing firms are relatively more profitable than non investing ones. Thus profitability rather plays a selection role.

negative.

Again, taking the analysis to the sectoral level, as well as adding information about increases in the number of plants gives a more precise picture of the effect of investment spikes on performance. Indeed French firms in the special suppliers sector incur a negative impact on their productivity level in the years after a spike, while French science based firms gain in productivity after a two-year lag. By controlling for expansionary investment episodes we confirm the positive two-year lag effect in the science based sector and a robust negative effect in the special suppliers sector. In addition, we reveal a short and long term positive effect in the supplier dominated sector. Indeed, the negative coefficient on D_0 was actually due to mispecification: it is only when the investment episodes are coupled with the setting of a new plant that we observe a negative effect on productivity.

When we consider productivity growth as the dependent variable we do not detect any effect of investment spikes for Italian firms, contrary to what we find for France. Among the reasons that might explain the lack of this effect for Italy is the pervasive stagnation of the economy during the period, that one might observe both at the aggregate (OECD, 2008) and, although to a lesser extent, also at the firm level (Dosi et al., forthcoming). In addition, the low variability of the dependent variable makes it more difficult to clearly identify factors that contributed to productivity growth over the last twenty years. Only in the science based sector we find a dynamic as well as differentiating effect of investment spikes on productivity growth. In this group, recent investment episodes are related to a relatively lower growth of productivity while having invested at all in the period selects firms with a higher productivity growth.

The results on French firms instead helps to learn more on the dynamics of productivity growth after an investment episode. Model 7 shows a negative contemporaneous effect of spikes, and a positive effect of having had one in $t-1$. This would suggest that spikes represent a negative shock on productivity growth at first. The gains associated to investing become apparent only once the firm is able to integrate the new capital into its routines of production, but such gains vanish after a year. In model 8 such dynamics is confirmed by the differentiated effect of investing and setting up a new plant (which is negative in the short run, then becomes positive) and investing in new machines (which is positive in the short run). Such results, common to all sectors, suggest that firms are able to integrate new capital relatively shortly (within one year) and fully (there is no long term effect) into their production line. However, setting up a new plant requires a longer process which is costly in the short run (thus the negative effect at time t), and whose gains can be observed partially after one year and fully only in the second year after the investment event.

Table 5: Effects of investment spikes, Kernel rule (1)

	Productivity			**Productivity Growth**		
	France		**Italy**	**France**		**Italy**
	model (7)	model (8)	model (7)	model (7)	model (8)	model (7)
D_0	-0.013**	0.021***	0.075***	-0.020***	0.019***	-0.002
	(0.0063)	(0.0064)	(0.024)	(0.0055)	(0.0058)	(0.023)
D_0*δ Plant	-	-0.384***	-	-	-0.514***	-
		(0.0103)			(0.0099)	
D_1	-0.007	0.013**	0.063***	0.011**	0.001	0,007
	(0.0064)	(0.0065)	-0,024	(0.0058)	(0.0056)	(0.023)
D_1*δ Plant	-	-0.214***	-	-	0.198***	-
		(0.0133)			(0.0129)	
D_2	-0.004	0.007	0.052**	0.009	0.003	-0.006
	(0.0063)	(0.0064)	(0.024)	(0.0058)	(0.0060)	(0.024)
D_2*δ Plant	-	-0.138***	-	-	0.088***	-
		(0.0143)			(0.0140)	
D_{before}	-0.001	0.004	0.052**	0.004	0.005	-0.004
	(0.0057)	(0.0056)	(0.023)	(0.0053)	(0.0053)	(0.023)
D_{least}	0.084***	0.083***	-0.010	0.000	0.002	0.002
	(0.0101)	(0.0101)	(0.026)	(0.0052)	(0.0053)	(0.022)
Obs	132351	113051	21947	132072	112833	21736
R^2	0.0580	0.0728	0,101	0.0038	0.0303	0.0057

Sales and sales growth

The effect of investment spikes on sales is similar in both countries and is coherent with an expansion of sales as a consequence to an expansion in firms' production capacity. Firms that have invested at least once in the period have relatively higher sales, and investment episodes have a positive effect on the amount sold by the firm up to two years after the event. It is common to all sectors in France but limited to the scale intensive and specialized suppliers in Italy. This evidence appears to be quite robust as it continues to hold when we control for increases in number of plants in model 8. These latter events affect sales negatively for several years, although we might have expected an even stronger positive effect in that case (the addition of new plants belonging to an expansionary strategy).

When considering first differences of sales, they appear not be affected in the same way by investment spikes in Italy and in France. In Italy investing in t increases sales growth in the same year but not at a higher lag level. In France investment spikes incur instead a pervasive increase in sales growth and firms having invested at least once in the period enjoy a higher sales growth than their counterparts. Still, the coefficients decrease with time from last spike. However model 8 shows that such relative longer term effect mostly concerns firms incurring a change in their number of plants, for which the contemporaneous effect is negative and gains in sales growth are observed after one year. Thus the expansionary episodes we have defined (having an investment spike *and* increasing the number of plants) are indeed related to an increase in sales growth. Net of such effect, we only observe a contemporaneous increase of sales growth as a consequence to an investment spike.

Table 6: Effects of investment spikes, Kernel rule (2)

	Sales			**Sales Growth**		
	France		**Italy**	**France**		**Italy**
	model (7)	model (8)	model (7)	model (7)	model (8)	model (7)
D_0	0.050***	0.083***	0.061***	0.043***	0.076***	0.036**
	(0.0058)	(0.0059)	(0.021)	(0.0047)	(0.0048)	(0.018)
D_0*δ Plant	-	-0.336***	-	-	-0.485***	-
		(0.0097)			(0.0084)	
D_1	0.052***	0.067***	0.039*	0.018***	0.004	0,014
	(0.0059)	(0.0060)	(0.021)	(0.049)	(0.0050)	(0.018)
D_1*δ Plant	-	-0.142***	-	-	0.209***	-
		(0.0124)			(0.0109)	
D_2	0.043***	0.053***	0.038*	0.008*	0.001	0,019
	(0.0059)	(0.0060)	(0.021)	(0.0050)	(0.0051)	(0.018)
D_2*δ Plant	-	-0.090***	-	-	0.083***	-
		(0.0132)			(0.0119)	
D_{before}	0.039***	0.037***	0,03	0.000	0.002	0.009
	(0.0053)	(0.0052)	(0.021)	(0.0045)	(0.0045)	(0.018)
D_{least}	0.254***	0.265***	0.375***	0.013***	0.014***	0,0001
	(0.0147)	(0.0149)	(0.035)	(0.0044)	(0.0045)	(0.018)
Obs	132944	113530	22204	132933	113520	22122
R^2	0.1417	0.1421	0,029	0.0178	0.0491	0.0137

Number of employees and growth of number of employees

Our results mirror the findings of Asphjell et al. (2010) on the interrelation of investment and employment spikes. Indeed, in section 4.1 we have shown that firms invest after an increase in employment growth. Table 7 adds that employment also increases after an investment spike. Any investment event demands the hiring of additional employees, and it is even more so the case when the firm opens a new plant (in the case of the supplier dominated sector). Investing firms are relatively bigger in terms of their number of employees, in France, as well as in Italy, though no dynamic effect is noted in the latter case.

The effect of investment spikes on employment growth is common in France and Italy : it is positive but vanishes in the second year after the event. Italian firms in the special suppliers and science based sectors do not seem to benefit from such an effect. In France, there is even a statistically higher employment growth rate in firms investing relative to others, and results are robust when we control for an increase in the number of plants.

Table 7: Effects of investment spikes, Kernel rule (3)

	Employees			**Employees Growth**		
	France		**Italy**	**France**		**Italy**
D_0	0.045***	0.044***	0,013	0.049***	0.040***	0.041***
	(0.0038)	(0.0037)	(0.014)	(0.0028)	(0.0030)	(0.010)
D_0*δ Plant	-	0.016***	-	-	0.024***	-
		(0.0061)			(0.0049)	
D_1	0.049***	0.047***	0,011	0.015***	0.010***	0.025**
	(0.0038)	(0.0037)	(0.014)	(0.0029)	(0.0031)	(0.0029)
D_1*δ Plant	-	0.023***	-	-	0.005	-
		(0.0078)			(0.0065)	
D_2	0.040***	0.038***	0,006	0.000	-0.002	0.017*
	(0.0038)	(0.0037)	(0.014)	(0.0029)	(0.0031)	(0.010)
D_2*δ Plant	-	0.012	-	-	0.006	-
		(0.0083)			(0.0070)	
D_{before}	0.034***	0.028***	-0.003	-0.003	-0.004	0,01
	(0.0034)	(0.0032)	(0.014)	(0.0026)	(0.0026)	(0.010)
D_{least}	0.125***	0.134***	0.361***	0.013***	0.015***	-0.011
	(0.0128)	(0.0127)	(0.025)	(0.0021)	(0.0028)	(0.010)
Obs	132956	113538	22988	132934	113520	22988
R^2	0.0611	0.0610	0.054	0.0289	0.0264	0.010

5 Final remarks

This study has investigated investment patterns at the firm level in the French and Italian manufacturing industries. We have confirmed previous studies in showing that investment is lumpy at the firm level and compared different rules to define investment spikes. We have presented a new methodology that adresses the size bias present in the literature and used such measures to evaluate the dynamic link between spike events and firm performance.

Our study of the dynamic interrelation of investment spikes and firm performance leads us to conclude on robust and common results on the determinants of investment in France and Italy, but significant differences between countries as well as sectors with regards to the effects of investment spikes. Controlling for expansionary events (i.e. investing to set up new plants) adds value to our analysis. We show that those episodes are relatively more costly to the firm than other types of investments. Moreover, we observe significant differences between investing and non investing firms. The former are more profitable, bigger, and grow faster than the latter group of firms.

Investigating the dynamic relation between investment spikes and firm performance variables helps to disentangle the short term shocks from the longer term effects. Investment is first costly in terms of productivity but gains in sales are permanent. Finally, we confirm the result by Asphjell et al. (2010) and Sakellaris (2004) on the interrelation of investment and employment episodes.

In our investigation of the determinants of investment spikes we have shown that more performant firms have a higher probability to invest and that firms tend to cluster their investment episodes over time. Finally we have addressed the effect of such spikes on firm perfomance in the short and in the long term. Firms use their investments to increase their sales and their number of employees, but incur a short term productivity shock. We have enriched the existing literature on the subject by showing that in our sample productivity growth increases later on, as suggested by the "learning curve" hypothesis. The disruptive negative effect can be partly explained by the difficulty to set up new plants: as put forward by Winter and Szulanski (2001), replication is costly and finding similar levels of performance after such event takes times.

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Table 8: Variables definition

$Invrate$	Investment rate	I_t/K_{t-1}
$Empl$	Number of employees (log)	$log(N_t)$
$Gr.Empl$	Growth of employment	$g_t^N = log(N_t) - log(N_{t-1})$
$Prod$	Labour productivity (log)	$log(\Pi_t) = log(VA_t/N_t)$
$Gr.Prod$	Growth of labour productivity	$g_t^{\Pi} = log(\Pi_t) - log(\Pi_{t-1})$
$Sales$	Total Sales (log)	TS_t
$Gr.Sales$	Growth of total sales	$g_t^{TS} = log(TS_t) - log(TS_{t-1})$
$Profit$	Profitability rate	$P_t = GOM_t/TS_t$
$Cash$	Cash Flow ratio	CF_t/TS_t
$Plant$	Number of plants	
$Export$	Export dummy	=1 if Exports>0
D_t	Spike dummy	=1 if last spike in time t
D_{t-1}	Spike dummy	=1 if last spike in time t-1
D_{t-2}	Spike dummy	=1 if last spike in time t-2
D_{before}	Spike dummy	=1 if last spike before time t-2
D_{least}	Spike dummy	=1 if at least 1 spike in the period
$\delta Plant$	Expansion investment dummy	=1 if increase in nb of plants since previous year